Kaunas University of Technology
School of Economics and Business

Generative Artificial Intelligence for Enhancing Problem-Solving Capabilities of Non-Technical Roles

Master's Final Degree Project

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Kaunas, 2025

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Innovation Management and Entrepreneurship
(6211LX031)

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Rahouli, Sara. Generative Artificial Intelligence for Enhancing Problem-Solving Capabilities of Non-Technical Roles. Master's Final Degree Project / supervisor Assoc. Prof. Dr. Inga Stankevičė; School of Economics and Business, Kaunas University of Technology.

Study field and area (study field group): Management, Business and Public Management.

Keywords: Generative artificial intelligence (genAI), problem-solving capabilities, non-technical roles, technology acceptance, technology adoption, explanatory sequential mixed method.

Kaunas, 2025. 76 pages.

Summary

Generative Artificial Intelligence (GenAI) is transforming workplaces by shifting how organizations approach data analysis, insight generation, and problem-solving. While extensively adopted in technical fields such as software engineering and data science, its integration into non-technical roles remains underexplored. This research specifically investigates both the *perceptions* of non-technical employees regarding GenAI and the *measurable effects* of its use on their problem-solving capabilities in data-related workplace activities.

The **object of this research** is the application of Generative Artificial Intelligence in supporting problem-solving processes among non-technical employees engaged in data-centric tasks.

The **aim of the research** is to reveal how employees in non-technical roles perceive and apply generative AI tools to enhance their problem-solving capabilities while taking into consideration the organizational and contextual factors that support or prevent their effective use.

An explanatory sequential mixed-methods approach was implemented, comprising a quantitative survey of 32 respondents, behavioral experiments involving 8 participants, and semi-structured interviews with 5 managerial representatives at a German manufacturing company. This methodological design enabled triangulation of findings across perceptual, behavioral, and contextual dimensions, strengthening the validity of the results despite the exploratory case-study scope.

The **main findings** reveal significant barriers to effective genAI integration, including fragmented data systems, reliance on IT support for data access, cognitive overload resulting from complex AI outputs, and insufficient training in critical evaluation skills. Although survey responses indicated increased confidence and perceived efficiency when using genAI, particularly in creative, unstructured tasks, behavioral experiments demonstrated no measurable improvement in independent data reasoning or adaptive decision-making. These outcomes were assessed through task-based problem-solving exercises comparing performance with and without genAI assistance, revealing a clear perception-performance gap and highlighting the risk of over-reliance on AI-generated outputs.

The study contributes to theoretical understanding by refining the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI) theory. Contrary to TAM expectations, perceived ease of use was not a significant factor influencing adoption; instead, compatibility with existing workflows and trust in GenAI outputs emerged as critical determinants. This deviation is likely due to participants' relatively high levels of digital familiarity, where functional value and contextual relevance outweighed usability concerns. Additionally, applying a Systems Thinking perspective demonstrated

that task complexity moderates the perceived benefits of GenAI, with greater value observed in exploratory problem-solving rather than structured analytical activities.

Based on these findings, several practical recommendations are proposed. Organizations should integrate genAI tools directly into established workflows to improve contextual relevance and functionality. Leadership must actively demonstrate responsible genAI use by participating in data-driven decision-making processes and communicating clear ethical guidelines. Training programs should extend beyond technical onboarding to include structured critical thinking development, enabling employees to assess AI outputs rigorously. Furthermore, increasing genAI access to relevant organizational data is essential for improving the contextual accuracy of outputs, thereby strengthening user trust and supporting effective application in problem-solving contexts.

In conclusion, this research advances the understanding of genAI adoption within non-technical roles, demonstrating that while GenAI tools enhance perceived problem-solving confidence, they do not inherently develop independent reasoning capabilities. Effective capability development requires not only thoughtful technological integration, but also targeted interventions aimed at strengthening critical thinking skills and improving access to high-quality organizational data. Given the exploratory case-study design and limited sample size, these findings should be interpreted within the context of the studied organization, with caution in generalizing to broader industry settings.

Rahouli, Sara. Generatyvinis dirbtinis intelektas problemų sprendimo gebėjimų stiprinimui netechninėse pareigos. Magistro baigiamasis projektas / vadovė doc. dr. Inga Stankevičė; Kauno technologijos universitetas, Ekonomikos ir verslo fakultetas.

Studijų kryptis ir sritis (studijų krypčių grupė): Vadyba, Verslas ir viešoji vadyba.

Reikšminiai žodžiai: generatyvinis dirbtinis intelektas (GenAI), problemų sprendimo gebėjimai, netechniniai vaidmenys, technologijų priėmimas, technologijų diegimas, aiškinamasis nuoseklus mišrių metodų tyrimas.

Kaunas, 2025. 76 p.

Santrauka

Generatyvinis dirbtinis intelektas (GenAI) transformuoja darbo aplinkas, keisdamas organizacijų požiūrį į duomenų analizę, įžvalgų generavimą ir problemų sprendimą. Nors šios technologijos plačiai taikomos techninėse srityse, tokiose kaip programinės įrangos inžinerija ir duomenų mokslas, jų integracija į netechninius vaidmenis išlieka menkai ištirta. Šiame tyrime nagrinėjamos netechninių darbuotojų nuostatos apie GenAI bei kiekybiškai vertinamas šios technologijos poveikis jų problemų sprendimo gebėjimams, susijusiems su duomenimis pagrįsta veikla darbo aplinkoje.

Tyrimo objektas: generatyvinio dirbtinio intelekto taikymas problemų sprendimo procesuose tarp netechninių darbuotojų, dirbančių su duomenimis susijusiose užduotyse.

Tyrimo tikslas: atskleisti, kaip netechninių vaidmenų darbuotojai suvokia ir taiko generatyvinio dirbtinio intelekto įrankius, siekdami pagerinti savo problemų sprendimo gebėjimus, atsižvelgiant į organizacinius ir kontekstinius veiksnius, kurie skatina arba riboja šių įrankių veiksmingą naudojimą.

Buvo taikytas aiškinamasis nuoseklus mišrių metodų tyrimo dizainas, apimantis kiekybinę apklausą, kurioje dalyvavo 32 respondentai, elgsenos eksperimentus su 8 dalyviais ir pusiau struktūruotus interviu su 5 vadovaujančias pareigas užimančiais atstovais Vokietijos gamybos įmonėje. Tokia metodologinė prieiga leido trianguliuoti rezultatus suvokimo, elgsenos ir kontekstiniais aspektais, sustiprinant tyrimo rezultatų pagrįstumą niveliuojant tyrimo kaip atvejo analizės pobūdžį.

Pagrindiniai tyrimo rezultatai atskleidė reikšmingas kliūtis efektyviai GenAI integracijai, įskaitant fragmentuotą duomenų infrastruktūrą, priklausomybę nuo IT pagalbos siekiant prieigos prie duomenų, kognityvinę perkrovą dėl sudėtingų dirbtinio intelekto rezultatų ir nepakankamą darbuotojų pasirengimą kritiškai vertinti šiuos rezultatus. Nors apklausos duomenys parodė didesnį pasitikėjimą savimi ir suvokiamą darbo efektyvumą naudojant GenAI, ypač kūrybinėse ir neapibrėžtose užduotyse, elgsenos eksperimentai neparodė jokio išmatuojamo pagerėjimo savarankiškame duomenų interpretavime ar adaptyviame sprendimų priėmime. Tai buvo vertinama taikant užduotimis grįstus problemų sprendimo testus, lyginant dalyvių veiklą su GenAI pagalba ir be jos, o rezultatai atskleidė akivaizdų suvokimo ir realaus veikimo skirtumą bei pabrėžė per didelės priklausomybės nuo dirbtinio intelekto riziką.

Tyrimas prisideda prie teorinio pagrindo plėtojimo, papildant technologijų priėmimo modelį (TAM) ir inovacijų sklaidos teoriją (DOI). Priešingai nei numato TAM modelis, suvokiamas naudojimo paprastumas nebuvo reikšmingas veiksnys priimant sprendimus; vietoje to, esamų darbo procesų

suderinamumas ir pasitikėjimas GenAI rezultatais tapo esminiais veiksniais. Tokį nukrypimą, tikėtina, lėmė dalyvių pakankamai aukštas skaitmeninių įgūdžių lygis, kai funkcionalumo vertė ir kontekstinis aktualumas nusvėrė naudojimo patogumo aspektą. Be to, taikant sisteminio mąstymo (Systems Thinking) perspektyvą, nustatyta, kad užduočių sudėtingumas moderuoja suvokiamą GenAI naudą; didesnė nauda fiksuota sprendžiant kūrybines, tyrimo pobūdžio užduotis, o ne struktūruotas analitines veiklas.

Remiantis šiais rezultatais, pateikiamos kelios praktinės rekomendacijos. Organizacijos turėtų tiesiogiai integruoti GenAI įrankius į esamus darbo procesus, siekiant pagerinti jų kontekstinį aktualumą ir funkcionalumą. Lyderiai turėtų aktyviai demonstruoti atsakingą GenAI naudojimą, dalyvaudami duomenimis grįstuose sprendimų priėmimo procesuose ir aiškiai komunikuodami etines naudojimo gaires. Mokymų programos turėtų apimti ne tik techninį įrankių naudojimą, bet ir struktūruotą kritinio mąstymo ugdymą, suteikiant darbuotojams gebėjimą kritiškai vertinti GenAI pateikiamus rezultatus. Be to, svarbu išplėsti GenAI prieigą prie aktualių organizacinių duomenų, kad būtų pagerinta rezultatų kontekstinis tikslumas, stiprinamas vartotojų pasitikėjimas ir skatinamas efektyvesnis taikymas problemų sprendimo kontekste.

Apibendrinant, šis tyrimas praplečia GenAI diegimo netechniniuose vaidmenyse supratimą, parodant, kad nors GenAI įrankiai didina suvokiamą pasitikėjimą problemų sprendimu, jie savaime neskatina savarankiško mąstymo gebėjimų vystymo. Norint veiksmingai stiprinti šiuos gebėjimus, būtina ne tik apgalvota technologijų integracija, bet ir tikslingos intervencijos, orientuotos į kritinio mąstymo ugdymą bei prieigos prie aukštos kokybės organizacinių duomenų gerinimą. Atsižvelgiant į tyrimo kaip atvejo analizės pobūdį ir ribotą imties dydį, šiuos rezultatus reikėtų vertinti konkrečios organizacijos kontekste, atsargiai juos taikant kituose pramonės sektoriuose.

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Abbreviations:

AI – artificial intelligence;

Assoc. prof. – associate professor;

BI – business intelligence;

DOI – diffusion of innovations;

FMCG – fast-moving consumer goods;

GANs – generative adversarial networks;

GenAI – generative artificial intelligence;

GPT – generative pre-trained transformer;

HR – human resources;

IoT – internet of things;

IT – information technology;

KPI – key performance indicator;

Lect. – lecturer;

LLMs – large language models;

MIS – management information systems;

NLI – natural language interfaces;

PEOU – perceived ease of use;

Prof. – professor;

PSC – problem-solving capability;

PU – perceived usefulness;

ST – systems thinking;

TAM – technology acceptance model;

TOE – technology organization environment;

TPB – theory of planned behavior;

UTAUT – unified theory of acceptance and use of technology;

VAEs – variational autoencoders.

Introduction

Generative Artificial Intelligence (GenAI) has become a significant factor influencing workplaces, transforming organizational approaches to data analysis, insight generation, and the resolution of complex problems. In contrast to earlier forms of artificial intelligence, which were primarily developed for narrowly defined, task-specific applications, GenAI employs advanced neural network architectures capable of producing human-like language, processing unstructured data, and automating complex workflows with a high degree of adaptability and flexibility (Banh & Strobel, 2023; Epstein et al., 2023).

Even though the adoption of GenAI tools has progressed rapidly within technical domains, particularly in areas such as software engineering and data science, where such tools support code generation, debugging processes, and the creation of synthetic datasets (Krishna et al., 2024; Miller et al., 2024), their application within non-technical and hybrid occupational roles remains underexplored. This research gap is of particular importance as employees without technical backgrounds are increasingly required to participate in data-driven tasks. However, these employees frequently encounter challenges such as fragmented data systems, continued reliance on IT support, and the cognitive demands associated with the use of conventional analytics platforms, which often lack intuitive user interfaces (West et al., 2023; Shukla, 2024).

Despite the potential of GenAI to democratize data access and enhance decision-making independence for non-technical roles, its practical adoption remains constrained by organizational barriers and systemic challenges. Current academic research predominantly focuses on technical applications and productivity outcomes, with limited attention given to the difficulties experienced by non-technical users in integrating GenAI tools into their workflows (Reznikov, 2024). Although, the natural language interfaces have been introduced to improve accessibility, many non-technical employees face challenges while trying to critically assess AI-generated outputs and apply them effectively in decision-making contexts. Moreover, training initiatives are usually limited to the technical functionalities of these Artificial Intelligence tools, providing insufficient support for developing the critical thinking skills of users which are necessary for responsible and informed use (Miller et al., 2024).

Formulated Problem: The limited understanding of how employees in non-technical roles perceive and utilize GenAI tools to support problem-solving in data-related tasks.

Research Object: Generative Artificial Intelligence in the context of problem-solving in enhancing non-technical roles engaged in data-related tasks.

Research Question: How do employees in non-technical roles perceive and use generative AI tools to enhance their problem-solving capabilities in data-related tasks?

Aim of the Research: To reveal how employees in non-technical roles perceive and apply generative AI tools to enhance their problem-solving capabilities while taking into consideration the organizational and contextual factors that support or prevent their effective use.

Objectives of the Research:

1) To identify key challenges and contextual factors that affect the adoption of generative AI among employees in non-technical roles.

2) To explore theoretical frameworks that clarify the adoption and effective use of generative AI tools, including their impact on enhancing problem-solving capabilities.

3) To outline a methodology design capable of capturing perceptions, behavioral patterns, and organizational factors affecting the problem-solving capabilities of non-technical roles.

4) To provide recommendations by analyzing empirical data that aligns generative AI implementation with organizational strategies as well as problem-solving efficiency.

Research method: This research applies an explanatory sequential mixed-methods approach, combining quantitative surveys, behavioral experiments, and semi-structured interviews. Data collection is conducted within a multinational manufacturing company based in Germany (hereafter referred to as „Case Organization“; chosen for its data-intensive and innovation-enabling work environment, whereas, employees in non-technical roles regularly engage with data, yet, they have limited access to advanced analytics tools.

1. Identifying Organizational Barriers to GenAI Adoption in Non-Technical Problem Solving

This chapter investigates the potential organizational and systemic barriers to non-technical roles in problem-solving contexts and what prevents the application of generative artificial intelligence (GenAI) tools. While GenAI technology, including generative pre-trained transformer (GPT) based assistants and Microsoft Copilot, has transformed the professional landscape, from customer service to analytics and beyond, it has fostered success for those leveraging data-driven and information-focused applications; however, the potential to integrate this technology into everyday organizational tasks is often underutilized and remains unclear, especially for roles outside specialized knowledge (Pan Singh Dhoni, 2024). Nonetheless, organizations are creating a sense of urgency for all employees to tackle complicated information at some point, extending the potential need for using applications, software, and dashboards focused on data, visualization, and reporting metrics (Gonçalves, Gonçalves, & Campante, 2023). Therefore, the purpose of this chapter is to analyze the underlying barriers that limit the problem-solving capabilities of non-technical roles in data-driven environments: starting by establishing why data-related tasks are a focus of this research, then exploring the core structural and cognitive challenges faced by non-technical roles, and concluding by outlining the theoretical and empirical rationale for further research.

1.1. Generative AI in Data-Driven Problem Solving

Across sectors, the methods for solving problems in companies have transformed. Structured information systems and data analytics platforms now drive tasks that previously relied on experience, knowledge, or informal collaboration. This shift reflects the widespread data-driven culture (see Figure 1) , in which company decision-making, performance monitoring, and cross-departmental communication are based on accessible information and real-time data (Komolafe et al., 2024; Hossain, 2024).

The mentioned trend is not limited to technical departments. For instance, a global survey on Management Information Systems (MIS) and Business Intelligence (BI) revealed that over 75% of companies currently use data-based analysis in multiple functions, such as HR, operations, and finance (Erica et al., 2024). Similarly, cloud-enabled AI-based applications offer cross-functional, real-time, and just-in-time facilitation for decision-making in technical or non-technical areas (Ionescu & Diaconita, 2023). Therefore, employees with non-technical roles, especially those focused on governance, sustainability, marketing, and strategic coordination, are expected to engage with data-centric tools and interpret insights for implementing business objectives. However, the practical integration of non-technical roles in data workflows comes with its set of challenges. Studies have shown persistent barriers, from low data literacy and a lack of training programs to complex interactivity and dependency on IT support teams (Elufioye et al., 2024; Badmus et al., 2024). Such issues disconnect what organizations expect for evidence-based problem-solving from the actual capabilities of knowledge-based workers.

New technologies, particularly GenAI capabilities such as GPT and Copilot, represent a feasible solution to the identified skills gap. These tools provide the non-technical roles with the ability to pose questions regarding data, respond to analytical output, summarize dashboards, and render suggestions, all in natural language responses. Existing studies point out that such technologies lead to time savings, increased accessibility, and reduced cognitive barriers for non-technical users engaging with complex content (Andrade-Girón et al., 2024; Wang et al., 2024). Regardless, despite the growing implementation of GenAI tools in professional contexts, the literature reveals a distinct gap in academic assessment; few studies focus specifically on how personnel holding non-technical roles utilize GenAI tools to enhance their problem-solving within the workplace setting.

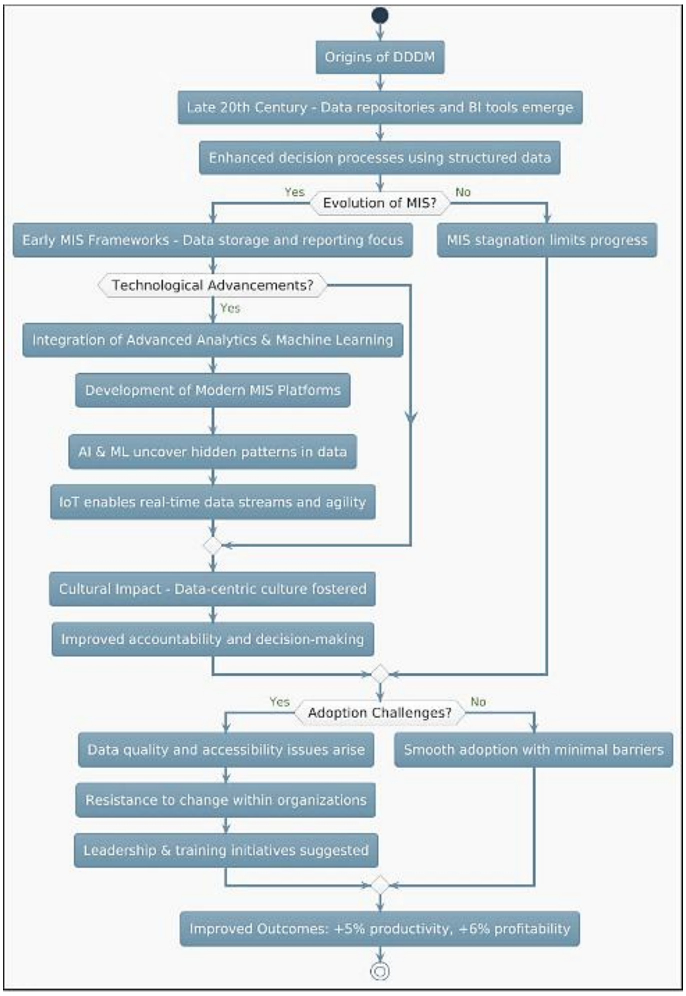

Fig. 1. Evolution of Data-Driven Decision-Making (DDDM) (Hossain, 2024).

Therefore, in the context of this research, the focus is on problem-solving abilities of employees , specifically working with data-related tasks, including their capability to independently access, interpret, and apply data in decision-making tasks; these are closely linked to cognitive factors such as working memory, decision methods, contextual awareness, and creativity which can be either supported or overwhelmed by digital tools. With a particular emphasis on the practical context when usefulness and suitability of GenAI for the organization can be explored; investigating this intersection is crucial to understanding technology acceptance and adoption and exploring the evolving nature of work in data-intensive environments.

1.2. Key Challenges for Non-Technical Roles in Data-Driven Organizations

In data-driven organizations, non-technical roles face notable challenges that hinder their ability to engage effectively with data. These obstacles stemming from organizational structures and personal skills restrict the independence and effectiveness of non-technical positions, even though these workers are more frequently entrusted with data-intensive decision-making (Masih, 2023). In this context, data-related tasks for non-technical roles may include reading and interpreting dashboards, compiling data for reports, monitoring KPIs, assessing business intelligence summaries, or coordinating interdepartmental insights, such tasks are often performed without coding or querying skills, yet they demand accurate data reasoning, also, the complexity of such tasks increases with real-time expectations, limited support, and ambiguous tool outputs, making the role of GenAI particularly relevant (Tankelevitch et al., 2024). The main challenges include data fragmentation, tool complexity, training gaps, and reliance on technical teams (Bhima, Az Zahra, & Nurtino, 2023). Below, the analysis explores each of these challenges in detail, using recent studies to support the analysis.

1.2.1. Data Silos and Information Fragmentation

One of the obstacles encountered by companies is the existence of data silos, which are isolated stores of information restricted to specific departments, systems, or teams preventing the seamless exchange of information throughout the organization and considerably limit the ability of employees in non-technical positions to access and interpret cross-functional data (Komolafe et al., 2024). Fragmented data not only weakens the range of insights but prolongs decision-making processes as well. Not to mention that non-technical roles usually require approval or assistance from technical teams to retrieve or process data across these silos (Hossain, 2024).

Federated learning[1] has emerged as a promising solution to the challenge of decentralized AI model training, allowing for the development of models across distributed systems without the direct exchange of sensitive data. This method, however, brings additional complexity and requires a significant investment in infrastructure and teamwork within the organization (Rischke et al., 2022). Although these solutions have promissing potential, numerous organizations continue to face barriers in dismantling existing silos, leaving employees with non-technical roles lacking the complete data insights necessary for making informed decisions.

1.2.2. Tool Complexity and Cognitive Load

A recognized obstacle for non-technical positions is the complexity of the data tools implemented by organizations; BI platforms, analytics software, and AI tools are often tailored for technical users, featuring complicated interfaces, jargon-laden outputs, and excessive learning curves (Elufioye et al., 2024). For non-technical roles, these tools can be discouraging and challenging to navigate, resulting in underutilization and, in some instances, complete disengagement from the data workflow (Farič et al., 2023).

In the context of operations and customer service, tools like GPT and Copilot are being integrated into workflows to assist non-specialist users in managing complex data and automating decision support (Cao & Zhai, 2023). Even with the development of more user-friendly tools, the absence of easy-to-navigate designs and clear user guidelines continues to be a significant obstacle to widespread use; studies show that focusing on user-centered design and utilizing natural language interfaces (NLI) can help in reducing this complexity, making interactions with data more approachable for employees without technical backgrounds (Durach & Gutierrez, 2024). Beyond interface complexity, non-technical employees also face cognitive strain from the interpretability of outputs generated by artificial intelligence, whereas studies show that when GenAI responses lack

[1] A machine learning technique that allows multiple entities to collaboratively train a model while keeping their data decentralized and private (Fraunhofer Heinrich-Hertz-Institut, n.d.)

clarity or contextual relevance, users experience hesitation and mental fatigue, even when using natural language interfaces (Ma & Lei, 2024; Muduli & Choudhury, 2024). Another dimension of a cognitive burden which comes from AI fatigue, is when users are overwhelmed by continuous prompts, updates, or decision suggestions generated by GenAI tools; these attempts, where in high-velocity operational contexts, alerts of overload has been shown to reduce engagement and can even cause avoidance behavior among non-technical users (Muduli & Choudhury, 2024; Alabduljabbar, 2024).

1.2.3. Lack of Structured Training and Data Literacy Initiatives

Employees with non-technical roles experience difficulties in understanding and utilizing data insights due to insufficient foundational data literacy; a study on AI integration across different industries shows that these roles face a challenging learning curve, mainly due to the lack of effective training programs that fail to equip them with the necessary skills or ongoing assistance (Badmus et al., 2024). The absence of comprehensive training prevents employees from making the most of the AI tools at their disposal, resulting in a constant dependence on IT teams for everyday tasks.

In industries like logistics, AI solutions are easily accessible. Yet, many non-technical employees struggle to utilize these technologies due to a lack of adequate digital skills and training. (Elufioye et al., 2024). These weaknesses in training not only restrain personal productivity but also block the organization's overall shift towards data-driven decision-making. If organizations neglect to provide non-technical employees with the crucial skills needed to utilize AI systems effectively, they may forfeit the full benefits that these advanced technologies offer.

A study conducted by Morandini et al. (2023) highlights the essential importance of ongoing skill development, especially for roles that are not technical in nature. With the growing complexity of AI systems, employees in non-technical roles are increasingly required to manage data-heavy tasks, thus, the lack of organized upskilling initiatives blocks the capacity of non-technical roles to keep up with technological changes, ultimately reducing their effectiveness in data-centric functions. The progression of AI tools, combined with a lack of focused training, presents a major obstacle to the effective integration of AI.

A research study by Rane (2024) emphasizes that companies often overlook the significance of providing customized training programs for employees in non-technical roles, which may lead to disengagement and hinder the incorporation of AI tools into current workflows. Furthermore, without appropriate training, employees who do not have a technical background find it challenging to fully utilize AI technologies, leading to the underutilization of the available platforms. Moreover, the insufficient enhancement of skills and lack of ongoing support exacerbate the problem, causing these employees to depend on IT departments for help with their daily activities (Rane, 2024).

As pointed out by Elufioye et al. (2024), failing to tackle these training deficiencies hinders the organization's ability to smoothly transition into a data-driven culture and may pose a risk to the long-term success of AI implementation. Consequently, to effectively tackle these issues, organizations should prioritize the development of robust training programs specifically designed for non-technical employees; these initiatives should focus on not just acquiring fundamental data skills but also providing practical experience with AI technologies. Continuous learning opportunities are vital for preparing employees to adapt to the changing requirements of technology. The mentioned training challenges are further combined with organizational inactiveness and even when tools are technically accessible and formal training exists, resistance to behavioral change within department limits the practical uptake of GenAI tools, especially in environments that rely on an amount of outdated technology (Alabduljabbar, 2024; Herath et al., 2020).

1.2.4. Dependence on Technical Teams for Data Tasks

A further challenge organizations face is their ongoing reliance on technical teams for routine data-related tasks. While AI tools and automated systems are widely accessible, non-technical roles frequently rely on IT departments to access, analyze, and interpret data (Bose, 2009). This reliance can lead to bottlenecks that impede decision-making and limit organizational agility. For instance, in sectors such as finance and logistics, despite the considerable promise of AI tools for decision support, non-technical users frequently require technical assistance to navigate complex data outputs or to integrate information from various systems (Durach & Gutierrez, 2024).

The issue of dependency is not limited to specific industries, for instance, in the area of marine conservation, AI technologies are used to aid in data collection and monitoring. Yet, the complexity of these tools results in delays in decision-making, as personnel lacking technical knowledge find it challenging to make full use of the data analysis features (Ditria et al. 2022). The research underscores the necessity of automation to improve data workflows and alleviate bottlenecks, suggesting that individuals without technical skills would greatly benefit from more user-friendly AI systems that allow them to work autonomously.

In industries such as supply chain management, particularly within the Fast-Moving Consumer Goods (FMCG) sector, Nozari et al. (2022) identified that the integration of AI and Internet of Things (IoT) technologies complicates matters, as non-technical employees struggle with disconnected real-time data and the sophistication of AI systems. This situation significantly deepens the reliance on IT teams for data interpretation and integration, leading to considerable bottlenecks. It also highlights the importance of continual training and the creation of simplified tools to connect technical and non-technical roles.

In addition to technical complexity, many GenAI tools present outputs that do not align with the actual decision scope or tasks of non-technical users; most of the reviewed studies highlight that when the insights provided by AI systems are too generic or misaligned with job-specific needs, employees are less likely to adopt or trust these tools in daily operations (Rane, 2024; Patil et al., 2024). This reliance not only increases the burden on technical teams; but also restricts the autonomy of non-technical personnel, hindering them from completely embracing their duties and managing their data. To address this challenge, organizations should prioritize offering user-friendly tools and equipping employees with the essential skills for independent usage. For instance, in the context of logistics management, a study by Shatat and Shatat (2023) emphasizes the significance of AI literacy initiatives, advocating for organized training that enables non-technical personnel to effectively utilize AI tools and reduce their reliance on technical specialists. Generative AI tools such as GPT and Copilot present promising opportunities, as they streamline data queries and automate routine tasks, thereby reducing the need for continuous technical support (Patil et al., 2024).

Moreover, the integration of AI tools in logistics and supply chain management, as noted by Eyo-Udo (2024), shows that although AI can improve demand forecasting and inventory control, numerous non-technical workers frequently struggle to understand AI-generated data insights; the research underscores the necessity for more intuitive AI interfaces and ongoing education to enable all employees to engage effectively in data-driven activities, reducing their reliance on IT teams.

1.3. Implications of Barriers for GenAI Adoption

The barriers outlined in this chapter, *data silos, tool complexity, insufficient training, and reliance on technical team*s, do not only prevent daily data work for non-technical employees; but they also affect the potential for effective GenAI adoption in organizational contexts. Each of these barriers poses a challenge to the conditions typically required for technology acceptance, as described in models such as the Technology Acceptance Model and Diffusion of Innovations. Consequently, understanding these implications is essential for framing realistic expectations and strategies around GenAI integration.

First, the persistence of data silos significantly weakens the promise of GenAI tools to generate cross-functional insights. Tools like GPT and Copilot depend on access to diverse and comprehensive datasets to produce accurate outputs. However, siloed systems fragment the available information, forcing GenAI tools to operate within partial or compartmentalized data environments (Komolafe et al., 2024; Hossain, 2024). Even advanced strategies like federated learning face implementation challenges due to coordination and infrastructure demands (Rischke et al., 2022), making seamless GenAI integration difficult.

Second, tool complexity undermines one of the most frequently cited benefits of GenAI: ease of use through natural language interaction. When non-technical users face jargon-laden outputs, unclear feedback loops, or non-intuitive interfaces, the perceived usefulness and usability of GenAI drops considerably (Elufioye et al., 2024; Durach & Gutierrez, 2024). Furthermore, interpretability problems, such as vague or overconfident responses, add to cognitive strain and reduce trust in GenAI-assisted outputs (Ma & Lei, 2024).

Third, the lack of structured training programs prevents GenAI adoption from advancing beyond surface-level engagement. Studies show that without continuous learning support and context-specific instruction, non-technical users either misuse AI tools or disengage entirely (Badmus et al., 2024; Morandini et al., 2023; Rane, 2024). This inhibits the development of confident, self-directed problem solvers, one of the core aims of GenAI deployment in knowledge work.

Finally, reliance on IT teams remains a structural bottleneck. GenAI tools are intended to empower users to independently retrieve and interpret data; yet, when employees must wait for technical validation or assistance, the time-sensitive value of these tools diminishes (Nozari et al., 2022; Ditria et al., 2022; Eyo-Udo, 2024). As a result, organizations risk reinforcing the very dependencies GenAI is meant to reduce.

These interconnected barriers underscore that GenAI adoption is not simply a matter of tool availability, it is shaped by cultural, structural, and educational readiness. As such, addressing these challenges is not only about improving systems, but also about rethinking how technology, roles, and skills align within data-driven organizations.

1.4. Research Gap and Rationale for the Study

While significant research has focused on data-driven decision-making and the application of AI tools in technical positions, there is still a notable gap in empirical studies exploring and understanding how non-technical employees utilize these tools for tasks related to data. Although the integration of GenAI tools like GPT and Microsoft Copilot has been examined in technical environments, such as those involving developers, data scientists, and IT professionals (Wang et al., 2024; Andrade-Girón et al., 2024), non-technical positions, especially those related to data governance, coordination, and decision-making, have received minimal attention.

This gap indicates that GenAI can make data interactions easier for non-technical employees; however, these studies tend to be specific to certain sectors and are limited in their reach. Furthermore, although challenges related to data access and tool usability have been well-documented (Hossain, 2024; Badmus et al., 2024), there remains a lack of longitudinal research examining how GenAI can reduce dependency on technical teams and empower non-technical employees to take more independent roles in data-driven decision-making. Another constraint, which is frequently overlooked, relates to the uncertainty surrounding accountability. Non-technical users might be reluctant to trust GenAI outputs when it is uncertain who is responsible for the decisions made. This lack of clarity, particularly in important situations or environments that have strict rules and standards, reduces trust in AI tools and restricts their adoption in autonomous workflows (Kim et al., 2025; Baroni et al., 2022).

Moreover, while studies on data literacy acknowledge that insufficient training and complex interfaces hinder effective use, there is still little investigation into how GenAI might simplify data queries, improve interpretability, and increase tool usability for non-technical roles (Elufioye et al., 2024; Erica et al., 2024). A further overlooked factor is the limited observability of GenAI success among peers. Without visible, role-relevant use cases, non-technical employees lack social proof, which hinders confidence in the tools' legitimacy and slows informal diffusion (Raman et al., 2024; Xu et al., 2023). Relatedly, trust in GenAI does not arise automatically. It builds through direct, repeated experience with reliable AI outputs. In its absence, non-technical users often remain cautious, even skeptical, despite having tool access and basic skills (Kim et al., 2025; Baroni et al., 2022). Additionally, few studies assess the adoption of GenAI by using metrics tailored to non-technical functions without role-specific indicators, such as ease of interpretation, decision independence, or the level of integration into reporting workflows; organizations struggle to evaluate whether GenAI tools are truly effective outside technical domains (Badmus et al., 2024; Dwivedi, 2024).

This research addresses the above-stated gap through understanding the perception, usage trends, and organizational factors related to generative artificial intelligence tools among non-technical roles. By exploring how employees holding non-technical roles engage with generative AI tools in data governance and decision-making tasks, the study will magnify both theoretical and practical insights into generative AI's potential to reduce obstacles in data-driven decision-making and enhance problem-solving capabilities in non-technical roles. Thus, a multinational manufacturing company based in Germany was selected as the case organization, this selection is grounded in the company‘s dual emphasis on operational excellence and innovation through digital tools, as a company operating globally in manufacturing and logistics-intensive sectors, it represents a prototypical setting where staff holding non-technical or hybrid roles routinely interact with dashboards, planning systems, and cross-functional reporting, making it a compelling environment to assess GenAI-enabled problem solving.

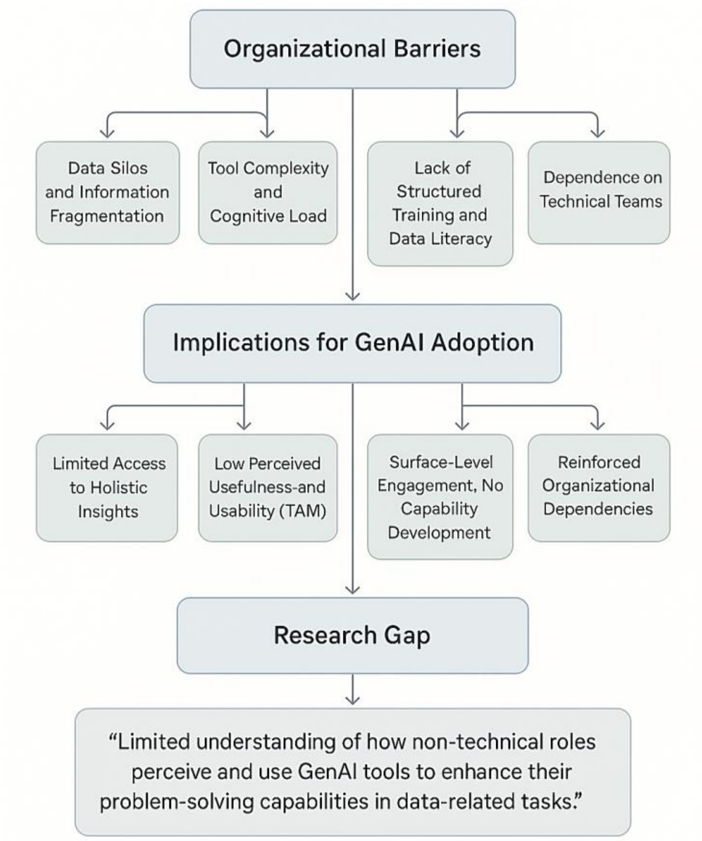

Fig. 2. Organizational barriers to GenAI adoption and the resulting research gap (author).

Note. Figure 2, illustrates how the key organizational barriers hinder GenAI adoption among employees in non-technical roles, which lead to unmet expectations for enhanced problem-solving capabilities. The resulting research gap emphasizes the lack of empirical understanding regarding GenAI's practical integration in non-technical work environments.

To summarize, this chapter explored key barriers that limit the effective use of GenAI in organizations, focusing on data silos, tool complexity, insufficient training, and continued reliance on IT teams. It has been noted that such challenges not only prevent employees in non-technical roles from effectively working with data but also restrict the wider adoption of GenAI tools that are intended to help independent decision-making. Despite the growing expectations for non-technical roles to be involved with data-driven tasks, little is known about how these roles actually perceive and use GenAI tools in their daily work. Therefore, this gap in understanding forms the basis of the research problem, which centers on examining how non-technical employees interact with GenAI to support problem-solving in data-related tasks and what organizational factors enable or hinder this process.

2. Theoretical Solutions for Enhancing Problem-Solving with Generative AI in Non-Technical Roles

The integration of Generative Artificial Intelligence (GenAI) tools into non-technical positions within companies offers distinct challenges as well as considerable benefits. The potential of advanced technologies such as ChatGPT and Microsoft Copilot is immense; however, successfully utilizing them necessitates a thorough understanding of how GenAI can tackle fundamental issues like data silos, complicated tools, and restricted independence in tasks related to data. These barriers often hinder the problem-solving capabilities of non-technical employees (Shah, 2023; Pan, 2024).

GenAI tools have the potential to minimize the dependence on technical teams, expand access to sophisticated information, and support data-driven decisions. However, achieving this potential on a large scale depends on a chain of factors that are connected, those are user adoption, alignment with existing workflows, and the organizational environment where the tool is introduced. These factors are often influenced by concerns regarding ethical usage, explainability, and trust (Shah, 2023; Pan, 2024). Thus, advancing beyond superficial deployments necessitates that GenAI initiatives are grounded in robust theoretical frameworks, which can guide implementation and elucidate user behavior, adoption challenges, and organizational readiness.

This chapter establishes the theoretical foundation for this study, commencing with a well-organized literature review combining academic research and practical applications related to GenAI in non-technical contexts. The review emphasizes three theoretical frameworks: the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI) theory, and Systems Thinking (ST), which are particularly useful in understanding the various factors influencing GenAI adoption. The discussed frameworks provide further insights taking into account user perceptions, their integration into social systems, and organizational complexities.

Furthermore, the chapter explains the essential concepts that underpin the research: Generative AI, problem-solving capabilities, and non-technical roles, followed by an in-depth analysis of the chosen frameworks. The rationale for opting for these frameworks rather than alternative models such as UTAUT, TOE, and TPB is articulated clearly, leading to a theoretical synthesis that creates a conceptual model to guide the empirical design and analysis of the study.

2.1. Structured Literature Review on Generative AI Adoption and Use in Non-Technical Contexts

Incorporating generative AI tools into non-technical workflows necessitates a thorough comprehension of the technological and organizational aspects that can either facilitate or obstruct their adoption. To shape the theoretical framework of this research, we performed a structured literature review to synthesize the current academic perspectives on how Generative AI can enhance the problem-solving skills of non-technical employees. This review also highlights pertinent theoretical models and adoption mechanisms that aid in forming the study's conceptual framework. The literature search was conducted across four academic platforms: *Consensus*, *Google Scholar*, *R Discovery*, and *SciSpace*. No date restrictions were imposed on the search, thereby allowing the inclusion of both foundational and recent publications. The following keywords were utilized:

"*Generative Artificial Intelligence*," "*non-technical roles*," "*problem-solving capabilities/skills/abilities*," "*Technology Acceptance Model*," "*Diffusion of Innovations*," and "*Systems Thinking*."

Eligible studies were those that (1) studied the adoption of Generative AI by non-technical roles/users/employees, (2) used relevant theoretical frameworks such as TAM, DOI, or ST, and (3) were peer-reviewed and published in English. An analysis was ruled out for those studies that were exclusively concerned with technical adoption, unpublished in English language, or methodologically unsophisticated, thereby ensuring the significance and rigor of the findings. From an initial aggregate of 957 sources, 97 articles were selected, and later, 30 studies were included in the theoretical solutions, all of which closely aligned with the theoretical aims of this research. Figure 3 illustrates the review procedure, following established systematic-like mapping methodologies.

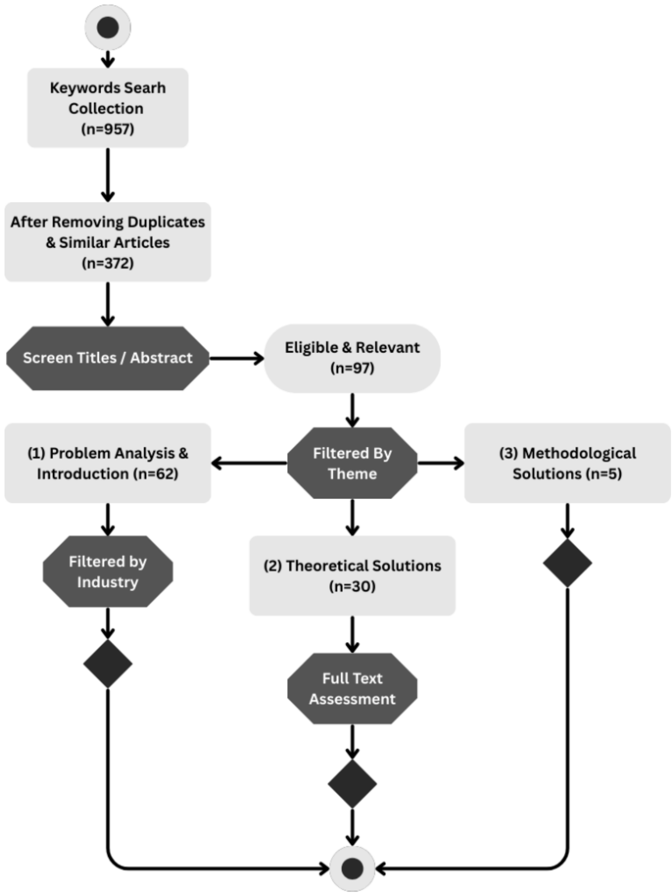

Fig. 3. Overview of the structured literature review and screening process (author).

The selected literature is thematically organized into five principal domains that collectively shape the theoretical orientation of this study:

1) **Technology Adoption Models:** Technology Acceptance Model based studies have highlighted Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust, and Output Quality as crucial factors determining the acceptance of the GenAI tools (Davis, 1989; Ma & Lei, 2024; Kim et al., 2025); these elements are especially relevant for comprehending how non-technical users assess and interact with GenAI tools in their everyday workflows.

2) **Innovation Diffusion:** Concepts guided by theory of Diffusion of Innovations have highlighted that the most critical variables in influencing technology adoption are Compatibility, Trialability, Relative Advantage, and Observability as key factors influencing technology adoption (Rogers, 2003; Russo, 2024; Xu et al., 2023; Raman et al., 2024); of these mentioned, it has been emphasized that compatibility is particularly important for non-tech staff, i.e., how far GenAI tools could be efficiently integrated into the current operational practices.
3) **Systems Thinking and Organizational Complexity:** Research in this area has shown how task interdependencies, structural ambiguity, and cross-functional flows affect the deployment of GenAI in a complex organizational setting (Senge, 1990; Kim & Senge, 1994; Muduli & Choudhury, 2024); analyses in such a manner suggests that the challenges in adopting the technology cannot be understood simply from the users' viewpoint; rather, they need to be looked into in the wider context and the systemic factors that are present.
4) **Problem-Solving Capability Development:** Some studies have noted critical key skills such as Data Reasoning and Adaptive Decision-Making as key to enabling non-technical users to effectively utilize GenAI (Akinnagbe, 2024; De Laat et al., 2020); these skills encompass the ability of users to make sense of AI-derived insights as well as the ability to adapt their decision-making based on that information.
5) **Role-Specific Adoption Dynamics:** Several studies have highlighted the unique challenges of non-technical users when adopting GenAI tools, differentiating their experiences from those of individuals in technical or hybrid roles (Baron & Bielby, 1982; Van Diggele et al., 2020; Tammaro et al., 2019); the findings stated here underscore the importance of designing role-specific adoption processes on the cognitive, procedural, and contextual aspects that are typical in non-technical work.

Together, these thematic areas capture the increasing significance of GenAI in organizational settings as well as exposing both theoretical and empirical gaps. Particularly, it is worth noting that limited studies have directly connected the integration of GenAI to the improved problem-solving abilities among staff in non-technical roles. A considerable portion of the current literature tends to either concentrate on general AI adoption or limit its scope to specific industries, for instance, healthcare and education, failing to adequately theorize the cognitive aspects related to data interpretation and the adaptations required in decision-making.

This gap highlights the necessity for a unified theoretical framework that thoroughly addresses the complex adoption environment faced by employees in non-technical roles. By integrating factors from TAM, DOI, and ST, this research aims to offer a comprehensive perspective to understand the impact of GenAI tools on problem-solving for non-technical positions. This effort seeks to close the existing gap between empirical findings and theoretical explanations.
The insights gained from this structured review will be the foundation for the theoretical frameworks and conceptual model to be developed in the subsequent sections of this chapter.

2.2. Applications and Cross-Industry Insights on the Integration of GenAI

Frameworks like TAM, DOI, and ST provide organized methods for understanding the acceptance and use of Generative AI. However, real-world examples from various industries offer crucial insights into their practical implementation and impact on organizations. This section gathers case studies from marketing, education, healthcare, finance, and logistics to illustrate how generative AI tools are being applied in non-technical positions. The examples shared below help establish context-specific metrics, such as efficiency, usability, and decision quality, which will inform this study's investigation of problem-solving aided by generative AI.

In various industries, GenAI has enhanced automation and decision-making in tasks and processes that were previously considered non-technical; for instance, digital marketing benefits from GenAI to boost customer engagement, create tailored content, and optimize campaign results. According to Dwivedi (2024), AI-driven recommendation systems have increased sales effectiveness by as much as 20% by minimizing manual processes and encouraging data-driven approaches; these technologies allow marketers, including those without programming skills, to use advanced analytics via easy-to-use interfaces, which is consistent with the principles of the TAM, including Perceived Usefulness and Output Quality.

In the healthcare sector, large language models (LLMs) have been integrated into clinical workflows to assist with documentation, patient triage, and communication. According to Yu et al. (2023), these technologies have reduced the time required for diagnostics and decreased administrative burdens. However, adoption among non-technical personnel, like administrators and support staff, remains low due to worries about data privacy and a lack of training tailored to the specific domain. These challenges highlight issues related to system compatibility (DOI) and task complexity (ST), especially in regulated environments.

In finance, GenAI is utilized for risk modeling in real-time, scenario analysis, and predictive insights. Idiyatullin et al. (2024) illustrate how AI tools assist in decision-making amidst uncertainty, yet they warn that users lacking technical expertise might misinterpret the outputs of algorithms without proper features for interpretability or sufficient onboarding. Within this framework, the Systems Thinking approach, especially concerning interdependent tasks and user feedback loops, is essential for identifying shortcomings in effective adoption.

In logistics and supply chain management, optimization systems powered by GenAI have realized considerable enhancements in operational efficiency. Reznikov (2024) indicates that delivery times have been reduced by as much as 25%, and these improvements are linked to the integration of AI tools with the workflows of current employees. This example demonstrates the DOI principle of Compatibility and reinforces TAM findings that emphasize the significance of user-friendliness and alignment with everyday tasks for adoption by non-technical staff.

The examples above collectively suggest that although Generative AI holds tremendous potential to enhance access to high-end tools, challenges persist. Trust in AI-created content, cognitive overload, comprehension difficulties, and workflow incompatibilities are persistent obstacles to further integration, particularly in domains involving more complicated tasks or heightened regulatory pressures. Additionally, the adoption rate varies by function, with marketing and logistics functions more integrated than finance or healthcare. GenAI has sped up automation and decision-making across industries in jobs that have traditionally been viewed as non-technical.

In **digital marketing**, for example, GenAI is applied in personalizing customer experiences, creating targeted content, and streamlining campaign efficiency. According to Dwivedi (2024), recommendation systems powered by AI have boosted sales performance by as much as 20%, primarily by minimizing manual efforts and aiding in the execution of data-driven strategies. These instruments enable marketers without programming skills to use advanced analytics through user-friendly interfaces, aligning closely with Technology Acceptance Model constructs such as Perceived Usefulness and Output Quality.

From the above mentioned cases, four key metrics were identified to evaluate the impact of Generative AI on non-technical roles (refer to Table 1).

Table 1. Key metrics for generative AI adoption across arganizational contexts (author).

Metric Category	What It Measures	Sources of Examples
Efficiency Gains	Task speed, error reduction, productivity improvements	Noy & Zhang (2023); Reznikov (2024)
Usability & Accessibility	Interface simplicity, cognitive load, user satisfaction	Alabduljabbar (2024); Badmus et al. (2024)
Decision-Making Support	Accuracy, transparency, and trust in AI-generated outputs	Badmus et al. (2024); Yu et al. (2023)
User Empowerment	Reduced reliance on IT, increased autonomy in workflows	Damiano et al. (2024); Dwivedi (2024)

These metrics map directly to theoretical constructs discussed earlier: Perceived Usefulness and Output Quality (TAM), Compatibility (DOI), and Task Complexity (ST). They also reflect practical criteria for assessing how well GenAI tools are integrated into everyday workflows.

Despite the breadth of current applications, critical gaps remain in the literature on GenAI adoption among non-technical employees. Although many studies report productivity improvements, time savings, or task automation, few explore the development of specific problem-solving capabilities such as data reasoning or adaptive decision-making. For instance, research by Dwivedi (2024) and Reznikov (2024) prioritize performance indicators like campaign success or delivery speed yet do not examine how users engage cognitively with GenAI outputs. Similarly, Yu et al. (2023) and Badmus et al. (2024) emphasize workflows optimization in healthcare and business analytics areas but have limited insight into how non-technical users interpret, trust, or adapt GenAI-generated content.

In addition, much of the existing research analyzes adoption at the organizational or team level, without disaggregating findings by role type or technical expertise. This makes it difficult to distinguish the unique adoption experiences of non-technical employees from those of technical or hybrid users. Research by Damiano et al. (2024) and Idiyatullin et al. (2024) highlights this limitation, with their research addressing general user groups without assessing cognitive engagement applicable to particular roles. Additionally, qualitative features, like perceived control, user trust, interpretability, and workflow alignment, are likely to be consistently overlooked. Even when usability problems are addressed, they are not necessarily traced back to more fundamental cognitive or decision processes, although Alabduljabbar (2024) and Badmus et al. (2024) point this out. This lack implies that implementation approaches in current use are not fully effective for non-technical functions, especially where data is unclear, complex tasks, or training support is weak, thus, filling such gaps is essential to streamlining overall efficiency and user experience.

2.3. Key Concepts and Definitions

This section presents the primary conceptual elements that underpin this study: Generative Artificial Intelligence, Problem-Solving Capabilities, and Non-Technical Roles. A definition of each term is provided in accordance with existing academic research and contextualized within the framework of GenAI-assisted data-driven work. Following the definitions, there is an explanation of how each concept is implemented in the framework of this study. To enhance clarity, summary tables are provided to aggregate scholarly definitions and demonstrate the criteria used for each construct in the empirical analysis.

2.3.1. Generative Artificial Intelligence

Generative Artificial Intelligence refers to a category of machine learning systems that produces original and contextually relevant content by learning from pre-existing data inputs (Mannuru et al., 2023). Such systems are able to create various types of content, including text, images, audio, code, and design elements, in addition to the ability to replicate human-like creativity with semantic consistency. Unlike conventional forecast or classification AI based on historical patterns, GenAI produces novel outputs from sophisticated frameworks including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and transformer-based large language models (Rios-Campos et al., 2023).

GenAI has captured interest across various fields, including education, healthcare, marketing, and creative industries, attributed to its ability to automate intricate content generation, customize outputs on a large scale, and improve task efficiency (Maity & Deroy, 2024). However, its implementation comes with certain hurdles, for instance, transparency, explainability, ethical use, and unintended bias problems persist, especially in the workplace where human oversight is paramount (Mannuru et al., 2023). These are of specific concern to non-technical users who do not have the technical knowledge to critically evaluate AI-generated content, raising issues with usability, trust, and interpretability.

Table 2. Definitions and operationalization of generative AI (author).

Author(s)	Scholarly Definition	Application in This Research
Mannuru et al. (2023)	GenAI systems create novel, contextually appropriate content beyond reactive functions	Frames GenAI as a tool for enabling non-technical employees to independently generate data summaries, insights, and decision support outputs
Rios-Campos et al. (2023)	Defines GenAI by its shift from predictive to generative models, including GANs and LLMs	Justifies the inclusion of transformer-based tools (e.g., ChatGPT, Copilot) in analyzing natural language querying and content creation in data tasks
Yan et al., (2024)	Highlights that ChatGPT’s natural language capabilities support users in data exploration, interpretation, and decision-making tasks.	
Maity & Deroy (2024)	Highlights GenAI’s capacity for personalization, automation, and productivity across sectors	Supports this study’s focus on evaluating improvements in autonomy, efficiency, and task performance for non-technical employees using GenAI

In this research, generative AI is a set of machine learning technologies that can produce high-quality, original content, including text, images, and structured results. The technologies use historical data to generate responses that mimic human communication. The technologies in question, e.g., ChatGPT and Microsoft Copilot, are especially significant in workplaces, particularly in data-intensive settings. Designed to be user-friendly, such systems use natural language interfaces to assist problem-solving tasks such as data interpretation, analysis of dashboards, and decision-making; especially for workers who do not have formal technical expertise (Yan et al., 2024).

2.3.2. Problem-Solving Capabilities

The ability to solve problems includes a range of cognitive, metacognitive, and affective abilities that enable the evaluation, resolution, and solution of new or complex problems in dynamic contexts (Greiff et al., 2013). They are particularly crucial in data-driven environments, where there is a need to rapidly make informed decisions from artificial intelligence tools (Drigas & Karyotaki, 2019). Essential steps involved in resolving issues are observation, reasoning, adaptive thinking, and critical judgment; abilities that are increasingly codified by computer systems in today's workplace.

Conventional models of problem-solving have focused on structured approaches like computational thinking and systems-based reasoning to improve decision quality and adaptability (Belski, 2009; Singh & Kaunert, 2024). However, with the rise of GenAI in routine workflows, the landscape of problem-solving is evolving: employees now need to not only process information but also critically assess AI-generated results and make adaptive decisions based on real-time responses from machines.

In this research, problem-solving capabilities are described as the capacity to recognize, interpret, and tackle workplace challenges by integrating human cognitive strategies with the assistance of GenAI systems.

Table 3. Definitions and ooperationalization of problem-solving capabilities (author).

Author(s)	Scholarly Definition	Application in This Research
Greiff et al. (2013)	Problem-solving involves adapting responses to complex, changing tasks	Used to understand how participants adjust their approach when interacting with GenAI tools in data-related tasks
Drigas & Karyotaki (2019)	Includes mental self-regulation and confidence when solving novel problems	Informs the observation of how participants reflect on their AI-supported decisions and maintain confidence in unfamiliar scenarios
Akinnagbe (2024)	AI systems improve how users interpret and apply data in decision-making	Guides the analysis of how non-technical employees make use of GenAI-generated summaries or outputs when solving problems
Singh & Kaunert (2024)	Computational approaches enhance flexible and creative thinking	Used to identify when and how users modify plans or decisions after receiving feedback from GenAI systems

Two primary aspects are emphasized:

- **Data Reasoning,** includes the ability to interact with AI-generated content, evaluate its significance, and formulate practical conclusions (Akinnagbe, 2024; De Laat et al., 2020).
- **Adaptive Decision-Making,** involves the ability to adjust decisions, tactics, or workflows based on information produced by GenAI tools (Singh & Kaunert, 2024; Drigas & Karyotaki, 2019).

These dimensions illustrate how GenAI transforms problem-solving from a task solely performed by humans into a collaborative process that requires judgment, oversight, and strategic engagement with algorithmic systems.

2.3.3. Non-Technical and Hybrid Roles

The differentiation between technical and non-technical positions in organizations is at the core of this research; technical positions are defined by their expert knowledge in systems, software, hardware, or engineering processes with hands-on work on programming, analytics, or system development (Baron & Bielby, 1982). On the other hand, non-technical positions primarily emphasize leadership, coordination, strategic decision-making, and communication, without direct obligations related to the creation or maintenance of technological infrastructure.

Van Diggele et al. (2020) point out that non-technical professionals play a crucial role in enhancing organizational performance through soft skills such as teamwork, strategic facilitation, and leadership across different functions. At the same time, Kumar et al. (2009) and Tammaro et al. (2019) underscore the emergence of hybrid roles, positions that combine both technical and non-technical tasks, especially in data-driven sectors like logistics, healthcare, and education.

Table 4. Definitions and ooperationalization of problem-solving capabilities (author).

Author(s)	Scholarly Definition	Application in This Research
Baron & Bielby (1982)	Technical roles focus on system control and technical interdependence	Supports exclusion of participants whose main tasks involve system development, coding, or engineering
Van Diggele et al. (2020)	Non-technical professionals contribute through coordination and communication	Used to identify participants whose main responsibilities involve team leadership, reporting, or decision-making support
Kumar et al. (2009); Steele (2009)	Hybrid roles mix technical and non-technical functions	Hybrid employees are included if their main work involves organizing, interpreting, or explaining data—not creating software or tools
Tammaro et al. (2019)	Hybrid roles are emerging in fields with growing data complexity	Used to refine the inclusion criteria: participants must describe their daily role as primarily analytical, managerial, or interpretive—not technical build-oriented

In light of these developments, this study characterizes non-technical roles as positions within organizations where the primary responsibilities revolve around interpreting, communicating, and implementing data-driven insights, rather than directly creating technical systems. Hybrid roles are considered if a significant portion of their duties corresponds with non-technical functions (e.g., strategic coordination, decision facilitation) instead of fundamental technical tasks (e.g., software development, database management). Examples of applicable roles include marketing managers, HR specialists, project coordinators, business analysts, and operations supervisors; positions that engage with GenAI-generated insights without designing or engineering technical systems themselves.

2.4. Theoretical Frameworks for Understanding GenAI Adoption

Effective implementation and use of Generative AI (GenAI) tools by individuals with no technical background requires a theoretical model that explains not just the individual behavior and perception but also the organizational and systemic factors that affect technology adoption. Although there are numerous frameworks to account for technology adoption, including the Unified Theory of Acceptance and Use of Technology (UTAUT), the Theory of Planned Behavior (TPB), and the

Technology Organization Environment (TOE) framework, this study draws upon three complementary paradigms: the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and Systems Thinking (ST).

This selection demonstrates both theoretical importance and practical applicability. TAM, developed by Davis in 1989, continues to be one of the most thoroughly validated frameworks for understanding user acceptance of technology, focusing on two main elements: perceived usefulness and perceived ease of use. Nevertheless, TAM has been criticized for not considering social, emotional, and contextual factors that affect technology adoption in real-world situations (Legris et al., 2003; Bagozzi, 2007). Seeking to overcome such a limitation, this study does not solely depend on TAM but combines it with the DOI and ST in order to formulate an explanatory model that is more inclusive.

Other frameworks were considered but found less suitable for the context of this research, for instance, the UTAUT (see Figure 4), although it enhances predictive capabilities by integrating several previous models, its synthesized nature might minimize theoretical clarity and restrict interpretative richness (Venkatesh et al., 2003; Dwivedi et al., 2019). On the other hand, the TOE framework (see Figure 5) is useful for comprehending organizational and environmental preparedness but does not adequately address user-level perceptions that are crucial for GenAI adoption. While TPB (see Figure 6) is effective in foreseeing general behavioral intentions, it fails to consider technology-specific factors such as usability, interface design, or system feedback (Ajzen, 1991).

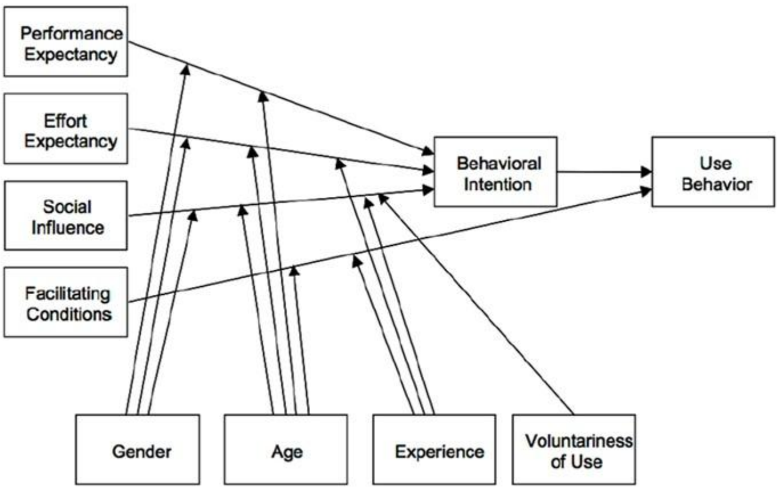

Fig. 4. Interaction of the elements of the UTAUT model. (Source: Venkatesh et al., 2003, p. 447).

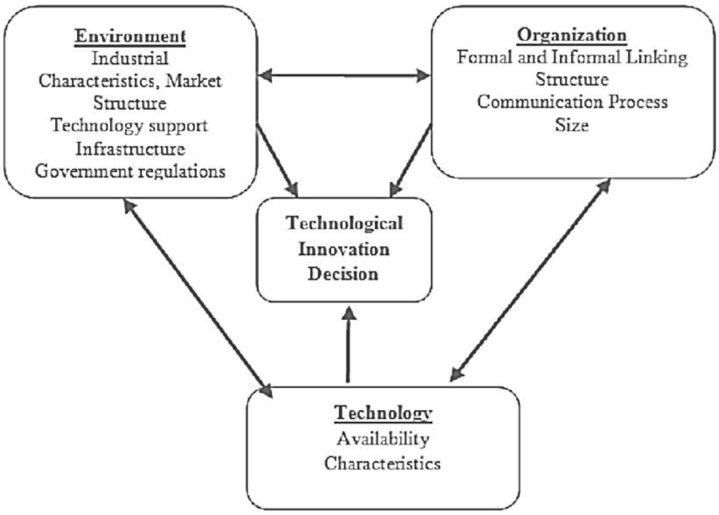

Fig. 5. TOE framework. (Source: Tornatzky and Fleischer, 1990).

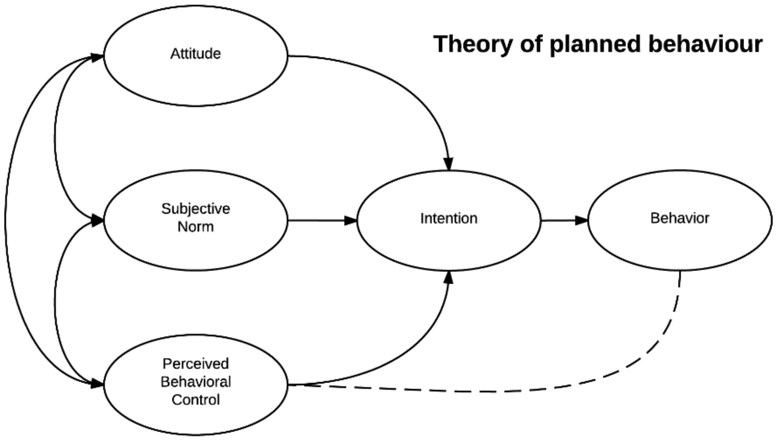

Fig. 6. A visual representation of TPB (Source: Robert Orzanna, CC BY-SA 4).

The holistic perspective illustrated in the following sub-sections, provides a multi-layered understanding of how generative AI adoption occurs in regular data-oriented environments, where tool usability, workflow alignment, and institutional support are closely connected. Also, present an overview of each of the three selected frameworks, which support establishing the theoretical foundation for the conceptual model and research approach provided later in this chapter.

2.4.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), created by Davis in 1989 (see Figure 7), is among the most thoroughly validated models for understanding how individuals adopt technology. It suggests that two fundamental beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), affect users' attitudes toward a technology, subsequently influencing their intentions to use it and their actual usage.

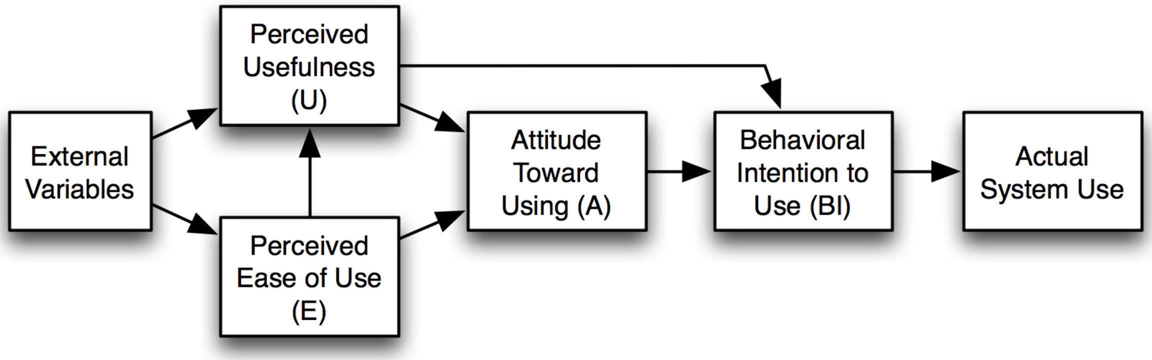

Fig. 7. Visual representation of TAM model (Source: Nippie, CC BY 3.0).

Over time, TAM has been adapted several times, for instance, TAM2 (see Figure 8) included constructs like Subjective Norm, Job Relevance, and Output Quality that consider social influence and task-context compatibility in influencing perceived usefulness (Venkatesh & Davis, 2000) while TAM3 (see Figure 9) included affective and cognitive constructs like Perceived Enjoyment, Computer Anxiety, and Self-Efficacy that are particularly applicable to users who would feel less secure with technology (Venkatesh & Bala, 2008).

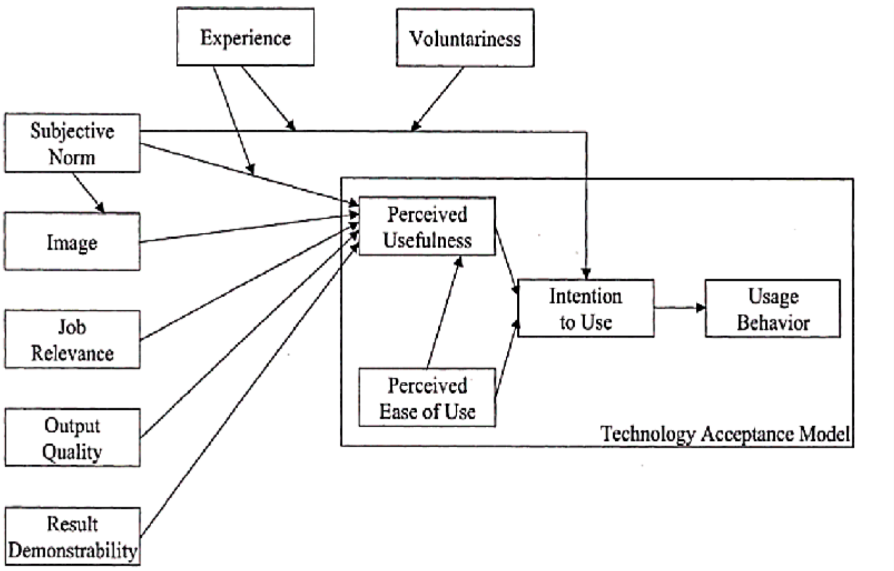

Fig. 8. Visual representation of TAM 2 (Source: Venkatesh and Davis, 2000).

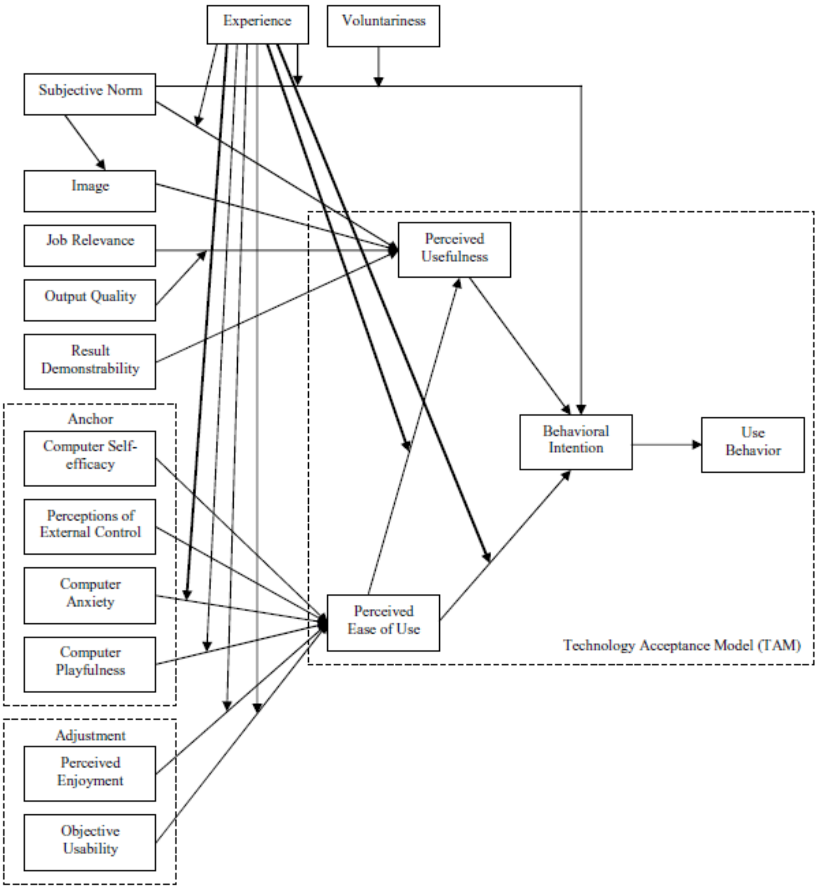

Fig. 9. Visual representation of TAM 3 (Source: Venkatesh and Bala, 2008).

To address the challenges related to AI, recent developments have incorporated concepts like Trust in AI and Perceived AI Intelligence to reflect the changing dynamics of the human–AI relationship (Baroni et al., 2022; Kim et al., 2025), these concepts are especially significant when using GenAI tools like ChatGPT, where issues related to transparency, control, and ethical usage are critical.

The TAM has been effectively utilized in non-technical fields like healthcare, education, and service roles, where individuals frequently interact with sophisticated systems without having formal technical training (Holden & Karsh, 2010; Turner et al., 2010). Its simplicity and flexibility render it particularly appropriate for examining the adoption of GenAI among workers in data-driven yet non-technical roles.

This research intentionally includes four constructs related to TAM (see Table 5), those are selected for their theoretical alignment and empirical significance in GenAI-supported work environments:

- **Perceived Usefulness:** The degree to which users feel that GenAI tools (such as ChatGPT, and Copilot) enhance task performance and support decision-making.
- **Perceived Ease of Use:** The extent to which GenAI tools are user-friendly and require minimal training or technical expertise.
- **Output Quality:** The perceived clarity, relevance, and dependability of outputs generated by GenAI tools, which directly shape judgements about usefulness (Venkatesh & Davis, 2000; Ma & Lei, 2024).
- **Trust in AI:** The confidence that GenAI systems are reliable, ethically aligned, and safe to use for task support (Kim et al., 2025; Aini et al., 2023).

Table 5. TAM constructs and their application to GenAI adoption in non-technical roles (author).

Construct	Definition	Application in This Research
Perceived Usefulness (PU)	The belief that using a GenAI tool enhances task performance, particularly in decision-making, data interpretation, or communication (Davis, 1989; Venkatesh & Davis, 2000).	This study examines how users perceive GenAI tools (e.g., SAP Joule, ChatGPT) as improving efficiency or decision quality in everyday work.
Perceived Ease of Use (PEOU)	The belief that a GenAI tool is easy to operate and learn, requiring minimal effort or technical training (Venkatesh & Bala, 2008).	This study investigates user perceptions of GenAI interfaces as intuitive, especially for employees without technical backgrounds.
Output Quality	The perceived accuracy, clarity, and relevance of AI-generated outputs (Venkatesh & Davis, 2000; Ma & Lei, 2024).	This study assesses whether users consider GenAI outputs trustworthy and useful enough to support work-related problem-solving.
Trust in AI	The belief that GenAI systems are reliable, consistent, and ethically aligned with user expectations (Kim et al., 2025; Aini et al., 2023).	This study explores how trust influences user reliance on GenAI for semi-autonomous decision-making and task completion.

These constructs provide an organized perspective to analyze the ways in which non-technical roles view and interact with GenAI tools in functions like human resources, marketing, and project management. Additional extensions of the Technology Acceptance Model (e.g., Subjective Norm, Enjoyment) are recognized in the wider literature but are excluded from this research.

2.4.2. Diffusion of Innovations (DOI)

The Diffusion of Innovations theory (see Figure 10), proposed by Everett M. Rogers in 1962, provides a structured approach for understanding how new technologies are shared, accepted, and disseminated across social systems over time. In contrast to models that concentrate on individual behavior, such as the TAM, DOI emphasizes the impact of organizational culture, social norms, communication channels, and systemic frameworks on the outcomes of adoption. Five key characteristics, *relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability* (see Table 6), are vital in shaping the rate and extent of innovation diffusion within organizations.

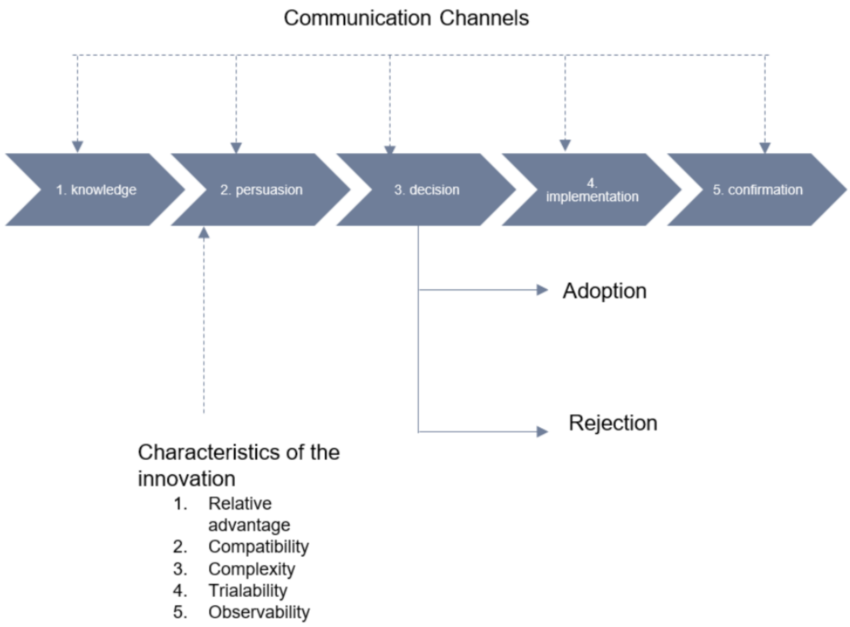

Fig. 10. Visual representation of DOI Innovation-Decision process (Source: Rogers, 2003)

In settings that are not focused on technology, the DOI framework effectively illustrates how emerging technologies such as GenAI are embraced, influenced not only by individual perspectives but also by their incorporation into day-to-day activities, prevailing cultural norms, and the overall readiness of the organization (Rogers, 2003; Miranda et al., 2016); for GenAI, since it depends on user-friendliness and trust to attract non-technical users, DOI provides insights beyond the simple cognitive evaluations by focusing on the structural and social elements that enable ongoing interaction with the tool. Current uses of DOI frequently combine additional models (such as TAM and TOE) to encompass both personal thought processes and organizational environments (Valencia-Arias et al., 2022; Herath et al., 2020). In non-technical environments, compatibility and complexity consistently rank as the most significant predictors of successful adoption, while trialability and observability enhance user assurance and social validation (Radhakrishnan & Chattopadhyay, 2020; Hubert et al., 2019).

Existing research has highlighted various attributes of innovation that play a role in the adoption of GenAI tools, especially among users with limited technical skills: *Compatibility*, which refers to how well a technology fits into existing workflows, has been found to significantly improve adoption rates, particularly in contexts where users lack technical expertise (Miranda et al., 2016; Russo, 2024). *Trialability*, having the chance to try out GenAI systems without a long-term commitment, helps alleviate initial fears and promotes user familiarity (Raman et al., 2024). *Observability*, or the ability to see peers successfully using these tools, enhances their perceived legitimacy and encourages wider organizational adoption through social proof (Xu et al., 2023). *Relative Advantage*, such as improved efficiency or productivity, also increases usage of GenAI-enabled workflows (Valencia-Arias et al., 2022). On the other hand, *Complexity*, especially when user interfaces are not intuitive or require high cognitive effort, continues to be a major obstacle to adoption in non-technical settings (Herath et al., 2020; Alabduljabbar, 2024).

Factors within the organization, like the backing of management and the implementation of training programs, affect how these traits affect the outcomes of adoption (Herath et al., 2020), this suggests that users do not solely drive the process of diffusion but is also influenced by systemic factors.

Table 6. DOI constructs and their application to GenAI adoption in non-technical roles (author)

Construct	Definition (Rogers, 2003)	Application in This Research
Compatibility	The degree to which GenAI tools align with existing workflows, values, or expectations	This study focuses on how well GenAI tools integrate into current routines and job responsibilities.
Complexity	The perceived difficulty of learning or using GenAI tools	The concept is discussed as a potential barrier, particularly when users report cognitive overload or interface friction.
Observability	The degree to which benefits of GenAI use are visible to others	This study uses observability to explain how peer usage or visible success stories influence tool legitimacy.
Relative Advantage	The extent to which GenAI tools are seen as improvements over prior solutions	This study considers how perceived improvements in speed, independence, or accuracy shape interest in GenAI use.
Trialability	The extent to which users can experiment with GenAI tools before committing to full use	This study interprets trialability as a condition that supports early-stage confidence and experimentation.

Although the DOI theory has been criticized for its limited ability to predict individual behavior (Legris et al., 2003; Dwivedi et al., 2019), it stands out at representing the environmental, social, and structural factors that facilitate or obstruct adoption. Thus, the DOI framework is applied in this research to explore how organizational norms, alignment of workflows, and observing peers using GenAI tools affect their adoption by employees without technical backgrounds.

Among the five attributes of DOI, *Compatibility* is emphasized as a significant contextual element in this study, as it represents the perceived alignment between GenAI tools and the existing routines of users. The other constructs, Relative Advantage, Trialability, Observability, and Complexity, are regarded as theoretically significant but are treated as supportive conditions. They provide context for the challenges of adoption and aid in interpreting users' stories but are not directly assessed in the analysis.

2.4.3. Systems Thinking (ST)

Systems Thinking provides a perspective for exploring complex, interconnected systems whose behaviors evolve over time (see Figure 11). Jay W. Forrester formally introduced this concept through his significant works, "Industrial Dynamics" (1961) and "World Dynamics" (1971), which presented essential ideas such as feedback loops, system structure, and non-linear causation in dynamic modeling. The work of Forrester laid the foundational technical and computational basis for what is now known as System Dynamics, an important field within Systems Thinking (Sterman, 2018; Rahmandad, 2015).

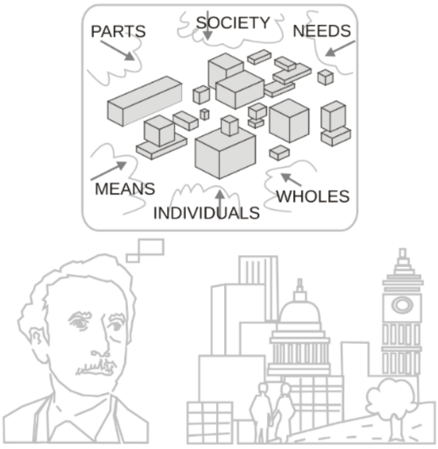

Fig. 11. Visual representation of DOI Concept (Source: Marcel Douwe Dekker, 2007)

In his book, "The Fifth Discipline" (1990), Peter Senge underscored the idea of Systems Thinking, which focused on management and organizational learning. Senge stressed the importance of comprehensive thinking, mental frameworks, and collaborative education as essential elements for effective management of complex systems (Reese, 2020; Hoe, 2019; Hansen et al., 2020); unlike the reductionist methods, ST explores how individual behaviors align with wider systemic patterns, shaped by feedback mechanisms and structural delays.

Technology adoption literature demonstrates that Systems Thinking framework offers an insightful lens for examining how new tools are not just utilized by individuals, but integrated into ongoing processes, communication tools, and interdepartmental dynamics (Russo, 2024; Oyekunle & Boohene, 2024); which is particularly relevant to the use of GenAI by employees in non-technical roles, who often work in complex systems that affect tool accessibility, trust, and sustained use.

Roles that include a non-technical background, such as project coordination, HR, data governance, or sustainability, are frequently involved in highly interconnected organizational settings, in such environments, GenAI tools are expected to be not only user-friendly, but also, integrate seamlessly with existing processes, support in decision-making across various functions, and be compatible with the ways teams communicate and act on information; as highlighted by Russo (2024), structural alignment often takes precedence over perceived usefulness in these situations. While TAM emphasizes the individual user beliefs and DOI highlights the organizational norms and social influences, ST introduces a structural aspect, it illustrates how systemic obstacles, such as ambiguous data ownership, disorganized workflows, or insufficient feedback mechanisms, can hinder adoption, even when the tools themselves are technically effective (Senge, 1990; Bhima et al., 2023).

The literature outlines a number of fundamental principles of ST that assist in understanding the adoption of GenAI within organizations, including Interconnectivity, Feedback Loops, Leverage Points, Holistic Perspective, Task Complexity (see Table 7). Although these principles are not specifically evaluated in this study, they provide a broader theoretical context and aid in interpreting the behaviors exhibited by organizations. Thus, the Systems Thinking lens as stated above provides a comprehensive viewpoint on adoption challenges, including structural, informational, and relational aspects. Hence, one key concept considered is Task Complexity, which refers to cognitive effort, the level of uncertainty, and coordination constraints linked to a user's responsibilities and tasks. Additionally, this concept represents the organizational and procedural aspects that affect how individuals interact with GenAI tools in their everyday work.

Table 7. The five core ST principles and their relevance to the study context (author).

Principle	Definition	Application in This Research
Interconnectivity	Emphasizes the relationships between people, tools, and workflows in organizational systems (Senge, 1990; Reese, 2020).	This study uses the principle to interpret how GenAI tools align with collaborative workflows in non-technical settings.
Feedback Loops	Describes how outputs are reintegrated into systems as inputs, shaping future behavior over time (Katsamakas et al., 2024).	The principle informs how repeated GenAI use contributes to learning, refinement, and trust-building over time.
Leverage Points	Refers to small, strategic areas in a system where targeted intervention can yield large effects (Senge, 1990; Oyekunle & Boohene, 2024).	This study uses the principle to identify high-impact opportunities for GenAI integration in workplace processes.
Holistic Perspective	Encourages viewing systems as wholes, not as discrete parts, to understand interdependent outcomes (Senge, 1990; Radhakrishnan & Chattopadhyay, 2020).	The principle frames GenAI adoption as part of systemic organizational change rather than isolated user behavior.
Task Complexity	Describes the cognitive, informational, and coordination-related difficulty inherent in task execution (Muduli & Choudhury, 2024).	This study examines how role-based complexity, such as ambiguity, overload, and coordination demands, shapes GenAI use.

This research utilizes Systems Thinking as a qualitative framework while integrating Task Complexity into the research methodology. Therefore, Task Complexity is employed to examine how cognitive demands associated with roles, including information ambiguity, coordination across multiple departments, and restricted technical support, affect the utilization of GenAI tools. The other principles of Systems Thinking offer interpretative assistance in assessing participant experiences and observed actions, especially in settings marked by feedback loops and systemic limitations. By broadening the analytical perspective beyond just the single user or tool interface, Systems Thinking emphasizes the importance of considering GenAI adoption as a systemic process, shaped by role design, information frameworks, and the organization’s preparedness.

2.5. Integration of Behavioral and Systemic Theories for GenAI Use in Non-Technical Roles

This research seeks to develop a solid base for exploring how non-technical roles adopt and use generative AI tools to enhance their problem-solving capabilities by combining the three interconnected frameworks that are presented in the above sections: the Technology Acceptance Model, the Diffusion of Innovations theory, and Systems Thinking; each of these introduced frameworks provide a distinct outlook, focusing on individual perception, adoption into social systems, and the complexity within organizations, thereby delivering a combined insight into understanding GenAI acceptance.

TAM describes the user-centric cognitive assessments using constructs like Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI, and Output Quality, which all have a joint effect on behavioral intention and the actual use of technology tools (Davis, 1989; Ma & Lei, 2024; Kim et al., 2025).

DOI through compatibility presents the contextual moderator, which indicates how well GenAI systems align with current workflows, standards, and values (Rogers, 2003; Russo, 2024) and this concept is especially important for ongoing adoption by non-technical users who have minimal technical independence.

ST integrates the moderating factors of Task Complexity and Interdependencies, emphasizing the cognitive and procedural difficulties encountered in resolving problems within distributed and frequently unclear work context (Senge, 1990; Oyekunle & Boohene, 2024), thereby facilitating the analysis of how systemic structures affects the perceived value and inclusion of GenAI tools within organizational contexts.

Combined together, these frameworks contribute to a triangulated model where user perceptions (TAM) are influenced and shaped by contextual compatibility (DOI) and the complexity at the system level (Systems Thinking). This integration allows the research to extend beyond singular behaviorist models and to factor in the wider conditions that affect substantial GenAI utilization.

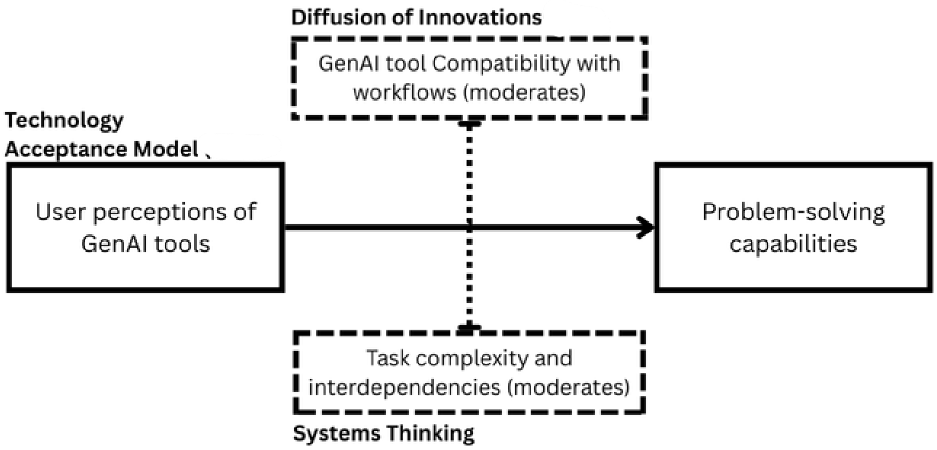

Fig. 12. Integrated conceptual framework linking GenAI perceptions to problem-solving capabilities in non-technical roles (author).

Figure 12, illustrate a broad visual representation of this cohesive structure; it shows how perceptions, which are shaped by usefulness, usability, trust, and output quality, connect to problem-solving capabilities, this connection is affected by how well GenAI tools integrate into existing workflows (DOI) and the complexity of the roles and systems they are utilized within (ST). This theoretical blend forms the foundation for the conceptual model portrayed in Section 2.7 and directly shapes the empirical design discussed in Chapter 3, by combining these frameworks the research also responds to earlier criticisms of the limited adoption models (Legris et al., 2003; Dwivedi et al., 2019) and includes both individual and structural factors in adoption are included.

2.6. Problem-Solving Capability Dimensions in the Context of Generative AI

Organizations progressively recognize that effective problem-solving necessitates combining human cognitive skills with advanced digital technology (Drigas & Karyotaki, 2019). Within the scope of this research, employees without technical backgrounds interact with generative AI, which is a system designed to assist with data-driven activities such as analysis, decision-making, and communication. Therefore, it is essential to conceptualize problem-solving abilities through dimensions that represent traditional reasoning skills and AI-enhanced methods. Table 8, offers a systematic summary of the three dimensions and their significance for GenAI-assisted problem-solving.

Table 8. Problem-solving capability dimensions and their application to GenAI-supported flows (author).

Dimension	**Definition**	**Application in This Research**
Data Reasoning	The ability to interpret, critically evaluate, and apply AI-generated outputs in context (Akinnagbe, 2024; De Laat et al., 2020).	This study examines how non-technical users engage with GenAI content to derive insights, verify information, and solve problems.
Adaptive Decision-Making	The capacity to revise decisions or workflows based on real-time AI feedback (Singh & Kaunert, 2024; Drigas & Karyotaki, 2019).	This study analyzes how users update their responses or strategies based on evolving GenAI-generated insights, particularly when applying technical and creative tasks.
Problem-Solving Efficiency	The enhancement of task speed, decision quality, and user independence through AI support (Ma & Lei, 2024; Wang et al., 2023).	This study captures both perceived and observed improvements in efficiency when GenAI tools are used in workflow execution.

This research builds on the structured literature review and aligns with the previously discussed theoretical frameworks (TAM, DOI, and ST). It emphasizes three outcome dimensions that illustrate how GenAI tools aid and improve problem-solving capabilities among non-technical roles: Data Reasoning, Adaptive Decision-Making, and Problem-Solving Efficiency.

2.6.1. Data Reasoning

Data Reasoning refers to the cognitive skills required to analyze, evaluate, and utilize AI-generated content to tackle challenges in the workplace (Akinnagbe, 2024). This dimension emphasizes the importance of engaging actively and critically with GenAI-produced content rather than merely accepting it to ensure accuracy, relevance, and decision-making based on data (De Laat et al., 2020; Muduli & Choudhury, 2024).

Studies show that GenAI tools can significantly improve the ability of non-technical users to comprehend complex data and derive valuable insights, which can enhance their confidence and critical thinking abilities (Akinnagbe, 2024; De Laat et al., 2020). However, practical reasoning requires individuals to critically assess, verify, and contextualize outputs, particularly in circumstances where the information is unclear or subject to change (Muduli & Choudhury, 2024).

This research defines Data Reasoning as the ability of non-technical roles to interpret, question, and utilize GenAI outputs in order to address data-related problems within their organization.

2.6.2. Adaptive Decision-Making

Adaptive Decision-Making refers to the ability to change or adapt processes and decisions based on new input or feedback generated by GenAI agents; especially when the need for flexible, ongoing decision-making is increasingly essential in fast-changing organizational settings (Singh & Kaunert, 2024; Drigas & Karyotaki, 2019).

GenAI tools are recognized as enablers of adaptable behavior, as they allow users to explore various scenarios, adjust plans, and alter decisions in real time (Singh & Kaunert, 2024; Drigas & Karyotaki, 2019); this becomes especially crucial for non-technical roles, where decisions may be required in unpredictable situations or require a space for creative exploration without immediate technical guidance or assistance.

This research defines Adaptive Decision-Making as the ability of individuals in non-technical roles to adjust strategies or actions according to changing insights offered by GenAI tools in both structured technical and creative tasks.

2.6.3. Problem-Solving Efficiency

Problem-Solving Efficiency refers to the enhancements in the speed, quality, and independence in the task completion when GenAI tools are incorporated into non-technical processes; It showcases the clear and significant benefits of GenAI in enhancing productivity and reducing dependence on technical teams (Ma & Lei, 2024; Wang et al., 2023).

Studies indicate that non-technical employees employing GenAI systems experience reduced dependency on technical teams, quicker task fulfillment, and better access to data for making decisions (Ma & Lei, 2024; Wang et al., 2023). These improvements are particularly significant for roles that have traditionally relied on technical mediation.

This research characterizes Problem-Solving Efficiency as the perceived and observed enhancements in task speed, decision-making accuracy, and user autonomy when GenAI tools are utilized for data-driven tasks.

2.7. Conceptual Model Linking GenAI Tool Perceptions to Problem-Solving Capability Enhancement

This section presents a conceptual framework designed to demonstrate how non-technical personnel adopt and utilize generative AI tools to enhance their problem-solving abilities within organizational settings. The model integrates insights from TAM, DOI, and Systems Thinking, offering a comprehensive explanation that combines individual perceptions, contextual significance, and the complexities of the overall system. As illustrated in Figure 13, the framework outlines the process from users' perceptions of GenAI tools to the development of advanced problem-solving skills, considering the perceptional, behavioral, and contextual factors that impact this progression.

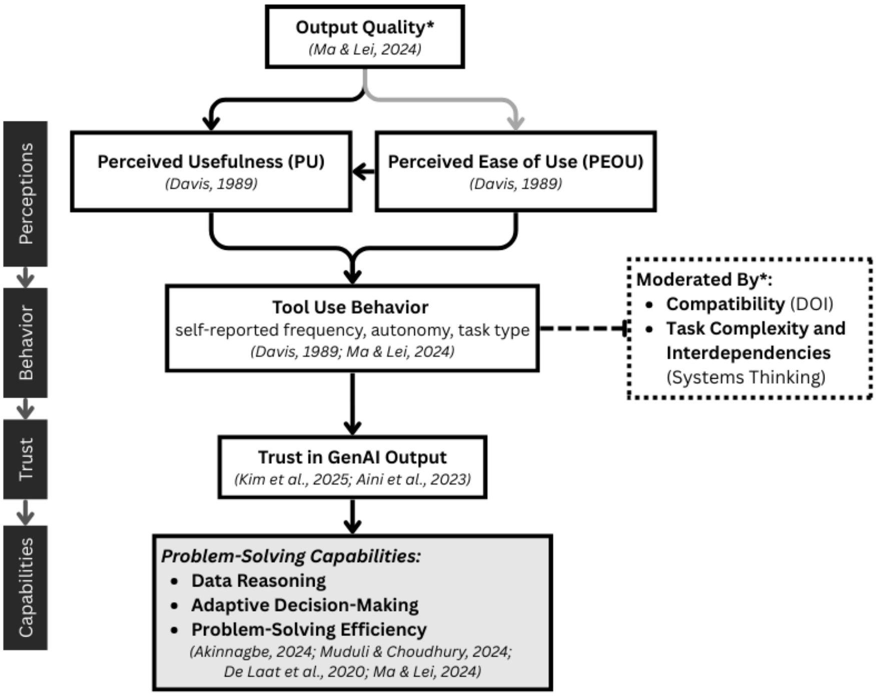

Fig. 13. Conceptual model linking GenAI perceptions to enhancing problem-solving capabilities in non-technical roles (author).

Note. The *solid arrows* indicate the suggested direct relationships, while the *dashed arrows* denote moderation effects that are assessed qualitatively. The *lighter arrow* connecting Output Quality to PEOU implies a theoretically supported, yet less empirically confirmed relationship, especially in comparison to its effect on PU, as highlighted by the research carried out by Ma & Lei (2024).

2.7.1. Core Constructs and Relationships

At the core of the model are two perceptual constructs derived from the Technology Acceptance Model: **Perceived Usefulness (PU)** and **Perceived Ease of Use (PEOU)** (Davis, 1989). PU measures how much users think GenAI tools improve their performance in tasks related to data, while PEOU indicates how easily the tools can be utilized without needing technical skills.

Both constructs are affected by **Output Quality**, which is characterized by the clarity, precision, and contextual relevance of responses generated by AI (Ma & Lei, 2024). Output Quality is suggested to be a predictor of both PU and PEOU, showing a more significant empirical effect on PU. This relationship illustrates how the quality of content impacts both the perceived importance and usability of GenAI tools.

Combined, PU and PEOU influence **Tool Use Behavior**, which is defined in this model as the frequency of GenAI tool usage, the degree of autonomy with which tools are utilized, and the type of tasks supported (Davis, 1989; Ma & Lei, 2024). This behavioral involvement signifies the transition from perception to action; an essential aspect of understanding the adoption of technology in real-life scenarios.

Following this, **Trust** in GenAI Output arises as a subsequent construct that is acquired through experience. Trust is described as the confidence in the dependability, ethical considerations, and consistency of content generated by AI (Kim et al., 2025; Aini et al., 2023). Instead of being viewed as a prerequisite, trust is represented as a result of interacting with the tools, illustrating how users gain confidence through demonstrated performance.

Trust, in turn, facilitates the development of three interconnected problem-solving skills (a) **Data Reasoning**, (b) **Adaptive Decision-Making** in technical and creative contexts, (c) **Problem-Solving Efficiency**. These three skills are conceptualized as elevated outcomes of sustained engagement with GenAI. They extend beyond simple tool usage to reflect a deeper integration of AI into users' problem-solving reasoning and workflow behavior.

2.7.2. Moderating Factors

The model includes two contextual moderators grounded in Diffusion of Innovations (DOI) and Systems Thinking to address broader organizational influences:

- **GenAI Tool Compatibility** (as outlined by DOI): This indicates the degree to which GenAI tools fit with current workflows, cultural norms, and values (Rogers, 2003; Russo, 2024). It is expected that this factor will strengthen the relationship between Perceived Ease of Use (PEOU) and Tool Use Behavior, as users are more likely to adopt tools that smoothly fit into their daily activities.
- **Task Complexity and Interdependencies** (from a ST lens): This indicates the level of uncertainty, cognitive demands, and collaboration required to accomplish tasks (Senge, 1990; Muduli & Choudhury, 2024). A higher level of complexity is expected to intensify the impact of PU on Tool Use, as users are more likely to seek AI support for difficult or unfamiliar tasks.

The above-stated moderators will be observed qualitatively through user observations in experimental settings and self-reports rather than undergoing statistical testing. Their inclusion highlights the research's dedication to capturing both individual and systemic elements that affect the adoption of GenAI.

To summarize, this suggested model describes a step-by-step approach that starts with initial perceptions (Output Quality, PU, PEOU) and progresses to active engagement, which nurtures trust development, ultimately resulting in the enhancement of three essential problem-solving abilities. While the contextual factors like compatibility and complexity help clarify the circumstances under which this progression can be facilitated or blocked within organizational settings.

3. Methodological Solutions for Exploring GenAI Adoption and Problem-Solving Capabilities

This chapter describes the research process (see Figure 14), design, instruments, data collection procedures, and analytical strategies applied to explore how employees in non-technical including hybrid roles perceive, use, and benefit from Generative AI tools in solving data-related problems.

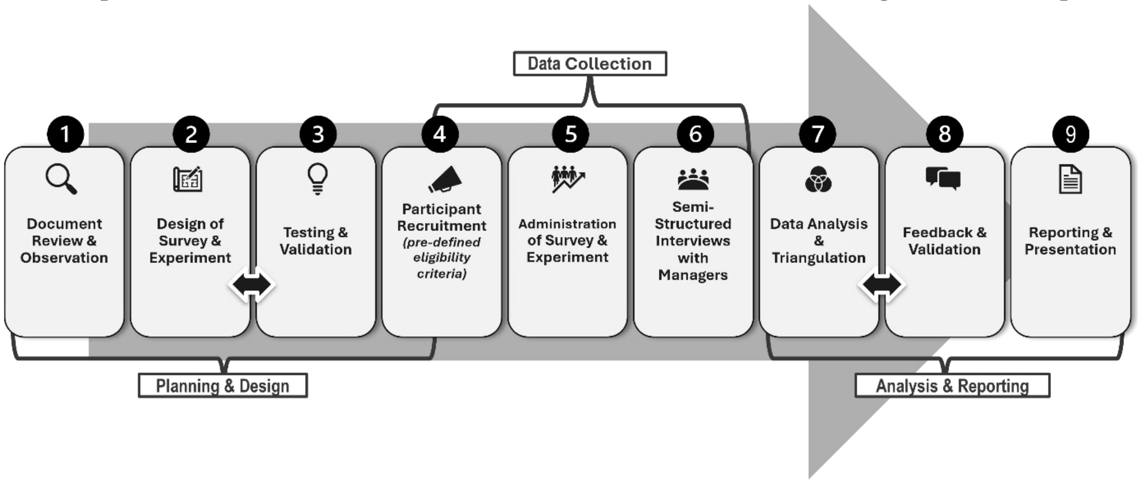

Fig. 14. A visual representation of the research process (author).

The methodology design directly aligns with the conceptual framework presented in Chapter 2, covering constructs such as perceived usefulness, trust, task complexity, and problem-solving capability from three different lenses:

— ***Perception lens*** is assessed through survey data, which combines quantitative composite measures (such as Perceived Usefulness, Perceived Ease of Use, Trust in AI, Tool Use Behavior, Output Quality, and Problem-Solving Capability) with qualitative open-ended responses.

— ***Behavioral lens*** is observed through structured experimental observations that evaluate participants' independence, strategic approach, and adaptability when executing data-related tasks with or without the assistance of GenAI, in technical and creative tasks.

— ***Contextual lens*** is informed by semi-structured interviews with managers engaged in AI enablement initiatives, alongside qualitative insights from surveys and observation reflections from the author.

Through the stated three lenses, this chapter examines four interconnected areas of research: (1) how employees perceive the usefulness, usability, and trustworthiness of GenAI tools (perception and adoption); (2) how GenAI influences the capabilities of non-technical roles in data reasoning and adaptive decision-making (capability development); and (3) how organizational factors such as leadership support, training, and collaboration affect the GenAI tools effectiveness (contextual conditions).

3.1. Mixed-Methods Research Design Overview

This research followed an *explanatory sequential mixed-methods design* (see Figure 15), integrating three empirical lenses: *perception*, *behavior*, and *context*. Data collection proceeded in three phases:

1) A structured survey to explore perceptions and adoption patterns of GenAI tools.

2) A controlled experiment to observe behavioral responses under GenAI-supported and unsupported task conditions.

3) Semi-structured managerial interviews to assess organizational enablers and contextual factors influencing GenAI integration.

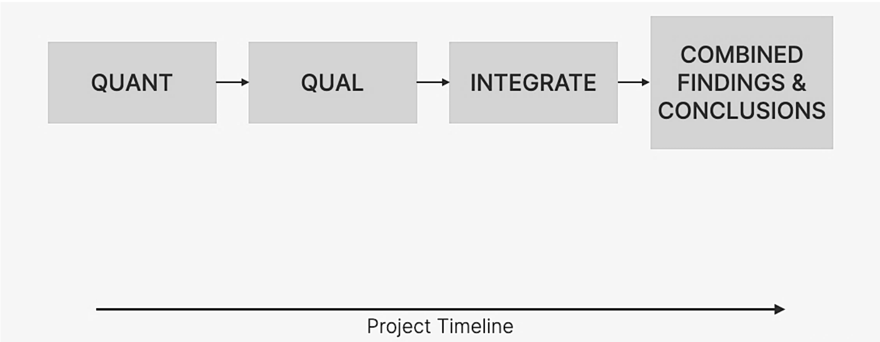

Fig. 15. A visual representation of the explanatory sequential design (Source: Drill Bit Labs)

Supporting documentation and field observations were collected to support the contextual understanding and driving the findings within the organizational setting. This layered triangulation approach facilitates both convergence and divergence analysis across data types (Denzin & Lincoln, 2018).

3.2. Research Instruments and Procedures

3.2.1. Survey Instrument

The first phase of data collection, included a structured survey which targeted employees from the „Case Organization“ whom are in non-technical and hybrid roles engaged in data-related tasks. A total of 32 responses were collected, with 27 completed surveys forming the basis of analysis.

The survey consisted of 49 questions across eight thematic sections (see example in Table 9), covering demographic data, role classification, GenAI usage patterns, technology perceptions, problem-solving development, enablement conditions, and cross-functional collaboration (refer to Appendix 1).

Table 9. Sample survey questions with construct alignment, classification and sources (author).

Code	Example Question	Construct	Classification	Author(s) / Year
Q12	GenAI tools are easy to use without technical expertise.	Perceived Ease of Use (TAM)	Core	Davis (1989)
Q17	GenAI tools help me evaluate and interpret data insights.	Data Reasoning (Problem-Solving)	Core	Akinnagbe (2024); De Laat et al. (2020)
Q23	I believe I would benefit from tailored training or role-specific support.	Compatibility (DOI); Task Complexity (ST)	Functional	Rogers (2003); Senge (1990)
Q25	What would make your day-to-day use of GenAI tools more effective?	Perceived Usefulness (TAM)	Supportive	Davis (1989)

Questions were mapped to the conceptual framework and classified as core, functional, or supportive. Composite variables were constructed for key constructs, as detailed in Appendix 2. For example, Perceived Usefulness (PU) was based on two items (Q11, Q21), and Problem-Solving Capability (PSC) was constructed from three items (Q17, Q18, Q26). Output Quality was measured using a two-item composite, acknowledging the exploratory nature of this decision.

The survey was distributed via the company's internal communication channels to employees working with data across business units.

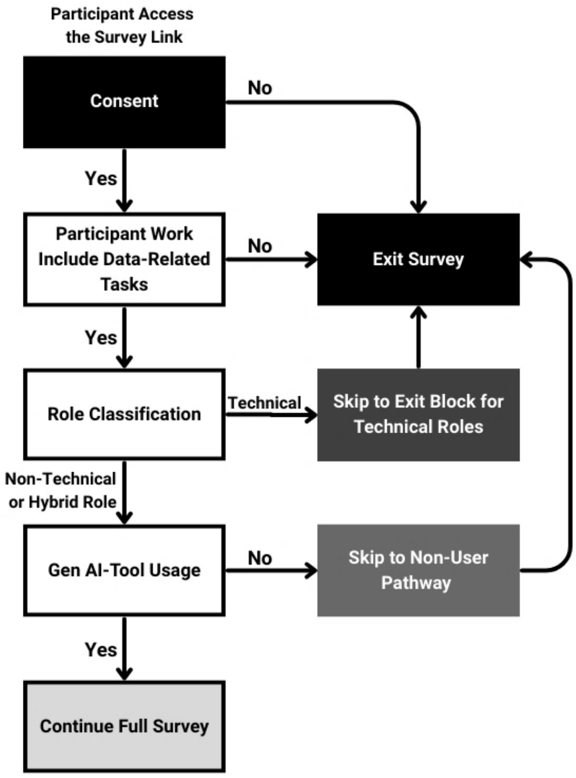

Fig. 16. Visual representation of the survey structure (author).

The survey flow was managed using „KoboToolbox" with conditional skip logic to ensure question relevance and minimize respondent fatigue, also, role classification was conducted using a two-step filter, to reduce bias (see Figure 16). While, open-ended responses were reviewed for illustrative insights but not formally coded.

3.2.2. Experimental Task

The second data source included the experimental phase involving 8 participants (50% are females) from non-technical and hybrid roles, recognized as data experts or data analytics specialists. A within-subject, counterbalanced design allowed participants to complete both structured and creative problem-solving tasks under alternating GenAI-supported and unsupported conditions.

The experimental design was grounded in the dual dimensions of problem-solving capabilities defined in the theoretical framework:

— **Task 1** focused on interpreting a business report and summarizing key insights. This represents a structured, technical problem-solving scenario aligned with data reasoning, the ability to evaluate structured information, identify trends, and synthesize conclusions.

- **Task 2** required participants to define a new business term for use in internal metadata systems. This task reflected an open-ended, creative challenge that emphasized adaptive decision-making, the capacity to navigate uncertainty, contextualize outputs, and refine solutions when supported by GenAI tools.

Table 10. Task and GenAI condition distribution by group (author).

Group	Task 1 (Report Data Interpretation)	Task 2 (Business Term Creation)
A	Without GenAI	With GenAI
B	With GenAI	Without GenAI

Behavioral outcomes such as independence, confidence, and efficiency were captured through post-task reflections and researcher observations. A detailed overview of the experimental procedure and task assignments is provided in Appendix 3.

Participants engaged in 30-minute individual sessions, receiving instructions and a consent form 15 minutes beforehand. At the start, they confirmed consent and provided demographic information. They completed the two tasks, with each task taking 10–12 minutes. One task utilized GenAI support with tools like Microsoft Copilot, while the other did not. After each task, participants reflected on their experience (see Appendix 4 for reflection question and Appendix 5 for questions constructs mapping), and the author conducted structured observations (see Appendix 6) in addition to a final comparative reflection where participants assessed their perceived changes between the two conditions. Each interview lasted approximately 15–20 minutes and followed a standard protocol.

3.2.3. Interviews with Managers

To contextualize findings, the third data source consisted of conducting 5 semi-structured interviews with managers engaged in AI enablement, data governance, and business leadership. Interviews focused on organizational enablers such as leadership support, training provision, and cross-functional collaboration (see Table 11 for examples). Data collection was conducted both in-person and online via Microsoft Teams, with transcripts reviewed for accuracy.

Table 11. Alignment of interview theme with conceptual constructs (author).

Theme	Example Interview Question	Construct
Strategic Enablement	What role does GenAI play in supporting non-technical employees?	Systems Thinking – Organizational Learning
Compatibility & Barriers	What are the biggest barriers to adoption or effective use of GenAI?	DOI – Compatibility, Trialability
Trust and Framing	What structural changes are needed to unlock the full value of GenAI?	TAM Extension – Trust, Output Quality

While the interview sample was limited, managerial insights served as contextual triangulators rather than sources of statistical inference. Full interview questions and construct mappings are included in Appendix 7.

3.3. Participant Recruitment and Ethical Considerations

Participants across all research phases were recruited voluntarily and provided informed consent. Ethical approval was obtained from the „Case Organization“, and the study adhered to corporate research governance and privacy policies. No personally identifiable information was collected. Observation protocols and reflection forms were designed to minimize participant discomfort and ensure data confidentiality.

3.4. Data Analysis Strategy

For analysis, a multi-level data integration approach was applied, described as follows:

Survey Analysis

- Using „Jamovi“ statistical software, quantitative responses were analyzed through descriptive statistics and exploratory correlations across TAM, DOI, and ST constructs was applied.
- Composite variable reliability was assessed using Cronbach’s Alpha, and limitations of certain scales are acknowledged (e.g., PU $\alpha = 0.44$).
- Open-ended responses were reviewed for illustrative quotes but not subjected to formal thematic coding.

Experimental Analysis

- Small-sample non-parametric methods, including the Wilcoxon signed-rank test, were used to explore within-subject differences in performance under GenAI-supported and unsupported conditions (Behjat et al., 2016; Madeyski & Kitchenham, 2017).
- Behavioral observations and participant reflections were synthesized using case-level pattern recognition to identify common themes in independence, confidence, and problem-solving efficiency.

Interview Analysis

- Interview transcripts were coded using thematic analysis in Microsoft Excel, guided by the conceptual framework constructs (leadership support, compatibility, task complexity).
- Findings were integrated with experimental and survey data to assess convergence and divergence across perspectives.

Triangulation Approach was applied analytically at the construct level and across empirical lenses (as explained in section 3.1) where Managerial interviews provided contextual anchoring, while the experiment validated behavioral outcomes against self-reported perceptions (see Figure 17).

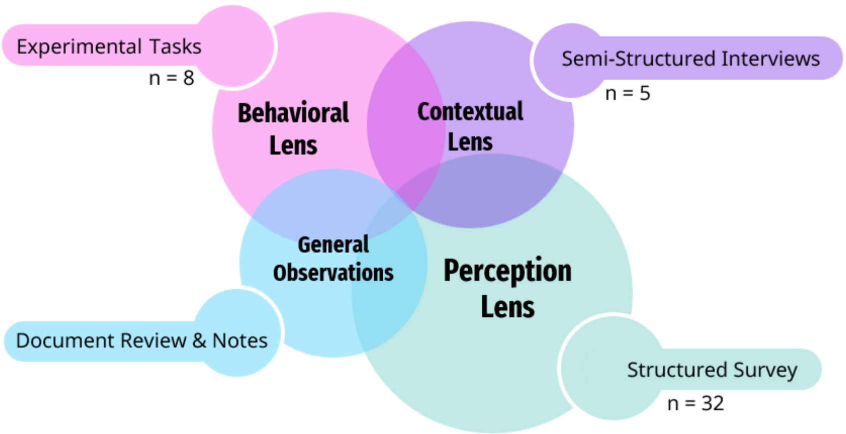

Fig. 17. Triangulation illustration of empirical lenses and instruments integration (author).

Divergences between data sources were treated as valuable indicators of underlying complexity rather than contradictions.

3.5. Methodological Limitations

The research faced several limitations. The small sample sizes in the survey (n = 27) out of 32 respondents met the criteria described in section 3.3.1, experimental (n = 8) and interview (n = 5) which limit statistical generalizability. However, the planned triangulation across empirical lenses (described in section 3.5) supports interpretive depth and mitigates reliance on any single data source.

The survey design incorporated single-item measures for some constructs (e.g., PEOU, Output Quality), which constrains construct validity but was considered as a practical way to reduce respondent fatigue; this limitation is explicitly addressed through triangulation with behavioral and qualitative data.

Finally, data collection was conducted within a single organizational context, limiting external generalizability. Nonetheless, the findings provide analytical generalization relevant for organizations engaged in digital transformation and AI tool adoption.

To summarize, together, the presented three instruments formed the empirical core of this research, enabling construct triangulation across perception, behavior, and managerial framing. Each instrument was mapped to one or more theoretical constructs from the conceptual framework to ensure full operationalization of the study’s core concepts, including PU, PEOU, task complexity, data reasoning, and trust. This alignment ensured that the data collected could be meaningfully interpreted in light of the research questions and theoretical lens. The resulting design integrates diverse but complementary sources of insight, quantitative, behavioral, and qualitative, ensuring a robust foundation for the interpretive and comparative analyses presented in the following chapter.

4. Empirical Results and Integrated Discussion on GenAI-Enhanced Problem-Solving

4.1. Perception and Adoption Lens

RQ1: How do non-technical, including hybrid-role employees perceive the usefulness, ease of use, and trustworthiness of GenAI tools? (Anchored in TAM and DOI)

This section tackles RQ1 by employing a mixed-methods strategy based on the Technology Acceptance Model, the Diffusion of Innovations theory, and Systems Thinking. The survey consisted of 32 participants, with 27 finishing the entire questionnaire. The other five left before completion due to either not using GenAI tools (n = 3) or being categorized as technical-role employees (n = 2). All quantitative analyses below are based on the 27 full responses. *(Item codes (e.g., Q11) refer to survey questions detailed in Appendices 1 and 2).* Composite variables were constructed as follows:

- **Perceived Usefulness (PU)**: Mean of two items (Q11, Q21), Cronbach's α = 0.44
- **Trust in GenAI**: Mean of two items (Q13, Q14), Cronbach's α = 0.52
- **Output Quality**: Mean of two items (Q14 and Q15), Cronbach's α = 0.75
- **Problem-Solving Capability (PSC)**: Mean of three items (Q17, Q18, Q26), Cronbach's α = 0.83
- **Perceived Ease of Use (PEOU)**: Single item (Q12), not subject to reliability testing

Although PSC was constructed and reliability assessed, it is not analyzed further in this section, as it serves as the primary outcome variable in RQ2. Output Quality was assessed using a two-item composite, including a revised item explicitly covering both transparency and output quality perceptions. While this dual-purpose item introduces some construct overlap, it was considered an acceptable trade-off given the exploratory nature of the study and the aim to reduce respondent burden (Bergkvist & Rossiter, 2007). This limitation is acknowledged and compensated for through triangulation with qualitative reflections.

4.1.1. Perceived Usefulness (PU)

Participants generally expressed a high perceived usefulness of GenAI tools ($M = 3.85$, $SD = 1.03$), supporting TAM's core idea that task relevance drives technology adoption (Davis, 1989). PU did not show significant differences based on role ($t(25) = 0.51$, $p = 0.62$, $d = 0.20$), nor by usage frequency, though frequent users reported a descriptively higher PU ($M = 4.19$) than infrequent users ($M = 3.33$). Welch's ANOVA resulted in a non-significant outcome ($p = 0.29$), but Tukey post hoc analysses approached significance ($p = 0.06$), indicating a trend that may be worth exploring in larger samples. Likewise, younger participants indicated higher PU scores ($M = 4.19$) compared to their older counterparts ($M = 3.59$), $t(25) = 1.53$, $p = 0.14$, $d = 0.66$. Although this finding was not statistically significant, the observed finding aligns with DOI's focus on early adopter characteristics (Rogers, 2003) and implies that frequency of exposure and digital familiarity might have a moderating role.

Table 12. PU comparisons by role, age group, and use frequency (author).

Group Comparison	N	Mean (SD)	t/F Statistic	p-value	Cohen's d
Role (Non-Tech vs Hybrid)	27	4.18 (0.75) / 4.03 (0.76)	t(25) = 0.507	0.617	0.199

Group Comparison	N	Mean (SD)	t/F Statistic	p-value	Cohen's d
Age (Under 40 vs 40+)	26	4.28 (0.60) / 3.81 (0.92)	t(24) = 1.540	0.136	0.656
Use Frequency (Frequent vs Infrequent)	27	4.19 (0.67) / 3.33 (1.04)	F(1,2) = 1.920	0.289	0.854 (Tukey p = 0.060)

Note. t(df) = t-test statistic with degrees of freedom; *p* = significance level; *d* = Cohen's *d* (effect size).

"GenAI saves me hours each week writing technical documentation" (respondent reflection)

"I frequently utilize GenAI for streamlining reporting tasks" (respondent reflection)

These quotes reflect practical benefits and efficiency; confirming that participants associate usefulness with the automation and simplification of tasks.

4.1.2. Trust in GenAI

The overall trust was moderate (M = 4.07, SD = 0.78), with participants in hybrid roles demonstrating higher trust (M = 3.66) compared to non-technical users (M = 3.36), t(25) = -1.42, p = 0.17, d = -0.56. While not statistically significant, the moderate effect size and consistent trend indicate that Individuals in hybrid roles may have greater assurance regarding the precision or validity of outputs generated by GenAI, likely due to a better understanding of how GenAI tools function. Trust demonstrated a notable and significant correlation with PU (r = 0.50, p = 0.009), confirming the TAM extension that positions trust as a prerequisite for perceived usefulness in AI contexts (Venkatesh & Davis, 2000).

Table 13. Trust in GenAI comparisons by role and age group (author).

Group Comparison	N	Mean (SD)	t/F Statistic	p-value	Cohen's d
Role (Non-Tech vs Hybrid)	27	3.36 (0.55) / 3.66 (0.51)	t(25) = –1.42	0.168	–0.557
Age (Under 40 vs 40+)	26	3.61 (0.53) / 3.38 (0.58)	t(24) = 1.020	0.319	0.432

Note. t(df) = t-test statistic with degrees of freedom; *p* = significance level; *d* = Cohen's *d* (effect size).

"I trust GenAI to get me started, but I always double-check the results"
(respondent reflection)

"Gen AI tools can help with many tasks but sometimes create hallucinated results"
(respondent reflection)

The remarks shared by respondents illustrate their cautious or context-dependent trust in GenAI; although users recognize the usefulness of such tools, they remain skeptical of the output reliability. The use behaviors indicated in the survey demonstrate a strong sense of Usefulness alongside a moderate to low level of Trust in AI, which aligns with the Technology Acceptance Model. (refer to section 2.7). Additionally, the tendency to double-check AI output shows that users encounter issues with Output Quality or lack of trust in AI Outputs; potentially leading to persistent hesitation in the generated output despite acknowledging the possible efficiency advantages of utilizing GenAI tools to complete tasks.

4.1.3. Perceived Ease of Use (PEOU)

The GenAI tools Ease of Use was overall rated positive by the survey respondents (M = 3.85, SD = 0.60). Notably, non-technical users reported a higher PEOU (M = 4.27) compared to those in hybrid roles (M = 3.81), t(25) = 1.65, $p = 0.11$, d = 0.65. This finding contradicts with the expectations specified by TAM, which suggests that individuals with greater technical skills usually experience easier use due to their familiarity with complex digital systems (Davis, 1989; Venkatesh & Davis, 2000). Specifically, in the case of generative AI, this trend seems reversed, as summarized in Table 14, with GenAI tools like ChatGPT being explicitly designed with natural language interfaces that reduce interaction complexity, making it simple to use (Yan et al., 2024). Thus, the integrated design features reduce technical barriers and align tool usage with communication styles that are more familiar to non-technical roles, consequently resulting in higher perceptions of usability within this group.

"Interacting with the tool is like talking to someone, not difficult at all"
(respondent reflection)

On the other hand, individuals in hybrid roles, who engage with specialized and technically complex tasks more often, may find GenAI tools less capable of supporting their advanced workflow needs; this mismatch could lead to lower PEOU ratings despite their higher technical proficiency; as for these users usability may not be only assessed in terms of interface simplicity but also functional adequacy for complex problem-solving scenarios.

Moreover, the findings indicate that although GenAI tools provide user-friendly interfaces, effective use still depends on basic skills such as prompt formulation and continuous refinement.

"Not hard, but not always clear how to get the best results"
(respondent reflection)

"It is a skill that needs to be learned as prompting and its quality determine the results"
(respondent reflection)

Table 14. Perceived ease of use comparisons by role and age group (author).

Group Comparison	N	Mean (SD)	t/F Statistic	p-value	Cohen's d
Role (Non-Tech vs Hybrid)	27	4.27 (0.47) / 3.81 (0.83)	t(25) = 1.650	0.111	0.648
Age (Under 40 vs 40+)	26	4.11 (0.68) / 3.88 (0.83)	t(24) = 0.765	0.452	0.325

Note. t(df) = t-test statistic with degrees of freedom; *p* = significance level; *d* = Cohen's *d* (effect size).

The weak and statistically non-significant correlation between PEOU and PU (r = 0.25, p = 0.22) further reinforces this point, indicating that ease of use alone does not necessarily lead to higher perceptions of usefulness, particularly in tasks requiring complex problem-solving.

4.1.4. Correlational Insights

The correlation analysis explored the relationships between PU and key constructs defined in the conceptual model of this research. The observed strongest positive correlations with PU are illustrated in Table 15 (see Appendix 8 for correlation plot).

Table 15. Correlations significance with PU (author).

Variable	Correlation Coefficient (*r*)	*p*-value	Significance Level
PSC_Mean	0.665	p < 0.001	Highly Significant
Behavioral Intention	0.593	p = 0.001	Highly Significant

Variable	Correlation Coefficient (*r*)	*p*-value	Significance Level
Compatibility	0.519	p = 0.006	Significant
Trust_Mean	0.495	p = 0.009	Significant
Complexity_Mean	0.461	p = 0.015	Significant
Output_Quality_Mean	0.289	p = 0.144	Not Significant

Note. r = Pearson's correlation coefficient; p = significance level. Significance levels follow conventional thresholds: $p < 0.05$ (Significant), $p < 0.01$ (Highly Significant).

Although the introduced conceptual model in Chapter 2 highlights Output Quality as a predictor of PU, the correlation analysis indicated a weak and statistically insignificant relationship ($r = 0.289$, $p = 0.144$); this result likely stems from the practical decision to determine Output Quality using a short two-question composite, with one question performing a dual purpose by satisfying both fairness and output quality perceptions. While this approach was justified to reduce cognitive load (Bergkvist & Rossiter, 2007), it may have limited the ability to capture the full complexity of Output Quality's influence on PU.

This finding reinforces the mixed-methods approach employed in the study. The triangulation of qualitative insights indicated that although quantitative findings did not identify Output Quality as a statistically significant contributor to PU, qualitative data and participant insights imply that output quality is still a crucial factor affecting the integration of GenAI tools in problem-solving tasks.

"Gen AI tools can help with many things but sometimes it does not help with purely technical solutions & configurations with correct answers" (respondent reflection)

"I tested to create a PPT with AI and realized that I have to put nearly the same effort in preparing it than without AI" (respondent reflection)

Additionally, analysis of Output Quality revealed a strong, significant relationship with Trust in GenAI ($r = 0.722$, $p < 0.001$), which point out its essential role in building user trust, even though it may not directly affect perceived usefulness. Finally, the weak correlation between PU and PEOU ($r = 0.245$, $p = 0.217$*) reinforces the view that ease of use alone does not necessarily lead to higher perceptions of usefulness, particularly for tasks requiring complex data reasoning and advanced problem-solving.

4.1.5. Theoretical Interpretation and Integration of Survey Findings

The findings of this analysis directly respond to *RQ1: How do non-technical and hybrid-role employees perceive the usefulness, ease of use, and trustworthiness of GenAI tools?*, Which provides both confirming evidence and deviations from the theoretical anticipations detailed in Chapter 2, while also addressing the organizational challenges discussed in Chapter 1. The respondents in non-technical and hybrid roles predominantly indicated positive views regarding GenAI tools, especially for their perceived capability to assist with tasks and resolving issues. This signifies initial progress in overcoming the perceived technological complexity barrier presented in Chapter 1. Nonetheless, the findings also reveal significant nuances that must be taken into account in future adoption strategies.

Perceived Usefulness was generally rated high, but the predictors differed from those suggested by TAM. Although later extensions of TAM position Output Quality as a primary determinant of PU

(Venkatesh & Davis, 2000), the quantitative results in this study revealed only a weak and non-significant relationship ($r = 0.289$, $p = 0.144$). Rather, the most significant factors affecting PU were found to be constructs of PSC including data reasoning, adaptive decision making and efficiency, in addition to DOI, compatibility; this indicates that employees are more inclined to see GenAI tools as valuable when they believe they can effectively use them on their own (which reflects improved digital self-efficacy) and when these tools fit smoothly into their current workflows; this aligns with the concept of Compatibility from Diffusion of Innovations (Rogers, 2003).

Trust in GenAI demonstrated a positive correlation with PU ($r = 0.495$, $p = 0.009$), highlighting the essential effect of content credibility on user perceptions. Although Output Quality was not a direct predictor of PU, it showed a highly significant relationship with Trust ($r = 0.722$, $p < 0.001$), Which reinforces the idea that perceived quality of GenAI output primarily impact the trust instead of immediate evaluations of usefulness, thus, this result addresses the challenge mentioned in Chapter 1 concerning uncertainty about the reliability and fairness of GenAI outputs.

Perceived Ease of Use, while generally rated positively, did not significantly predict PU ($r = 0.245$, $p = 0.217$); this finding support the argument made in Chapter 2 that non-technical employees increasingly expect AI systems to provide functional value rather than just ease of interaction, also, participant reflections reinforced this distinction, highlighting the importance of prompt formulation skills and the demand for actionable, high-quality outputs over simplistic interfaces.

Behavioral Intention maintained a strong correlation with PU ($r = 0.593$, $p = 0.001$), supporting TAM's core proposition that perceived usefulness is a key driver of future tool use decisions (Davis, 1989).

From a theoretical viewpoint, these findings partially validate the assumptions of TAM and DOI. While the link between PU and Behavioral Intention is established, the anticipated role of Output Quality as a direct contributor to PU was not statistically validated; this inconsistency is attributed to limitations in measurement (as discussed in section 4.1.1) and is further contextualized by qualitative findings, which consistently highlighted that while output quality is vital for building trust, it does not always directly influence perceptions of task-related usefulness without a strong personal ability to solve problems.

The essential role of Compatibility highlights the necessity of integrating generative AI tools into current business operations, a factor noted in Chapter 2 as necessary for overcoming resistance within organizations. Although Task Complexity was found to be positively correlated with PU ($r = 0.461$, $p = 0.015$), its moderating influence was examined qualitatively instead of through statistical interaction as initially planned in the conceptual framework, aligning with the Systems Thinking perspective that organizational complexity influences the perceived value of technological solutions, especially when tasks require significant cognitive effort and cross-departmental collaboration.

For organizations looking to enhance the adoption of generative AI, these findings stress the importance of moving beyond just user-friendly interfaces and concentrating on fostering employee confidence and skill development; future applications should focus on integrating GenAI tools into everyday practices (addressing Compatibility) and guaranteeing that these tools deliver outputs that are based on the organization databases providing high-quality and understandable content, fostering trust. Moreover, the limited effect of PEOU indicates that enhancing usability needs to go hand-in-hand with initiatives for training to strengthen employees' skills in prompt creation and assist them in using generative AI tools for complex and data-heavy tasks effectively.

4.2. Behavioral Lens

RQ2: "How does the use of GenAI influence data reasoning and adaptive decision-making in structured versus creative tasks?" (Anchored in Problem-Solving Capability)

This section addresses RQ2 by analyzing how the use of GenAI tools affects Data Reasoning, Adaptive Decision-Making, and Problem-Solving Efficiency in both structured and creative workplace situations. The experimental design followed a counterbalanced within-subjects approach, involving n = 8 participants from non-technical and hybrid business participants who are considered data experts or data analytics specialists. The demographic distribution was homogeneous, with the majority of participants under 40 years of age, with only two individuals in the 40–49 age group. Seven participants reported having prior familiarity with GenAI tools in their workplace. Participants were informed in advance of each task whether assistance from GenAI was permitted, and they filled out post-task reflection forms to capture their subjective assessments of the experience. This experimental design allows for a direct comparison of GenAI's influence across different task categories. The analysis incorporates:

- Quantitative findings from experimental measures like confidence, independence, and efficiency.
- Subjective reflections including perceived variations in speed, output quality, and confidence.
- Author observation notes that document behavioral engagement, cognitive load, and patterns of emerging dependency.

4.2.1. Quantitative Insights on Confidence, Independence, and Efficiency Metrics

In this section the quantitative analysis of the experimental data is presented while focusing on the effects of GenAI with regards to Confidence, Independence, and perceived Efficiency. Analyses include between-group and within-group comparisons (see Tables 16, 17 and 18). Given the small sample size (n = 4 per group), statistical significance tests alone may not fully capture the practical relevance of the findings. As a result, effect sizes (Cohen's d) are reported alongside p-values to provide a more comprehensive understanding of the results, in line with the recommended practices in applied behavioral research (Gaeta & Brydges, 2020; Lovakov & Agadullina, 2021; Nordahl-Hansen et al., 2023). The evaluation of effect sizes follows the traditional benchmarks established by Cohen (1988), which categorize effects as small ($d = 0.20$), moderate ($d = 0.50$), and large ($d = 0.80$). For detailed visual figures refer to Appendix 9.

Confidence Across Tasks

The quantitative findings show that participants typically expressed greater confidence when utilizing GenAI tools, especially for creative activities. Although the statistical analysis did not demonstrate a significant difference between the tasks ($t(7) = -1.59$, $p = 0.155$), the moderate effect size (Cohen's $d = -0.564$) implies a notable practical difference. Specifically, the average confidence ratings increased from 3.25 (SD = 1.49) for tasks accomplished without the use of GenAI to 4.13

(SD = 0.84) when GenAI was included. This pattern indicates that there is a perceived enhancement in task mastery when GenAI help is available, even in the absence of statistical validation. These findings emphasize the need to consider both statistical and practical significance, particularly in light of the study's small sample size.

Table 16. Between-group and within-group comparisons of task performance (author).

Comparison Type	Task / Group Transition	M (SD)	t(df)	p	d (Effect Size)
Between-Group	Task 1 (Structured): Group A (Without GenAI)	3.50 (1.29)	—	—	—
	Task 1 (Structured): Group B (With GenAI)	3.00 (1.83)	t(6) = 0.45	p = 0.672	0.32 (small)
	Task 2 (Creative): Group A (With GenAI)	4.25 (0.96)			
	Task 2 (Creative): Group B (Without GenAI)	4.00 (0.82)	t(6) = 0.40	p = 0.705	0.24 (small)
Within-Group	Group A: Without → With GenAI	—	t(3) = -1.00	p = 0.391	-0.50 (moderate)
	Group B: With → Without GenAI	—	t(3) = -1.10	p = 0.353	-0.55 (moderate)
Between-Group	Task 1 (Structured): Group A (Without GenAI)	3.50 (1.29)	—	—	—

Note. M = Mean; SD = Standard Deviation; t(df) = t-test statistic with degrees of freedom; p = significance level; d = Cohen's d (effect size).

Independence Across Tasks

The perceived independence analysis showed no notable differences among the tasks (t(7) = 0.205, p = 0.844), and the effect size was minimal (Cohen's d = 0.072). Participants displayed matching perceptions of independence, whether GenAI was included or not, with a minor decrease observed from M = 4.00 (SD = 1.07) in Task 1 (without GenAI) to M = 3.88 (SD = 1.36) in Task 2 (with GenAI). Which indicates that although GenAI may impact the confidence of participants, it does not greatly change how they perceive their own problem-solving abilities. The slight difference also suggests that participants likely see GenAI as a helpful tool rather than a replacement for their own reasoning.

Table 17. Between-group and within-group comparisons of independence across tasks (author).

Comparison Type	Task / Group Transition	t(df)	p	d (Effect Size)
Between-Group	Task 1 (Structured)	t(6) = 1.41	p = 0.228	0.99 (large)
	Task 2 (Creative)	t(6) = -0.24	p = 0.820	-0.17 (negligible)
Within-Group	Group A: Without → With GenAI	t(3) = 0.88	p = 0.444	0.44 (moderate)
	Group B: With → Without GenAI	t(3) = -0.58	p = 0.604	-0.29 (small)

Note. t(df) = t-test statistic with degrees of freedom; p = significance level; d = Cohen's d (effect size).

Efficiency Reflections (Post-Task Comparison Evaluations)

After the completion of both tasks, subjective reflections were gathered, revealing that they recognized the benefits and advantages related to efficiency, output quality, and confidence when using GenAI tools; on a scale from 1 to 5, participants rated their perceived speed while using GenAI as higher (M = 4.13), along with an improvement in output quality (M = 4.38) and boosted confidence levels (M = 4.25). While these perceptions weren't supported by corresponding statistically significant improvements in performance, they highlight a notable psychological effect of GenAI tools on perceived task success. This difference between subjective assessments and objective data suggests that GenAI tools may lead to exaggerated beliefs about one's capabilities, a finding that deserves further exploration regarding long-term capability development.

Table 18. Perceived efficiency reflections - post-comparison evaluations (author).

Perception Metric	Mean (5-Point Scale)	Interpretation
Speed	4.13	Perceived faster performance with GenAI.
Output Quality	4.38	Perceived improvement in output quality.
Confidence	4.25	Perceived increase in confidence.

Note. Ratings are based on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Quantitative Data Analysis and Interpretation

The experimental findings indicate a clear gap among participants' subjective perceptions and their actual behavior when attempting to solve work-related problems; although participants consistently reported increased confidence when utilizing GenAI tools, especially in a creative task, these perceptions did not result in tangible enhancements in independence or efficiency in tasks.

Moderate effect sizes in confidence (Table 16) demonstrated that participants rated higher confidence in completing their task when they were using GenAI, compared to wihout using the tool, despite the fact that this difference was not statistically significant. This suggests that GenAI plays a substantial role in how employees perceive their performance and success in tasks, even though there isn't clear proof in their actions. On the other hand, the slight variations in independence scores suggest that participants did not feel they were working more independently when GenAI was present. This indicates that while GenAI tools might boost participants' confidence, they are still perceived primarily as assistive resources rather than alternatives to autonomous problem-solving. The findings that were backed by insights from the comparisons, presented that participants rated their perceived speed, quality of output, and confidence while using GenAI quite positively. However, these subjective improvements were not supported by objective performance measures, revealing a gap between the participants' perceptions of their performance and their actual results in tasks.

In summary, the findings imply that the main effect of GenAI tools in this experimental setting was to elevate participants' subjective feelings of confidence and productivity, rather than to foster independent problem-solving skills or enhance quantifiable task results.

4.2.2. Qualitative Insights from Reflections on GenAI Use in Structured vs. Creative Tasks

The qualitative analysis of post-task reflections provides insights into how participants experienced GenAI tool use during both structured and creative problem-solving tasks. The reflections highlight distinct patterns in engagement, emotional responses, cognitive load, and perceived output quality, offering essential perspectives on how participants approached their work with and without GenAI assistance (see Figure18).

Fig. 18. Word cloud of participant reflections highlighting GenAI's support (author).

Engagement and Emotional Response

Participants noted an increased engagement, as well as a more positive reactions while utilizing GenAI tools, especially in creative assignments that demanded open-ended thinking. Several participants characterized the experience as engaging and inspiring:

"It felt like brainstorming with a creative partner" (participant reflectiont)

"I enjoyed exploring different prompts to refine my ideas" (participant reflection)

By contrast, during structured tasks without GenAI, participants often expressed lower motivation and difficulty initiating their work:

"Without the tool, I didn't know where to begin" (participant reflection)

"I felt stuck and unsure about where to look for information" (participant reflection)

These reflections suggest that GenAI significantly facilitated task engagement and reduced initial barriers to problem-solving, especially when the task required generating unknown and new ideas.

Cognitive Load and Problem-Solving Strategies

Participants stated feeling an increased cognitive tension and some mental fatigue when GenAI was not used, particularly, during tasks which required a structured analysis:

"I had to rely completely on my memory and manual searches, which felt exhausting" (participant reflection)

In contrast, when GenAI was used, participants reported adopting more exploratory and iterative problem-solving strategies:

"I tried several prompts before getting the output that made sense. It felt like co-creating solutions" (participant reflection)

This shift toward experimentation suggests that GenAI helped participants manage cognitive load, allowing them to focus more on evaluating ideas rather than generating them entirely from scratch.

Perceived Creativity and Output Quality

Participants reported that using generative AI contributed to their enhanced creativity, additionally, they observed improvements in their output quality; notably, after completing the creative task with the tool:

"It helped me come up with ideas I wouldn't have thought of on my own" (participant reflection)

However, some concerns about originality were raised:

"It was hard to know if the ideas were really mine or just the AI's suggestions" (participant reflection)

These reflections state that while GenAI effectively supported participants in the idea generation process, they remained aware of the potential effects of the tool on the originality of their outputs.

Trust and Emerging Dependency

Although the participants maintained a generally critical perspective toward the content generated by the genAI, some, recognized an increased reliance on the tool support, particularly, when asked to complete open-ended tasks without genAI:

"I missed the AI when I got stuck" (participant reflection)

"It's a great tool for first drafts, but I wouldn't submit anything without reviewing it myself" (participant reflection)

These reflections suggest an early pattern of tool reliance, especially for overcoming creative blocks, while still recognizing the importance of final human judgment.

Table 19. Observed behavioral and cognitive patterns during experimental tasks (author).

Theme	With GenAI	Without GenAI
Engagement	High, exploratory	Low, hesitant
Emotional State	Positive, confident	Frustration, confusion
Cognitive Load	Reduced cognitive effort	High, reliance on memory
Creativity	Elevated, originality concerns	Lower idea fluency
Trust	Critical but appreciative	N/A
Dependency	Emerging reliance	N/A

Note. Observations reflect the author's notes on participant behavior during experimental tasks under both tool-supported and unsupported conditions.

As outlined in Table 19, the experiences of participants with GenAI tools differed depending on the type of task. Although GenAI enabled greater engagement and creativity in open-ended tasks, it did not notably change participants' feelings of independence or decrease their reliance on external help. The reflections demonstrate a clear trend: participants primarily appreciated GenAI tools for reducing cognitive load and improving the perceived quality of their work rather than for encouraging self-sufficient problem-solving skills; thus, highlight the need to comprehend how the availability of tools affects not only the outcomes of tasks but also the cognitive and emotional involvement of participants during problem-solving processes.

4.2.3. Observation Notes and Insights on Cognitive and Emotional Responses

Author observation notes were captured during the experimental tasks, these documented notes aim to providing complementary insights regarding participants' behavioral engagement, expressive reactions, and problem-solving strategies, offering an external perspective on how GenAI use affected participant behavior during both structured and creative tasks.

Task Initiation and Planning Behavior

Participants who engaged in tasks without the support of GenAI often exhibited indecisiveness and postponed starting their tasks. In many instances, they devoted a significant amount of time to reviewing the task instructions before making any moves, especially, with structured tasks that demanded analytical reasoning. Conversely, when GenAI tools were accessible, participants began tasks more quickly, interacting directly with the tool and formulating prompts early in the process. This difference in behavior suggests that having access to GenAI might have lowered the cognitive burdens related to starting tasks.

Cognitive Engagement and Adaptation Strategies

During the participants interactions with the GenAI tool, it was noted that they displayed a preference for exploration, often, revising their prompts and trying out various inputs to achieve better results. This trend was especially noticeable in creative tasks, where participants continuously developed GenAI-generated content; in contrast, when they did not use a GenAI tool, participants' problem-solving methods were typically more straightforward and hesitant, as they tended to adhere to their initial strategies and demonstrated minimal adaptability during the task.

Time Management and Efficiency

The behaviors related to time management also differed depending on the availability of GenAI, where those utilizing GenAI tools showed consistent progress on tasks, often depending on the tool to quickly move past obstacles in content creation; on the other hand, participants without the support of a GenAI tool tended to take frequent breaks and made slower progress, especially, in the creative task where generating ideas demanded more effort and time.

Emotional Responses and Behavioral Indicators

Observable expressive reactions further emphasized the differences between the two conditions, it was noted that p articipants who completed their task without a GenAI tool often displayed clear signs of frustration, which included verbal expressions of struggle and instances of disengagement. Multiple participants openly communicated their need for technological support during these times; while, those using GenAI often showed signs of satisfaction and positive involvement, such as smiling, nodding in response to satisfactory outputs, and moving through tasks more easily.

Dependency Patterns and Behavioral Reliance on GenAI

Notable trends regarding the dependence on GenAI were identified, especially, in creative tasks, where it was observed that individuals who initiated the experiment using a GenAI tool found it challenging to adapt when they later undertook the task without the tool assistance; these individuals showed a greater tendency to express frustration during the second task and struggled to come up with ideas on their own, resulting in a behavioral pattern that suggests an initial reliance on GenAI to help them address cognitive difficulties and carry out tasks.

Table 20. Behavioral differences in task approach with and without genai support (author).

Aspect	With GenAI	Without GenAI
Task Initiation	Immediate or after minimal planning	Hesitant, delayed
Engagement	High, exploratory	Mixed, some disengagement
Decision Adaptation	Frequent prompt revisions	Rarely revised decisions
Time Management	Steady progression	Frequent pauses, slower pace
Emotional State	Positive, confident	Frustration, uncertainty
Dependency Patterns	Emerging reliance	N/A

Note. Authors' observations based on participant behavior during experimental tasks, highlighting differences in task engagement, decision strategies, and emotional responses under GenAI-supported and unsupported conditions.

As detailed in Table 20, the behavioral observations reveal distinct differences in task initiation, engagement, and emotional reactions based on the presence of GenAI tools. While the use of GenAI promoted prompt task engagement and aided in exploratory problem-solving techniques, its absence led to hesitation, slower task advancement, and noticeable frustration. The stated trends, offer essential context to the experimental results, suggesting that GenAI mainly served as a facilitator of perceived task simplicity rather than a promoter of independent cognitive effort. This behavioral data will be further analyzed in the subsequent section through a thorough triangulation of experimental findings, participant insights, and observed behaviors.

4.2.4. Theoretical Interpretation and Integration of Experimental Findings

In response to *RQ2: How does the use of Generative AI impact data reasoning and adaptive decision-making in structured versus creative tasks?*. The analysis combines quantitative data, qualitative reflections, and behavioral observations to offer a thorough interpretation of the experimental findings.

A cross-comparison of the three data sources reveals consistent patterns in participants' subjective perceptions and behavioral engagement, while also highlighting differences between their perceived abilities and actual development in problem-solving skills.

Table 21. Triangulation of Quantitative Results, Participant Reflections, and Behavioral Observations (author).

Aspect	Quantitative Results	Participant Reflections	Behavioral Observations	Convergence
Confidence	Increased with GenAI; moderate effect sizes; no statistical significance.	High self-reported confidence with GenAI, especially in creative tasks.	Positive emotional expressions and faster task initiation with GenAI.	Yes

Independence	No significant changes; negligible effect sizes.	Participants did not report stronger independence despite higher confidence.	Linear problem-solving without GenAI; over-reliance behaviors with GenAI.	Yes
Efficiency	High perceived efficiency; no objective performance improvements.	Participants perceived faster task completion and better quality with GenAI.	Faster task progression with GenAI, but not necessarily more effective.	Partial
Creativity	Not directly measured.	GenAI improved idea generation but raised concerns about originality.	High exploratory behavior with GenAI; hesitation without it.	Yes
Dependency	Not directly measured.	Participants acknowledged missing GenAI when it was unavailable.	Observed behavioral reliance and frustration when GenAI was removed.	Yes

Note. This table summarizes the triangulation of experimental findings across quantitative data, self-reported participant reflections, and researcher behavioral observations. "Convergence" indicates whether consistent patterns emerged across all three data sources.

The triangulated evidence demonstrates that GenAI use mainly boosts participants' subjective feelings of confidence and efficiency and creativity especially during open-ended creative work. The perceived benefits from GenAI tools did not lead to measurable improvements in independence or data reasoning capability which shows a difference between perceived and actual problem-solving competence.

GenAI tools proved useful for starting tasks and generating ideas especially when tasks were ambiguous but they failed to enhance independent decision-making or critical analytical thinking abilities. The findings match the problem analysis in Chapter 1 which revealed that excessive dependence on technology and weak critical thinking skills act as major obstacles to capability development.

The quantitative results demonstrate moderate effect sizes for confidence but negligible effects for independence. The participant reflections show this dynamic because users reported increased confidence and reduced mental effort with GenAI but did not report improvements in their ability to work independently. The behavioral observations showed that participants relied on GenAI suggestions and struggled to work independently when the tool was taken away.

The results presented throughout section 4.2, show that genAI functioned as a magnifier of perceived ability; although it enhanced participants' self-assurance, it did not result in notable improvements in data reasoning or flexible decision-making, additionally, the elevated subjective evaluations for speed and output quality support this observation but also emphasize the danger of overestimating one's abilities because of the absence of objective performance assessment. Moreover, experimental findings show that genAI tools mainly affect users' perceptions of their problem-solving skills by boosting confidence and encouraging creative idea generation in challenging, unstructured tasks, while, in structured analytical settings, these tools have minimal effect on the development of independent thinking and adaptive decision-making.

Organizations need to implement systematic interventions aimed at encouraging a critical assessment of GenAI-generated outputs if they wish to convert perceived improvements into sustainable capacity growth. Before incorporating generative AI tools, it is essential to develop independent problem-solving techniques, genAI should be used in alignment with the complexity of the work to ensure that it enhances rather than replaces human thinking; while these tools are undeniably useful for task efficiency and creative support, its contribution to improving long-term problem-solving capacity remains limited without intentional initiatives to promote critical thinking and independent decision-making.

4.3. Contextual Lens and Enablers of GenAI Integration

RQ3: "How do contextual enablers, such as leadership support, training, and collaboration, shape the effectiveness and integration of GenAI tools?" (Anchored in DOI and ST)

In order to respond to the RQ3 question, qualitative data were collected through five semi-structured interviews conducted with managers in strategic positions related to data management, machine learning, AI implementation, and cross-functional business leadership. These managerial insights are critical for understanding how organizational factors may either facilitate or hinder the effective adoption and utilization of GenAI tools. The insights presented in this section aim to supplement the previously discussed quantitative findings, offering a more profound understanding of how leadership behaviors, enablement structures, and organizational culture influence the adoption of GenAI tools. As stated in the conceptual model, PSC remains the key outcome of interest, and this section explores how contextual enablers may either foster or obstruct its development.

Given the exploratory nature of this study and the limited qualitative sample, the findings shared should be viewed as contextual observations rather than definitive conclusions. Their main purpose is to enrich the overall research narrative by providing managerial insights and selected illustrative observations that offer context for comprehending how GenAI integration progresses within organizational settings.

4.3.1. Contextual Factors Influencing GenAI Adoption and Use

The qualitative analysis revealed several contextual elements that affect the efficacy and integration of GenAI tools; firgure 19, summarizes the key identified contextual factors, whereas **task complexity**, **compatibility** (moderators from DOI and ST) and **trust**, **critical Thinking** (mediating factor) are highlighted as core constructs derived from the conceptual model (refer to section 2.7.2) and explored qualitatively, while other enablers emerged from the data, emphasizing the importance of leadership support, training and enablement, fostering an experimental mindset, and promoting cross-department collaboration, all of which detailed in this section.

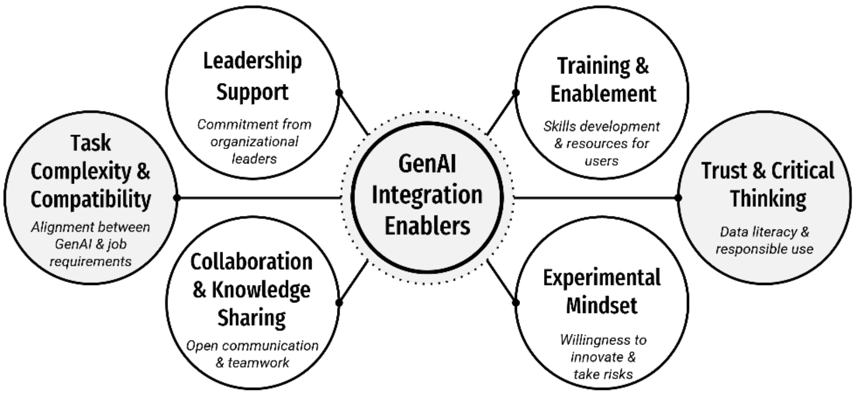

Fig. 19. Thematic map of contextual enablers for GenAI adoption (author).

Leadership support was identified as a critical enabler, with several participants emphasizing that visible engagement from senior leaders accelerates adoption across the organization. As explained by one of the participants, *"Unlocking GenAI's full potential starts with top-down commitment. People imitate what they see from upper management" (participant M04)*. Nevertheless, leadership involvement was noted as inconsistent, and the absence of clear organizational targets was seen as reducing motivation for adoption. Another participant marked, *"If there's a clear organizational goal, then people are more motivated to use them. Without such direction, individuals may lag behind" (participant M05).*

While access to tools was generally available, participants stressed that **training availability and enablement practices** must extend beyond this; training was considered most effective when role-specific and flexible, accommodating diverse learning preferences. One interviewee remarked, *"Brief 10-minute sessions with practical examples are more effective than long, theoretical trainings" (participant M02)*. Another added, *"You need to show people how it applies directly to their jobs—otherwise, the training doesn't stick" (participant M03)*. Overly rigid programs were seen as counterproductive, with the suggestion that *"giving people tools, space, and purpose—and they'll figure it out in their own way" (participant M05).*

Regarding **tool use behaviors**, participants emphasized the significance of encouraging an experimental mindset while regulating expectations; noting the possibility that the early excitement surrounding GenAI was perceived as a factor that led to disappointment and disengagement when the tools did not fulfill exaggerated expectations. One participant noted, *"The barrier is largely cultural, rooted in perception and inflated expectations" (participant M02)*. Importantly, some participants described how GenAI tools are being integrated into employees' everyday problem-solving approaches. *"GenAI helps unblock thinking when someone is stuck—it's like a sparring partner, not a final answer" (participant M04)*. The same participant added, *"If a colleague doesn't know how to move forward, I advise them to describe their problem to ChatGPT like they would to a friend" (participant M04)*; this demonstrates how GenAI is increasingly considered as a tool for enhancing creative thinking and overcoming cognitive barriers, leading to more efficient problem-solving methods, as summarized by participant M04, *"We do more in less time".*

Although experimentation with GenAI is encouraged in some areas, **cross-department collaboration and knowledge sharing** remain fragmented, often restricted to informal exchanges. Participants noted that while some AI ambassadors exist, their power is limited without formal support structures, one participant described, *"We see isolated champions of GenAI, but no established communities or forums to exchange experiences" (participant M01).*

The **barriers to trust and effective use of GenAI** tools were frequently mentioned, especially, regarding the tendency of non-technical users to agree with the GenAI generated outputs without proper critical assessment, as noted by one participant, *"To use GenAI effectively, people must be trained to question results, not accept them blindly" (participant M04)*. Additionally, unrealistic expectations also play an important role in this issue, with another manager stressing that *"GenAI is very powerful—perhaps 80% of the way there—but users must accept the remaining 20% as a margin where human judgment is required" (participant M03)*. Relying excessively on GenAI outputs without adaptation was recognized as a risk, potentially leading to reduced trust, *"You shouldn't just copy-paste; the results need to be tailored to the business context" (participant M05).*

Finally, participants consistently observed that **task complexity and compatibility** moderate the extent to which GenAI is integrated into daily work. One interviewee remarked, *"GenAI supports the early stages of problem-solving but is rarely used for execution-critical tasks" (participant M03),* another added, *"In structured tasks, people still prefer to stick to Excel—But for ideation and brainstorming, GenAI is becoming the go-to partner" (participant M04)*. This reflects the moderating role of task complexity and compatibility in determining where GenAI tools offer the greatest value.

Table 22. Thematic summary of contextual enablers for genai integration (author).

Theme	Key Insights	Illustrative Quotes
Leadership Support	Inconsistent but critical for widespread adoption.	"Unlocking GenAI's full potential starts with top-down commitment." (M04)
Training & Enablement	Role-specific, practical training preferred over theoretical sessions.	"Brief 10-minute sessions with practical examples are more effective." (M02)
Experimental Mindset	Encouraged, but inflated expectations may lead to disappointment.	"The barrier is largely cultural, rooted in perception and inflated expectations." (M02)
Trust & Critical Use	Users must develop skills to critically assess AI outputs.	"To use GenAI effectively, people must be trained to question results." (M04)
Collaboration	Knowledge sharing is fragmented; lacks formal structures.	"We see isolated champions of GenAI, but no established communities or forums." (M01)
Task Complexity	GenAI primarily supports ideation; less effective for execution-critical tasks.	"GenAI supports the early stages of problem-solving but is rarely used for execution-critical tasks." (M03)

Note. Participant identifiers (e.g., M04) refer to managerial interview participants.

In Addition to the managerial interviews, a few illustrative comments were collected through the survey, as a result of the skip-logic, from two non-GenAI users and two respondents in technical roles; while the limited number of responses prevents any significant analysis, the perspectives of these respondents offer anecdotal support for the broader themes identified. Respondents who are classified themselves as non-users mainly indicated a low **awareness of GenAI tools and uncertainty** about their relevance to daily work. As one respondent revealed, *"I am not aware of any tools that can help me with my day-to-day tasks"(respondent note),* while another stated, *"I'm not really sure what GenAI tools stand for or how I could use them"(respondent note).* Even so, a willingness to consider future adoption was observed if practical tools relevant to their roles were made available, as indicated in the survey comment, *"Advanced data analysis: tools that can analyze complex datasets would make a difference"(respondent note).*

Participants in technical roles underlined the importance of **critical evaluation and structured support** for responsible GenAI use, a respondent warned, *"Non-technical roles should only have independence with strong guidelines to avoid misinterpretation of data" (respondent note),* while another noted, *"GenAI tools are great to get non-techies started with data, but they need structured frameworks to avoid incorrect conclusions"(respondent note).* These comments, although inadequate for extensive analysis, highlight the significance of focused training and leadership support to ensure the responsible and effective adoption of GenAI tools.

4.3.2. Theoretical Interpretation and Integration of Interview Findings

In response to *RQ3: How do contextual enablers, such as leadership support, training, and collaboration, shape the effectiveness and integration of GenAI tools?*, the findings indicate that the effectiveness and integration of GenAI tools are primarily affected by three interconnected contextual enablers: support from leadership, training and enablement practices, and collaboration structures; and these factors affect not only the adoption of GenAI tools but also their role in enhancing the problem-solving capabilities in non-technical and hybrid roles.

Leadership support is crucial, as it underscores the strategic significance of GenAI and fosters an environment conducive to its experimentation and application. From a Systems Thinking viewpoint, leadership acts as an essential leverage point for initiating cultural change and promoting organizational learning. When leadership involvement is evident and the strategic goals for GenAI adoption are communicated clearly, employees are more inclined to perceive GenAI tools as legitimate and valuable assets in their problem-solving endeavors. In contrast, a deficit in leadership modeling and guidance results in fragmented efforts and reluctance among employees to weave GenAI into their daily tasks.

Training and enablement practices were recognized as key factors affecting the integration of GenAI tools. Although the availability of tools was not an obstacle, the absence of role-specific, practical, and flexible training limited the effective use of these tools. This observation highlights the importance of Compatibility as a moderating factor in the conceptual model; without training that directly connects GenAI to employees' daily tasks and improves their critical skills, the adoption of these tools tends to be superficial and not fully discovered. Instruction that only addresses technical functionalities, rather than practical application and critical analysis, does not empower employees to utilize GenAI in an effective and responsible manner.

Collaboration structures, or their absence, further affects how organizations cultivate and maintain competencies related to GenAI. The results showed that knowledge sharing often occurs informally and is limited to specific supporters of GenAI implementation. Without established structures for cross-departmental collaboration, like communities of practice or structured knowledge-sharing platforms, successful experiences and insights are often kept separate, therefore, limiting the overall organizational learning and reducing the potential for GenAI to enhance collective problem-solving capabilities.

The moderating influence of **Task Complexity** was clearly observed; as GenAI tools were found to be most beneficial when used in creative, exploratory phases of problem-solving, thus acting as a trigger for generating ideas and a supporting partner when it comes to overcoming cognitive obstacles. Yet, while using these tools for tasks that demand accuracy and specialized expertise, certain constraints were noted; this was particularly evident in fields where conventional tools and proven analytical techniques are still preferred. This finding underscores the necessity for organizations to thoughtfully coordinate the implementation of generative AI with the complexity of the tasks at hand, rather than applying it indiscriminately across all work processes.

The effectiveness and successful integration of GenAI tools rely on the alignment of leadership dedication, tailored and specific practices for enablement, as well as organized collaboration methods, all moderated by task complexity. Thereby, addressing these contextual enablers is crucial for organizations to unlock the full potential and value of GenAI in enhancing problem-solving capability and decision-making efficiency, while without these factors, GenAI adoption is likely to remain fragmented and its strategic value underutilized.

4.4. Interpretation and Discussion of Results

To answer the main research question of this study "*How do employees in non-technical, including hybrid roles, perceive and use Generative AI tools to enhance their problem-solving capabilities in data-related workplace tasks?"*

The integrated analysis across perception, behavioral, and contextual lenses showed that the adoption of GenAI in non-technical roles including hybrid ones primarily enhances perceived problem-solving capabilities rather than objectively improving independent analytical skills; while employees report increased confidence, efficiency, and creative support through GenAI, these benefits are largely subjective and not consistently supported by behavioral performance metrics or critical data reasoning improvements.

A Multi-Lens Perspective Triangulation of Findings

Table 23. Triangulation of survey, experimental, and contextual findings (author).

Lens	Key Insights	Implications
Perception (Survey)	High PU driven by Compatibility and Problem-Solving Confidence rather than Output Quality. Trust is critical but acts primarily as a mediator through Output Quality ($r = 0.722$, $p < 0.001$). PEOU was not a significant predictor of PU.	GenAI adoption is more likely when tools integrate seamlessly into workflows and employees feel confident using them. However, ease of use alone is insufficient to drive sustained usage.
Behavioral (Experiment & Observations)	GenAI increased confidence and creative output, particularly for exploratory tasks. However, independence and critical data reasoning did not improve. Dependency patterns emerged, with participants struggling when GenAI was unavailable.	GenAI serves as a cognitive support tool rather than a replacement for analytical thinking. There is a risk of over-reliance without developing independent problem-solving capabilities.
Contextual (Interviews, and Input from Non-Users, Technical Roles)	Effective adoption is enabled by Leadership Support, Role-Specific Training, and Collaboration Structures. Adoption remains superficial when training focuses only on technical skills without fostering critical evaluation. Task Complexity further moderates adoption effectiveness.	Organizational efforts should focus on creating learning environments, leadership modeling, and knowledge-sharing platforms to fully realize GenAI's potential. GenAI is most effective in creative, less-structured problem spaces.

Note. PU = Perceived Usefulness; PEOU = Perceived Ease of Use.

Theoretical and Practical Integration

The findings of this analysis partially validate the Technology Acceptance Model and Diffusion of Innovations, but also highlight critical deviations. While PU remains a strong predictor of Behavioral Intention ($r = 0.593$, $p = 0.001$), while it was shown that Output Quality's direct impact on PU was weak and statistically insignificant ($r = 0.289$, $p = 0.144$). Instead, Compatibility and Trust play central roles, aligning more closely with DOI's focus on innovation fit (Rogers, 2003) and with later TAM extensions that incorporate Trust as a critical enabler (Venkatesh & Davis, 2000). As for Task Complexity, which is grounded in Systems Thinking, was a critical moderator across findings. GenAI demonstrated clear value for creative, exploratory tasks but offered limited effectiveness for structured analytical activities which reinforces that GenAI adoption strategies should carefully consider task characteristics rather than promoting blanket usage across workflows.

Analysis Limitations and Generalizability

- This research is exploratory in nature, and it involves a small sample size (Survey n = 27 eligible for analysis; Experiment n = 8).
- The findings and results of this research should be approached cautiously, and they are context-specific to organizations that are data-driven as well as focused on innovation.
- Generalization to industries or sectors with lower digital maturity or higher regulatory constraints (e.g., healthcare, public administration) is limited.
- Measurement constraints must be taken into account, particularly in assessing Output Quality, as it could further restrict the strength of statistical conclusions.

Recommendations for Future Research and Practice

Future research should aim to expand their sample and explore cross-industry differences in the adoption of GenAI patterns, particularly, examining and focusing on the role of Compatibility and Trust in environments where varying task complexity and technological maturity are in place.

To effectively put the findings into practice, organizations should:

1) Encourage leadership to demonstrate responsible GenAI usage and set clear strategic goals for adoption, as visible support from the management was found to directly affect employees motivation and enable a more coordinated and consistent tool use.
2) Prioritize the integration of GenAI in existing workflows, confirming compatibility, and design training programs that are focused on critical thinking and role-specific, rather than only technical onboarding.
3) Strategically align GenAI implementation with task complexity, ensuring that the human expertise remains central in critical analytical decision-making.
4) Encourage employees to evaluate the outputs of GenAI critically during their decision-making, while also, emphasizing that GenAI is a supportive tool, not a replacement for decision-making; this promotes ethical usage and reinforces the importance of critical thinking alongside GenAI adoption.
5) Ensure GenAI tools are connected to internal data sources and provide pre-designed prompts that are specific to roles or departments to improve output relevance and build user trust, helping to address the observed challenges of low content credibility and inconsistent adoption.
6) Establish engaging collaboration structures (e.g., communities of practice, knowledge-sharing workshops) to facilitate knowledge exchange and reduce fragmented adoption efforts.

In summary, although GenAI tools enhance confidence and are viewed as more efficient, their role in individual problem-solving and critical reasoning with data is still restricted. Effective implementation depends on tackling essential contextual factors, support from leadership, focused enablement, and organized collaboration, while being aware of the restrictions created by the complexity of tasks. If these aspects are not addressed, GenAI may lead to increased overconfidence without genuine advancements in long-term analytical skills.

Conclusions

1. In relation to the first objective, the research confirmed that key organizational and contextual barriers continue to hinder effective GenAI integration. Data fragmentation remains a primary obstacle, restricting access to relevant and high-quality datasets needed for GenAI tools to generate valuable outputs. Furthermore, despite advances in natural language interfaces, the complexity of tool outputs and cognitive overload persist, particularly among non-technical employees. Training deficits also contribute to limited adoption, as most available programs fail to address role-specific application and critical evaluation skills. Finally, the ongoing reliance on technical teams for data access and analytical support undermines the promise of GenAI to foster autonomy in non-technical roles. These barriers emphasize the need for organizations to focus not only on technology provision but also on fostering an environment where GenAI can be meaningfully embedded into existing workflows.

2. Addressing the second objective, the research contributed to refining theoretical understandings by partially validating TAM, DOI, and ST perspectives. While perceived usefulness remained a critical determinant of adoption, this study found that compatibility with existing workflows and trust in GenAI outputs played a far more central role than anticipated. Contrary to TAM expectations, perceived ease of use did not significantly influence adoption decisions, suggesting that in mature digital environments, users prioritize functional value and reliability over simple usability. Furthermore, ST proved valuable in explaining how task complexity moderates the perceived benefits of GenAI, with greater effectiveness observed in creative, exploratory tasks than in structured, analytical work. These insights highlight the importance of aligning GenAI strategies with the nature of the tasks and reinforcing trust through reliable, contextually relevant outputs.

3. In fulfilling the third objective, the application of an explanatory sequential mixed-methods design enabled a comprehensive understanding of the research problem. By integrating survey results, experimental behavioral observations, and managerial interviews, the study achieved triangulation across perceptual, behavioral, and contextual lenses. This approach ensured greater internal validity despite the limitations posed by small sample sizes. The research also demonstrated ethical rigor and methodological coherence, although it acknowledges that the single-case study design limits the generalizability of its findings. Future research should therefore expand sample diversity and refine measurement instruments to capture long-term effects and cross-industry applicability.

4. Regarding the fourth objective, the empirical findings revealed a critical divergence between employees' perceived problem-solving enhancements and their actual demonstrated capabilities. While GenAI boosts confidence and perceived efficiency in creative tasks, it does not result in measurable improvements in independent reasoning or decision-making. This raises concerns about over-reliance on GenAI, as participants struggled with tasks when support was removed. To address this, organizations should integrate GenAI into existing workflows, ensure leadership models responsible usage, and focus training on enhancing critical thinking. Additionally, creating platforms for collaboration will strengthen problem-solving skills, and improving access to data resources will enhance the accuracy of GenAI outputs, fostering user trust.

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Appendices

Appendix 1. Full Survey

Detailed Survey

Introduction & Consent

Survey Title: Survey on the Use of Generative AI Tools to Support Problem-Solving Capabilities in Non-Technical Roles at "Case Organization"

Purpose of the Survey

This survey is part of a Master's thesis conducted within the framework of a double degree in Global Technology, Innovation Management & Entrepreneurship (GTIME), coordinated by the Technical University of Hamburg (TUHH) and Kaunas University of Technology (KTU).
The study investigates how non-technical employees independently perceive and use Generative Artificial Intelligence (GenAI) tools (e.g., Microsoft Copilot) in solving data-related problems at "Case Organization". It explores usability, adoption drivers, and the impact on autonomy and workflow integration.
Your participation will help the researcher understand the implications of GenAI in enhancing problem-solving abilities within business environments.

Estimated Time

Approximately 15-20 minutes.

Voluntary Participation

Participation in this survey is entirely voluntary. You can choose to stop at any time. Only eligible participants will proceed based on their answers.

Confidentiality

This survey is **anonymous**. No names, emails, or identifiable information will be collected. The data will be analyzed in aggregate for academic and organizational insights. Responses will not be shared with any individual or department within "Case Organization".

Consent Checkbox

☑ I understand that my responses will be used for academic research and agree to participate. *(Check Required to Proceed)*

Section 1: Demographics & Role Classification

D1. What is your age group? (Single choice)

- ○ Under 30
- ○ 30–39
- ○ 40–49
- ○ 50–59
- ○ 60 or older
- ○ Prefer not to say

D2. What is your gender? (Single choice)

- ○ Woman
- ○ Man
- ○ Non-binary / Prefer to self-describe
- ○ Prefer not to say

D3. How long have you worked at "Case Organization"**? (Single choice)**

- ○ Less than 1 year

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- ○ 1–3 years
- ○ 4–7 years
- ○ More than 7 years
- ○ Prefer not to say

Q1. Do you work with data as part of your role? (Single choice)

- ○ No, my role does not involve working with data. (Exit Survey)
- ○ Yes, I work with data for decision-making, reporting, or compliance. (Continue to Q2)

Q2. What department/unit are you part of? (Single choice)

- ○ Controlling & Accounting
- ○ Corporate Communications
- ○ Customer Solution Center
- ○ Corporate Tax and Customs
- ○ Digital, Information and Technology
- ○ Finance Operations & Business Solutions
- ○ Global Industry Marketing and Digital
- ○ Global Operations
- ○ Global Procurement
- ○ Human Resources
- ○ Legal Department
- ○ Production Excellence
- ○ Safety, Health, Environment, Quality
- ○ Sustainability
- ○ Technology and Product Development
- ○ Total Cost Management
- ○ Other (please specify)

Q3. What are your primary responsibilities? (Multiple choice)

- ☐ Analyzing data for business insights
- ☐ Developing, coding, or maintaining data systems
- ☐ Designing AI models or data infrastructure
- ☐ Ensuring compliance and governance of data policies
- ☐ Maintaining and managing data in enterprise systems (e.g., SAP, SAC, LIMS, Power BI) **without** coding or system modification
- ☐ Maintaining and managing enterprise systems (e.g., SAP, SAC, LIMS, Power BI) **with** coding, automation, or system configuration
- ☐ Managing supplier data & logistics reporting
- ☐ Managing workforce data and HR analytics
- ☐ Monitoring production data & operational analytics
- ☐ Other (please specify)

Q4. Based on the definitions below, how would you classify your role at "Case Organization"**? (Single choice)**

Primarily Non-Technical

Roles focused on data interpretation, governance, communication, or strategic decisions—without hands-on coding or automation. *(Baron & Bielby, 1982; Van Diggele et al., 2020)*

Hybrid

Roles with partial technical exposure (e.g., low-code automation, technical collaboration). *(Kumar et al., 2009; Tammaro et al., 2019)*

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Primarily Technical

Roles requiring core technical execution (e.g., programming, data pipelines, AI model building). *(Baron & Bielby, 1982; Kumar et al., 2009)*

- ○ Non-Technical → Continue
- ○ Hybrid → Continue (flagged separately)
- ○ Technical → Skip to Exit Block

Section 2: GenAI Tool Usage

Q5. Have you used GenAI tools in your current role at "Case Organization"? (Single choice)

- ○ Yes → If selected, Continue to Q6
- ○ No, I have not used any GenAI tools → If selected, Skip to Non-User

Q6. Which of the following GenAI tools have you used in your current role at "Case Organization"? (Multiple choice)

- ☐ Hour One (AI-generated videos for training)
- ☐ Microsoft Copilot (Integrated in MS365 apps: Teams, Outlook, Word, etc.)
- ☐ "Case Organization"GPT (Secure internal version of ChatGPT)
- ☐ SAC "Just Ask" (Quickly provides insights from SAC data models when asked).
- ☐ Other (please specify)

Q7. How frequently do you use GenAI tools in your current role? (Single Choice)

- ○ I have only tested them once or twice
- ○ Rarely (e.g., once a month or less)
- ○ Occasionally (a few times per month)
- ○ Regularly (once or twice per week)
- ○ Frequently (several times per week)
- ○ Daily

Q8. What types of tasks do you typically use GenAI tools for in your current role? (Multiple choice)

- ☐ Brainstorming ideas
- ☐ Creating presentations or visual content
- ☐ Drafting or rewriting texts (emails, reports, documentation)
- ☐ Exploring data or generating summaries
- ☐ Getting support with procurement or supplier-related tasks
- ☐ Helping with HR workflows or communication
- ☐ Improving customer or partner communication
- ☐ Learning about company processes or systems
- ☐ Searching for internal information or documents
- ☐ Other (please specify)

Q9. What best describes the complexity of your GenAI-related tasks? (Single Choice)

- ○ Low-complexity (e.g., summaries, lookups, simple drafts)
- ○ Moderate-complexity (e.g., decision support, basic analysis)
- ○ High-complexity (e.g., cross-functional problem-solving, strategy development)

Q10. I plan to keep using GenAI tools in my work when available. (Likert)

Section 3: Perceptions & Problem-Solving Capability

This section explores your views and experiences with using GenAI tools in your work tasks.

Q12. GenAI tools are easy to use without technical expertise. (Likert)
Q13. I trust the content provided by GenAI tools. (Likert)
Q14. I believe GenAI tools used at "Case Organization" provide transparent and good quality outputs. (Likert)
Q15. The quality of GenAI output meets my expectations. (Likert)
Q16. GenAI tools help me work independently without relying on technical colleagues. (Likert)
Q17. GenAI tools help me evaluate and interpret data insights. (Likert)
Q18. I adjust my decisions based on GenAI tool suggestions. (Likert)
Q19. GenAI tools are well integrated into our department's current tools and workflows. (Likert)
Q20. The tasks I perform with GenAI are cognitively demanding or complex. (Likert)
Q21. I find that GenAI tools are useful for supporting my daily work tasks. (Likert)

Section 4: Training, Enablement & Experience

Q22. I received sufficient training or guidance to use GenAI tools effectively. (Likert)
Q23. I believe I would benefit from a tailored training or role-specific support to use GenAI tools effectively. (Likert)
Q24. What type of training or support would be most helpful? (Multiple choice)

- ☐ Onboarding & access to GenAI tools
- ☐ Prompt engineering & asking the right questions
- ☐ Workflow integration examples
- ☐ Policy or compliance clarification
- ☐ Knowledge shared by colleagues
- ☐ Other (please specify)

Q25. In your own words, what would make your day-to-day use of GenAI tools more effective? (Open-ended)
Q26. Using GenAI tools has helped me improve my individual approach to problem-solving. (Likert)
Q27. What is the biggest limitation of using GenAI tools in your role? (Open text)
Q28. GenAI tools support my learning or skill development. (Likert)
Q29. Describe an example where a GenAI tool helped (or could have helped) you solve a data-related task or make a better decision at work. (Open text)

Section 5: Organizational & Peer Influence

Q30. My collaboration with other departments has improved since I started using GenAI tool. (Likert)
Q31. GenAI tools have influenced how knowledge is shared within my team. (Likert)
Q32. I have observed colleagues benefiting from GenAI tools before adopting them. (Likert)
Q33. I had the chance to test GenAI tools before using them in my daily work. (Likert)
Q34. What insights or experiences did you gain from testing or exploring GenAI tools that influenced your opinion about their usefulness or relevance in your work? (Open text)

Section 6: Closing

Q35. Do you have any final comments or suggestions about using GenAI tools in your work? (Open text)

Thank You Message: Thank you for participating in this study. Your insights are valuable and will contribute to better understanding how GenAI tools support problem-solving capabilities in hybrid and non-technical roles.

- **Exit Survey.**

Non-User Pathway (If "I have not used any GenAI tools")

NU1. Are you aware that GenAI tools are available at "Case Organization"? (Single Choice)

- ○ Yes, and I know how to access them
- ○ Yes, but I don't know how to access them
- ○ No, I was not aware
- ○ I'm not sure

NU2. Which of the following would make you more open to using GenAI tools in your role? (Multiple choice)

- ☐ If I receive proper training or onboarding (Training - TAM)
- ☐ If I can observe colleagues benefiting from it (Observability - DOI)
- ☐ If the tool fits well with my workflow (Compatibility - DOI)
- ☐ If I can try the tool in a low-risk setting (Trialability - DOI)
- ☐ If the tool earns my trust over time (Trust - TAM extension)
- ☐ If it helps with tasks I already do (Perceived Usefulness - TAM)
- ☐ Other (please specify)

NU3. I believe I would need tailored training or role-specific support to use GenAI tools effectively. (Likert)
NU4. I believe GenAI tools could be helpful in my role. (Likert)
NU5. What types of tasks do you think GenAI tools could support in your role, if you were to use them? (Multiple choice)

- ☐ Brainstorming ideas
- ☐ Creating presentations or visual content
- ☐ Drafting or rewriting texts (emails, reports, documentation)
- ☐ Exploring data or generating summaries
- ☐ Getting support with procurement or supplier-related tasks
- ☐ Helping with HR workflows or communication
- ☐ Improving customer or partner communication
- ☐ Learning about company processes or systems
- ☐ Searching for internal information or documents
- ☐ Other (please specify)

NU6. In your opinion, what would make GenAI tools more relevant or useful in your role? (Open text)
NU7. Please share any other reason why you have not used GenAI tools, or any concerns you'd like us to know. (Open text)

Thank You Message: Thank you for participating in this study. Your insights are valuable and will contribute to better understanding how GenAI tools can support the problem-solving capabilities in hybrid and non-technical roles.

- **Exit Survey.**

Exit Block for Technical Roles

E1. Since your role is classified as Technical, your participation in this survey is limited. However, would you like to answer a few high-level questions before exiting? (Single Choice)

- ○ No, I prefer to exit now. → *Exit Survey Immediately*
- ○ Yes, I would like to answer a few general questions before exiting. → *Continue to E2*

E2. How often do you collaborate with Non-Technical or Hybrid roles for data-related tasks? (Single Choice)

- ○ Daily
- ○ Weekly
- ○ Monthly
- ○ Rarely

E3. Do you believe Non-Technical roles should have more independence in data-related problem-solving? (Single Choice)

- ○ No, they should always rely on technical experts.
- ○ Somewhat, but only with strong guidelines.
- ○ Yes, with proper training and AI assistance.
- ○ Yes, they should be fully independent.

E4. In your opinion, what is/are the biggest barrier(s) preventing non-technical roles from becoming more data-driven? (Open text)
E5. From your perspective, what would help non-technical roles use GenAI tools more effectively in their daily work? (Open text)

Thank You Message: Thank you for participating in this study. Your insights are valuable and will contribute to better understanding how GenAI tools can support the problem-solving capabilities in hybrid and non-technical roles.

- **Exit Survey.**

Appendix 2. Constructs Mapping of Survey Questions

Code	Full Survey Question	Classification	Construct	Author(s) / Year	Theoretical Justification	Methodological Role Justification	Type
D1	What is your age group?	Supportive	Systems Thinking → Task Complexity (contextual moderator)	Senge (1990); Kim & Senge (1994)	Age influences cognitive flexibility, technology adoption tendencies, and problem-solving approaches (Senge, 1990). Controlling for age is essential to isolate how GenAI impacts problem-solving independent of generational effects, directly supporting the conceptual model where Task Complexity and Systems interdependencies are moderators. Answer options use standard organizational age brackets, ensuring comparability with broader workforce studies (aligned with HR practice standards).	Age is captured to control for generational cognitive flexibility differences that could influence GenAI adoption success (Systems Thinking). While not a model construct, age variability could affect perceived task complexity or trust levels, impacting how GenAI supports problem-solving. Without it, hidden demographic effects could bias analysis.	select_one
D2	What is your gender?	Supportive	Systems Thinking → Organizational Diversity (indirect system influence)	Senge (1990)	Gender diversity shapes collaborative dynamics and openness to new workflows (Senge, 1990). Capturing gender is essential to analyze if cross-functional collaboration changes differently across groups when GenAI is introduced. Answer options reflect inclusive, ethical research practices, ensuring representation and reliability for sub-group analysis (aligned with literature on team diversity impacts).	Gender diversity is collected to identify any systemic differences in collaboration patterns or openness to GenAI support (Systems Thinking). Although not a direct construct, gender dynamics could moderate knowledge sharing or independence development, crucial for interpreting variance. Without it, gender-based biases would remain hidden.	select_one
D3	How long have you worked at "Case Organization"?	Supportive	Systems Thinking → Knowledge Sharing; DOI → Compatibility	Senge (1990); Rogers (2003)	Tenure shapes familiarity with workflows and data systems (Senge, 1990; Rogers, 2003). Longer tenure may increase perceived compatibility or resistance to GenAI, affecting problem-solving strategies. Capturing tenure allows interpreting adaptive decision-making and knowledge sharing evolution when GenAI is introduced. Tenure brackets mirror organizational research standards for experience segmentation.	Tenure is measured to control for experience with organizational workflows and systems, influencing Compatibility perceptions (DOI) and adaptation speed (Systems Thinking). It indirectly affects GenAI integration readiness; omitting it risks misinterpreting differences in user adaptation pathways.	select_one
Q1	Do you work with data as part of your role?	Core	Systems Thinking → Task Complexity; DOI → Compatibility	Senge (1990); Rogers (2003)	This eligibility filter ensures that only participants relevant to GenAI-supported data tasks are included, critical for answering the research question on enhancing data-driven problem-solving (Senge, 1990; Rogers, 2003). Data engagement also relates to Task Complexity framing in Systems Thinking. Binary choice structure ensures clear differentiation without introducing ambiguity at this early stage.	Direct eligibility filter to ensure participants are engaged in data-related tasks where GenAI application to problem-solving can realistically occur. Without this control, responses from irrelevant roles would distort findings on GenAI's impact on problem-solving capabilities.	select_one
Q2	What department/unit are you part of?	Functional	Systems Thinking → Cross-functional Collaboration	Senge (1990)	Different departments face varied data complexities and workflows (Senge, 1990). Understanding department context supports analyzing how GenAI impacts collaboration and decision-making across workflows, directly linked to the Systems Thinking lens on interdependencies. Predefined department options ensure consistent coding and respect "Case Organization"'s real organizational structure.	Departmental affiliation affects access to data complexity, collaboration demands, and readiness for GenAI-supported decision-making (Systems Thinking). It enables subgroup analysis of Compatibility and workflow integration factors influencing the Core problem-solving constructs. Missing it would prevent contextual understanding of differences across business units.	select_one
Q3	What are your primary responsibilities?	Core	Systems Thinking → Task Complexity; TAM → Perceived Usefulness (PU) (indirect)	Davis (1989); Senge (1990)	Mapping primary responsibilities is crucial to determine the alignment between GenAI capabilities and users' tasks (Davis, 1989; Senge, 1990). If responsibilities involve interpretation, communication, or strategic decisions, GenAI's impact on problem-solving can be realistically assessed. Options provided (e.g., data analysis, compliance, HR analytics) align with typical non-technical but data-relevant roles identified in the literature review (Baron & Bielby, 1982).	Understanding participants' primary responsibilities anchors the analysis of task complexity, relevance of GenAI support, and perceived usefulness (TAM, Systems Thinking). Essential for validating alignment between GenAI capabilities and real-world non-technical data-related tasks. Without it, construct measurement would be detached from work reality.	select_multiple
Q4	Based on the definitions below, how would you classify your role at "Case Organization"?	Core	DOI → Compatibility; Systems Thinking → Task Complexity	Rogers (2003); Senge (1990)	Self-classification allows capturing perceived role-technology fit, critical in DOI frameworks (Rogers, 2003) and Systems Thinking (task complexity). Participant classification ensures modeling of Compatibility effects and moderating role of task structure, necessary for answering the research question on GenAI-enabled decision-making. Standardized Non-Technical / Hybrid / Technical role definitions sourced from academic literature (Van Diggele et al., 2020).	Self-classification into Non-Technical, Hybrid, or Technical roles is critical to operationalizing perceived Compatibility and task complexity within the conceptual model (DOI; Systems Thinking). Essential for testing how GenAI impacts independence and problem-solving capacity across role types. Without it, role-based adoption pathways could not be modeled.	select_one
Q5	Have you used GenAI tools in your current role at "Case Organization"?	Core	DOI → Compatibility; Trialability (early adoption filter)	Rogers (2003)	Essential for segregating users from non-users and tracing adoption pathways (Rogers, 2003). Exposure to GenAI determines experience-based reasoning and adaptive problem-solving behaviors, critical for understanding enhancement capabilities. Binary format ensures clean survey branching, preventing contamination of post-use experience questions.	Captures actual usage behavior, which is critical for differentiating between experienced GenAI users and non-users in the context of problem-solving capability evaluation. Core to tracing exposure effects on Data Reasoning, Decision-Making, and Efficiency. No GenAI experience segmentation would severely bias causal interpretation.	select_one
Q6	Which of the following GenAI tools have you used in your current role at "Case Organization"?	Functional	TAM → PU; Output Quality	Davis (1989); Venkatesh & Davis (2000)	Identifies specific tools shaping user experience with GenAI, supporting analysis of perceived usefulness and output reliability (Davis, 1989; Venkatesh & Davis, 2000). Recognizing exposure differences aligns with understanding if problem-solving improvements are generalized or tool-specific. Multiple-choice matches the real available systems (Copilot, "Case Organization"GPT), aligning with organizational context.	Tool exposure (Copilot, "Case Organization"GPT, etc.) provides necessary context for interpreting differences in PU, Output Quality, and problem-solving efficiency. Although not directly measuring a construct, tool-specific variance shapes user outcomes. Omission would obscure how tool design differences influence perceived effectiveness.	select_multiple
Q7	How frequently do you use GenAI tools in your current role?	Core	TAM → Tool Use Behavior; DOI → Observability (supportive moderator)	Davis (1989); Rogers (2003)	Frequency reflects adoption depth and habitual integration into workflows (Davis, 1989; Rogers, 2003). Higher frequency likely enhances problem-solving efficiency and adaptive decision-making confidence, answering how deeply GenAI capabilities penetrate daily routines. Frequency bands (e.g., Daily, Weekly) reflect typical adoption curve studies in innovation research.	Frequency of GenAI use operationalizes depth of integration into daily workflows, essential for modeling habitual reinforcement of perceived usefulness and problem-solving improvement (TAM; DOI Observability). No frequency measure would cripple adoption intensity analysis.	select_one
Q8	What types of tasks do you typically use GenAI tools for in your current role?	Core	TAM → Perceived Usefulness (PU); Systems Thinking → Task Complexity	Davis (1989); Senge (1990)	Captures which task categories participants feel GenAI supports, validating perceived usefulness in realistic business contexts (Davis, 1989; Senge, 1990). Task type (e.g., data summaries, procurement support) connects to the conceptual framework's focus on enhancing problem-solving efficiency and adaptive decision-making. Options were selected based on real-world GenAI application domains identified in sector literature (Dwivedi, 2024; Badmus et al., 2024).	Identifies the types of tasks GenAI supports, directly measuring Perceived Usefulness (PU) and mapping real-world problem-solving areas where cognitive support occurs. Without it, usefulness evaluation would lack practical grounding.	select_multiple
Q9	What best describes the complexity of your GenAI-related tasks?	Core	Systems Thinking → Task Complexity; TAM → Output Quality (perceived task demands)	Senge (1990); Venkatesh & Davis (2000)	Measures how users experience cognitive load when working with GenAI (Senge, 1990; Venkatesh & Davis, 2000). Understanding perceived task complexity supports interpreting how GenAI influences problem-solving approaches. Simple Low/Moderate/High scale follows best practice in task complexity studies (Muduli & Choudhury, 2024).	Captures perceived cognitive demand of GenAI-supported tasks, essential for validating Task Complexity hypotheses from Systems Thinking. Determines if GenAI reduces or exacerbates problem-solving difficulty. Omission would prevent correct complexity analysis.	select_one

Code	Full Survey Question	Classification	Construct	Author(s) / Year	Theoretical Justification	Methodological Role Justification	Type
Q10	I plan to keep using GenAI tools in my work when available.	Core	TAM → Behavioral Intention (derived from PU & PEOU)	Davis (1989)	Future behavioral intention is crucial for modeling the sustained impact of GenAI tools on problem-solving behavior (Davis, 1989). Likert scale from Strongly Disagree to Strongly Agree matches standard TAM instrument design, allowing gradient assessment of intention strength.	Behavioral Intention is essential in TAM for predicting future GenAI usage and continued support for problem-solving efficiency. Without it, no projection of sustainability or longitudinal adoption effects could be modeled.	select_one (Likert 5-point)
Q11	GenAI tools help me complete tasks more efficiently, regardless of task complexity.	Core	TAM → Perceived Usefulness (PU)	Davis (1989)	Captures the direct impact of GenAI on perceived productivity improvement (Davis, 1989). Measuring efficiency perception is essential for validating GenAI's role in enhancing problem-solving efficiency as hypothesized. Likert scaling captures intensity of agreement across participants.	Directly measures perceived productivity (PU) gains through GenAI, a fundamental outcome dimension tied to problem-solving efficiency in the research model. Omission would sever the link between tool adoption and perceived work enhancement.	select_one (Likert 5-point)
Q12	GenAI tools are easy to use without technical expertise.	Core	TAM → Perceived Ease of Use (PEOU)	Davis (1989)	Measures usability perception, a core predictor of technology acceptance for non-technical roles (Davis, 1989). Critical for understanding ease-of-access barriers in enhancing problem-solving strategies. 5-point Likert scale matches Davis's original operationalization.	Captures Perceived Ease of Use (PEOU), a critical TAM factor determining whether non-technical roles feel capable of independently solving data-related tasks with GenAI. Excluding it would ignore a key predictor of GenAI integration success.	select_one (Likert 5-point)
Q13	I trust the content provided by GenAI tools.	Core	TAM Extension → Trust in AI	Kim et al. (2025)	Trust is crucial for GenAI adoption because users must rely on outputs for decision-making without direct verification (Kim et al., 2025). Trust influences confidence in reasoning with AI-generated insights. Likert scaling ensures nuanced perception measurement.	Measures Trust in GenAI outputs, critical for assessing whether users feel confident enough to base decisions and reasoning processes on AI support. Trust moderates PU and Adaptive Decision-Making; omission would leave adoption dynamics unexplained.	select_one (Likert 5-point)
Q14	I believe GenAI tools used at "Case Organization" provide transparent and fair outputs.	Core	TAM Extension → Trust and Output Quality	Kim et al. (2025); Venkatesh & Davis (2000)	Transparency and fairness perceptions strongly affect trust and perceived output quality, influencing willingness to adapt decisions based on GenAI (Kim et al., 2025; Venkatesh & Davis, 2000). Likert response captures subtle transparency concerns.	Captures perceived Transparency and Fairness, essential subdimensions of Trust and Output Quality, which affect reliance on GenAI in complex problem-solving. Without it, systemic credibility issues would be invisible.	select_one (Likert 5-point)
Q15	The quality of GenAI output meets my expectations.	Core	TAM → Output Quality	Venkatesh & Davis (2000)	Perceived output quality impacts perceived usefulness, trust, and continuation of GenAI usage (Venkatesh & Davis, 2000). Essential to understand if GenAI enhances problem-solving efficiency through reliable outputs. Likert scale consistent with TAM standards.	Directly evaluates Output Quality satisfaction, central to understanding GenAI's ability to support high-stakes decision-making without manual verification. Missing it would undercut analysis of GenAI's impact on problem-solving trust and effectiveness.	select_one (Likert 5-point)
Q16	GenAI tools help me work independently without relying on technical colleagues.	Core	Systems Thinking → Cross-functional Collaboration; Task Complexity	Senge (1990)	Demonstrates how GenAI empowers non-technical roles to perform data-driven problem-solving independently (Senge, 1990). Independence links directly to Systems Thinking focus on task decentralization and self-sufficiency. Likert captures autonomy perception.	Measures self-perceived independence enhancement, supporting Systems Thinking principles of decentralization and cross-functional empowerment through GenAI. Without it, empowerment effects on problem-solving autonomy would be hidden.	select_one (Likert 5-point)
Q17	GenAI tools help me evaluate and interpret data insights.	Core	Problem-Solving Capability → Data Reasoning	Akinnagbe (2024); De Laat et al. (2020)	Data Reasoning is a core cognitive skill enhanced by effective GenAI use (Akinnagbe, 2024; De Laat et al., 2020). Interpretation ability supports adaptive decision-making processes, answering the research question. Likert scaling assesses degrees of perceived cognitive support.	Direct measurement of Data Reasoning support through GenAI assistance — a critical cognitive capability under investigation in the research question. Omitting this would cripple validation of reasoning enhancement hypotheses.	select_one (Likert 5-point)
Q18	I adjust my decisions based on GenAI tool suggestions.	Core	TAM → Behavioral Intention	Muduli & Choudhury (2024); Singh & Kaunert (2024)	Captures users' cognitive flexibility and iterative decision-making influenced by GenAI support (Muduli & Choudhury, 2024; Singh & Kaunert, 2024). Adaptive use of GenAI suggestions is crucial to understand enhancements in problem-solving capabilities. Likert scaling captures subtle differences in adaptivity.	Directly measures Adaptive Decision-Making influenced by GenAI suggestions, a core cognitive capability being investigated. Without it, flexibility in decision adjustment, critical for GenAI-supported problem-solving, could not be validated.	select_one (Likert 5-point)
Q19	GenAI tools are well integrated into our department's current tools and workflows.	Core	TAM → Perceived Usefulness (PU)	Rogers (2003)	Measures perceived organizational workflow fit, directly influencing GenAI adoption success (Rogers, 2003). Compatibility is critical in predicting sustainable integration into problem-solving activities. Likert scale structure allows capturing perceived fit nuances.	Captures perceived Compatibility of GenAI tools with departmental workflows, a central DOI construct affecting sustained adoption and problem-solving integration. Omission would obscure key adoption fit factors.	select_one (Likert 5-point)
Q20	The tasks I perform with GenAI are cognitively demanding or complex.	Core	TAM → Perceived Ease of Use (PEOU)	Senge (1990)	Measures perceived cognitive load associated with GenAI tasks, informing whether GenAI reduces or exacerbates complexity (Senge, 1990). Essential for interpreting the cognitive impact of GenAI on problem-solving workflows. Likert scaling standardizes complexity perception assessment.	Measures if GenAI tasks are perceived as cognitively demanding, validating whether GenAI reduces or intensifies task complexity under Systems Thinking assumptions. Without it, cognitive load implications could not be tested.	select_one (Likert 5-point)
Q21	I find that GenAI tools are useful for supporting my daily work tasks.	Core	TAM → Trust in AI	Davis (1989)	Directly assesses the generalized utility perception of GenAI, confirming its role in daily data-driven decision-making improvements (Davis, 1989). PU is central to your conceptual framework for understanding tool-enhanced problem-solving. Likert scaling supports fine-grained usefulness mapping.	Assesses broad Perceived Usefulness (PU) in daily tasks, providing direct evidence of GenAI's real-world problem-solving support. Without it, the main utility claim underpinning the research would be unprovable.	select_one (Likert 5-point)
Q22	I received sufficient training or guidance to use GenAI tools effectively.	Functional	TAM → Trust in AI	Rogers (2003); Senge (1990)	Measures organizational support structures that facilitate early tool experimentation and adoption (Rogers, 2003; Senge, 1990). Training improves trialability and builds knowledge networks, critical for successful GenAI integration into workflows. Likert captures perceived enablement levels.	Training adequacy influences users' readiness for GenAI engagement and experimentation (Trialability). Including it explains why some participants succeed in leveraging GenAI for problem-solving while others do not. Without it, variations in preparedness would be uninterpretable.	select_one (Likert 5-point)
Q23	I believe I would benefit from a tailored training or role-specific support to use GenAI tools effectively.	Functional	TAM → Output Quality	Rogers (2003); Senge (1990)	Role-specific support enhances perceived compatibility and task ease (Rogers, 2003; Senge, 1990). Tailored enablement reduces perceived cognitive burden and increases trust in GenAI for problem-solving. Likert structure allows clear expression of personalized support needs.	Tailored training need captures latent Compatibility gaps, helping explain why certain users perceive barriers despite GenAI availability. Without it, misalignment between user needs and tool design would remain hidden.	select_one (Likert 5-point)
Q24	What type of training or support would be most helpful?	Functional	Systems Thinking → Task Complexity	Rogers (2003); Senge (1990)	Explores practical enablement strategies to foster GenAI adoption and cross-departmental knowledge sharing (Rogers, 2003; Senge, 1990). Multiple-choice format reflects common support methods identified in organizational change management literature, maintaining alignment with DOI focus on adoption facilitation.	Identifies preferred enablement strategies, crucial for understanding organizational intervention points that could increase GenAI-supported problem-solving success. Without it, enablement pathway design would be uninformed.	select_multiple
Q25	In your own words, what would make your day-to-day use of GenAI tools more effective?	Supportive	Problem-Solving Capability → Data Reasoning	Davis (1989)	Open-ended capture of user-defined friction points and improvement ideas is critical for understanding real-world obstacles to maximizing PU (Davis, 1989). Supports practical refinement of GenAI integration strategies directly linked to adoption and effectiveness.	Open-ended capture of user-defined GenAI improvement suggestions enhances practical understanding of how to maximize PU. While exploratory, it enriches the problem-solving improvement narrative and supports future system refinements.	text

Code	Full Survey Question	Classification	Construct	Author(s) / Year	Theoretical Justification	Methodological Role Justification	Type
Q26	Using GenAI has helped me improve my individual approach to problem-solving.	Core	Problem-Solving Capability → Adaptive Decision-Making	Akinnagbe (2024); Muduli & Choudhury (2024)	Captures self-perceived improvement in critical cognitive skills like interpretation and decision flexibility through GenAI use (Akinnagbe, 2024; Muduli & Choudhury, 2024). Directly linked to assessing capability enhancement answering the research question. Likert scaling allows nuanced measurement of self-reported growth.	Measures user-perceived improvement in problem-solving approach, critically validating whether GenAI use strengthens Data Reasoning and Adaptive Decision-Making capabilities — central to answering the research question. Without it, capability enhancement could not be confirmed.	select_one (Likert 5-point)
Q27	What is the biggest limitation of using GenAI tools in your role?	Functional	DOI → Compatibility	Venkatesh & Davis (2000); Kim et al. (2025)	Identifies perceived barriers blocking full integration of GenAI into workflows, affecting sustained usefulness and reliability perceptions (Venkatesh & Davis, 2000; Kim et al., 2025). Open-ended format allows exploration beyond predefined categories, essential for uncovering unexpected barriers.	Captures perceived GenAI limitations (e.g., Output Quality, Trust issues) that moderate adoption and effectiveness. Provides necessary explanatory depth when problem-solving enhancements are inconsistent. Without it, critical barriers would be overlooked.	text
Q28	GenAI tools support my learning or skill development.	Functional	Systems Thinking → Task Complexity	Senge (1990)	Measures GenAI's role in facilitating informal professional learning cycles and adaptation capacity, crucial for system-wide technology integration (Senge, 1990). Likert format captures levels of perceived learning support.	Measures GenAI's role in supporting skill development and organizational learning cycles. Helps explain broader Systems Thinking dynamics affecting long-term GenAI integration beyond immediate problem-solving. Without it, organizational learning processes would remain unexplored.	select_one (Likert 5-point)
Q29	Describe an example where a GenAI tool helped (or could have helped) you solve a data-related task or make a better decision at work.	Core	TAM → Perceived Usefulness (PU)	Akinnagbe (2024); Muduli & Choudhury (2024)	Concrete task examples validate theoretical constructs in real-world contexts, demonstrating how GenAI supports reasoning or flexibility (Akinnagbe, 2024; Muduli & Choudhury, 2024). Open-ended structure enables authentic task scenario collection.	Collects concrete task-based examples where GenAI contributed to data-driven decisions or reasoning. Essential for triangulating theoretical model assumptions with real-world cognitive improvements. Without it, application evidence would be missing.	text
Q30	My collaboration with other departments has improved since I started using GenAI tools.	Functional	Systems Thinking → Knowledge Sharing	Senge (1990); Rogers (2003)	Captures cross-departmental knowledge sharing changes and workflow synchronization improvements linked to GenAI (Senge, 1990; Rogers, 2003). Critical for assessing system-level effects. Likert format measures collaboration perception shifts precisely.	Measures perceived cross-department collaboration improvements enabled by GenAI tools. Important for interpreting systemic adoption effects under Systems Thinking, though not a primary construct. Without it, inter-unit dynamic shifts would go unnoticed.	select_one (Likert 5-point)
Q31	GenAI tools have influenced how knowledge is shared within my team.	Functional	Systems Thinking → Task Complexity (Skill Fit)	Senge (1990)	Assesses whether GenAI tools facilitate better internal communication and knowledge diffusion, aligned with organizational learning principles (Senge, 1990). Likert scaling ensures gradation in perceived knowledge dynamics.	Captures changes in intra-team knowledge sharing attributed to GenAI, enriching Systems Thinking interpretation of how workflows adapt with AI support. Without it, knowledge diffusion dynamics would be missing.	select_one (Likert 5-point)
Q32	I have observed colleagues benefiting from GenAI tools before adopting them myself.	Functional	Problem-Solving Capability → Adaptive Decision-Making	Rogers (2003)	Observing positive peer outcomes enhances perceived legitimacy and speeds up adoption curve in DOI theory (Rogers, 2003). Observability affects trial decisions and later habitual use. Likert response range measures intensity of observational influence.	Observability (seeing colleagues benefit from GenAI) influences adoption likelihood according to DOI. Important for contextualizing behavioral pathways to adoption even if not a direct Core construct.	select_one (Likert 5-point)
Q33	I had the chance to test GenAI tools before using them in my daily work.	Functional	Systems Thinking → Organizational Learning	Rogers (2003)	Early testing opportunities reduce perceived risk and encourage GenAI adoption, supporting DOI trialability dynamics (Rogers, 2003). Likert scale captures variations in exposure to trial opportunities.	Measures whether users had trial exposure before adopting GenAI, supporting DOI Trialability assumptions. Helps explain differences in problem-solving adaptation without being a Core measurement itself.	select_one (Likert 5-point)
Q34	What insights or experiences did you gain from testing or exploring GenAI tools that influenced your opinion about their usefulness or relevance in your work?	Supportive	Systems Thinking → Cross-functional Collaboration	Rogers (2003)	Collects qualitative insights into early learning or changes in perception triggered by GenAI exposure, important for understanding social diffusion processes (Rogers, 2003). Open-ended ensures depth and variety of reflections.	Collects qualitative reflections on how early experimentation shaped GenAI perceptions. Valuable for enriching Observability/Trialability interpretation but not directly tied to quantitative model constructs.	text
Q35	Do you have any final comments or suggestions about using GenAI tools in your work?	Supportive	Systems Thinking → Knowledge Sharing	Senge (1990)	Provides an open forum to capture residual insights, improvement suggestions, or concerns not addressed by structured items, supporting systemic learning feedback loops (Senge, 1990). Open-ended format invites broad, uninfluenced commentary.	Final open feedback captures unexpected concerns or suggestions beyond structured model variables. Useful for practical system improvements and closing triangulation gaps but non-essential to core construct validation.	text
NU1	Are you aware that GenAI tools are available at "Case Organization"?	Functional	DOI → Observability	Rogers (2003)	Captures awareness, a critical prerequisite for technology adoption according to DOI (Rogers, 2003). Without visibility, GenAI diffusion cannot progress. Simple select_one format reflects binary awareness levels needed for segmentation.	Measures GenAI tool awareness, a prerequisite in DOI for adoption to occur. Provides necessary segmentation to understand latent non-use causes. Without it, invisibility barriers would be misinterpreted as resistance.	select_one
NU2	Which of the following would make you more open to using GenAI tools in your role?	Core	DOI → Trialability	Rogers (2003); Davis (1989); Kim et al. (2025)	Identifies primary adoption drivers mapped to theoretical constructs: perceived fit (Compatibility), ability to experiment (Trialability), perceived usefulness, and trust (Rogers, 2003; Davis, 1989; Kim et al., 2025). Multi-select structure allows respondents to identify multiple influencing factors, critical for modeling complex adoption drivers.	Identifies perceived enablers (training, workflow fit, observability) tied to PU, Compatibility, Trialability, and Trust — directly informing why adoption might be blocked or supported. Critical for modeling latent adoption dynamics among non-users.	select_multiple
NU2a	If other, please specify.	Supportive	Systems Thinking → Task Complexity (Skill Fit)	Rogers (2003)	Captures adoption enablers not pre-listed, allowing the emergence of unexpected compatibility or experimentation facilitators (Rogers, 2003). Open-ended enriches data collection for strategic analysis.	Captures additional enablers not foreseen in structured options. Adds flexibility to the adoption model enrichment but remains exploratory.	text
NU3	I believe I would need tailored training or role-specific support to use GenAI tools effectively.	Functional	TAM → Perceived Usefulness (PU)	Rogers (2003); Senge (1990)	Assesses non-users' perceived need for role-specific onboarding, aligning with Compatibility and reduction of perceived complexity barriers (Rogers, 2003; Senge, 1990). Likert scale captures gradation of support expectations.	Tailored support need captures perceived Compatibility gaps among non-users. Important for understanding how missing enablement prevents GenAI adoption for problem-solving, but not a direct construct measure.	select_one (Likert 5-point)
NU4	I believe GenAI tools could be helpful in my role.	Core	TAM → Perceived Usefulness (PU)	Davis (1989)	Evaluates non-users' perception of potential task-related utility from GenAI, critical for predicting future adoption intentions (Davis, 1989). Likert scaling ensures sensitivity to openness levels.	Measures latent Perceived Usefulness (PU) among non-users, essential for predicting future openness to GenAI-enhanced problem-solving. Without it, user potential could not be modeled.	select_one (Likert 5-point)
NU5	What types of tasks do you think GenAI tools could support in your role, if you were to use them?	Core	TAM → Perceived Usefulness (PU); Systems Thinking → Task Complexity	Davis (1989); Senge (1990)	Identifies domains where non-users anticipate GenAI adding value, mapping usefulness perceptions against organizational task complexity structures (Davis, 1989; Senge, 1990). Multiple choice reflects practical work tasks discussed in literature.	Maps anticipated task relevance of GenAI tools for non-users, tying back to PU and Task Complexity framing. Necessary for validating future expansion pathways in non-technical roles.	select_multiple
NU5a	If other, please specify.	Supportive	TAM → PU (qualitative extension)	Davis (1989)	Allows participants to suggest additional task types not listed, ensuring the PU construct captures all perceived application areas (Davis, 1989). Open-ended flexibility supports completeness.	Captures additional task types non-technical employees envision for GenAI application, ensuring completeness in perceived usefulness mapping.	text
NU6	In your opinion, what would make GenAI tools more relevant or useful in your role?	Functional	TAM → PU; DOI → Compatibility	Davis (1989); Rogers (2003)	Explores specific perceived gaps in functionality or integration that hinder perceived usefulness or workflow fit (Davis, 1989; Rogers, 2003). Open-ended responses allow nuanced barrier identification.	Explores factors that would increase perceived GenAI relevance, supporting PU and Compatibility understanding for system improvement but does not measure constructs directly.	text
NU7	Please share any other reason why you have not used GenAI tools, or any concerns you'd like us to know.	Functional	TAM → Trust / Complexity Barriers; DOI → Trialability concerns	Kim et al. (2025); Rogers (2003)	Identifies deeper psychological or systemic barriers like trust issues, complexity fears, or perceived lack of trialability affecting GenAI adoption (Kim et al., 2025; Rogers, 2003). Open-ended structure ensures no critical barrier is missed.	Captures hidden concerns (trust, complexity, effort) moderating GenAI resistance among non-users. Critical for interpreting why expected problem-solving enhancements might not materialize despite tool availability.	text
E2	How often do you collaborate with Non-Technical or Hybrid roles for data-related tasks?	Functional	Systems Thinking → Cross-functional Collaboration	Senge (1990)	Captures interaction frequency critical for understanding how collaboration patterns influence GenAI diffusion across role types (Senge, 1990). Single-choice frequency options mirror cross-functional study best practices.	Measures collaboration frequency with Non-Technical or Hybrid roles, enriching Systems Thinking interpretation of GenAI's systemic diffusion but not modeling a direct construct.	select_one
E3	Do you believe Non-Technical roles should have more independence in data-related problem-solving?	Functional	Systems Thinking → Cross-functional Collaboration; DOI → Compatibility	Senge (1990); Rogers (2003)	Captures normative beliefs about expanding data problem-solving beyond technical roles, key for understanding adoption potential (Senge, 1990; Rogers, 2003). Structured responses enable comparison across attitudes.	Captures normative beliefs about empowering non-technical decision-making through GenAI. Important for contextualizing organizational readiness but supportive in nature.	select_one
E4	In your opinion, what is/are the biggest barrier(s) preventing non-technical roles from becoming more data-driven?	Functional	Systems Thinking → Task Complexity; TAM → Trust and PEOU	Senge (1990); Davis (1989)	Captures real-world systemic and cognitive barriers, such as perceived difficulty, complexity, or lack of trust, affecting empowerment efforts (Senge, 1990; Davis, 1989). Open-ended format ensures deep exploration of perceived obstacles.	Identifies systemic and cognitive barriers preventing non-technical roles from becoming more data-driven. Supports interpreting GenAI's role in lowering Task Complexity barriers.	text
E5	From your perspective, what would help non-technical roles use GenAI tools more effectively in their daily work?	Functional	Systems Thinking → Knowledge Sharing; DOI → Compatibility	Senge (1990); Rogers (2003)	Collects practical strategies to foster GenAI adoption among non-technical employees, aligning with system-level and adoption theory solutions (Senge, 1990; Rogers, 2003). Open-ended allows emergence of creative enablers and organizational recommendations.	Gathers participant-suggested enablers for expanding GenAI effectiveness across non-technical roles, supporting future adoption strategy design aligned to DOI-Compatibility logic.	text

Appendix 3. Experiment Participant Instructions

📄 Instructions

This experiment is part of a Master's thesis focused on understanding how Generative AI (GenAI) tools may support problem-solving in data-related tasks. You will complete **two short tasks**, each designed to simulate realistic work scenarios involving data.

Each task is expected to take **no more than 10–12 minutes**, with **a total session time of 30 minutes**, including reflection.

🧩 Task Descriptions

You will complete two different types of tasks:

- **Task 1 – Structured Interpretation:**
  You will receive a simple data report or summary and will be asked to extract key points and complete a short template based on your interpretation.
  This simulates structured, analytical work (e.g., interpreting KPIs or dashboards).

- **Task 2 – Creative Extension:**
  You will be asked to create a new business term (could be fictional) for "Case Organization" data catalog, drawing from your own experience, and ideas.
  This simulates open-ended, creative thinking with minimal constraints.

🔀 Tool Use Variation

In one of the two tasks, you will be allowed to use a **Generative AI tool (e.g., Copilot)**. In the other task, you will complete the task **manually** without tool support.
You will be told at the beginning of each task whether the tool is available.

📋 What You Should Know

- There are **no right or wrong answers**. We are interested in **your thought process and experience**.
- Your **participation is anonymous**.
- After each task, you'll complete a **short reflection form** (~4–5 questions).

Appendix 4. Experimental Task Reflection Questionnaire

Experimental Task Reflection Questionnaire

This instrument was used to capture participants' reflections after completing each task in the experiment. Each participant completed the questionnaire twice: once after completing Task 1 (Structured Interpretation) and again after Task 2 (Creative Extension). The questionnaire includes rating-scale and open-ended questions designed to assess problem-solving confidence, independence, and tool-supported behavior in alignment with the conceptual framework.

Demographic Information

D1. What is your age group?

- Under 30
- 30–39
- 40–49
- 50–59
- 60 or older
- Prefer not to say

D2. What is your gender?

- Woman
- Man
- Non-binary / Prefer to self-describe
- Prefer not to say

D3. How long have you worked at "Case Organization"?

- Less than 1 year
- 1–3 years
- 4–7 years
- More than 7 years
- Prefer not to say

D4. Which department or business unit are you currently part of?
(Dropdown list — same as in the survey, alphabetically ordered)

D5. Before this session, have you used any Generative AI tools at work (e.g., Copilot)?

- Yes
- No
- I'm not sure

Section 3 – GenAI-Specific Reflections

(This section appears only if the task was completed with a GenAI tool.)

Q3.1 How helpful was the GenAI tool in supporting your task completion?
ⓘ *Think about whether the tool made the task easier or helped you generate useful results.* ***(Likert)***

Q3.2 How easy was it to interact with the GenAI tool for this task?
ⓘ *Consider whether the tool was intuitive, clear, and easy to use without technical expertise.* ***(Likert)***

Q3.3 Did you fully follow, partly follow, or not follow the GenAI tool's suggestions? Why or why not?
ⓘ *You can describe whether you used the tool's output directly or made changes to it.*
(Open-ended)

Section 4 – Post-Comparison Reflection

(Completed only after both tasks have been completed.)

Q4.1 Compared to completing the task without a GenAI tool, how would you rate your speed when using a GenAI tool?
ⓘ *Speed refers to how quickly you completed the task overall.* ***(Likert)***

Q4.2 Compared to completing the task without a GenAI tool, how would you rate the quality of your output when using a GenAI tool?
ⓘ *Quality refers to the accuracy, completeness, and clarity of your final output.* ***(Likert)***

Q4.3 Compared to completing the task without a GenAI tool, how would you rate your confidence in your final output when using a GenAI tool?
ⓘ *Confidence means how sure you were that your output was good and correct.* ***(Likert)***

Q4.4 In your own words, describe any additional differences you noticed when working with vs. without a GenAI tool.
(Open-ended)

- **Exit Questionnaire.**

Section 1 – Post-Task Reflection (Repeated/Completed After Each Task)

Q0. Please upload your output for this task

Q1.1 How confident were you in your ability to complete this task?
ⓘ *Think about how sure you were that your approach would work, from start to finish.*
1 – Not at all confident
2 – Slightly confident
3 – Moderately confident
4 – Very confident
5 – Extremely confident

Q1.2 To what extent did you complete this task independently, without relying on others or external resources?
ⓘ *Consider whether you needed help from a colleague, external document, or manual steps.*
1 – Not at all independently
2 – Slightly independently
3 – Somewhat independently
4 – Mostly independently
5 – Completely independently

Section 2 – Non-GenAI Task Reflection

(This section appears only if the task was completed without a GenAI tool.)

Q2.1 Which of the following strategies did you primarily use to complete the task without GenAI tools?
ⓘ *Select all that apply.*
☐ Relied on prior knowledge or experience
☐ Searched internal documentation (e.g., guidelines, policies)
☐ Made assumptions based on logic or best guesses
☐ Consulted external resources (e.g., internet, external documents)
☐ Asked for help from a colleague or team member
☐ Other (please specify): __________

Q2.2 What challenges, if any, did you encounter while completing this task without a GenAI tool?
ⓘ *This helps us understand which steps were difficult, confusing, or time-consuming.*
(Open-ended)

Appendix 5. Constructs Mapping of Experiment Questions

Code	Full Survey Question	Classification	Construct	Author(s) / Year	Theoretical Justification	Methodological Role Justification	Type
D1	What is your age group?	Supportive	Task Complexity (moderator)	Senge (1990)	Systems Thinking: Cognitive flexibility and learning openness vary with age, affecting GenAI adoption and problem-solving (Senge, 1990).	Captures generational background factors that could bias task performance and GenAI-supported cognitive shifts; ensures demographic control.	select_one
D2	What is your gender?	Supportive	Organizational Diversity (indirect influence)	Senge (1990)	Systems Thinking: Gender diversity shapes collaboration and learning system behavior (Senge, 1990).	Ensures diversity control for potential collaboration or independence differences during problem-solving with GenAI; supports subgroup validity.	select_one
D3	How long have you worked at "Case Organization"?	Supportive	Compatibility (moderator); Knowledge Sharing	Senge (1990); Rogers (2003)	Systems Thinking; DOI: Tenure affects familiarity with data systems and openness to innovation, influencing Compatibility and knowledge loops (Rogers, 2003; Senge, 1990).	Controls for experience-driven adaptation readiness that could affect how GenAI improves problem-solving skills.	select_one
D4	Which department or business unit are you currently part of?	Supportive	Task Complexity; Cross-functional Collaboration	Senge (1990)	Systems Thinking: Department shapes task interdependencies and complexity exposure (Senge, 1990).	Provides context for interpreting cognitive task differences across units; essential for subgroup comparison but not directly testing constructs.	select_one
D5	Before this session, have you used any Generative AI tools at work (e.g., Copilot, "Case Organization"GPT)?	Core	PU; Trust; Trialability	Rogers (2003); Davis (1989)	DOI; TAM: Prior exposure to GenAI affects Trialability, perceived usefulness (PU), and initial trust levels (Rogers, 2003; Davis, 1989).	Critical for segmenting participants based on pre-existing familiarity; directly moderates behavior and performance during experimental tasks.	select_one
Q0	Please upload your output for this task.	Supportive	Problem-Solving Efficiency (indirect validation)	-	Practical necessity: Ensures that task performance can be verified, compared, and qualitatively analyzed if needed.	Uploading task output provides objective evidence for validating participants' reflections on confidence, independence, and problem-solving efficiency. It mitigates self-report bias and supports triangulation of cognitive outcomes. Essential for verifying GenAI's real impact on observed task performance.	upload
Q1.1	How confident were you in your ability to complete this task?	Core	Data Reasoning; Adaptive Decision-Making	Akinnagbe (2024); De Laat et al. (2020)	Confidence reflects perceived cognitive ability to reason with or without GenAI support, tied to enhanced Data Reasoning and Adaptive Decision-Making skills (Akinnagbe, 2024).	Captures real-time confidence shifts as a key outcome of GenAI cognitive support. Central to testing whether GenAI enhances self-efficacy in problem-solving.	select_one (5-point scale)
Q1.2	To what extent did you complete this task independently, without relying on others or external resources?	Core	Adaptive Decision-Making; Problem-Solving Efficiency	Muduli & Choudhury (2024); Senge (1990)	Independence reflects cognitive ownership of the task, linked to Adaptive Decision-Making and efficient autonomous problem-solving (Muduli & Choudhury, 2024; Senge, 1990).	Critical to validate if GenAI tools support greater independence in problem-solving, a core Research Question objective.	select_one (5-point scale)
Q2.1	Which of the following strategies did you primarily use to complete the task without GenAI tools?	Functional	Data Reasoning; Problem-Solving Efficiency	Akinnagbe (2024); De Laat et al. (2020)	Strategy use reflects cognitive approaches to data-driven problem-solving (Akinnagbe, 2024). Capturing strategies (e.g., reliance on prior knowledge, external search) helps profile natural reasoning without AI support.	Helps explain baseline problem-solving behaviors and cognitive effort, creating a benchmark for comparing manual vs. GenAI-supported problem-solving processes. Essential for interpreting GenAI cognitive contribution.	select_multiple
Q2.2	What challenges, if any, did you encounter while completing this task without a GenAI tool?	Supportive	Task Complexity	Senge (1990)	Challenges reflect subjective task complexity and friction points, informing Systems Thinking analysis of whether GenAI simplifies workflows (Senge, 1990).	Provides qualitative depth to baseline difficulty; necessary for contrasting perceived task burdens between manual and GenAI-assisted conditions.	text
Q3.1	How helpful was the GenAI tool in supporting your task completion?	Core	Perceived Usefulness (PU)	Davis (1989)	Captures direct perception of GenAI's usefulness in task support, critical for validating the PU construct from TAM in the experimental context.	Central measure to test whether GenAI enhances perceived problem-solving capabilities. Without it, PU effects on cognitive outcomes could not be modeled.	select_one (5-point scale)
Q3.2	How easy was it to interact with the GenAI tool for this task?	Core	Perceived Ease of Use (PEOU)	Davis (1989)	Captures perceived cognitive effort in interacting with GenAI, operationalizing PEOU under TAM. Essential for modeling usability influences on task efficiency and confidence.	Core predictor of whether non-technical users can independently and effectively leverage GenAI. Without it, usability barriers would remain invisible.	select_one (5-point scale)
Q3.3	Did you fully follow, partly follow, or not follow the GenAI tool's suggestions? Why or why not?	Core	Trust; Adaptive Decision-Making	Kim et al. (2025); Muduli & Choudhury (2024)	Measures trust in GenAI outputs and the degree of adaptive use of AI suggestions. Trust is essential for reliance, while adaptivity reflects decision flexibility.	Critical to analyze whether users critically evaluate GenAI outputs or passively accept/reject them — essential for understanding GenAI's cognitive integration.	select_one (follow level) + text (explanation)
Q4.1	Compared to completing the task without a GenAI tool, how would you rate your speed when using a GenAI tool?	Core	Problem-Solving Efficiency	Wang et al. (2024)	Task completion speed is a direct behavioral indicator of Problem-Solving Efficiency. Critical for evaluating GenAI's role in accelerating cognitive workflows.	Measures whether GenAI improves task execution speed, answering part of the Research Question on efficiency enhancement.	select_one (5-point scale)
Q4.2	Compared to completing the task without a GenAI tool, how would you rate the quality of your output when using a GenAI tool?	Core	Output Quality	Venkatesh & Davis (2000)	Perceived Output Quality is critical for continued use and trust; it validates whether GenAI improves reasoning outcomes without degrading deliverable standards.	Captures cognitive effectiveness and task output improvements, essential for modeling GenAI's impact on problem-solving capabilities.	select_one (5-point scale)
Q4.3	Compared to completing the task without a GenAI tool, how would you rate your confidence in your final output when using a GenAI tool?	Core	Data Reasoning; Trust	Akinnagbe (2024); Kim et al. (2025)	Confidence in final output reflects trust in one's reasoning and the validity of GenAI-supported cognitive processes.	Tests whether GenAI boosts self-efficacy in cognitive validation of results — key for answering how GenAI enhances problem-solving trust and confidence.	select_one (5-point scale)
Q4.4	In your own words, describe any additional differences you noticed when working with vs. without a GenAI tool.	Supportive	Problem-Solving Adaptation	Senge (1990); Muduli & Choudhury (2024)	Open-ended reflections capture nuanced cognitive, strategic, or workflow adaptations influenced by GenAI that structured items may miss.	Provides qualitative depth for triangulating how GenAI affects problem-solving processes beyond speed/quality/confidence metrics. Supports richer understanding of system learning loops.	text

Appendix 6. Experiment Observation Notes Example

Task 1

2. **GenAI Support**

- ◯ Yes
- ◯ No

3. **Structured Cognitive Indicators**

	Yes	No	N/A
The participant understood task instructions without major clarifications.	◯	◯	◯
The participant demonstrated an initial planning strategy **(paused to organize steps, outlined ideas).**	◯	◯	◯
(If GenAI used) The participant critically engaged with GenAI suggestions (edited, customized, or improved outputs).	◯	◯	◯
The participant adapted their decision making based on feedback or new ideas **(revised approach if necessary).**	◯	◯	◯
The participant managed time efficiently **(steady progression, no excessive hesitation or rushing).**	◯	◯	◯

4. Observed unexpected behavior, emergent strategies, or innovative uses of GenAI (if any):

Enter your answer

5. Observed signs of over-reliance or skepticism towards GenAI outputs:

Enter your answer

6. Observed indications of frustration, uncertainty, or high self-confidence:

Enter your answer

7. **Global Cognitive Performance Impression**

- ◯ High independence and strategic flexibility
- ◯ Moderate independence with occasional reliance
- ◯ Low independence with heavy reliance on external sources or GenAI outputs

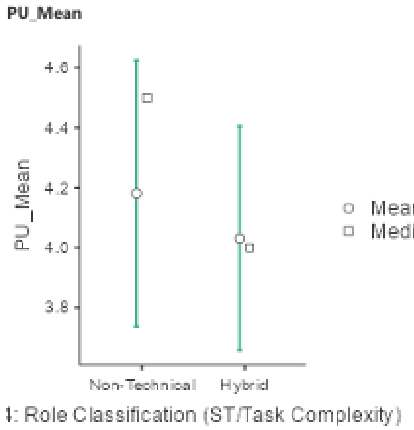
8. Comments

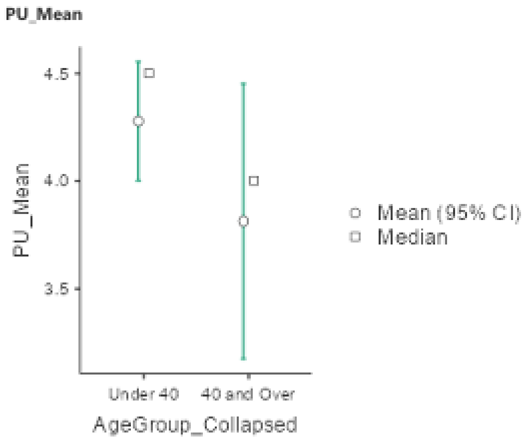
Appendix 7. Interview Questions and Constructs Mapping

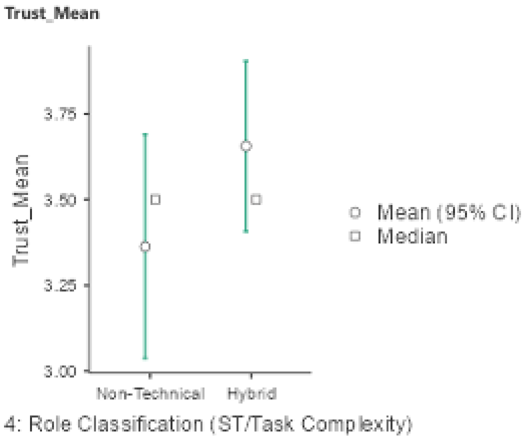
Theme	Code	Full Survey Question	Construct	Author(s) / Year	Theoretical Justification	Methodological Justification
Strategic Enablement	Q1	What role does GenAI play in supporting non-technical employees at tesa today?	Systems Thinking → Organizational Learning & Leadership Enablement	Senge (1990); Rogers (2003)	Leadership defines system-wide support structures and norms for technology integration. Understanding their view is critical to assess cross-functional alignment.	Adds a system-level validation layer to the participant data. Captures policy, structural, and process enablers not visible in employee responses.
Organizational Fit and Compatibility	Q2	What are the biggest barriers to adoption or effective use of GenAI across business functions?	DOI → Compatibility, Trialability	Rogers (2003)	Adoption success depends on perceived compatibility with workflows. Managers are best positioned to assess structural alignment.	Captures cross-department tool integration, fit with business units, and internal enablement strategies. Complements survey and reflection insights.
Trust and Risk Framing	Q3	(Optional) What kind of support or structural changes are needed to unlock the full value of GenAI?	TAM Extension → Trust; Output Quality	Venkatesh & Davis (2000); Kim et al. (2025)	Managerial framing strongly influences how GenAI is positioned (safe, fair, explainable). Trust is a key adoption filter.	Provides insight into leadership-driven narratives shaping trust and responsible use, often missing from user-only data.
Non-Technical Empowerment	Q4	Do you believe GenAI has helped employees become more independent in working with data or solving problems?	Systems Thinking → Task Complexity; Cross-functional Collaboration	Senge (1990); De Laat et al. (2020)	Managerial perception reveals if GenAI reduces complexity and empowers autonomy in data tasks.	Validates the observed and self-reported independence from a team-leadership viewpoint.
Capability Development	Q5	Have you seen any change in how employees approach problem-solving or decision-making with GenAI? (Optional rephrasing of Q4)	Problem-Solving Capability → Data Reasoning, Adaptive Decision-Making	Muduli & Choudhury (2024); Akinnagbe (2024)	Leadership can assess if GenAI is contributing to capability growth beyond tool usage — i.e., cognitive improvement.	Strengthens the cognitive claims of your study by linking observed user behavior to organizational learning outcomes.

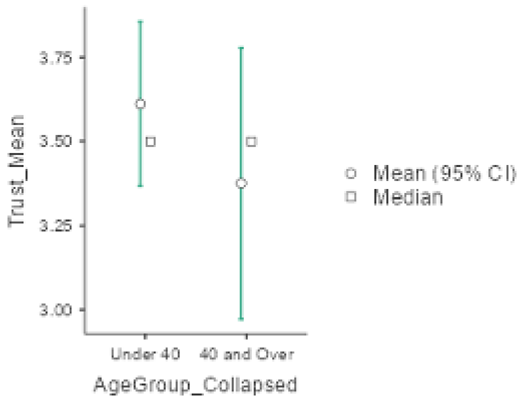
Appendix 8. Jamovi Visual Data Analysis of the Survey

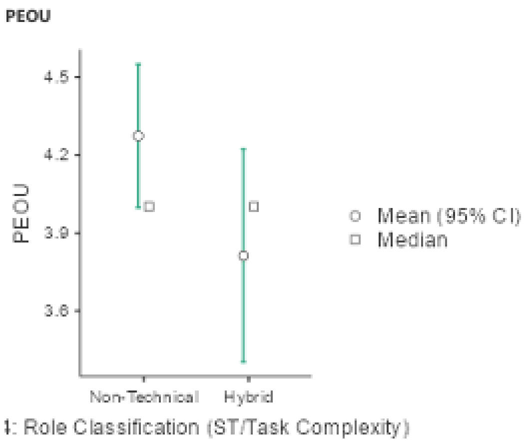
Independent T-Test

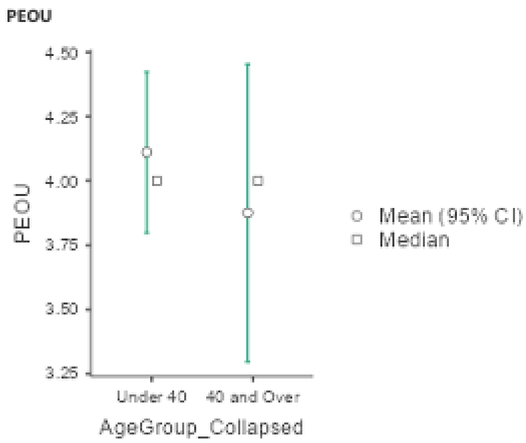












One-Way Annova

One-Way ANOVA (Welch's)

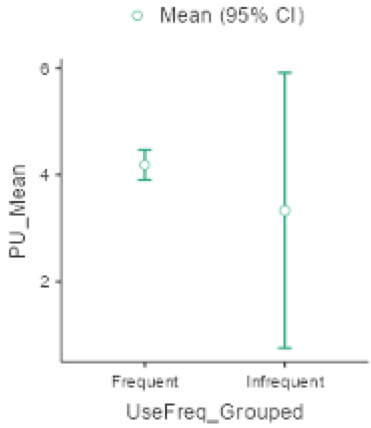
	F	df1	df2	p
PU_Mean	1.92	1	2.21	0.289

Group Descriptives

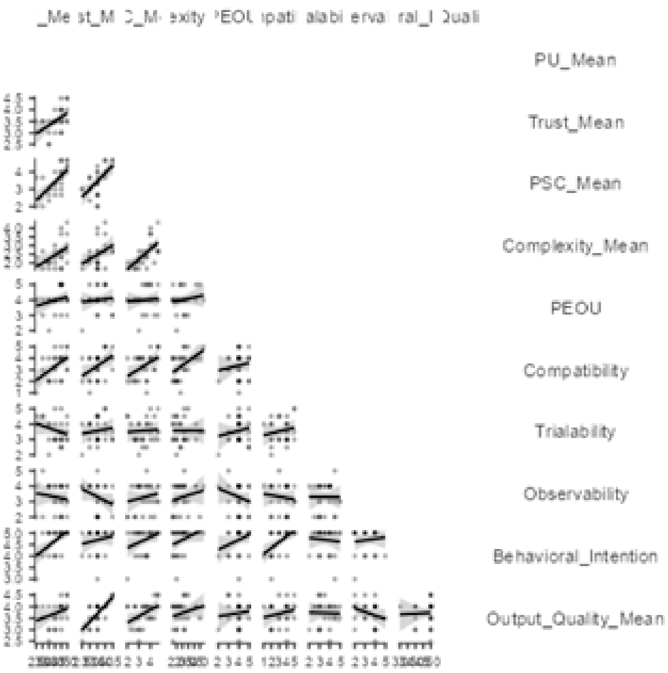
	UseFreq_Grouped	N	Mean	SD	SE
PU_Mean	**Frequent**	24	4.19	0.673	0.137
	Infrequent	3	3.33	1.041	0.601

Plots

PU_Mean



Correlation Plot



Appendix 9. Visual Representation of Experiment Data Analysis

Group	Task 1 (Report Data Interpretation)	Task 2 (Business Term Creation)
A	Without GenAI	With GenAI
B	With GenAI	Without GenAI