Generative AI Adoption: The Interplay of Individual Effort and Multi-Level Organisational Support

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Abstract

This paper aims to develop an understanding of the factors that influence the adoption of generative AI in a public sector organisation by conducting a longitudinal case study. The adoption of GenAI is examined from both individual and organisational perspectives. The findings of this study highlight the impact of organisational adoption of GenAI on individuals and their ability to innovate viable use cases, share knowledge and learn together. The key findings of this study emphasize the need for clear AI ownership and support functions to be established prior to initial adoption, how the relative advantage experienced by individuals overcomes hindering factors, and, most importantly, how the adoption of AI may achieve a higher success rate when the experience becomes communal. The main contribution is the insight that GenAI adoption is shaped by the interplay among individual use-case exploration, communal learning, and organisational support. This extends beyond conventional technology acceptance and adoption models. The results suggest that future GenAI adoption studies should examine the adoption processes of individuals and organisations in parallel to better understand the reciprocal relationship between organisations and their members.

Keywords

generative AI, artificial intelligence, information systems, socio-technical research, diffusion of innovations, technology adoption, public sector

1. Introduction

The Finnish public sector has struggled with long-term fiscal sustainability challenges, and both state guidance and internal pressures within the public sector are driving municipalities and central government bodies to seek greater efficiency through the adoption of artificial intelligence (AI). While the private sector also seeks efficiency, AI may also provide opportunities for new products and services as well as create new sources of income. For some organisations, adopting AI may also serve as a part of their image-building, helping them to stay relevant. For municipalities, generating new income is not a top priority; rather, the focus is on finding ways to save money without it having an effect on service levels. However, practical implications remain scarce, and the sector as a whole is still in the early stages of AI adoption. Generative AI (GenAI) tools provide an easily accessible solution for the initial steps. Adopting GenAI at work differs from the adoption of traditional, operative information systems

STPIS2026: Proceedings of the 12th International Conference on Socio-Technical Perspectives in IS, September 16-17th L'Aquila, Italy

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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

published 2026-11-10

CEUR-WS.org/Vol-4325/paper22.pdf

or tools designed for a specific purpose (e.g. financial IS, e-services, content management). Every organisation adopting GenAI must determine its own guidelines and boundaries for use, and users must find viable use cases for prompts and agents within those boundaries.

Based on earlier studies on RPA adoption [1][2][3], we were interested to find out whether RPA and AI adoption patterns have similarities and what makes AI Adoption unique. We assumed on the basis of literature that AI adoption differs from traditional frameworks. As our earlier studies were also conducted in the public sector this study was also conducted in a public-sector context. However, studies on AI in the public sector are scarce and non-specific with regard to how public sector employees, especially those in administrative positions, experience GenAI adoption. Most relevant studies have been conducted in education or healthcare, which have very specific characteristics, constraints and thresholds that differ from other municipal units. Municipalities are also relatively different organisations compared to private companies. For example, the external environment does not exert the same pressure on remaining competitive as it does on companies. Instead, external pressure is primarily political, stemming from legislation, state governance, and the expectations of residents and businesses. While organisations can learn from the private sector, this learning is often selective and adapted to the public sector context.

The aim of this study is to deepen the theoretical and practical understanding of GenAI adoption at an organisational level by investigating two separate Microsoft Copilot proof-of-concept projects (Pilot 1 and Pilot 2) within a large Finnish municipal organisation (City). This longitudinal case study explored answers to two research questions in an organisational context. The first question aimed to establish whether GenAI adoption in organisations faces similar challenges and enablers to RPA, while the second, more exploratory question aimed to provide new insights into GenAI adoption.

RQ1: What are the key challenges and enabling factors in GenAI adoption? In particular, how are the following factors related to the outcome?

- Resistance to change (either active or passive), fear and lack of trust
- Support
- Structural or systemic factors
- Ideas and knowledge (or lack thereof)
- Operating models (inadequate or otherwise)

RQ2: How does the adoption of GenAI differ from traditional technology and acceptance models?

This paper explores the adoption of AI through literature review and an empirical study of GenAI pilot projects within a municipal organisation. It begins with a brief introduction to earlier literature, which provides the context for the following longitudinal case study of GenAI. Section 3 introduces the study method that incorporates mixed qualitative methods, followed by an introduction to the pilot projects. The main section of the paper focuses on the study's key findings in section 4, and presents its conclusions in section 5, with a discussion of the study's theoretical and practical implications and suggestions for further research into AI adoption.

2. Adoption frameworks in AI studies

The growing body of research on AI adoption over the past few years is encouraging. Undoubtedly, it is not only the hype that has generated interest among scholars, but also the way in which it shapes businesses and people's lives. However, due to the limited prior literature on the adoption of generative AI (GenAI) in public organisations, the following literature review has been expanded to cover the private sector as well. Theories of technology adoption, diffusion and acceptance have been widely used in both public and private sector information systems (IS) research and several established theories have already been successfully built on, adapted to, and extended in the context of organisational AI adoption. Literature review over peer-reviewed studies of technology adoption and acceptance of AI and GenAI provided recognition and adaptions of established theories as well as newer capability-centred or -based views.

Table 1
Theoretical frameworks in AI adoption research

Theory or framework	Examples
Technology–Organisation–Environment (TOE) framework [[4]cited in [5]]	[6][7][8][9][10]
the Diffusion of Innovation (DOI)[11] theory	[6][14][10]
the Technology Acceptance Model (TAM) [12] or reviewed TAM3 theory [13]	[7] [14]
Unified theory if acceptance and use of technology (UTAUT or UTAUT2) [15]	[16] [17] [18]
the Dynamic Capabilities View/Theory [19]	[20] [21]
AI Capability by [22] discussed in [23][24]	[23][24]

AI adoption research has also adapted theories from outside the field of IS research to frame the challenges that organisations and their members face with AI, for example Social Exchange Theory (SET) [25] [26] and Perceived Organisational Support (POS) [14].

The reliance of AI adoption research on multiple theoretical perspectives and newly developed frameworks suggests that, rather than applying a single established theory in research, AI may constitute a distinct category of technology with adoption characteristics that differ from those addressed by traditional models. This diversity is also evident in the heterogeneous findings and conclusions reported in the literature. It is possible that the current literature does not yet provide all the tools necessary to understand the implications of AI for different types of organisations and industries or to explain the contextual factors that shape its adoption and use.

2.1. The individual's adoption journey as part of a community

This study incorporates elements of the DOI theory, which are suitable for describing the adoption processes of both individuals and organisations as adoption units. This, however, does not preclude the possibility of utilizing other theoretical. One of the key concepts repeated in this paper, adapted from DOI, is the concept of innovativeness, *"the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than the other members of a*

system." In DOI, innovativeness is classified through the five adoption categories of innovators, early adopters, early majority, late majority and laggards. [11] Later in this paper, we discuss the concept of innovativeness through the DOI classification, but also through adopters' ability to innovate GenAI use cases. Earlier studies on Robotic Process Automation (RPA) adoption suggested that a slow learning curve and a lack of knowledge play a key role in the lack of viable RPA use case ideas [3].

DOI theory identifies four types of Innovation-Decision: 1. Optional, 2. Collective, 3. Authority and 4. Contingent. Contingent innovation-decisions can only be made after a prior innovation decision has been made [11]. In the context of organisational GenAI adoption, decisions can be viewed as a continuum ranging from an initial authority-driven decision to subsequent collective or optional decisions made by organisational units or individual users. An organisation's initial adoption decision for licenced software is an authority innovation-decision to some extent, as it typically involves financial decisions. However, further decisions at an individual level may be optional when not forced, as is the case in this study. However, although the decision made by the employee is optional, it is not independent of the influence of the surrounding work community and the rest of the environment. An employee's decision to adopt GenAI at work is guided by socio-technical factors. The following socio-technical characteristics (Table 2) were identified in the AI adoption literature as possible influencers, and these are roughly categorized as either social or technical innovation factors, with the aim of harmonizing the categorization caused by different theories (this division is to some extent artificial). These factors are often interrelated and interoperative.

Table 2
Socio-technical AI adoption enablers and barriers and their position on the socio-technical continuum.

	Socio-technical enablers (+) and barriers (-)	**Socio-technical emphasis**
+	Innovation-driven culture [6]	Social
-	Organisational conservatism and lack of an innovative mindset [7] [6]	Social
-	Organisation's operational slack [21]	Social
+	Management and organisational support [8][7][32][30] [45]	Social
-	Fear [6], anxiety and technostress [24] [31] [28], job insecurity [31] [33] and perceived risk [30]	Social
-	Lack of responsible AI governance [6]	Social
+	Social influence and dynamics [16][18][30] [29]	Social
-	Weak collaboration with partners [8]	Social
+	Compatibility [8], technology–task fit [30]	Social, Technical
+	Perceived value [16]	Social, Technical
+	Strong governance and clear regulations [26] [45]	Social, Technical
-	Privacy concerns, data security risks and ethical issues [26]	Social, Technical
-	Lack of trust [16] [34] [29]	Social, Technical
+	Clear benefits (productivity, stability) [8]	Social, Technical
+	Knowledge, expertise, skills [6] [21][28] [29]	Social, Technical

-	Lack of knowledge and limited knowledge sharing [30] [5]	Social, Technical
+	Relative advantage [8] and effort expectancy [29]	Technical
+	User-friendliness [16], perceived usefulness and ease of use [30] [26]	Technical
+	Reliability [31] [26]	Technical
-	Financial Limitations [6]	Technical

Some of the aforementioned factors resonate with *resistance to change* (RC) [27], which can manifest on a spectrum ranging from apathy [35] to direct resistance. GenAI's versatile nature poses new threats for both organisations and individuals, for instance due to decreased transparency [36] and the impact on trust [34]. A loss of control may lead to non-adoption and resistance within organisations [37]. Resistance to change can also adversely affect employee's innovativeness [38]. Managerial *support* is a key mediating factor in building trust [29], but internal resistance within an organisation can also be reduced with the help of innovation *champions*, internal brokers and arrangers who promote the innovation, help overcome resistance and indifference, and ease its integration into the organisational context [11]. Champions are not necessarily high-ranking within the organisational hierarchy. Numerous studies demonstrate the importance of champion-like roles in facilitating peer support, fostering trust, promoting knowledge sharing and exerting social influence, thereby shaping individual adoption decisions.

Some studies (e.g. [39]) highlight the issue, often raised in non-scientific statements, that not adopting AI may directly harm employees. To *lessen anxiety and build trust* AI's impact on careers should be openly communicated [28], and organisations should inform clearly their intentions for AI adoption [40]. Employees may well view AI skills positively as a means of remaining competitive in the labour market [41].

2.2. Recommendations for organisations from earlier studies

One of the reasons for the slow adoption of AI, particularly in Europe, has been the low level of innovativeness and slow learning within organisations [20][6]. In September 2025, Gartner predicted that "CIOs have three- to six-month window to define their agentic AI strategy", as 40 percent of enterprise applications would feature task-specific AI agents by 2026 [42].

Organisations can boost their employees' willingness to adopt AI by providing *endorsement and support* and fostering a positive atmosphere for adopting and learning new technologies. This includes promoting creativity, experimentation and proactivity engagement with new ideas [6], as well as fostering a positive attitude towards GenAI adoption in general [30], particularly to bolster employees' self-efficacy [41]. Emotional support has been found to be a key element in enhancing long-term innovative readiness by fostering trust and willingness to learn new technologies [14]. By *investing in training and skills development* organisations can reduce resistance to change and alleviate employees' fears and anxieties, and at the same time also promote innovation and a greater willingness to experiment with new technologies [6] [41] for example by giving emotional support [14].

Some recent studies have highlighted the concept of *brain fog* caused by the cognitive stress related to AI usage [43]. To avoid overburdening employees during the AI adoption process,

organisations should consider starting with small-scale *pilot projects* and gradually scaling them up over time [6]. From an organisational perspective, it may also be beneficial to start with low-risk initiatives [30]. Combining knowledge should begin before AI adoption [9]. Sandboxing without fear of failure supports continuous learning [6] and targeted education [33], and training can be moderated to fit users' initial skill levels [41]. Targeted training can also be developed based on known obstacles, skills gaps, the adoption stage and the innovativeness of employees. Part of skills development and piloting involves *sharing knowledge and information.* Various approaches can be used to this: application case libraries [30], transparent communication channels [14], using real-life examples [41] and the inclusion of partners [6][8].

Before AI adoption or in the early stages of adoption other capabilities should be built, such as *cybersecurity management* [9], AI *process documentation* [44], and managing *AI strategy* and *governing data assets* [24] among technical knowledge. As GenAI specifically suffers from *bias and hallucinations* [36], risk management is required before advancing with adoption: *robust governance, clear policies*, and user *education* on GenAI capabilities and limitations are needed to reduce risks [32]. Sustained strategic value from AI adoption is more likely to be achieved when the necessary skills, governance and other capabilities are developed [23].

3. Research method and case overview

3.1. Introduction to the research method

The research took a mixed qualitative method approach, incorporating mainly a qualitative case study with some elements of action research and the main researcher interfering Pilot 2. The aim was to learn from earlier project experiences, avoid the same challenges and boost adoption in the subsequent pilot project. Action research elements were included because the problems to be solved were very practical, while the goal was to contribute new theoretical insights to IS research [46]. The chosen method aimed to validate the recommendations and other results collected in Pilot 1 in practise and theoretical evaluation. Additionally, the chosen method helped proceeding beyond the results of Pilot 1 by trying to eliminate extraneous factors related to the loosely structured Pilot 1. The purpose was to gain a clearer understanding of the phenomenon and obtain deeper insights.

The data collection method included interviews, observation and documents. Pilot 1 included 14 semi-structured interviews, pre-discussions with co-ordinator, examination of supporting material for background information. Pilot 2 included 13 semi-structured interviews, pre-discussions with co-ordinators and the Pilot planning team, observations during weekly Copilot clinics, examination of supporting material for background information. Other supporting material from the organisation, such as internal news, updated policies, instructions and orientation guides was helpful in understanding the timeline of changes and the overall context between 2024 and 2026, but this material was not analysed directly.

The mixed qualitative methods approach was chosen to gain a deeper understanding of the adoption of GenAI, rather than simply collecting attributes affecting GenAI adoption. The interview data were analysed through both inductive and deductive coding process, mainly the first. Initial themes were developed from the interview material rather than from a predefined theoretical coding scheme, while the subsequent interpretation of the themes was informed by the theoretical perspectives discussed in the study. More detailed steps of the research process are introduced in Appendix A and coding process illustrated in Appendix C. Themes from Pilot

1 were revisited, re-evaluated and harmonized during the analysis of Pilot 2 data and drawing the final conclusion.

In both pilots, the interviewees were chosen based on the recommendations of the organisers and their peers. In Pilot 1, the ICT co-ordinator shortlisted the first interviewees based on her perception of their general activity or willingness to participate and tried to find participants from all the units involved in Pilot 1. The interviewees were also asked to recommend new interviewees. The group included active and passive adopters, enthusiasts and critical observers. One of the organisers of Pilot 2 was a pre-graduate student who provided survey-based results of Pilot 2 activity level and suggested a shortlist of interviewees categorized into three levels of activity in GenAI use at the end of the pilot. Both active and passive adopters were included in the interviews. As active users were also more willing to agree to interviews, team leaders asked at team meetings whether any passive users would like to participate. When the interviews reached a point where the information repeated earlier themes, the data collection phase closed on both occasions (Pilot 1 and 2).

3.2. Pilot 1: Initial exposure to GenAI use

The first data collection took place between August and December 2024, following the City's initial Microsoft Copilot pilots conducted between May and September of the same year. The first pilots were joint efforts where the ICT department gathered users, provided them with basic instructions and allocated licences. City leaders were keen to implement GenAI and suitable, voluntary pilot users were gathered from different City units. The pilot users came from diverse professional backgrounds, but were all highly educated employees working in expert roles.

Pilot 1 began very quickly without extensive knowledge-building or analysis of competencies. The ICT department briefed the pilot users on security basics and tool installation, as well as co-ordinated the pilot group's knowledge sharing (use cases and experiences). However, every department was responsible for their own pilot planning and support. Copilot licences were allocated from late April 2024 to October 2024, and each user was given basic instructions and asked to clean their local and M365 storage of any sensitive material before the start. GenAI courses were available from an outsourced training partner, and the pilot units were recommended to book them.

The pilot phase consisted of several small pilots that were neither carefully planned nor strongly goal-oriented. In practice, their main purpose was to gather experiences over a limited period. At a higher level, the purpose was to evaluate whether Copilot could enhance productivity in knowledge work across the city organisation. The pilot use was mainly experimental.

3.3. Pilot 2: Applying lessons learned during unit-level adoption

The second pilot (Pilot 2) took place in the procurement department with around 30 users between November 2025 and February 2026. Interviews were then held between March and May 2026. This time, the pilot project was limited to one organisational unit, with all employees invited to participate. The pre-pilot users organised and co-ordinated the pilot mostly by themselves (the ICT department took care of the technical licence allocation). The pilot unit had planned to start their project approximately six months earlier, but decided to postpone it due

to competing priorities. Also, the use of GenAI was suspended City-wide for several months after Pilot 1 due to security concerns while the use of AI and its constraints were re-evaluated based on benchmarking experiences. Before the unit-wide pilot, three users were given pre-pilot licences to develop their GenAI skills, define the pilot's objectives and identify concrete use cases. In May 2025, we reviewed key observations from Pilot 1 to inform the planning. Following a postponement of a few months, the plan was revisited shortly before the November kick-off. By then, the pre-pilot users and organisers had prepared instructions, training materials and links to further training. The pilot began with department-wide training, covering basic GenAI use, security and initial use cases. This was followed by voluntary, 30-minute weekly online clinics for peer support and for sharing experiences and test results.

The goal of Pilot 2 was to test through a set of test use cases whether GenAI could help address eight common and time-consuming problems in procurement work, at least to some extent. These use cases were designed by the pre-pilot users in consultation with the person responsible or data protection within the organisation. The more overarching goal of the pilot was to determine through use cases whether GenAI as a tool could save time and improve quality in procurement work. The use cases were intended to be specific enough to enable users to get started, yet flexible enough to allow for variation and new ideas within the security guidelines and boundaries.

3.4. Initials finding and analysis of Pilot 1

First, we reviewed the key points from the thematic analysis of the Pilot 1 interviews. These were*: lack of ideas*, *lack of skills* (i.e. difficulty understanding how generative AI operates), *technical issues and limitations*, *lack of support*, *absence of hands-on guidance*, and *data security concerns*. In the early phase, there were technical challenges related to installation, but Pilot 1 users also reported several technical limitations in Copilot. Overall, users were uncertain about where to begin with the pilot use. The use cases that emerged during the first pilot were primarily related to text editing, meeting notes, structuring large bodies of information, translations, summaries, images, and idea generation, as well as drafting different types of presentation outline.

Some key suggestions for Pilot 2 were derived from Pilot 1 interviews, either a) as direct recommendations from interviewees (e.g. *"I would have liked to see more concrete examples of what this could be used for"*), b) by converting an identified gap into a recommendation *Manage expectations appropriately: what Copilot can and cannot do.* (e.g. interviewees' numerous examples of limitations in the technology or disappointing outcomes of prompts*),* or c) a few recommendations made by the researchers themselves on the basis of interview observations and common best practices (e.g. *The objectives should be clearly explained to participants so that they understand the purpose and significance of the pilot.).* The key suggestions are available in Appendix B.

These initial-phase observations were largely supported by existing literature (none of them contradicted the literature review in section 2) as well as by other material collected within the organisation. The organisers of Pilot 2 took most of the recommendations from Pilot 1 into account when planning. Materials produced before training were reviewed by the researcher A to be compared with Pilot 1 outcomes, and no major changes were deemed necessary. Although the findings from the first study were intended to support adoption during Pilot 2, particularly by helping users to adopt the tool at least for the duration of the pilot period, the pilot unit's

objective also included the possibility of concluding that the tool would not help solve the identified problems. In other words, long-term adoption was not strictly required, but some level of adoption during the pilot was necessary to enable a proper proof of concept regarding problem solving.

Few topics covered in Pilot 1 were rejected during the planning stage. Firstly, the organisers were not prepared to provide differentiated training according to skill levels as they considered all participants to be beginners. Secondly, they did not expect resistance to change to be a significant issue, either, and consequently, no specific measures for managing RC were included in the pilot plan. RC did not emerge as a major factor in the first round either (only one unit noted that it might become an issue if the tool were widely deployed). Finally, earlier technical issues related to Copilot deployment and indexing had already been resolved between the pilots, so no further action was needed for Pilot 2.

4. Key findings from the final analysis

In the following sections we discuss the main themes that emerged from analysing the outcomes of Pilot 2 and re-evaluating Pilot 1. When discussing the findings and further conclusions, the key differences and similarities between the two pilots, as listed in Table 3, should be taken into consideration.

Table 3
Key differences and similarities between Pilots 1 and 2

GenAI Pilot 1		GenAI Pilot 2
Users from 5 organisation units	!=	Users from 1 organisation unit
Few participants per org. unit	!=	Whole org. unit invited to participate
Completely voluntary	=	Completely voluntary
Loosely controlled pilot	!=	Controlled pilot
Vaguely defined objectives	!=	Defined objectives
Limited peer support	!=	General user support organised, SPOC, peer support channels and meetings organised
Experimental, use cases were invented as pilot went on	!=	Predefined use cases related to department's work, with preliminary test prompts, which users could develop further
Very little resistance to change experienced or expected	=	No significant resistance to change experienced or expected
Future unclear for users after the pilot	!=	Future clear for users after the pilot (licences continued for active users if the pilot is successful)

In the following chapters we discuss themes that were either the most common (frequent occurrence) or otherwise considered significant in terms of the initial research questions. These themes are combined into four overarching topics: 1. Relative advantage experienced by the individual is one of the key attributes of innovation in the decision to adopt personally, 2. Unclear security guidelines and a lack of trust in quality hinder users' innovation efforts, 3. GenAI adoption is more likely to succeed when the experience becomes communal, and 4. AI tools require clear ownership at several organisational levels.

4.1. Relative advantage experienced by the individual is one of the key attributes of innovation in the decision to adopt personally

The interviews from Pilot 2 revealed that the *relative advantage* (or perceived usefulness) experienced by users was one of the key factors behind GenAI adoption and a motivator for using personal resources for learning and innovation. In both pilots, the experiences reported by the participants, both positive and negative, concerned primarily the use of the technology itself and security guidance issues. When asked about generic positive recollections and outcomes of the GenAI pilots, discussion invariably turned to recollections of successful GenAI use cases and personal breakthroughs, either experienced individually or with the help of peers. Negative recollections were dominated by technical disappointments and problems with certain use cases and prompting.

Although the interviewees in Pilot 2 almost without exception did not remember the officially communicated objectives of the pilot, the guidance and shared discourse during the pilot had embedded a common goal: to determine whether the tool had any real value for the unit and what it could be used for. During the interviews, the participants consistently reflected on these unasked questions in their responses: what can GenAI be used for in everyday work, and what kind of benefits does it provide? While attitudes towards usefulness, user activity levels and competence levels varied within the group, all wanted to keep their licences and actively voiced their intention to use the tool effectively and further develop their knowledge and skills. The *benefits appeared to outweigh the disadvantages of trust issues and the effort involved in learning new skills.* The most common benefits perceived by the users were:

- speeding up work related to text editing and translations (Pilot 1 & 2)
- speeding up internal information retrieval (Pilot 2)
- support with quality checks (Pilot 2)
- getting a sparring partner or sounding board to help move forward in stalled situations (Pilot 1 & 2)
- maintaining one's own skills and competitiveness in the labour market (Pilot 2)

These benefits can be seen as mainly considerations of *individual advantages*. Thus, the proposition is that *individual benefits were more significant factors in adoption than organisational benefits*. Neither the users, co-ordinators nor supporting material provide clear evidence that, at this stage of adoption and maturity, the organisation gains any significant benefits from GenAI adoption, at least not at a level that could be realized as savings in labour or other costs or as measurable quality achievements. The relative advantage seems so significant in the collected data that even those who participated very little in the pilot phase wanted to keep the licence and continued to use it a little. Most Pilot 1 users also wanted to keep their licences, but this group was recruited mainly from the ranks of early adopters who had already used some GenAI technology and wanted to try it out at work. As Pilot 1 users had fewer use cases for GenAI, they had greater hopes for its future usefulness. Two Pilot 1 users explicitly said that they or some of their peers might not continue to use Copilot before finding it useful.

4.2. Unclear security guidelines and a lack of trust in quality hinder users' innovation efforts

Issues related to data security and protection have had a negative impact on individual and organisational adoption, from the first pilots to Pilot 2. Security concerns emerged in three different ways among users and in two ways at organisational level:

1. A lack of security guidelines delayed pilots in new organisation units and hindered continued adoption in units that had already piloted the tool.
2. Users did not have the courage to try all their GenAI ideas because they were unsure whether a use case was allowed or not.
3. Users were hesitant to try new prompts because they did not trust that they would be able correctly to limit what data the GenAI tool uses.
4. The local organisation lacked the ability to support its users as it did not have authority over policies and the way they could be applied in unclear cases.
5. Adoption decisions within organisation units were delayed due to unclear security guidance (pilots were halted for almost a year).

The first GenAI pilots were very exploratory, and even though a basic introduction and security guidelines were provided before anyone was allowed to start using Copilot, no organisation-wide policies or guidelines had yet been properly established, let alone properly implemented. It was indicated that the reason was unclear responsibilities. Soon after the initial adoption, the security unit informed users that the AI policies were unclear and put a full halt on any use. Thus, those who had already started using GenAI were told to stop, and those who

had new pilots planned for them were told to postpone them. Once the initial guidelines for permitted and prohibited use had been established, GenAI licences could be allocated again. Our second pilot unit made an effort to properly specify and document their GenAI use cases, and received help from the security unit with risk assessment. This, however, did not completely solve the problem. Pilot 2 interviewees still wanted *guidance that was extensive, easy to understand and easy to apply*. Some users in both pilots even went so far as to claim that there were guidelines that made no sense to them and had perhaps made it even more unclear what was and what was not allowed.

Some users, primarily in Pilot 2, also had *ethical concerns*. These concerns were mostly related to how other people's data and stakeholder companies' classified data should be handled, and how sustainability and ecological issues should be addressed. Unlike security issues, ecological concerns were not reported to slow down work adoption in either pilot, but two Pilot 2 users reported that these affected their willingness to use GenAI at home. Concerns related to users' personal data were alleviated after the initial security briefing; this may have been due to GenAI being used in a controlled enterprise ICT environment and having been proofed by the employer.

Concerns related to *trust* were raised in most interviews. Primarily concerning the quality of results achieved with GenAI agents and even simple prompts. Users were also concerned that the quality of their departments' work would decline in time as people became more accustomed to using the GenAI tool in their everyday work and became complacent, forgetting to check the results promptly. While the interviewees were still interested in actively continuing to use GenAi in the future, they had concerns that appear to be theoretically associated with deskilling [48] caused by AI usage. Some interviewees suggested that continuous security awareness training should be considered to avoid relapsing in future.

As GenAI use cases have different life cycles depending on the user's tasks and the technical development of AI, and given the wide range of potential GenAI, introducing comprehensive and practical permanent guidelines may be challenging. Therefore, in light of the security and trust concerns discussed above, a more practical approach may be to provide *continuous security guidance and iteratively develop policies*.

4.3. GenAI adoption is more likely to succeed when the experience becomes communal

While earlier research suggested that an individual adopter prioritises their own perceived benefits over an organisation's goals and benefits, the case study findings also suggest that peer support and shared adoption greatly facilitate the achievement of these personal gains. As was found in earlier RPA studies [3], in organisations the adoption of new digital tools with no specified use cases is slowed down by the lack of, or slow emergence of, viable ideas. When comparing the findings of the first pilot with those of the second one, this also seems to be the case with GenAI. Even highly motivated users and champions struggle to drive adoption and achieve productivity gains if they cannot identify meaningful use cases or lack the skills to use Copilot effectively. Users found outsourced training programmes too generic to help them generate ideas or solve practical, prompt-related problems.

Neither pilot indicates that GenAI adoption at home is an absolute requirement for successful GenAI adoption at work. In both pilots, users adopted the tool despite having no prior experience. However, in Pilot 1, where the support system was weaker, prior experience

made it easier. Many of the interviewees in Pilot 2 mentioned peer support as a positive recollection and considered it a successful aspect of the pilot. *Shared learning with peers* in Pilot 2 made GenAI more accessible to new users and opened possibilities of use for those few with some prior experience. The recollections portrayed a shared learning journey, a *communal experience*. The initial goal of the pilot was simple and not particularly ambitious: to develop skills, learn, and determine whether GenAI delivers any value at all. The goal of Pilot 2 was, in summary, to obtain solid enough evidence from the pilot either to justify future licensing costs and secure the continuation of adoption or conclude that the money would be better invested elsewhere. Most importantly, the aim was to be able to make conclusions and base further continuation decisions on extensive real-world use by a sufficient number of pilot users. Therefore, shared learning was important factor to achieving their goals.

The organisation unit in Pilot 2 decided to continue with the adoption of GenAI, and all users who reported being active were permitted to keep their licences. Based on an activity check carried out in spring 2026, only one user was inactive. Some participants had no use for the predesigned use cases as they were designed for a procurement process task that they were not currently working on or that did not fit their job description. However, as the unit learned more and developed new ideas, these laggards were also able to grasp these ideas and adopt the tool. While GenAI was seen as an *"eager-to-please"*, *"overly positive"*, yet *"slightly clueless"* and *"lazy"* co-worker, reliance on actual colleagues and support from managers in the continued adoption appeared to build trust. As learning and adoption was supposed to continue, users in both pilots wished for a future in which they would continue to *share ideas and have channels for sharing agents and prompts,* and in which City-wide use would expand. While some wanted to find everyday use for GenAI, some also pondered whether the next step should be the adoption of more task-specific AI tools.

Neither Pilot 1 nor Pilot 2 users had encountered strong resistance to change within their local teams. RC could also be a communal experience, but in Pilot 1, critical users did not even have the opportunity to use it, and in Pilot 2, active criticism soon tapered into passivity in adoption, which manifested as *intentional delaying of learning efforts or procrastination.* The passivity of Pilot 2 interviewees was explained by a lack of enthusiasm-and, as a consequence, an unwillingness to use limited personal resources for learning during a busy time of the working year when holidays were approaching. While these observations from the interviewees may reflect potential technostress among some users, none of the interviewees in either pilot particularly brought this up as their own observation. Why did RC not spread within the pilot unit? One possible explanation can be found in the interviewees' observations that both management and active users maintained *a positive discourse around GenAI use while champions shared their experiences and advice* to help sustain a generally positive atmosphere. Furthermore, one interviewee suggested that the importance given to the pilot, combined with management's communication that access to licences was not initially guaranteed, may have discouraged open criticism. The Pilot 2 unit was determined to make active use of GenAI in the future by making a specific quality check use case mandatory before every new call for tender. This can be seen as a new authority innovation-decision [11], and it did not encounter any resistance from the interviewees that they would have expressed.

Both fostering a sense of community and reducing the individual burden of adoption become important when the focus shifts to well-being at work. These may have been supported in the

pilots by several factors. In Pilot 1, most participants were eager to participate, while in Pilot 2, support mechanisms, use case examples and practical instructions were in place. As the pilot progressed, open discussions among peers also revealed that not everyone was equally active, which may have reduced the social pressure associated with being a less active user. This support may have made it easier for laggards to engage with and eventually adopt GenAI. By the end of Pilot 2, only one user remained completely passive. Interviews and activity reports from Pilots 1 and 2 suggest that GenAI adoption is more likely to succeed when the experience becomes *communal through learning, innovating, sharing, and maintaining a positive and supportive atmosphere within the local team.*

4.4. AI tools require clear ownership at several organisational levels

Interviewees' notions, especially regarding challenges, highlighted the need for AI ownership at several organisational levels. The experiences of pilot users from Pilot 1 brought to light, and those of Pilot 2 confirmed, that *an effective proof of concept is better organised and led by the pilot unit itself* rather than another external organisation unit. While the ownership of adoption practices should lie with the pilot unit, other organisation units can provide important support functions depending on their area of expertise. Similarly, the positive experiences reported by Pilot 2 participants emphasized the importance of the following responsibilities being assigned within the pilot unit: *context-aware user support, co-ordinating knowledge sharing, pioneering* (i.e. taking the role of a champion) and *constant promotion from management.* When it came to peer support and the importance of local user support organised and provided by one of the peers (with some help from the researcher A), Pilot 2 interviewees highlighted the support and promotion they received from their own department's leaders. More precisely, this came in the form of 1) allowing work time to be used for the pilot, 2) actively promoting knowledge sharing in unit and team meetings, and 3) keeping the topic active in the unit's internal communications. Pilot 2 users said that, even though the pilot had ended and they had decided to adopt GenAI as a permanent tool in their everyday work, learning was still an ongoing process, and some of them said that they constantly needed to be pushed by their peers to try new ideas. As the pilot was brief, only three months, less innovative users had only passed the early adoption stages, and learning was still very much in progress. Some interviewees felt somewhat ashamed that they were slow to adopt. Positive support from peers and managers reduced this feeling and encouraged later adoption.

These local roles and responsibilities, which were identified mainly from the Pilot 2 interviews and confirmed by the organisers, are not contradicted by the re-evaluation of the Pilot 1 interviews. Themes and their more detailed, practical implementations, which emerged from the Pilot 1 and 2 interviews, are summarized in Table 4. While most themes emerge from all groups of interviewees – users, organisers, managers – financial themes were mostly covered in interviews with organisers and managers. Different support functions were either acknowledged as existing and praised, or identified as inadequate and desirable areas for improvement.

Table 4
Summary of ownership areas and support functions identified from the pilot interviews.

Ownership areas and support functions	Themes	Practical implementations
Vision and AI strategy	• Overarching objectives for AI use • Where and by whom GenAI should be used	• Who should use GenAI and in what work • Ethical guidelines
Information security and data protection	• Legal guidelines • General guidelines ~~of~~ on what data can be processed with AI and how	• Clear examples of legal guidelines in practise • To clarify why a specific use case or prompt is considered inappropriate and to suggest an alternative approach • Active support in security perspectives of use cases
Practical adoption support (initial and continued adoption)	• Planned pilots and rollouts • Tailored support model • Knowledge sharing • Library of useful prompts and agents	• Hands-on support and training • Local, context-aware knowledge sharing • Cross-unit knowledge sharing on general use-cases
Technical support	• Up-to-date instructions and training	• Effective prompting • Technical limits explained • Cross-unit knowledge sharing
Financial support	• Funding for licences • Business case	• Centralized budget and cost estimation instructions • Guidelines for justification • Practical support for budgeting

Pilot 2 users emphasized when expressing their expectations and concerns the need for ongoing support. Our case-study organisation's GenAI adoption journey suggests that organisations should, in following order: 1) assess areas of ownership around AI and relevant support functions, 2) clearly entrust these AI ownership areas and support functions before initial adoption and throughout the adoption process, and 3) review both the functions and their practices as technology emerges and organisational context changes over time. Our findings also suggest that policies and guidelines should be designed, maintained and supported in those parts of the organisation where the relevant knowledge and expertise is found, and that support should extend to concrete user support and assistance. AI is such a complex phenomenon that it is difficult to maintain all the relevant expertise in one organisational unit or level: these include strategic, ethical, legal, security, technological, domain-specific and subject-matter knowledge.

5. Conclusion and discussion

In conclusion, the findings of this study addressed the topics covered in RQ1 by identifying some of the key challenges and enablers of GenAI adoption, gaining a deeper understanding of the effects of a lack of trust and support on adoption, identifying structural or systemic factors related to AI ownership and support systems, and, finally, deepening our understanding of how a lack of ideas and knowledge affects GenAI adoption. The findings were more inconclusive in

terms of RC and fear, providing only limited insight into whether and how inadequate operating models hinder adoption. These factors and their conclusions are summarised in Appendix D.

The longitudinal journey of the city in our case study emphasises that the innovativeness of GenAI adoption relies on individual innovation skills. First, GenAI adoption requires real-life, subject-specific use cases, which are developed by employees themselves. Secondly, individuals need actively to participate in a group to support each other's learning in order to boost innovation. A lack of viable ideas hindered initial adoption in Pilot 1. In Pilot 2, pre-specified use cases made adoption easier. Pilot 2 was short, only a few months, and would probably not have met any of its goals if there had not been enough users willing to adopt GenAI quickly (i.e. users belonging to the two adopter categories of innovators and early adopters).

Pilot 2 did not face all the same obstacles as Pilot 1, possibly due to actions taken based on recommendations from Pilot 1 and technological development. Most likely enablers were related to support and shared learning and achieved by goal-oriented and controlled pilot assisted by pilot unit's culture. Pilot 2 managed to activate users, increase their willingness to put effort in learning and boost up their innovativeness. However, deeper understanding and slightly more advanced skill brought up new challenges as more advanced use cases ideas emerged. Efforts to improve work efficiency through GenAI should ensure that productivity gains are not offset by an excessive verification burden on users, which may cause brain fog, among other things. Therefore, GenAI adoption cannot be viewed solely as a means of improving well-being at work, despite it being highlighted as a positive factor in our interview results.

The Following themes emerged from the interviews regarding the use of GenAI at work compared to personal use outside of work: 1) Without pre-designed, work-related use cases, the tool was adopted for easy tasks typical of home use (e.g. image creation, gathering simple ideas, simple text editing). 2) After adopting the tool at work, users were interested in also using it at home. 3) Users were more concerned about the quality and security of the outcome at work. 4) They were also more concerned about ethics and sustainability in general at home. Thus, users indicated that the same factors affected their adoption decisions differently at home compared to at work.

The findings also emphasize the importance of clear security and data protection policies, guidelines, responsibilities and support systems. Organizational structures supporting information security and data protection should be robust, and organization units should benefit from clear instructions on how to apply security policies and guidelines when trying new prompts and agents. For example, although the employees of the Pilot 2 unit were experienced in working with legal jargon and familiar with GDPR, they still struggled to be confident that they were prompting GenAI within the permitted limits, sometimes abandoning new ideas due to a lack of confidence in security. This case study suggests that centralisation of responsibilities is preferable to decentralisation: those responsible for AI policies and guidelines should also be responsible for providing practical support. However, making recommendations in this area is challenging, as ambiguity in decision-making responsibilities can hinder innovation. In the public sector in particular, the capacity for risk-taking may be lower than in private organisations, due to the extent to which work is shaped by regulation, legislation, and state governance.

The concept of trust was found to be significant in the adoption of GenAI. Due to bias and hallucinations, users needed to exercise caution with the answers and results of their prompts.

Every user must understand the limits of the implemented tool as part of GenAI adoption. To avoid deskilling and a deterioration in quality, training must be provided on a regular basis, but in a way that does not lead to desensitisation. Perhaps short, thematic information sessions based on everyday examples are preferable to repetitive basic training.

Based on two GenAI pilots and earlier studies, it was concluded that employees are to a high degree responsible for the successful adoption of GenAI in organizations. Individuals need to be motivated to engage with change, and experiencing the benefits of adoption is one of the key elements of GenAI adoption. While individuals bear the brunt of the adoption process, perhaps this is why they also reap the greatest benefits at the early stages of adoption. Organizations should also implement ongoing and communicated procedures for goal setting and measurement to reap the benefits of AI use. While initial adoption of GenAI cannot really be forced due to the nature of the technology, pilot programmes tend to remain ineffective without concrete, practical use cases designed for the adopting unit's work. As a result, teams may fail to build sufficient capabilities and they may be unable properly to evaluate the benefits. Instead, motivation to engage with the technology stems from the benefits experienced by individuals, supported by interaction between leadership and peers. The organisation's responsibility is to provide vision, resources, policies and support, as well as to promote shared goals and discussion over an open understanding of the technology's potential and concerns related to it – in short, to establish a shared narrative.

As to RQ2, our findings suggest that adopting GenAI tools requires organisations to move beyond traditional information system implementations towards a more extensive, multi-layered approach to adoption planning, designing organisation-wide operating models and developing required capabilities from an early stage. When deploying GenAI tools, less emphasis is placed on project-based execution and divided responsibilities, and more on sustained change management and distributed ownership across multiple stakeholders. Even in a scenario where the technical improvement of GenAI tools is not significant, the surrounding environment continues to evolve, and, by their very nature, the use of GenAI tools typically involves more factors to consider is the case when adopting traditional information systems.

As discussed in section 4.4, many of the capabilities regarding ownership and support could not be developed solely within the adoption unit. Figure 1 illustrates the interaction between the different levels of organisation and individuals in GenAI adoption. Each level supports shared adoption and learning by actively participating and sharing knowledge within and across the different levels of the organisational hierarchy. Each level supports the adoption, but the final adoption decision of GenAI depends of individual user.

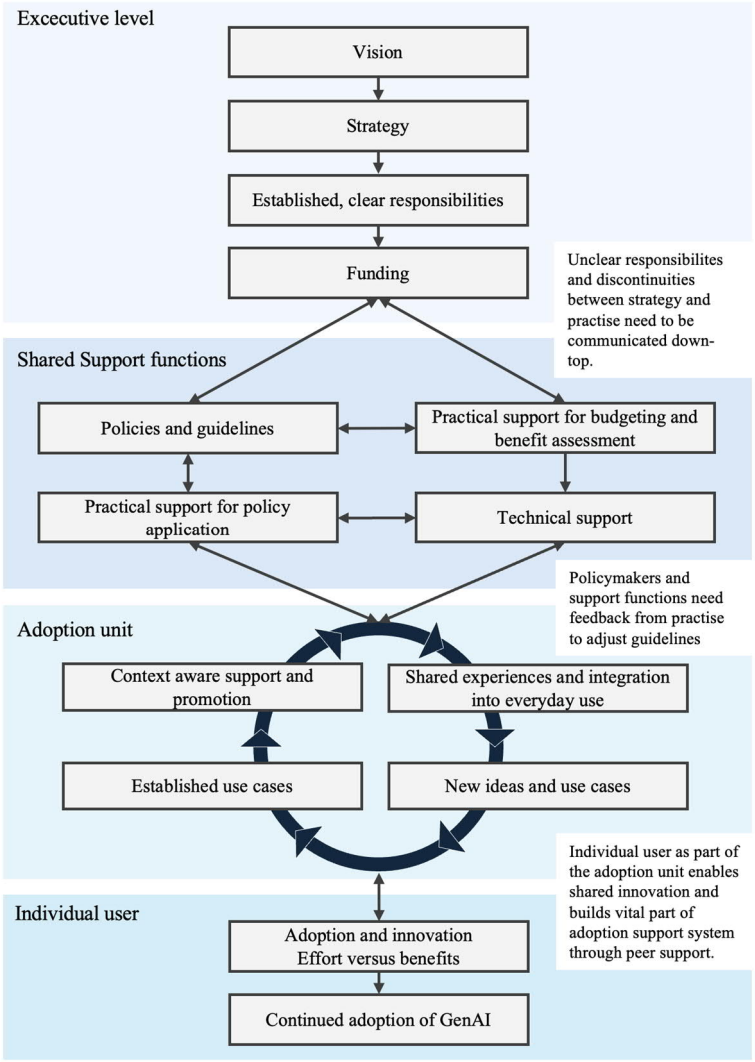


Figure 1: Key elements and interactions between units in GenAI adoption.

To conclude, the results of this case study suggest that GenAI adoption is unlikely to proceed successfully unless:

- centralized support functions are in place and usage is prompted continuously
- there is a peer network within the local organization that supports usage and innovation (generation and testing of new ideas)
- users understand how the technology can be used in their everyday work
- there are clear boundaries and guidelines defining permitted and prohibited use.
- there is clear ownership of AI, as adoption does not scale properly and remains fragmented across the organization without a clear vision or plan.

5.1. Theoretical implications for further studies

Our results suggest that future GenAI adoption studies should examine the adoption processes of individuals and organizations in parallel in order to understand better the reciprocal relationship between the individual and the organization and how they influence innovation-decisions and adoption rates.

Trust should be included as an attribute in AI adoption studies, regardless of the adoption or diffusion theory base (e.g. trust was not one of the five original attributes of innovations in DOI: *relative advantage, compatibility, complexity, trialability, observability*). The finding that trust, not only in security but also quality, along with perceived value, is a significant factor in AI adoption is also consistent with previous research on AI agents and how the sweet spot can be found where high adoption, trust and outcomes meet [49]. Furthermore, our findings suggest that trust should not merely be viewed narrowly as trust in technology, but considered more widely in an organisational context, where it is observed as a socio-technical factor affecting the adopter's perception of both the technology and the surrounding society. The question of how trust manifests over time in an organization, how it should be built and how it affects adoption seems to be a more complex one than simply how trust (or a lack of it) affects adoption intentions or resistance in the initial stages of adoption.

The rate of voluntariness in GenAI adoption and its relation to the adoption rate, innovativeness and resistance to change were merely touched on in this study. In earlier studies of RPA adoption, we found that passive resistance manifested itself as dithering (hesitancy to adopt and adapt), and that organizations and their key users only proceeded when both of them found that the relative advantage gained from adoption-related time consumption was high enough [3]. In the context of digitalization and motivation, force can be a strong motivator: the work community was faced with new, mostly unprofitable work arising from legislative changes that could be resolved with RPA [1]. GenAI probably does not replace any technology; rather, it replaces some procedures that are usually carried out manually. Individuals are not yet forced to adopt it (at least not on a deep level). As organizations face increasing pressure to adopt, the relation between direct or indirect force and individual innovativeness could deepen our understanding of the adoption process.

5.2. Practical implications for organizations

For organisations planning to adopt GenAI or looking to advance from initial adoption to wider use and adaptation, we suggest taking some of the following measures, regardless of the chosen technology:

- Keep adoption voluntary, but promote shared innovation.
- Set clear goals and be open about them.
- Acknowledge both opportunities and risks openly and transparently.
- Teach early with concrete examples driven from adopters' everyday work and resolve real problems.
- Set clear boundaries for GenAI: what can be done and what cannot.
- Name clear and non-superficial responsibilities and ownership in different areas of adoption, including support functions.

Without assuming that the use of GenAI is beneficial to organisations or improves efficiency, it is difficult to assess such outcomes if the above-described measures are absent. Validation should be a constant measure of whether the GenAI tool remains useful and whether improvements in quality, efficiency and work satisfaction are achieved. To plan continuation, we suggest:

- Provide continuous, appropriately scaled training.
- Keep interpretations of legislation, governance frameworks and technological developments up to date.
- Monitor the accumulation of potential negative impacts and assigning clear ownership for managing them (e.g. ethical concerns and employee well-being).

6. Contribution and limitations

This study contributes to the literature by providing enabling factors and challenges of GenAI adoption based on real-life findings for use in further research, and it adds to the theory with two key conclusions. First, organisational adoption of GenAI depends on the innovation skills of individuals and local teams, as well as their ability to innovate, learn together and actively share viable use cases and knowledge. The main contribution is the insight that GenAI adoption is shaped by the interplay among individual use-case exploration, communal learning and organisational support, extending beyond conventional technology acceptance and adoption models. Preliminary findings on the types of ownership and support systems that should be established before GenAI is adopted as one of an organisation's work tools were presented in this article. As this study relies on interviews, thematic analysis and interpretations by only two researchers, the interview findings and the overall adoption journey are described in detail to provide transparency and strengthen the rigour and credibility of the study.

However, further research is needed on the key contribution. The adoption of GenAI by individuals and organizations should be examined further in parallel better to understand the reciprocal relationship between organisations and their members. Moreover, this research was conducted in the public sector, and the participants were highly educated professionals in expert roles. Had the study been conducted in the private sector or with less educated participants, the results might have been somewhat different. Substantial further research in other domains is required to understand the implications of AI for different types of organizations and industries, and to explain the contextual factors that shape its adoption and use.

In terms of adoption support, this study does not take a position on which organisational unit or role should be responsible for implementation. While a city-wide organisational strategy should generally be set by senior city leadership, to use an example, this study does not examine the city's organisational structure, decision-making processes, or delegation of authority. Therefore, no implementation-specific recommendations are provided. Such arrangements must be developed and implemented within each organisation according to its own context.

Many of the factors identified in this study were similar to those in the earlier literature covered in section 2. The observations made in GenAI adoption were also partly the same as those made in RPA adoption. For example, both seem to rely on a constant flow of new ideas (use cases) to continue. The difference in adoption patterns possibly lies in the fact that RPA

operates in a controlled environment, whereas GenAI interacts with the work environment in a complex and dynamic way. Both AI and robotics have been seen as disruptive innovations that will severely affect the labour market, but due to their limitations, in neither of our studies did the professionals seem to be particularly threatened or actively resistant. One limitation of drawing conclusions about the perceived threat from this study is that it was carried out among highly educated expert units. If the focus group had been different, the results might also have been different. This limitation also affects the conclusion regarding how innovativeness and adoption are reliant on new ideas. Our users' workdays and tasks varied from day to day, and in more repetitive work, use cases may become more permanent.

Finally, both of our pilots were short, lasting only a few months, and GenAI adoption was still in its early stages. The units of the interviewees in Pilot 1 had only recently expanded their user base, with the city-wide user group still accounting for just over 3% of the personnel. Thus, our findings are preliminary and focus theoretically on the early stages of adoption. This study excludes recommendations for GenAI use cases and does not consider any actual efficiency gains from GenAI adoption in the workplace, although these topics were discussed by the interviewees. The question of how can the benefits of GenAI be capitalized on at an organisational level remains a challenge to be resolved.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT (GPT-5.6 Luna) in order to check grammar and spelling. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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A. Summary of the research process

Step	Phase	Description
1	Planning	Research design and scoping of research area
Pilot 1 (6 Organisation units)		
2	Data collection 1a	Initial interview and pre-discussions with Pilot 1 organiser. Collection of supportive material such as instructions given to pilot users.
3	Data collection 1b	14 semi-structured interviews *), including 2nd interview with the organiser. 13 pilot users included; 3 managers, 4 specialists and 6 senior specialists; 12 active and 1 non-active; 10 with intention to continue GenAI use if possible and 3 undecided or unclear. The interviews encouraged participants to freely and informally share their experiences and observations, with specific topics raised only when they did not emerge spontaneously.
4	Analysis	1) Thematic analysis of interviews by inductive and deductive coding that included firs open coding and subsequent theoretical coding [46] [47] by researcher A. **) 2) Combination of codes into broader themes by researcher A. 3) Discussion with supportive researcher B of themes and re-evaluation.
5	Specifying learning	1) Identification of key problems of Pilot 1. 2) Identification of recommendations for next pilots based on both common themes and more rare but significant findings. 2) Comparison to literature to gain additional proof.
Between Pilots 1 and 2		
6	Data collection 1.5	Observational notes and collection of new guidelines and instructions between Pilots.
Pilot 2 (1 Organisation unit)		
7	Planning (incl. interference from researcher A)	Pre-discussion 1: First discussion with pre-pilot team. Researcher A gave key recommendations Pilot 1. Discussion and support for Pilot 2 planning. Pre-discussion 2: Review final plans. Researcher A compares the pilot's preliminary material to see which recommendations have been considered.
8	Action taking	1) Pilot 1 recommendations put in action by pilot 2 organisation's co-ordinators (see Appendix B). 2) Researcher A participates as observer in kick off and later as a supportive role in weekly GenAI clinics (observing and taking notes, interfering by trying to help with prompting issues).
9	Data collection 2a	Middle-pilot discussion with organisers: how long the pilot will continue, should support be adjusted (no) and goal setting be adjusted (yes in future use, not in pilot). No changes were made to pilot projects
After Pilot 2		
10	Data collection 2b	12 semi-structured interviews *) (incl. 2 unit's own project co-ordinators); 1 manager, 2 specialist, 9 senior specialist; 6 active, 3 moderately active, 3 non-active; 12 with intention to continue GenAI use. New interview with GenAI ICT-co-ordinator (same as in Pilot 1).
12	Evaluating and Analysis	1) Similar thematic analysis process as in Pilot 1. **) 2) Re-evaluation of Pilot 1 findings and comparison of pilot results and literature. Thematic recoding and summarising and comparison to theory [47]. Discussion with supportive researcher B of themes and re-evaluation.
13	Specifying learning and Conclusion	Identification of what was learnt [46] from Pilot 2 and Conclusion of results and peer-evaluation of results with researcher B.

*) All the interviews were conducted by researcher A, online. The interviews were recorded and transliterated with MS Copilot. Data is to be used only as anonymized and by researcher A for original research purpose and doctoral dissertation. Interviews were designed not to cover sensitive information.

**) Coding was conducted over Interview notes by researcher A, supplemented with transcripts.

B. Pilot 1 recommendations to Pilot 2

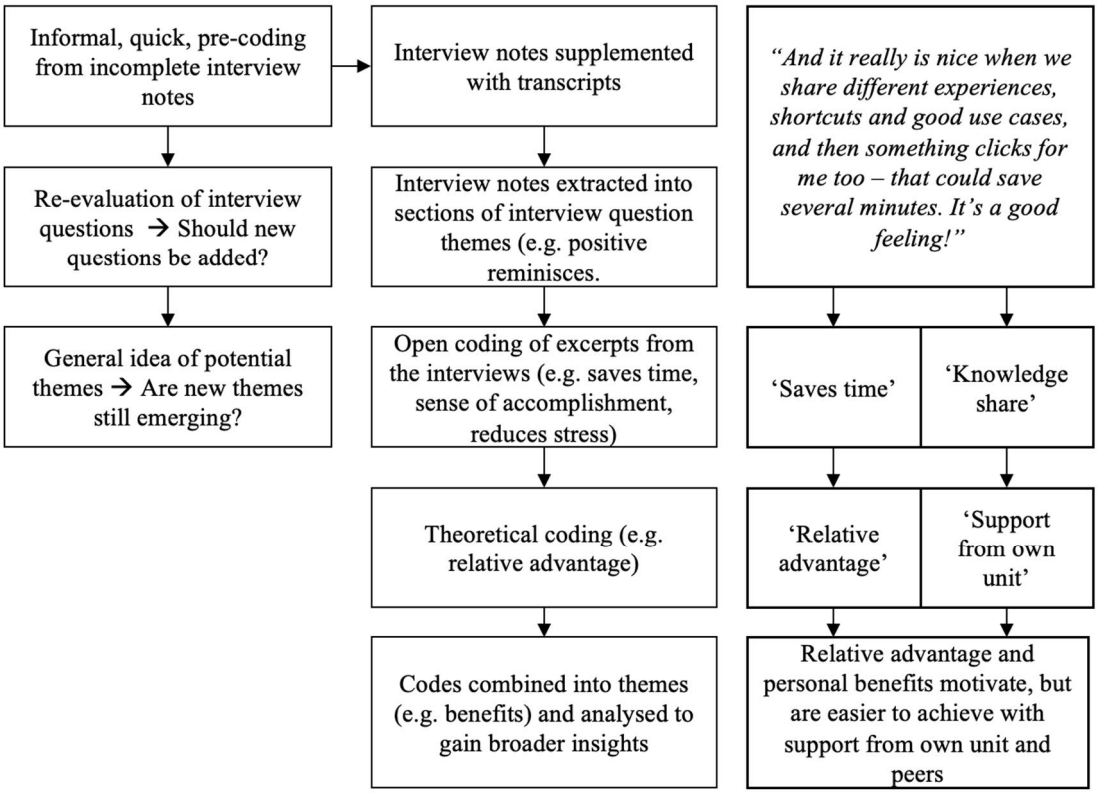
The suggestions to take into considerations in Pilot 2, drawn from Pilot 1 interviews were:

- Take initial Pilot objectives into account when designing the Pilot plan.
- Training, support for ideation, guidance and advice should be continuously available to users.
- Desing or purchase different types of training depending on user's skill level and existing experience in AI.
- Manage expectations appropriately – what Copilot can and cannot do.
- Rapidly incorporate lessons learned during the PoC.
- Share examples at a highly concrete level.
- Make data protection guidelines more concrete and relating them to the test use cases (clear rules of engagement).
- Plan for what happens after the PoC, including clear ownership and responsibility for the next phase.

The recommendations from the Pilot 1 interviews regarding communication and support:

- It is advisable to assess the attitudes within the respective unit in advance and plan communication and support throughout the pilot accordingly.
- Guidance should be clear and help users understand how Copilot works and what it is suitable for. Applying Copilot is difficult without a sufficient understanding of its capabilities.
- The objectives should be clearly explained to participants so that they understand the purpose and significance of the pilot.
- Avoid overhyping Copilot and maintain realistic expectations.
- Encourage users to experiment boldly within predefined boundaries (permitted use cases).
- Solve problems together.
- Avoid creating excessive fear around information security and data protection in communication.
- Data protection should be assessed realistically, and risk assessments should be conducted carefully to avoid unnecessarily restricting use. Ethical guidelines illustrated with concrete examples could be more important, if available.
- Successful experiments should be actively communicated and shared.
- Unsuccessful experiments should also be shared – including what did not work. Solutions can then be explored together and the guidance refined accordingly.

C. Coding technic with example



D. Conclusion of enablers and challenges as in RQ1

RQ1: Adoption factors	Conclusion
1. Key challenges	- Lack of ownership, support functions, skills and knowledge. - Unclear policies and guidelines. - Technical issues. - Security and data processing issues.
2. Key enablers	+ Local support and knowledge sharing. + Structured, planned piloting. + Hands-on instructions and concrete first use cases. + Perceived, personal benefits and relative advantage
3. Resistance to Change	- Implications of passive RC in terms of procrastination and dithering both on individual and organisational level. However, RC did not appear as major factor in neither Pilot.
4. Fear	+ Did not appear as major factor e.g. as in terms of job loss or fear of technology - Instead of fear, milder concerns (related to 5).
5. Trust	- Lack of trust manifested as concerns about declined quality and deskilling and belief that laziness will increase in time. + Support by peers and management appeared to increase trust in technology on some level (related to 6 and through 8).
6. Support	- Lack of proper support was found to hinder adoption in Pilot 1 + Local support was found as an enabler to adoption. Several types of support functions were identified (see Table 4).
7. Structural or systemic factors	- Lack of ownership in AI and practical support with policy adaptations (related to 7 and 9). + Established, local support system (related to 6) + Means for shared learning and peer support (related to 6)
8. Ideas and knowledge	- Lack of ideas and knowledge was one of major restrainers of adoption in Pilot 1 (related to 6, 7 and 8). + Shared, task specific ideas facilitated learning and adoption in Pilot 2 (related to 6 and 7).
9. Operating models	+Adoption through controlled, well planned pilot model was found to accelerate adoption in Pilot 2 (related to 7). - AI ownership related operating models were unclear and hindered innovation (related to 7).