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MOHAMMED BIN RASHID SCHOOL OF GOVERNMENT

Exploring the Future of Public Sector Work

Generative AI Adoption amongst Dubai Government Employees

Authors and Citation

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Executive Summary

The rapid adoption of generative artificial intelligence (GAI) applications and the plethora of use cases in government settings has continued to reshape business operations and affect human resource dynamics since 2023. Over the past two decades, the Government of Dubai has continued to be an early adopted of technological innovations in government; a trend that continued during the age of artificial intelligence.

Since the public deployment of ChatGPT in late 2022, the landscape of generative AI technologies has evolved exponentially, with increasingly sophisticated Large Language Models (LLMs) transforming how organizations, including governments, operate and manage workloads. As of early 2025, several advanced general models have emerged as powerful tools for public sector transformation. Google DeepMind's Gemini 2.0 has introduced enhanced multimodal capabilities, processing text, images, audio, and video simultaneously, while Anthropic›s Claude has gained traction in government applications, particularly in the UK, for its emphasis on safety and reliability. Perhaps the most disruptive, however, was likely China's DeepSeek V3, which has shown superior performance in reasoning tasks with a reported fraction of the compute cost for training, though its adoption in government contexts has been limited due to data privacy concerns. Meta›s LLaMA has made inroads in public sector applications through partnerships with U.S. government departments, while OpenAI›s GPT-4o continues to be widely used despite lacking real-time internet access. These rapid advancements underscore both the opportunities and challenges facing government entities as they navigate AI adoption, particularly in terms of data privacy, security considerations, and the need for careful evaluation of different models› capabilities and limitations. The proliferation of these tools has made it increasingly important for government organizations to develop comprehensive strategies for AI integration while ensuring responsible and effective implementation.

To explore the implications of the growing utilization of generative AI among government employees in Dubai, The Mohammed bin Rashid School of Government (MBRSG), in partnership with the Dubai Government Human Resources Department (DGHR), conducted a study on generative AI adoption by employees across all Dubai government entities. This included a large-scale and comprehensive survey deployed with government sector employees across all Dubai Government departments, as well as qualitative fieldwork in the form of in-depth interviews with Chief Artificial Intelligence officers (CIAOs) across five leading Dubai Government Departments in AI adoption. The survey tracked the usage trends of Dubai Government employees throughout three stages over 12 months between November 2023 and November 2024. It benefited from comprehensive responses from 2,480 Dubai government employees, with 1,531 completing the survey in full. The primary objective of the study was to explore how government employees in Dubai were interacting with and utilizing generative AI technologies, and how these tools shaped work behaviours. The research explored usage trends, perceptions, challenges, and opportunities related to generative AI applications at the critical first phase of expansion of generative AI tools use cases across the government.

Based on the fieldwork findings, the study then provides analysis aiming to assess high occupational exposure to the automation impacts of generative AI in the government of Dubai, benchmarked on the capabilities of GPT-4 *. The regression analysis suggests that the highest level of education, followed by the type of education specialization are the most important predictors of employee job exposure to automation. The greater the respondent's highest level of educational qualification, and the more quantitative their field of educational specialization, the lower is their estimated job exposure to automation due to gen AI. Less important, but significant nonetheless are, gender and age group, with females and younger people likelier to face job automation exposure to generative AI.

Collectively, the findings of this study aim to provide insights that can inform policy development as it regards skills and capabilities necessary for innovative and safe generative AI adoption within the Dubai government.

1. Key findings

1. Adoption and Usage

- During the period of the study, a third of government employees across all government departments in Dubai (36% of respondents) indicated that they either don't use generative AI tools or are beginner users, indicating early-stage adoption of generative AI technology.
- Employees in senior roles showed higher adoption rates, with 64% of senior managers indicating using AI tools weekly during the period of the study.
- Education levels and job seniority positively correlate with higher levels of expertise in generative AI usage.
- During the period of the study, ChatGPT was the predominant tool used among beginners, while advanced users employ a broader range of applications.
- As expertise levels increase, so does the variety and complexity of tasks for which employees use generative AI tools.
- Most common uses of generative AI amongst beginners included email drafting, content creation and research assistance, while advanced and expert users use generative AI applications for more advanced tasks like data analysis and in policy development stages.

2. Benefits and Impact

- Nearly all users (around 97%) reported at least one benefit from the adoption of generative AI in their work.
- Primary benefits identified by government employees included time savings, improved work quality, enhanced productivity, and increased creativity.
- During the period of the study, an overwhelming majority (94% of respondents) expressed optimism about generative AI's impact on government operations.

3. Key Challenges and Concerns

- The key concerns reported by users of generative AI among government employees included: 1. inaccurate outputs, 2. data privacy issues, 3. biased output, and 4. unreliable performance.
- 55% of users among government employees reported concerns related to the representativeness, availability, and quality of data.
- Environmental impact awareness related to generative AI development and use was notably low, with less than 10% of government employees expressing concerns related to the energy consumption and environmental impact of generative AI technology.

4. Skills and Capacity Building

- Among managers who are users of generative AI applications, a large majority (around 89%) considered generative AI skills important or very important for employees working in government settings.
- During the study period, around 63% of current users of generative AI have not received training but were interested in receiving it. Though several initiatives related to generative AI capacity building were introduced in the government.
- Around 87% of non-users are at least somewhat interested in receiving training related to generative AI tools, with only 5.7% of current users expressed no interest in AI training, highlighting wide interest among government employees.

5. Job Displacement Concerns

- During the period of the study, more than half of government employees who use generative AI tools (55%) expressed some concern over job displacement due to generative AI adoption.
- Higher education levels among employees correlate with lower concerns about job displacement.
- Respondents among the government employees anticipated higher impact of generative AI tools on the following sectors: advertising/marketing, customer service, research and development, education and training.

6. Trust and Ethics

- Around 23% of all users of generative AI in the government reported high confidence in outputs of the applications they use, while 63% expressed moderate confidence in generative AI outputs.
- During the period of the study, around 59% of current users of generative AI applications in the government reported that they are unaware of any guidelines on AI ethics.
- Meanwhile, 83% of users believe that the existence of ethical guidelines will positively impact their work with generative AI applications.

2. Policy Implications

The findings of this study reveal several implications that require attention from government leaders and those looking to successfully implement generative AI across their organizations:

1. Generative AI implementation and upskilling is a resource intensive endeavour with varying degrees of success and implementation across Dubai Government. **The nature of this technology and the resources it needs requires pursuing a cooperation-based and not competition-based approach to government transformation** through GAI implementation. Such an approach would enable sharing expertise, resources, good practices, and the burdens of training and upskilling in order to ensure that all departments are able to keep up with technical advancements and that departments can benefit from each other's' experience and use cases.
2. **There is the pressing need for comprehensive training programs for employees across Dubai government organizations**. These programs can be tailored to different levels and specializations from technical staff to administrative and front-line staff. Particular attention is needed at tasks and departments units that are most vulnerable to AI automation and augmentation like customer service and administrative departments like HR, administrative operations and finance.
3. **Risk management emerges as a priority, particularly as it concerns data privacy, and assessment of GAI outputs**. Organizations must develop robust protocols for categorizing and handling sensitive organizational data and establish clear procedures for verifying the accuracy and validity of generative AI generative content and analysis. This includes training employees in these skills and implementing "human in the loop" monitoring systems and developing clearly defined accountability chains for AI-assisted decisions.
4. **There is a growing need for comprehensive applicable ethics frameworks and guidelines that assist employees in understanding the ethical implications of using generative AI applications in their work**. While Dubai has in place data governance frameworks and ethical AI principles and initiatives since almost a decade, such frameworks may need adapting to the emerging use cases of generative AI to offer practical guidance and be unified across Dubai government, with specialized attention to entities that handle sensitive personal data. Integrating these ethical guidelines with existing governance frameworks, and training employees on them, is crucial to ensure consistent application.
5. **Organizations need to develop clear communication and change management strategies that help employees to transition to an AI augmented workforce**. This includes developing career paths and growth opportunities that incorporate generative AI skills and reward employees who participate in AI skills training and certification, particularly when generative AI can enhance productivity of tasks in their roles. Organizations must create cultures of technological adaptation that encourage experimentation with generative AI technologies and upskilling in areas crucial to the organization.
6. **There is a need for a context-specific GAI skills taxonomy and skill evaluation processes**. Such a taxonomy should identify and evaluate skills related to the effective use of general AI and generative AI, ranging from analytical skills to computational skills and bias detection. This will help organizations to understand their current skill gaps and develop strategies to bridge them. Such taxonomies must be continually updated to reflect ongoing technological and skill development.

Finally, given the nature of generative AI applications and the breakneck speed of development and exponential improvement in quality, growth in penetration and user adoption, and the expanding innovative use cases, it is important to highlight that the trends of using generative AI are also rapidly changing within government structures. The study is a first attempt to capture and explore the emerging trends at critical early stage of adoption of generative AI applications in government, and the impact of these applications on public sector employees' productivity, behaviours and their interaction with business processes and job tasks. It is important to continue observing the scope of change, expand data collection and expand deeper sectoral analysis to document the ever-changing dynamics of introducing this sociotechnical phenomenon rapidly transforming government operations. Such continuous assessment will be necessary to identify the emerging opportunities as well as address the ethical implications and risks.

Introduction

The rise of Generative AI (GAI) applications has led to a massive surge in adoption across various sectors. The wide availability, broad applicability and rapid evolution of generative AI has led to its wide deployment all over the world across institutions in both the private and public sectors (cf. MIT, 2023). This has profound implications for the public service and government work globally. While there is no single agreed upon definition of artificial intelligence or generative AI, it is widely accepted that GAI refers to AI algorithms that generate new outputs based on training data, distinct from traditional AI systems that recognize patterns and make predictions (Marr, 2023). Such AI technology creates content in various forms, including images, text, and audio (Fagan, 2023).

Though the development of GAI dates to the 1950s, it has seen a rise in use and publicity over the last six years with the development of Generative Pre-trained Transformers (GPTs) and expansive Large Language Models (LLMs) (Orchard & Tasiemski, 2023). By 2022, its global recognition surged with the advancement of GPT-powered chatbots such as ChatGPT and more recently, sophisticated multimodal generators, offering transformative potential in education, entertainment, healthcare and scientific research. Organizations across industries, including public sector organizations, are increasingly adopting AI for content generation, process automation, hypothesis formulation, and operational efficiency enhancement. Public sector entities are deploying generative AI for automated document processing, data analysis, policy analysis and development, and to support in decision making.

Generative AI technology presents a number of opportunities, ranging from the potential of massive gain in productivity and economic growth, to "democratizing" AI and making certain skills, like coding, accessible to the masses. However, it also presents now well-known risks like the potential for data breaches, misguided reliance on potentially hallucinatory outputs and black-box processing systems, potential for cyberattacks and intellectual property concerns (UNESCO, 2023; Isik et al, 2024; Beltran et al, 2024). Generative AI technology is changing the way we live and work, and organizations need to be prepared to benefit from this technology and mitigate its risks.

Dubai government has been at the forefront of artificial intelligence adoption in public service and delivery, with large number of AI principles, guidelines and initiatives introduced across the government during the past decade. More recently, the Dubai Universal Blueprint for Artificial Intelligence emphasizes the integration of AI across all strategic sectors as a core part of the digital transformation of Dubai Government. As a result of this blueprint, all Dubai Government departments have appointed Chief AI Officers and been mandated with delivering superior government services through the integration of cutting-edge technologies and AI. Given these ambitious plans, building AI and generative AI capabilities across the government has become a strategic imperative that is critical for the success of the AI/Generative AI projects they undertake.

1. Generative AI and the upskilling challenge

The barriers to using AI by the vast majority of employees are diminishing rapidly with time. This raises the criticality of AI upskilling for those interacting with AI applications directly across work processes and ecosystems. Grasp and awareness about the direct and indirect risks and consequences of AI usage in society and within government and business setup, are not catching up with the pace of growth AI applications, especially as the use of AI applications became universal with the maturity of generative AI tools.

Generative AI poses a unique upskilling challenge because of its wide use and usability. While traditional AI applications might have been behind the scenes, embedded into various software applications, generative AI applications require users to work directly with them, understand and calibrate their outputs, and integrate them into their workflows. As such, all employees and potential users must have some form of training on generative AI technology. The World Economic Forum Future of Jobs Report (2023) estimates that 60% of workers will require retraining by 2027. Global surveys (and our survey confirms these trends) indicate that a majority of employees worldwide are already using generative AI technology in their daily work (Oliver Wyman, 2024), regardless of whether they have already received training to use it.

Targeted reskilling programs, however, will be a crucial differentiator between organizations and their ability to harness this technology to their benefit - enabling them to rapidly develop internal capabilities and address essential skill gaps before their competitors, thereby creating a distinct competitive advantage (Tamayo et al., 2023).

The scope of generative AI skills includes a broad spectrum of competencies of both human skills such as analytical and critical thinking skills and numerical reasoning skills, as well as technical and AI literacy skills. Some key competencies include prompt engineering, data literacy and the ability to critically evaluate AI generated outputs, data cleaning and structuring skills, bias detection and mitigation, management of AI integrated projects and processes and AI ethics skills.

According to the WEF Skills-First framework (2023), upskilling efforts must include a standardized, dynamic skills taxonomy that enables organizations to identify and organize evolving AI related competencies that are relevant to their organization and their integration. This include identifying current and future AI skills, articulating these skills clearly in job descriptions, co-developing targeted training programs, and providing continuous learning opportunities and clear skills development pathways for employees within organizations.

2. Labour market transformations and GAI

Generative AI›s rapid adoption offers both opportunities and challenges for labour markets. It has potential to substantially reshape labour markets and boost economic growth by transitioning markets beyond the traditional human-versus-machine labour dichotomy (Carrasco, 2023). While GAI tools and applications may boost productivity, they also risk job displacement and skill obsolescence (Lorenz et al., 2023). In order for these technical transformations to result in a net positive for government employees, a dynamic, collaborative approach is needed that involves policymakers, employers, and workers to effectively manage the AI-enhanced future of work - balancing job augmentation with the risks of job displacement and skill gaps (Carrasco, 2023). The Global Partnership on Artificial Intelligence Working Group on the Future of Work emphasises GAI›s swift progress and extensive reach, predicting a more immediate and profound job impact than earlier AI innovations, urging a prompt and considered response from policymakers and stakeholders (Adamoli, 2023). The influence of generative AI on the socio-economic environment depends on how it is spread and managed. It is important to consider power dynamics, the involvement of workers in adapting to changes in the job market, adherence to norms and rights, and the use of social protection and skills training systems. These factors are essential for reducing risks and ensuring fair distribution of benefits (Gmyrek et al., 2023).

Industry forecasts estimate a $1.75 trillion annual productivity value for governments by 2033 due to GAI, signalling substantial economic promise (Carrasco, 2023). Nonetheless, the direct effect on productivity growth is unclear, with emerging research pointing out recent digital innovations› limited productivity improvements, suggesting potential overestimation of current GAI applications› economic impact (Glenster & Gilbert, 2023).

In the following sections of this report, we describe the goals, methodology, findings and key recommendations from a) detailed research interviews conducted with the Chief AI officers of 5 leading Dubai government entities, b) Survey results from a survey taken by 1433 government officials from several different organizational roles, levels of seniority, education, age groups and belonging to different government organizations in Dubai , and c) the findings of an analysis conducted on the extent and type of exposure to generative AI for different types of jobs, along with estimates of the number affected among employees in the Dubai government employees.

Generative AI Adoption and Skills:

Lessons from Dubai Government

As a part of this research project, the MBRSG research team conducted interviews with Chief AI Officers (CAIO) in 5 leading Dubai government departments who are already successfully implementing generative AI into their core business functions[1]. This section will introduce some of the lessons and best practices gleaned from these interviews.

1. Use case selection for strategic outcomes

In our interviews, CAIOs in leading Dubai government entities that have already successfully implemented generative AI discussed the importance of strategically selecting use cases based on (a) strategic goals, (b) process maturity, and (c) assessment of potential risks and benefits of projects. While integrating generative AI and AI into core functions has become necessary for most institutions, interviewees emphasized that measured and well-planned implementation was more important than implementation in general. Moreover, CAIOs stressed that while generative AI is an exciting new area with wide potential benefits, organizations should consider more traditional AI solutions as well, as these might be a better fit and more useful for most organizational purposes. Poorly chosen use cases can do more harm than good. Successful use case selection was based on several factors (a) mature processes and an in-depth understanding of the structure and processes involved in core functions of a department, (b) the availability of structured data or capacity to structure that data, (c) existing employee capabilities, and (d) potential impact and ROI.

Successful projects have required in-depth analysis, assessment and mapping of existing processes to understand gaps and areas that can potentially be assisted and augmented by generative AI technology. This was, according to interviewees, the most crucial step in the process. Use cases are now abundant, but not every successful use case will be successful in each organization.

The second most important step was to ensure that departments in which these projects were to be implemented were already sufficiently digitized, including to but not limited to having capacities for or availability of adequate data collection and structuring. As AI systems are highly dependent on available, clean data for their training, the potential value of these systems could be hindered if high quality data was not already available.

Finally, successful departments emphasized the importance of adequate and fit-for-purpose measurements to ensure that any use case that was piloted or rolled out could be assessed for its impact. Some departments implemented scoring systems to measure success and assess which use cases to implement.

2. Inclusive generative AI implementation and employee buy-in

Government departments that have successfully implemented generative AI and AI into their functions emphasized the importance of creating teams that bring together subject matter experts, process owners and AI experts to develop generative AI solutions and assess the risk and potential benefit of proposed use cases. This enables the implementation of AI solutions that genuinely address organizational needs while generating buy-in from the affected teams and departments. All the leaders we interviewed emphasized the importance of involving process owners and existing teams in the process of developing, fine tuning, and assessing AI/generative AI solutions. In many cases, organizational leadership set up a process whereby employees can suggest areas in which AI can be successfully and impactfully implemented. This inclusive approach has several benefits: (a) it allows those who are most experienced in their fields and institutional processes to suggest ways in which AI can augment their work, thereby ensuring positive

1 Interviews were conducted with CAIOs in the following departments: DGHR, DEWA, DHA, Dubai Customs and Dubai Police

impact, (b) it builds trust amongst employees in the proposed AI systems (c) it creates a positive feedback loop that ensures honest feedback on impact of these systems and how to fine tune and improve them and (d) it allows leadership to understand specific capability and skill challenges, so they can work to address them.

In Dubai Government departments that are already highly digitalized, organizational leadership is the driving force for technological adoptions and there are processes in place to ensure that HR, finance, and strategy departments are early partners in digital transformation efforts, which is critical to institutional technological transformation.

3. Training and up-skilling employees

All our interviewees emphasized the importance of developing employees' skills in generative AI technology. Successful departments reported implemented a tiered training strategy that differentiated between 1. technical staff and IT specialists, 2. employees in affected functional units and 3. employees more broadly.

Technical staff and IT specialists were provided with opportunities for training and upskilling in areas related to generative AI systems, training generative AI models, data structuring for generative AI systems, ethics in AI systems, and system maintenance. Affected business units were trained on the practical applications of generative AI systems, and on how to use them appropriately and safely in their day-to-day work. Finally, employees in general were given broad training on generative AI systems, prompting, and risks related to generative AI. In general, these departments were already training IT specialists and functional units who are employing GAI.

However, currently, awareness-raising efforts and training programs with general staff are not widely implemented in every department, but interviewees indicated plans to develop a broad range of training options across Dubai government.

4. Awareness raising and openness to new technology

Though not all the departments that we interviewed allowed the free use of generative AI applications like ChatGPT and Gemini, many did emphasize the importance of allowing employees to use these freely available tools in their day-to-day work. While interviewees understood the risks involved in generative AI usage and the reasons why some departments may block these tools at work, they acknowledged that employees are likely to access and use them even if on their personal mobile phones and tablets. As such, CIAOs emphasized the importance of being open to these tools and encouraging staff to experiment with them while also training staff on how they work, the risks involved and how they can be mitigated. While not yet broadly implemented, interviewees indicated that their departments already did or had plans to roll out employee awareness programs to teach employees how to write effective prompts, identify hallucinations and safeguard privacy and confidentiality while using freely available generative AI tools.

5. Feedback loops and continuous improvement

CAIOs in leading Dubai Government departments emphasized the importance of having clear and transparent feedback loops that allow and encourage employees to flag problems with generative AI technologies as they arise. Such feedback loops require employees to first be trained on generative AI systems and on how to identify and fix problems as they arise. Implementation of such technology requires a "human in the loop" and employees to understand the importance of constant assessment and validation of the performance of these systems.

In addition to making available processes for flagging and fixing issues, clear processes are also put in place to ensure that flagged issues are dealt with effectively and in a timely manner with transparent accountability systems in place and process owners clearly demarcated.

6. Impact measures and KPIs

Successful Dubai government entities emphasized the importance of establishing comprehensive measurement frameworks to assess the impact of generative AI projects. According to interviewees, effective measurement strategies were crucial for both justifying continued investment and guiding optimization efforts. CAIOs stressed that KPIs should extend beyond efficiency and cost savings to include measures of quality improvement, employee satisfaction, and service delivery enhancement.

Such KPIs should include measures of risk and potential challenges and issues. CAIOs emphasized the importance of feedback from employees, function owners, and customers (where possible) in the assessment of the success of these projects.

7. Competition vs collaboration

While competition between Dubai Government entities has been a crucial ingredient in government advancements thus far, CAIOs of leading government entities acknowledged that the unique nature of Generative AI technology and the kinds of resources and expertise it requires, necessitates cooperation and not competition. As such, interviewees emphasized that sharing experiences, resources, use-cases, and best practices was crucial for accelerating the adoption of GAI across Dubai government and to minimize the duplication of efforts and wasting of government resources.

Survey

1. Aims of the study

Between October 2023 and May 2024, an online survey was disseminated to the employees of various Dubai government entities to be filled in anonymously. The results of this survey inform the following study which aims to understand usage trends, skill levels, perceptions, challenges, and concerns regarding generative AI technologies among employees of various Dubai government entities. The goal of the study is to inform policies and initiatives related to the responsible and successful deployment of generative AI tools and applications. The study also aims to inform policymakers and government entities of the perception and adoption of generative AI amongst Dubai Government employees and the measures that can be taken to better prepare government agencies and the workforce in general for the challenges and opportunities that arise from working with generative AI technologies.

2. Methodology

The methodology of this study consisted of a comprehensive survey distributed to employees of various entities of the Dubai government, across various domains, educational specializations, departments, and organizational roles. The survey was launched on 23rd October 2023 and ran for 8 months. 47 entities of the Dubai government were invited to participate and 34 entities confirmed that they disseminated the survey.

The survey received a total of 2480 responses of which 1,531 responses are complete, representing a 61.7% completion rate. The total response sample represents approximately 4% of the size of Dubai Government which has approximately a total of 59,673 employees at the period of the study. Yet, this includes all type of jobs, including those that may not be exposed to generative AI or digital platforms. Hence, the sample size represents the voice of a larger proportion of the government employees that are potential users of generative AI applications.

Questions in the survey were of two types: the first type of questions were demographics questions, which included asking the respondent's gender, age group, specialization, highest educational level, departmental role, and department. The second type of questions were perception and usage related questions. Questions in the survey focused on understanding respondents' self-evaluated level of expertise and their opinions on the following key themes: usage trends, perceptions of risk, trust, issues, concerns, benefits, generative AI ethics, training, skills, impact on jobs, and barriers to usage.

The survey consisted of five sections. One section was shown only to those who responded as nonusers or unfamiliar with generative AI, and some questions from the remaining sections were shown exclusively to certain categories of respondents, such as supervisors and managers, advanced / expert users of AI, or to non-users of AI, to gauge specific opinions relevant to these subgroups.

3. Baseline statistics

Most respondents to the survey occupy technical, supervisory, or administrative positions. Only forty respondents, or 2% of all respondents, were part of senior management, holding positions such as Deputy Secretary General, Director General, or higher.

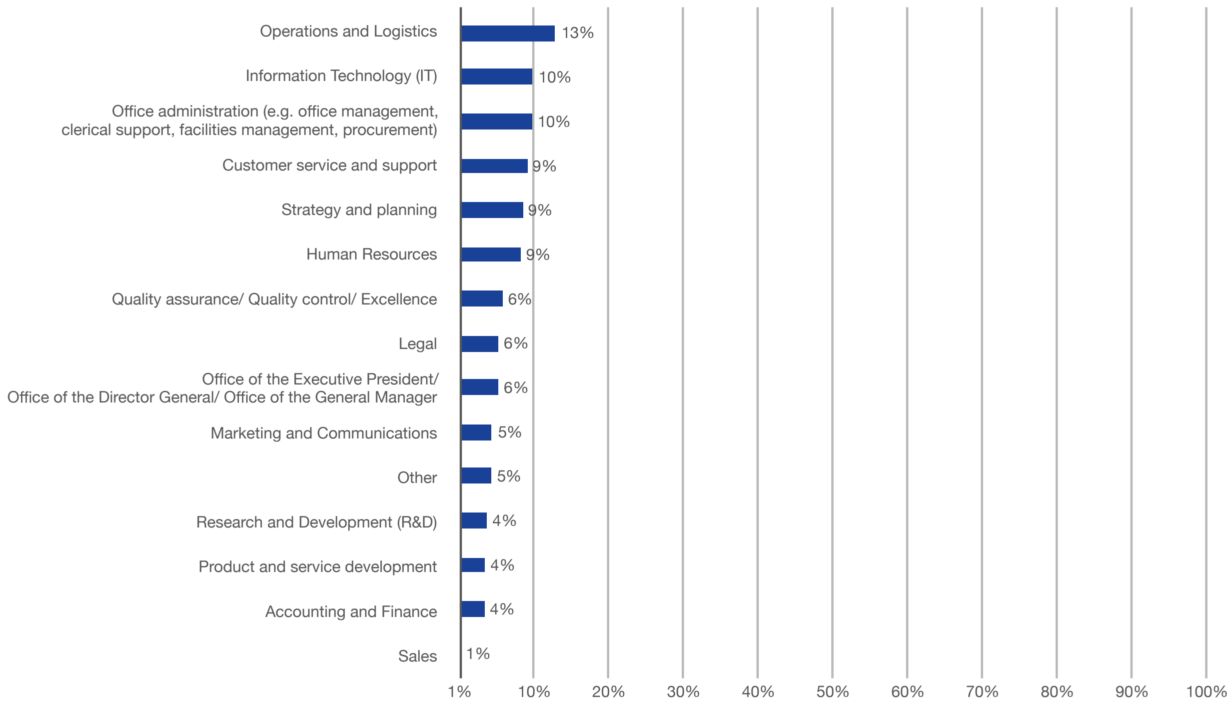
Over 50% of the respondents were over 40 years old. The gender distribution shows a slight skew, with 63% male and 37% female respondents.

While most organizational departments are well-represented, there appears to be an underrepresentation of the Accounting and Finance, Product Development, and Sales departments, with less than 3% respondents belonging to each of these departments Operations and logistics, IT, and office administration on the other hand, are well represented, with over 10% survey respondents belonging to each of these departments.

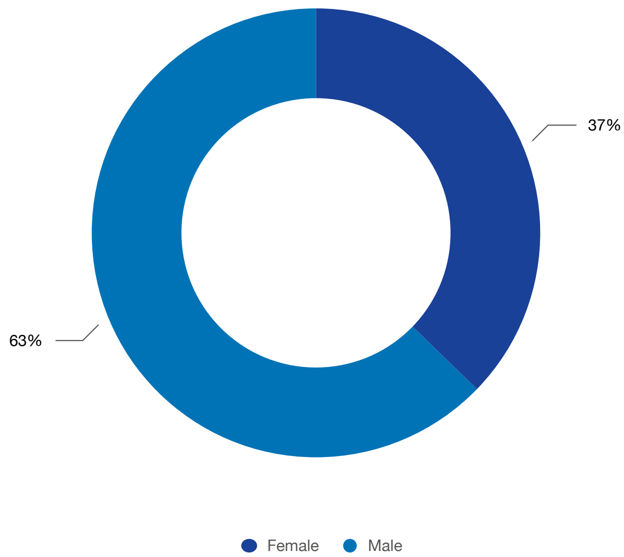
Nearly half of all respondents hold a bachelor's degree as their highest qualification. Additionally, 25% hold a master's degree, and 22% have a high school diploma as their highest level of education.

The charts below illustrate the distribution of survey respondents' baseline characteristics.

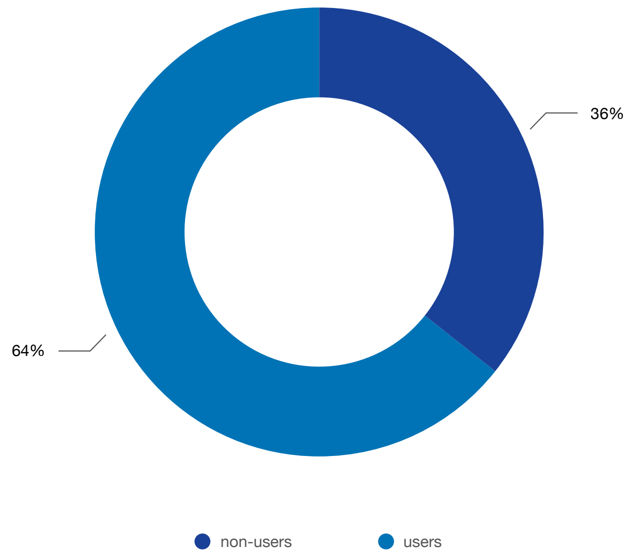
Organizational department of respondents



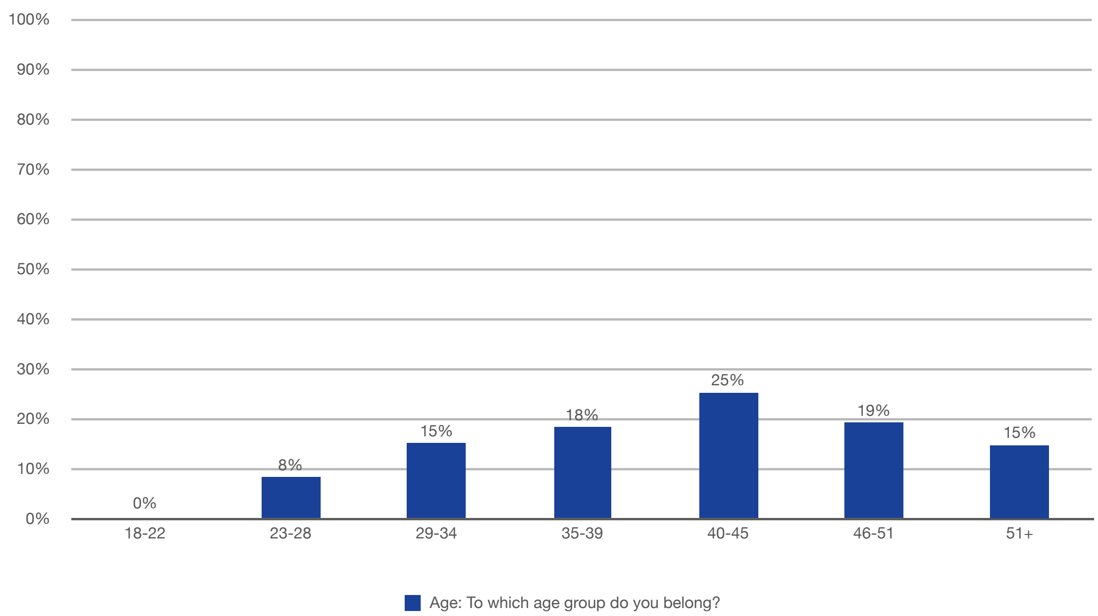
Gender composition of respondents



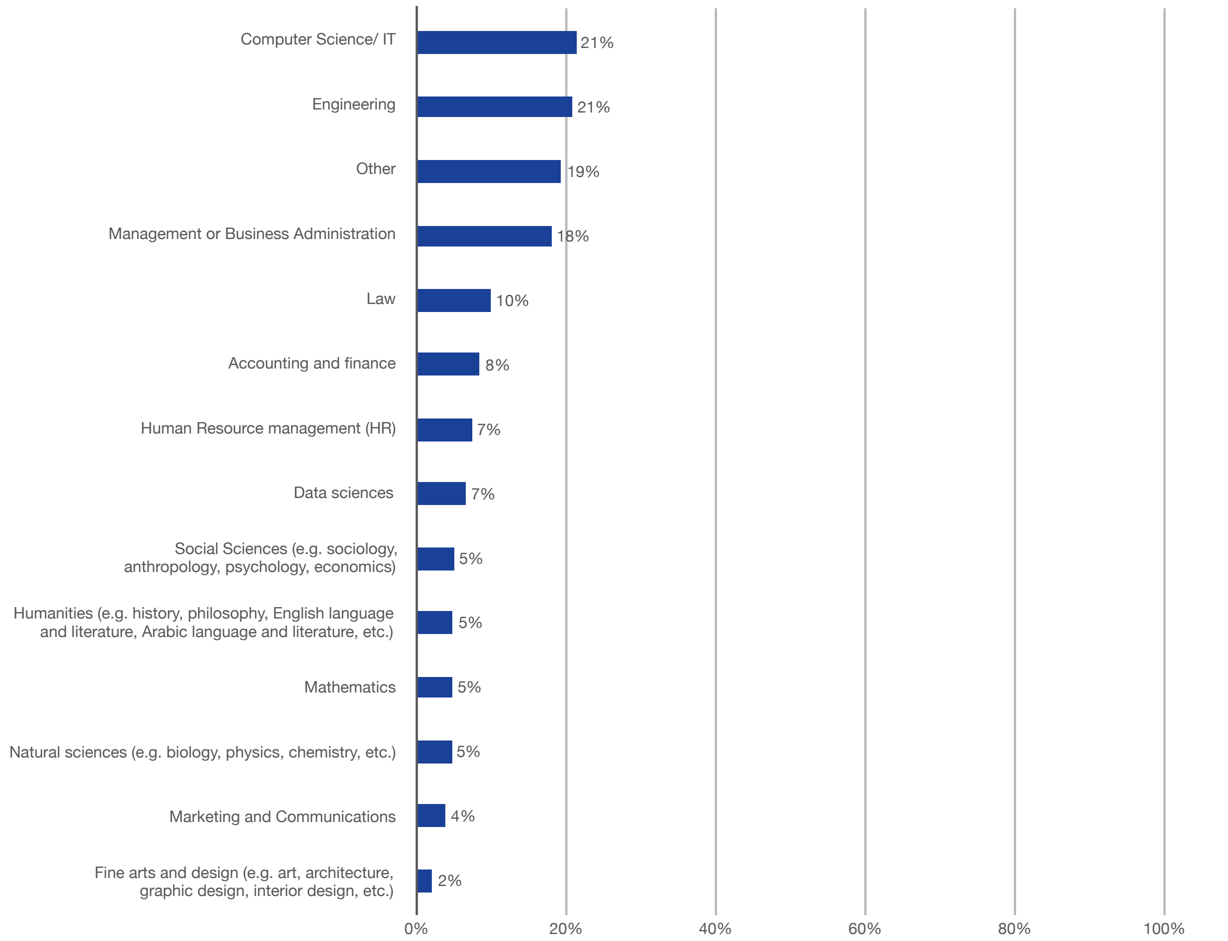
Proportion of respondents who are users vs non-users



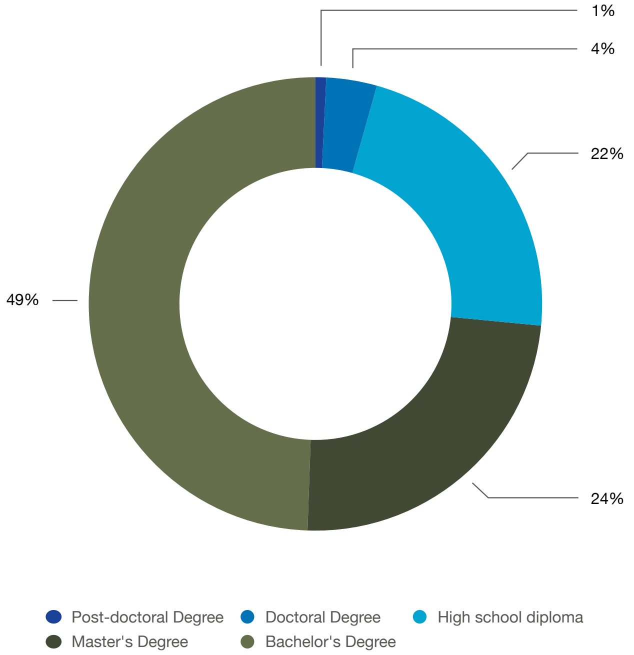
Age group of respondents



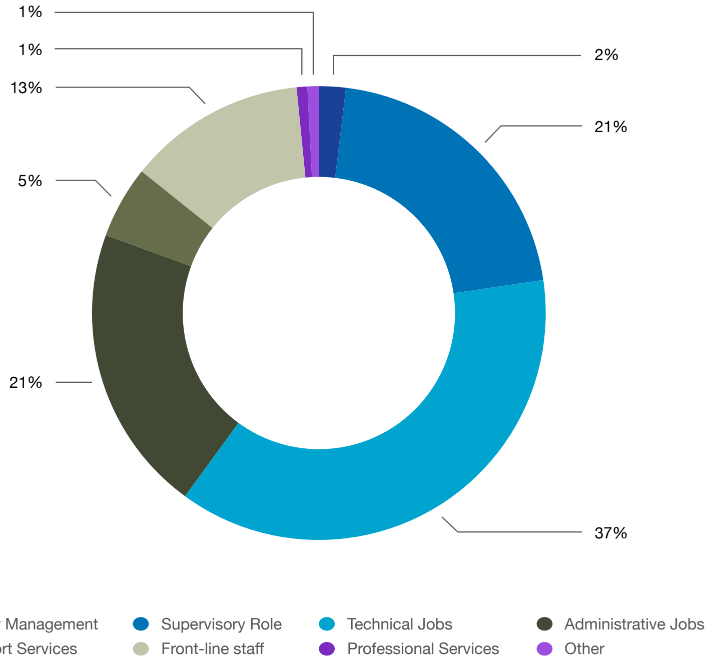
Areas of specialization (in education) of respondents



Highest education level of respondents



Organizational Role of Respondents



4. Survey Results

The sections below summarise key trends and conclusions that can be drawn from the survey results, across various dimensions regarding the adoption, perception and use of generative AI technologies.

4.1 Adoption trends

The survey found that respondents from different organizations and roles, have different levels of experience with generative AI. Only around 16% consider themselves advanced or expert users, while the majority (75%) fall into three categories: non-users or unfamiliar (36%), beginners (22%), or intermediate users (26%). This indicates that, at the time of the survey, generative AI was largely still in its early stages of adoption, both individually and within organizations.

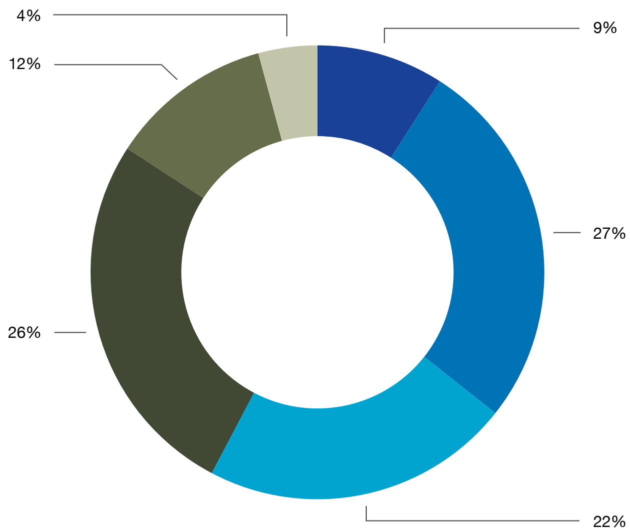
From the survey results, a connection can be observed between employees' educational specializations and their proficiency in or use of generative AI. A higher proportion of non-users are found in fields such as law, natural sciences, social sciences, humanities, and marketing and communications. On the other hand, data scientists, followed by computer scientists and engineers, demonstrate the highest levels of expertise in using generative AI. Interestingly however, a notable 21% of engineers and IT specialists have not yet utilized generative AI.

Further, survey results indicate that the extent of generative AI adoption depends substantially on an employee's job role. Positions such as customer service, legal, administration, and others have a higher proportion of individuals who are unfamiliar with or non-users of generative AI, with over 50% of respondents in these roles reporting limited or no experience. In contrast, information technology roles demonstrate a higher prevalence of advanced or expert users, with 28.8% of survey respondents in IT roles self-identifying as such.

Regression analysis on the survey results reveals a statistically significant, positive correlation between an employee's educational attainment and their proficiency in using generative AI. Individuals with higher levels of education tend to possess greater expertise in AI technologies. Specifically, each additional level of educational qualification corresponds to a 0.43 increase in the predicted level of AI expertise, as measured on a 6-point scale ranging from non-user to expert.

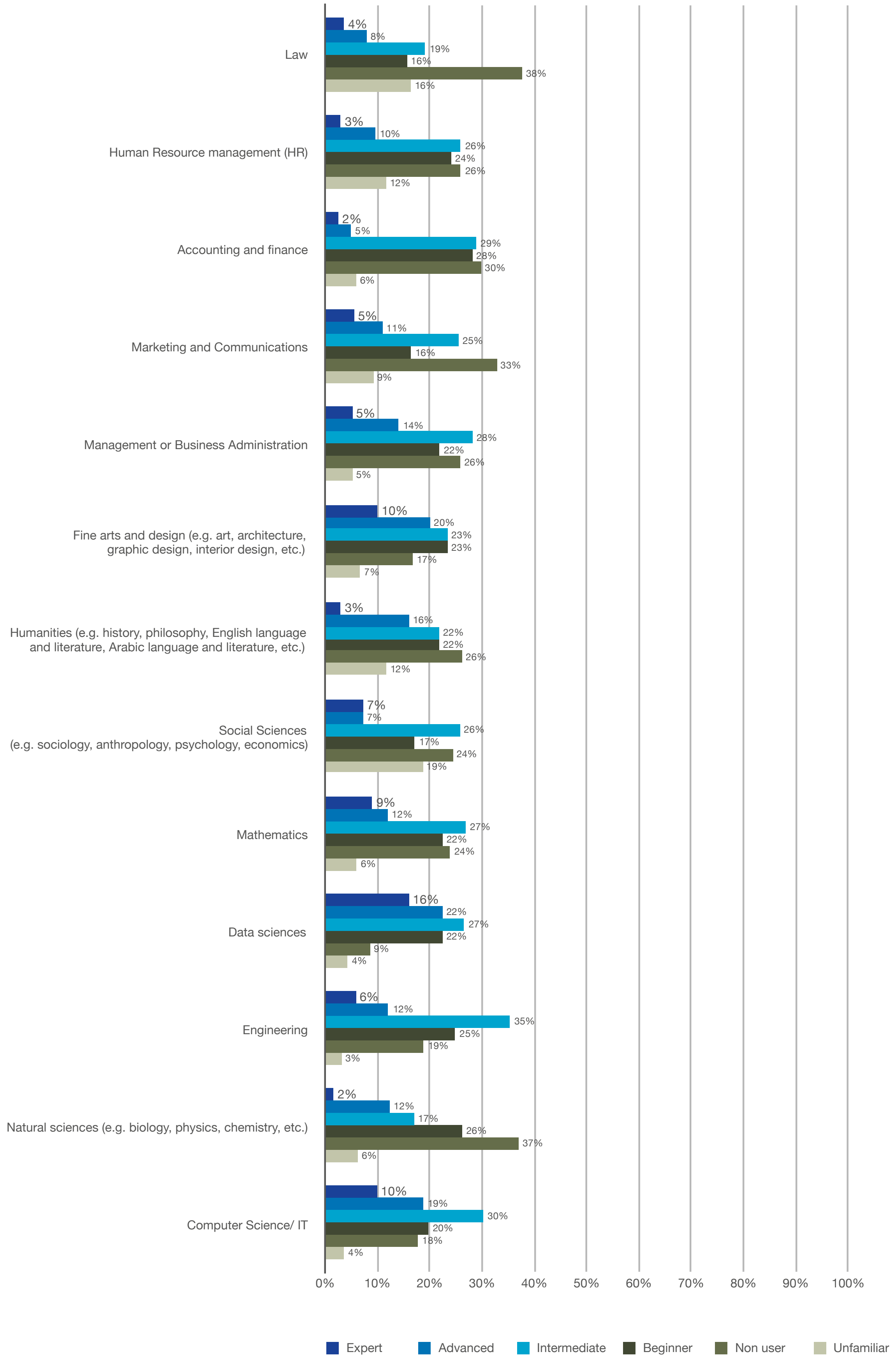
Furthermore, seniority within an organization, which is strongly correlated with higher educational attainment and age, emerges as another significant predictor of AI expertise. Employees holding senior positions are more likely to exhibit advanced levels of AI knowledge and skills. In conclusion, factors such as work seniority, educational qualifications, and organizational roles seem to play a crucial role in shaping an individual's proficiency in generative AI.

Composition of respondents by expertise level

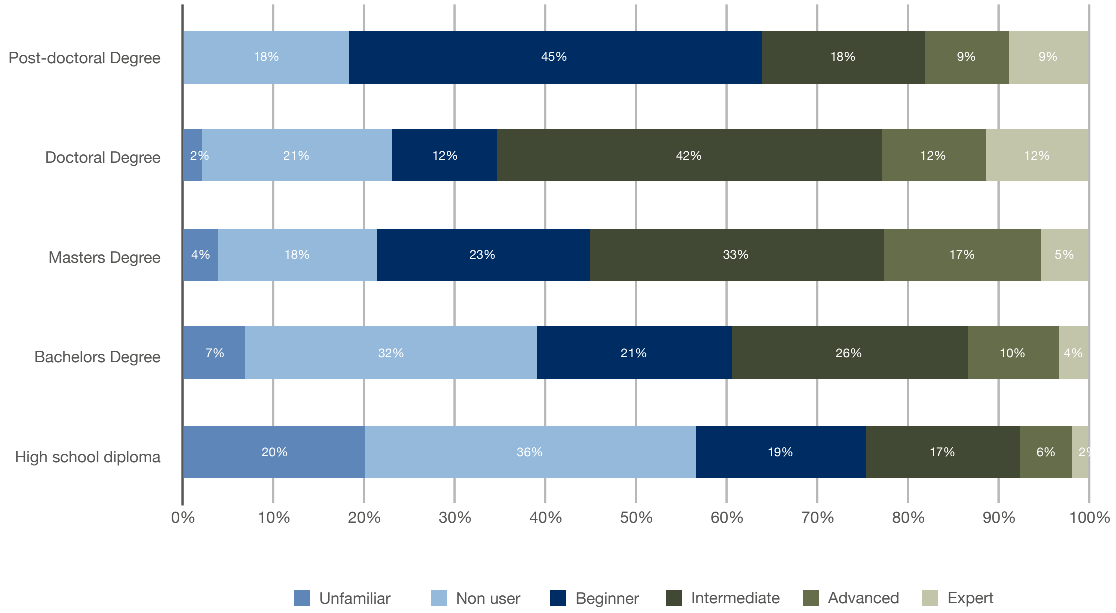


- Unfamiliar: I don't know what Generative AI is, and have never used it.
- Non-user: I have heard about Generative AI tools, but have never used them.
- Beginner: I have experimented with Generative AI tools but don't fully understand how to get the outcomes I want.
- Intermediate user: I use Generative AI tools regularly, am comfortable using their various features and understand how to get the desired outcomes.
- Advanced user: I use and customize Generative AI tools to achieve a desired outcome. I understand the limitations and biases inherent in the tools I use.
- Expert: I have mastered Generative AI tools I use; I have a deep understanding of their underlying mechanisms and can integrate them into broader systems or workflows. I am able rectify their biases when necessary

Expertise level of respondents by specialization in education



Expertise levels by highest educational qualification

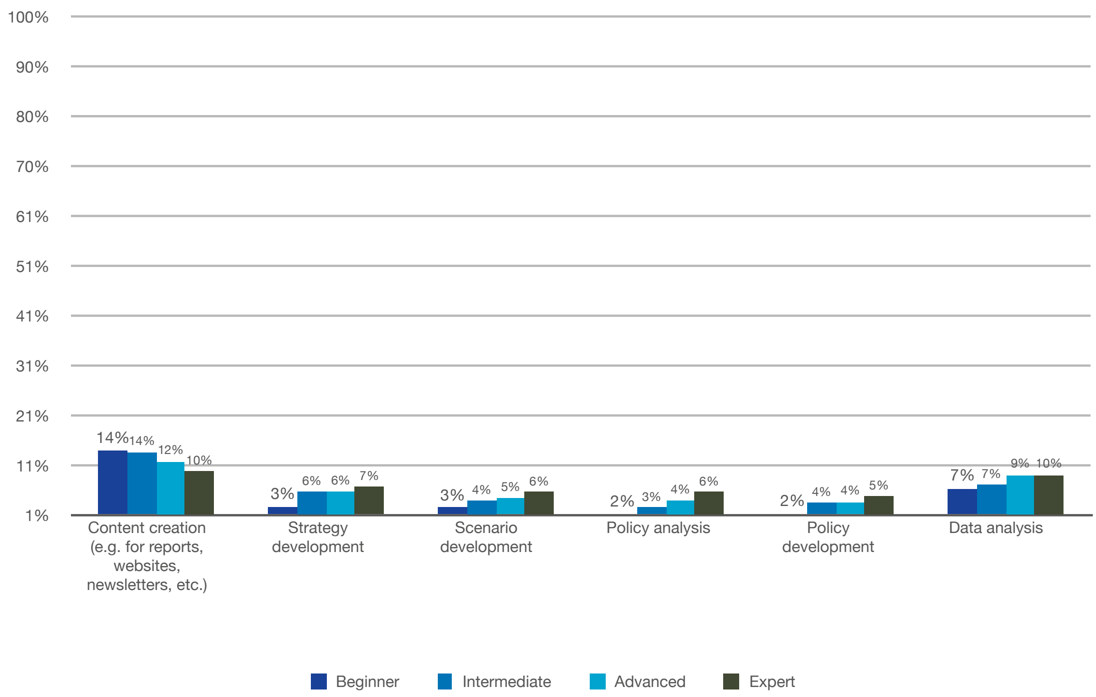


4.2 Usage trends

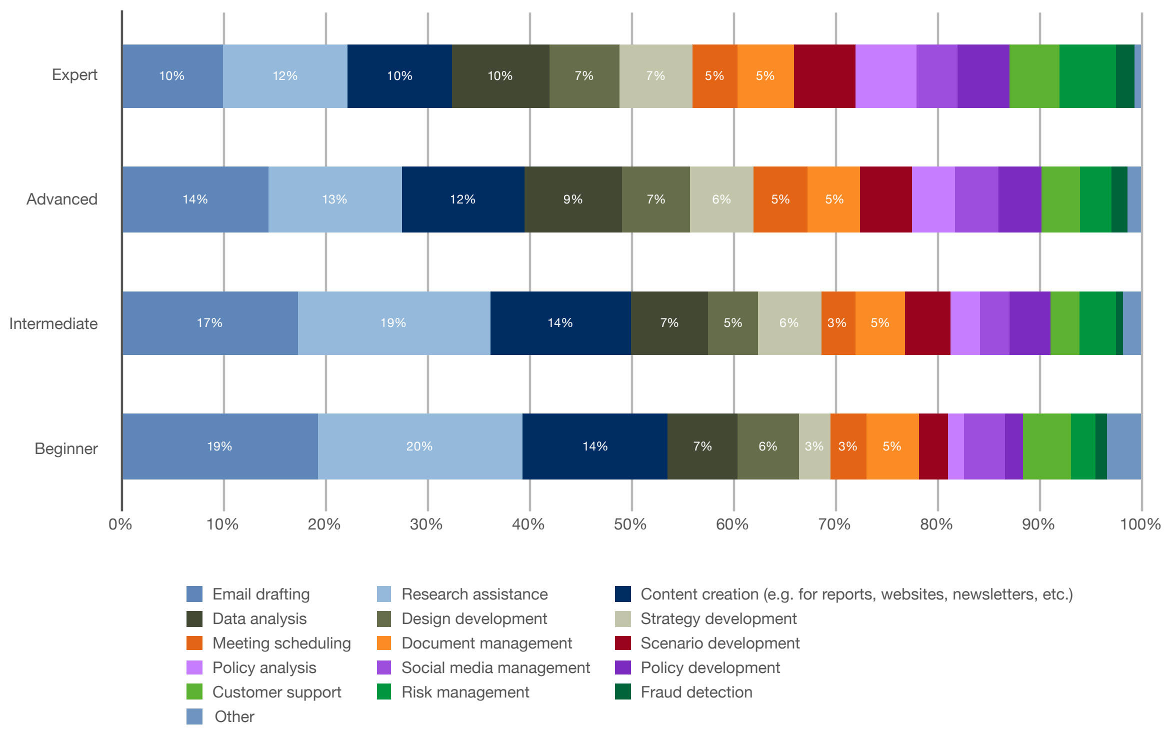
Use cases and trends for which generative AI technologies are leveraged vary significantly based on the respondent's level of expertise. Overall, survey respondents primarily utilize generative AI for email drafting, content creation, and research assistance. However, as user expertise increases, the proportional use of generative AI tools for such common applications decreases. For instance, while beginners frequently employ AI for content creation - which can be achieved with simple prompting skills and conversational language - experts utilize it less frequently for this purpose. As another example, beginners report using generative AI for research assistance around 20% of the time while experts use generative AI for the same purpose only 12.4% of the time.

This shift can be attributed to the expanding range of tasks for which advanced and expert users leverage generative AI. Advanced users are more likely to harness the technology for sophisticated applications and novel use cases such as data analysis, risk management, policy development, and scenario planning. Advanced and expert users are better equipped to leverage their awareness of potential risks and mitigation strategies, and their advanced prompting skills to utilize generative AI for niche use cases. This indicates that as expertise grows, users become better equipped to exploit generative AI for more diverse, complex and specialized tasks. Advanced and expert users are better equipped to craft complex prompts and are more aware of potential risks and mitigation strategies, enabling them to exploit generative AI for a wider range of specialized tasks.

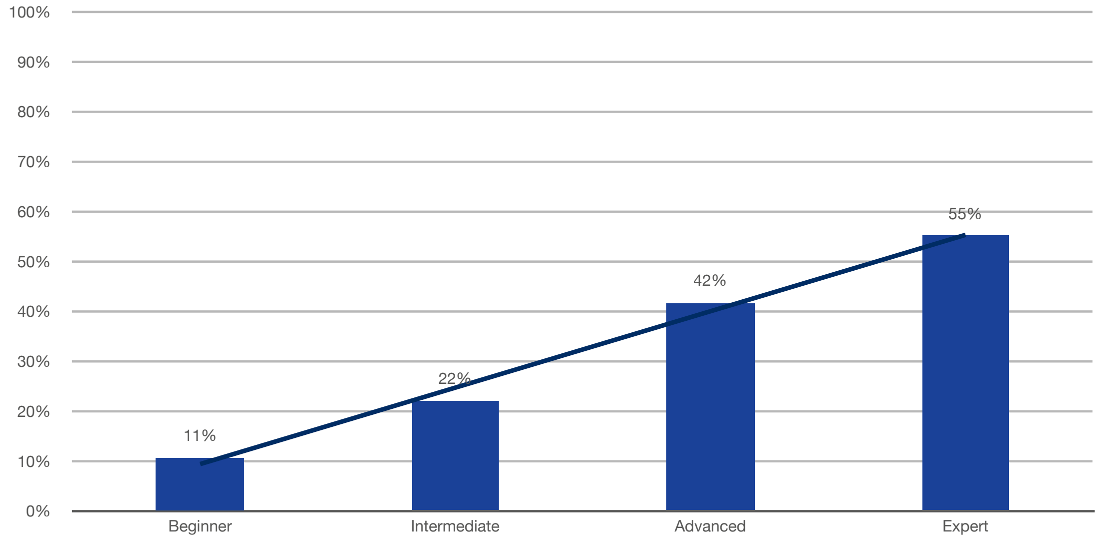
Some usecases with clear usage differences by expertise



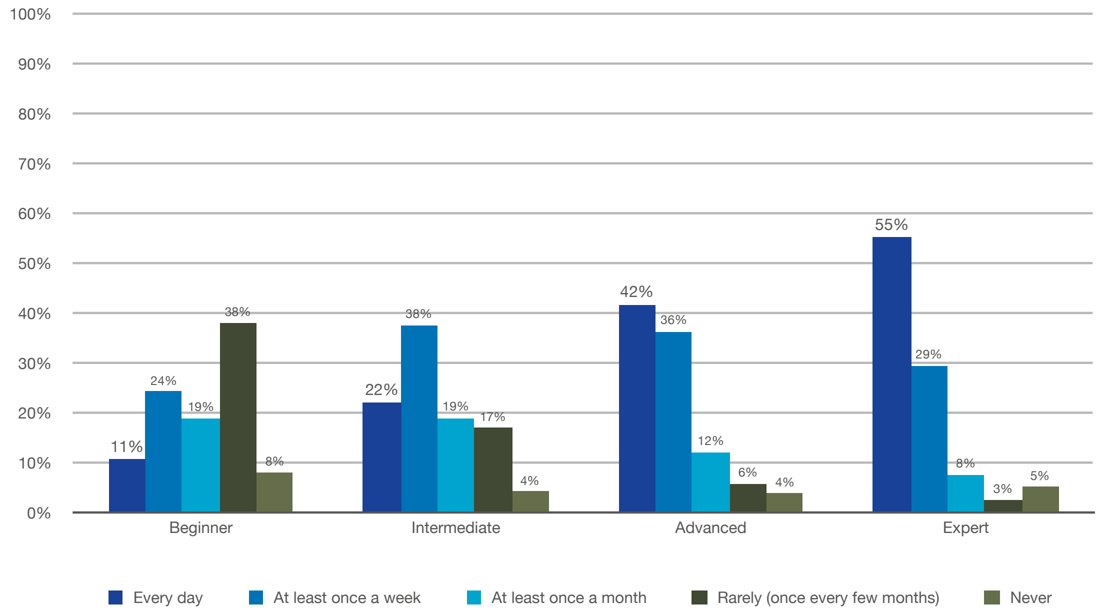
Usecases for generative AI applications by expertise

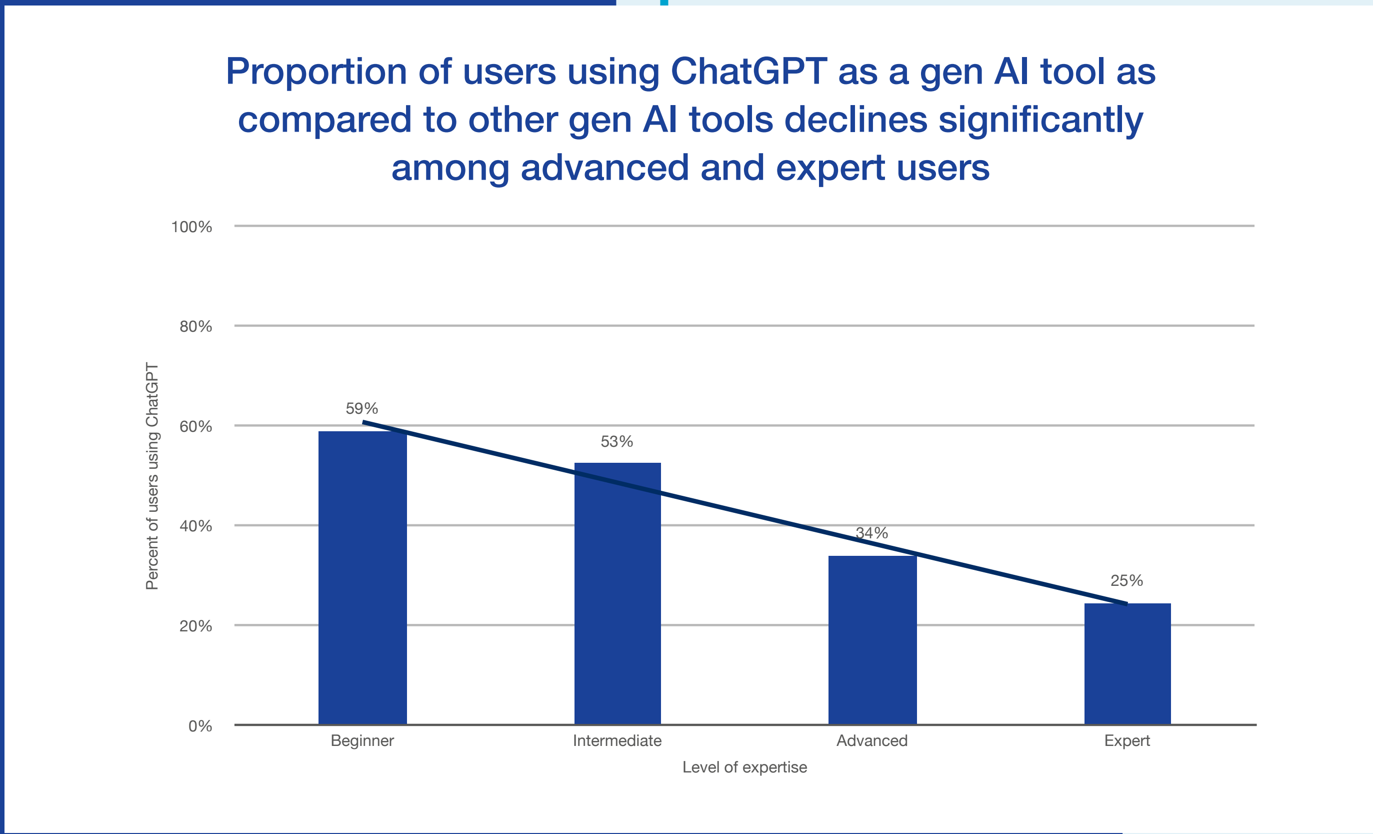


Likelihood of using gen AI tools everyday at work increases by expertise level



Frequency of use of gen AI tools increases with expertise





4.2.1 Generative AI Usage and Expertise

A strong positive correlation exists between generative AI expertise and frequency of use. Expert users, over half of whom use the technology daily, also leverage generative AI for a wider range of applications and are more adept at identifying and addressing potential issues. They also report a broader spectrum of benefits compared to less experienced users.

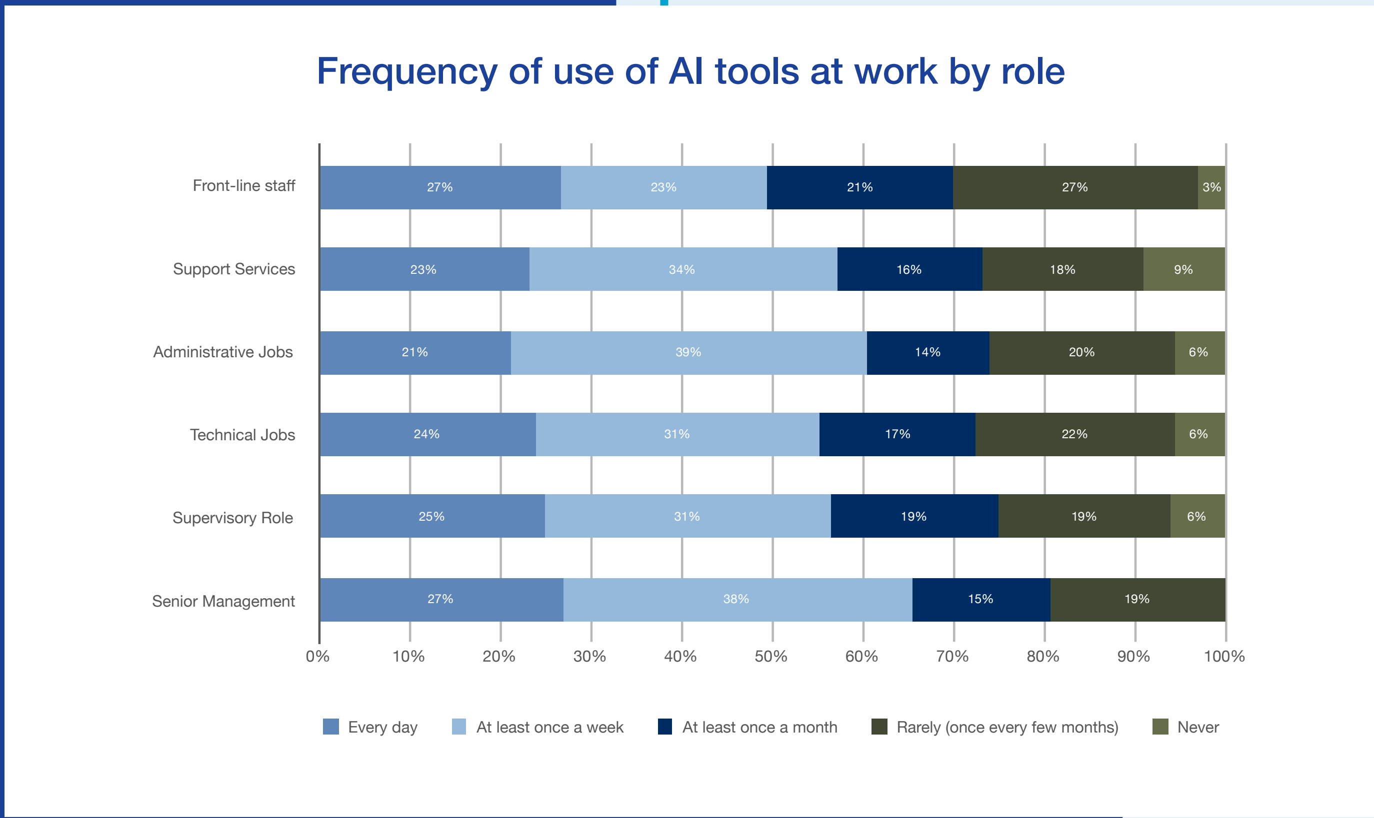
Regression analysis confirms that expertise level is a statistically robust predictor of generative AI usage frequency, with higher expertise predicting more frequent utilization.

4.2.2 Tool Preferences and Organizational Roles

ChatGPT is the most popular generative AI tool among beginner users, likely due to its user-friendly interface and advanced text generation capabilities. However, as users become more experienced, they tend to diversify their tool choices and are likelier to leverage tools like Midjourney and Meta AI.

For beginner users, the most frequently used generative AI application is ChatGPT, followed by Google Bard (which was later rebranded as Gemini), Microsoft 365 Copilot tools, and Microsoft Bing Chat.

Senior organizational roles are associated with higher rates of generative AI usage. Over 64% of senior managers utilize generative AI tools at least weekly. Administrative, support services, supervisory, and technical staff also demonstrate significant adoption rates, with over 50% using the technology weekly.

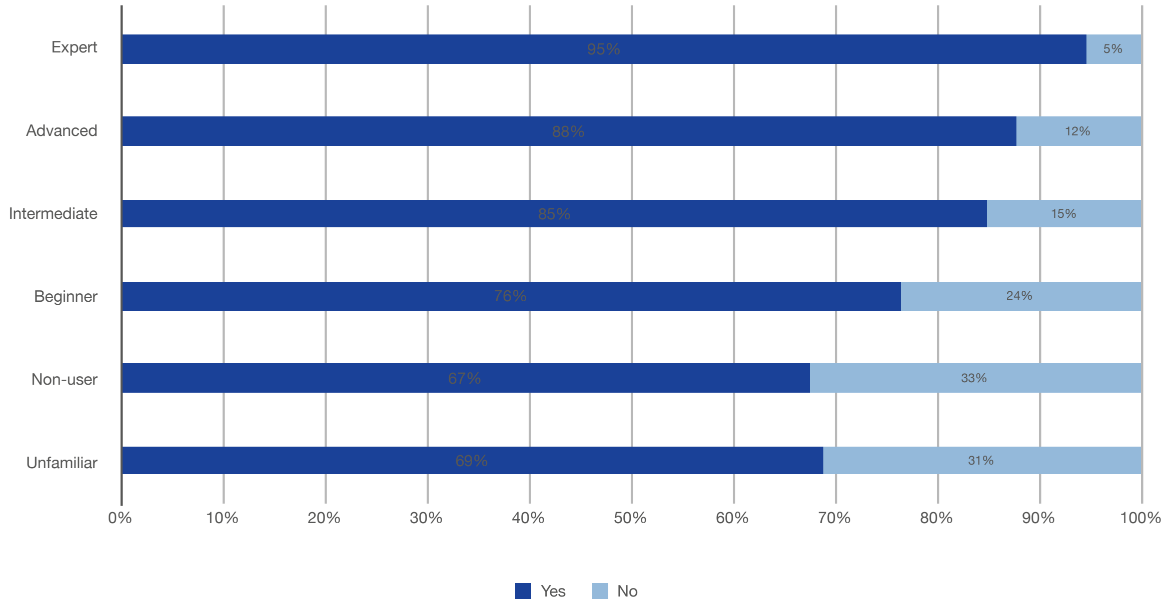


The table below shows the leading uses of generative AI among advanced and expert users. Both categories of users use generative AI most frequently for text generation, but the next most frequent use cases vary, as the table below shows.

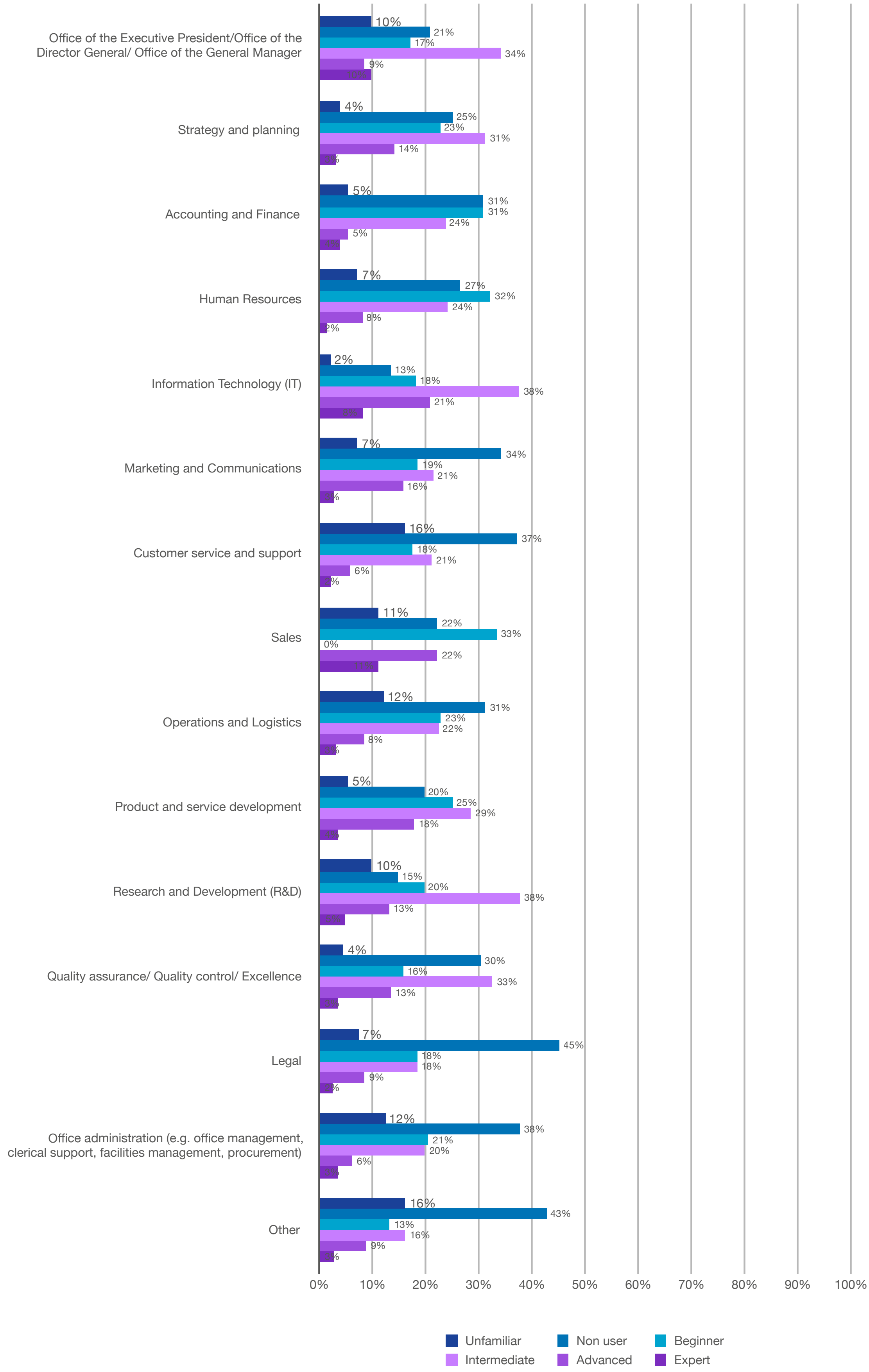
Advanced Users	Expert users
Text generation (22.45%)	Text generation (15.5%)
Image generation (12.5%)	Data synthesis (12.56%)
Text to speech generation (9.9%)	Code generation/completion/review/bug fixes (10.55%)

Most respondents, across expertise levels, self-identify as early adopters of technology. Even most non-users and those unfamiliar with AI self-report as early adopters of technology (67.4% and 68.8% respectively), while a significantly higher proportion (87.8% and 94.8%, respectively) of advanced and expert users consider themselves as early adopters. A strong positive correlation also exists between self-reported early adopter status and self-reported expertise level. Early adopters tend to report higher levels of expertise; on average they report a level of expertise that is 0.609 levels higher as compared to non-early adopters.

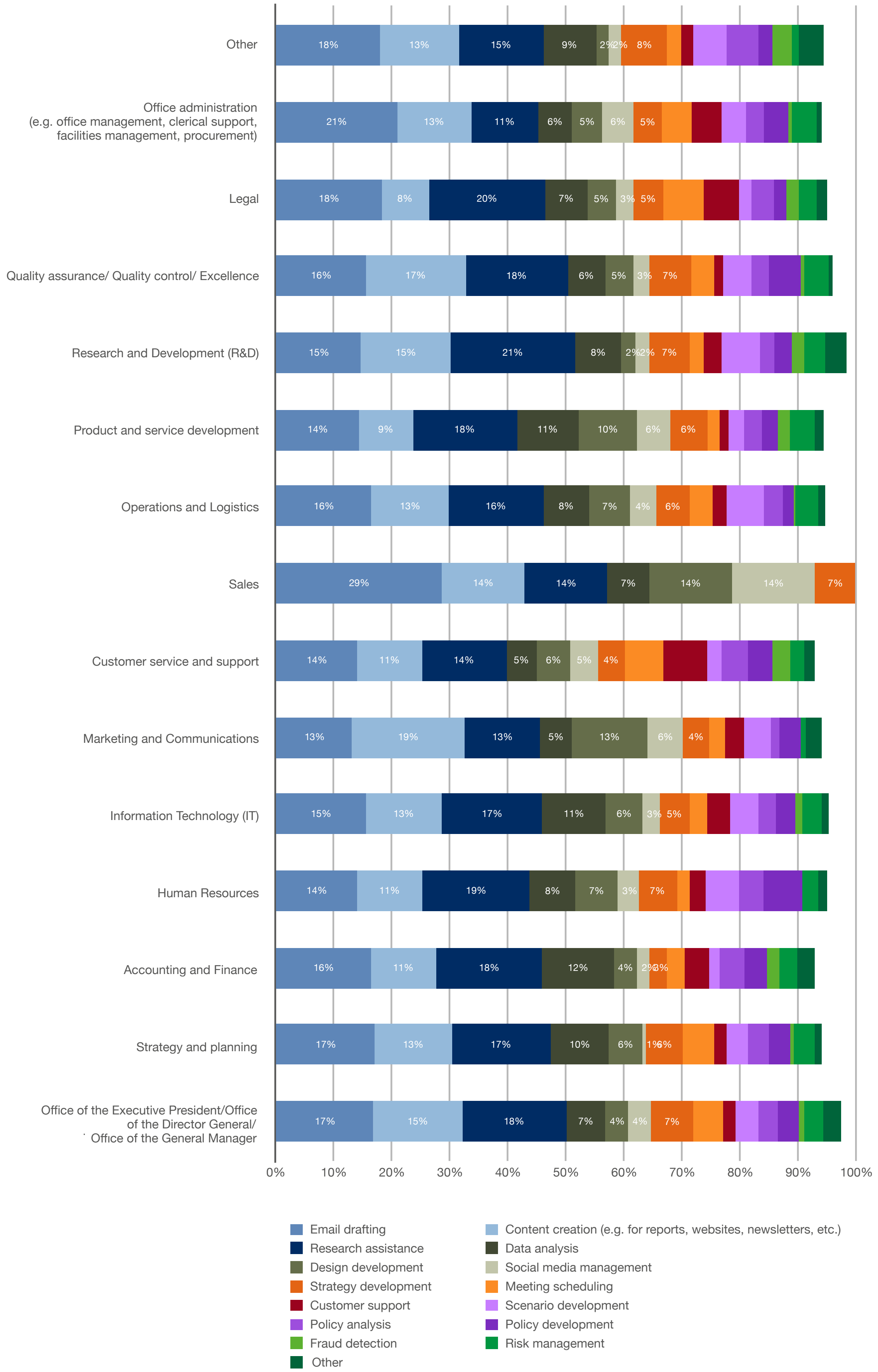
Do you consider yourself an early adopter of technology?



Expertise in gen AI by organizational role



Uses of Gen AI vary across organizational roles

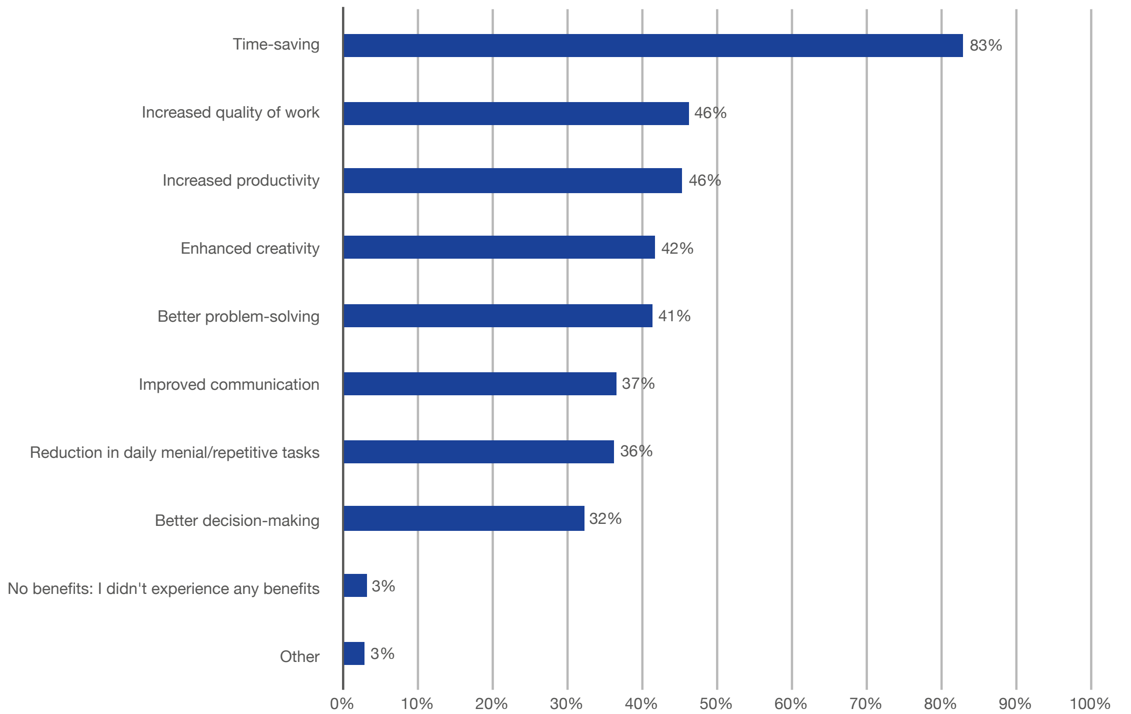


4.3 Benefits and Impact of generative AI

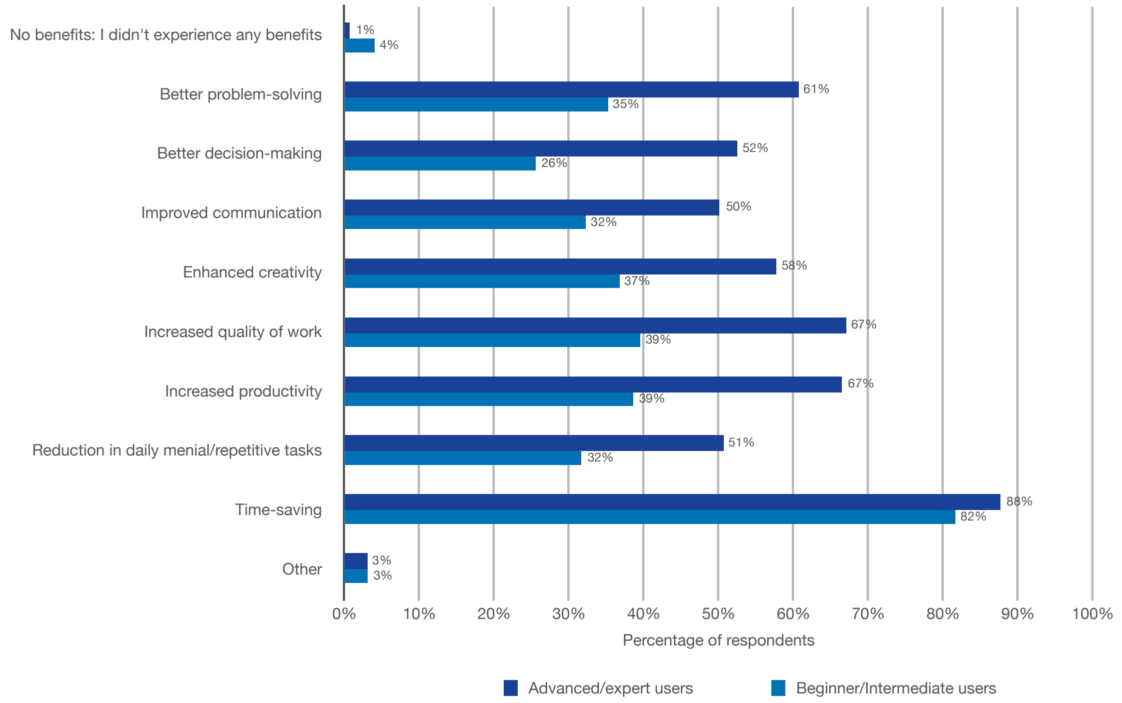
Most respondents across organizational roles and departments, reported experiencing significant or at least some benefits from generative AI (87%), including saved time, improved work quality, enhanced creativity, and problem-solving abilities. The consistency in reported benefits across diverse organizational contexts suggests that generative AI technology is assisting government employees in the bureaucratic elements of their daily jobs. Advanced and expert users consistently reported a broader range of benefits, likely due to their deeper understanding and more frequent use of the technology. This suggests that as users become more proficient in using generative AI, they have been able to unlock a greater range of its potential applications.

There is a consensus that generative AI has the potential to at least somewhat or even significantly benefit government operations, with just 6.5% respondents expressing concerns about potential harm. However, beginner users expressed more uncertainty about its impact, suggesting that familiarity with the technology may influence their confidence in its potential for impact.

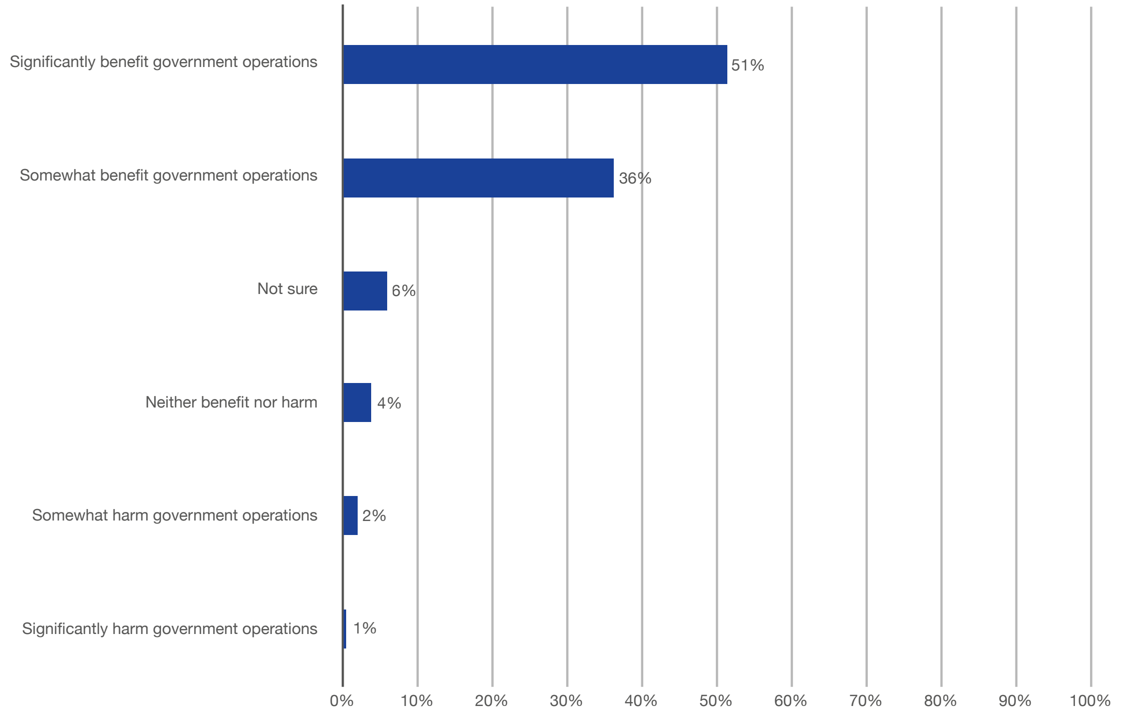
Benefits of Generative AI in daily tasks: What are the main benefits you have experienced as a result of using Generative AI in your day-to-day tasks?



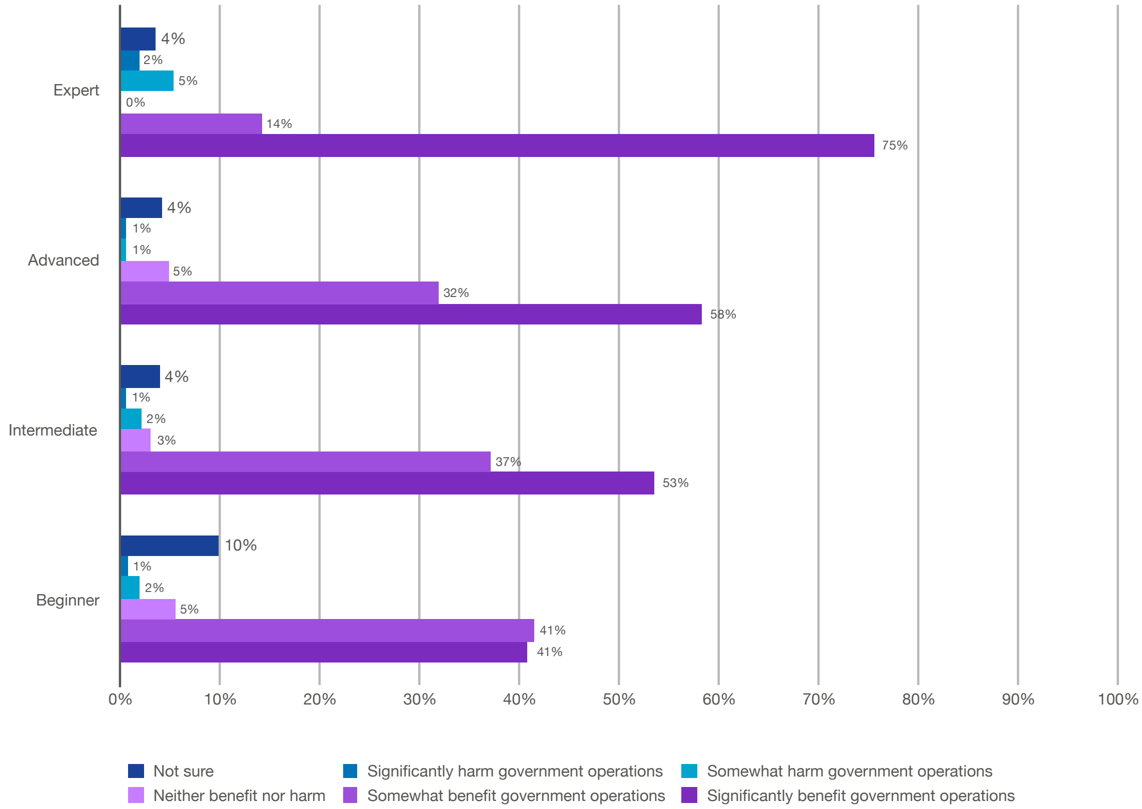
Benefits of Generative AI in daily tasks by expertise level



Impact of Generative AI on Government Operations: What kind of impact do you think Generative AI applications might have on government operations?



Users with more expertise are more confident that generative AI will benefit government operations



4.4 Concerns and issues related to generative AI

The most common concern among government employees using generative AI is the accuracy of outputs (reported by 40% of the users). This issue is prevalent across all expertise levels, departments, and roles, though it is more pronounced among advanced and expert users who may be more exposed to or aware of potential inaccuracies. This highlights the need for continued development of generative AI models to improve their accuracy and reliability.

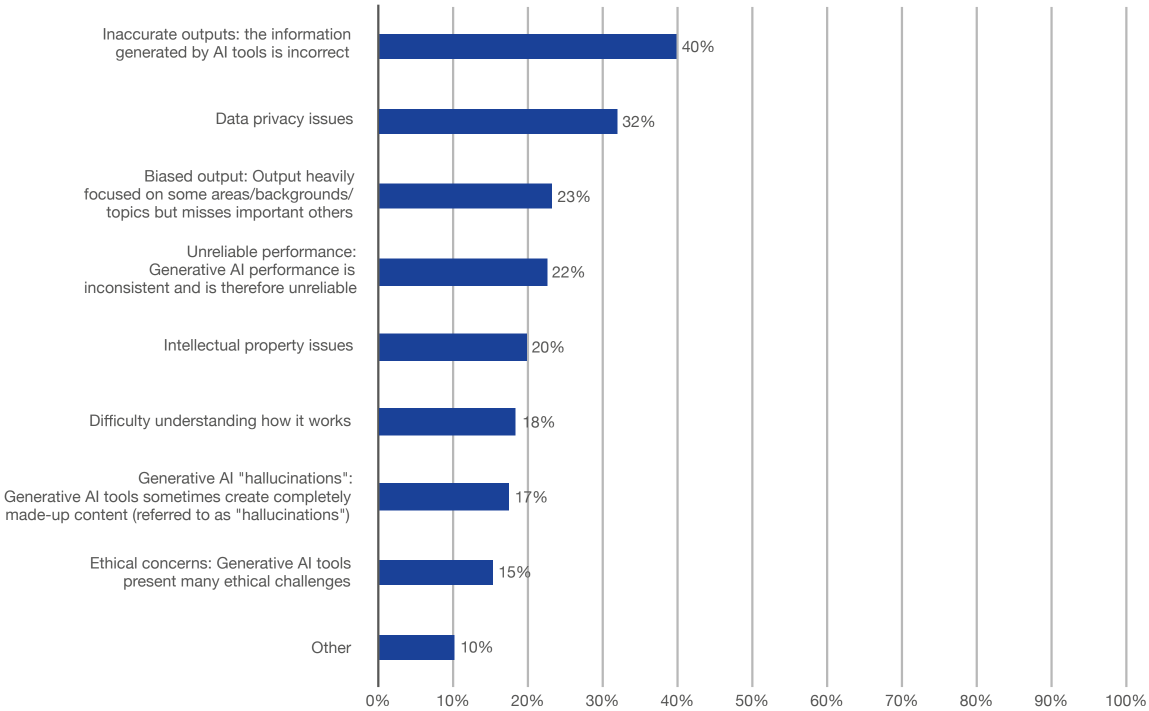
Other prevalently reported concerns include data privacy, biased outputs, and unreliable performance.

Data concerns, relating to limited data quality, availability, and representativeness of data in the use of generative AI tools emerged as most frequently reported concern, reported by more than 50% of users. These issues appear to be inherent to current generative AI technology. To address these challenges, organizations should prioritize raising employee awareness about the limitations of using generative AI, the importance of human oversight, and the ethical considerations associated with its use.

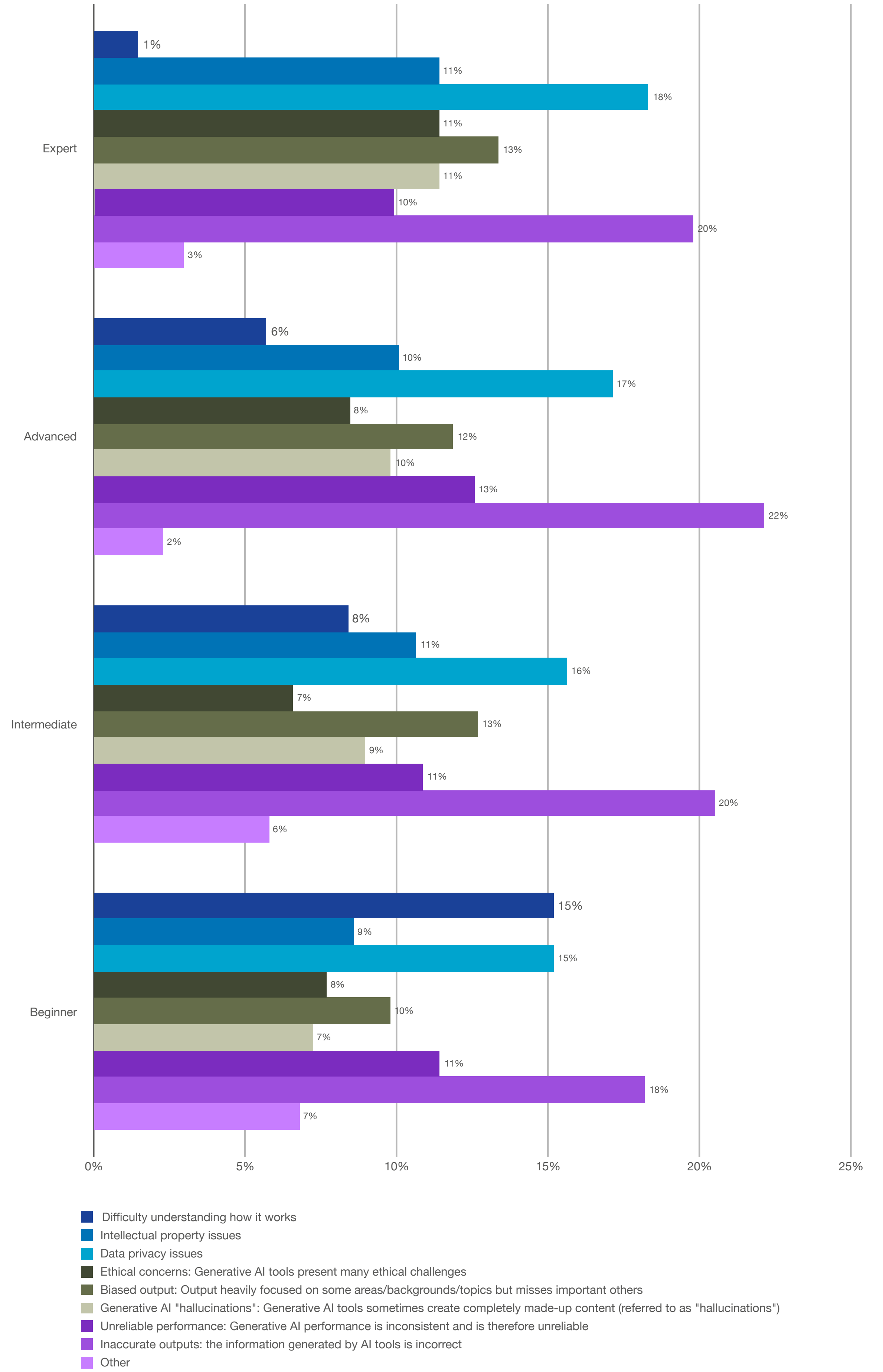
Users with different expertise levels, and in different organizational roles, face different challenges. Beginners often struggle with understanding the basic functioning of generative AI tools, highlighting the need for targeted training and support initiatives for them. Advanced and expert users, on the other hand, are more likely to identify complex issues such as ethical implications, performance reliability issues and data privacy risks as key challenges. This suggests that as users become more proficient, they are better equipped to identify potential issues associated with generative AI. Perhaps training programs should differentially cater to users of different expertise levels within an organization, instead of following a generic one-size-fits-all curriculum, to address the specific challenges they face based on their incumbent level of expertise and to further their expertise per the needs of that level.

Across organizational roles, a significant proportion of front-line staff (18.2%), professional services workers (17%), administrative staff (14%), and support services personnel (13%) reported difficulty understanding how generative AI works. This suggests a need for targeted training to equip these employees with the necessary knowledge and skills to effectively use or monitor generative AI systems. Since these roles are highly likely to be exposed to the impacts of automation or augmentation by generative AI, training personnel to leverage, monitor to reskill is important to minimize adverse effects of generative AI exposure in their lines of work.

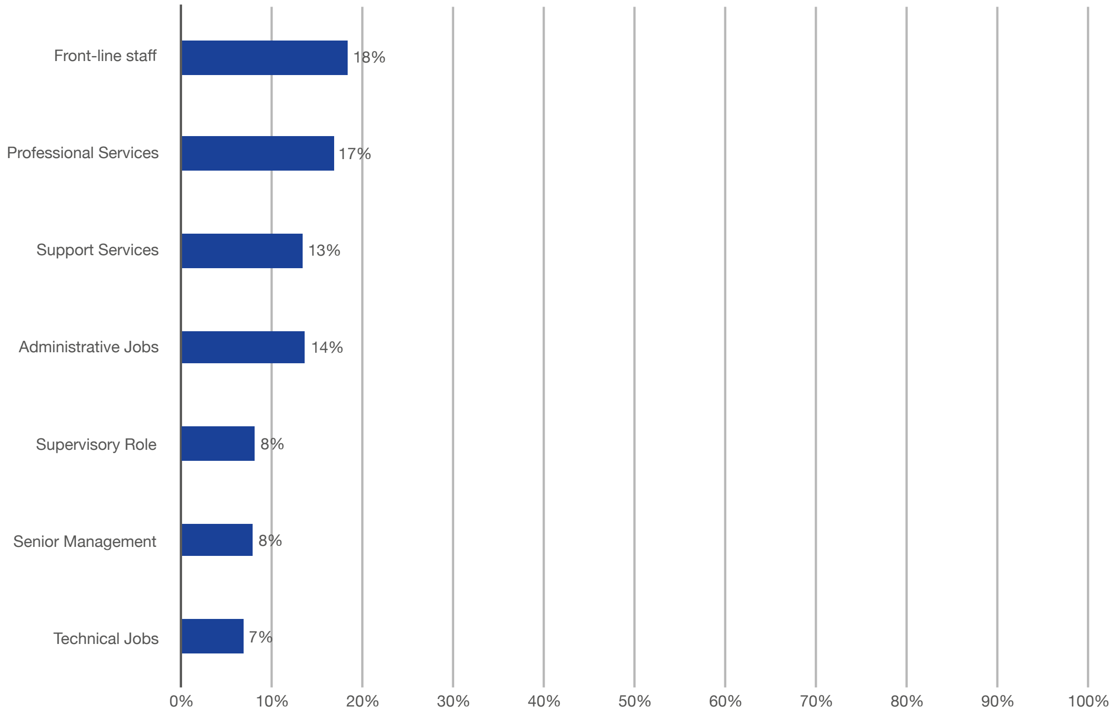
Issues of Generative AI at Work: Have you encountered any of the following issues when using Generative AI tools in your work?



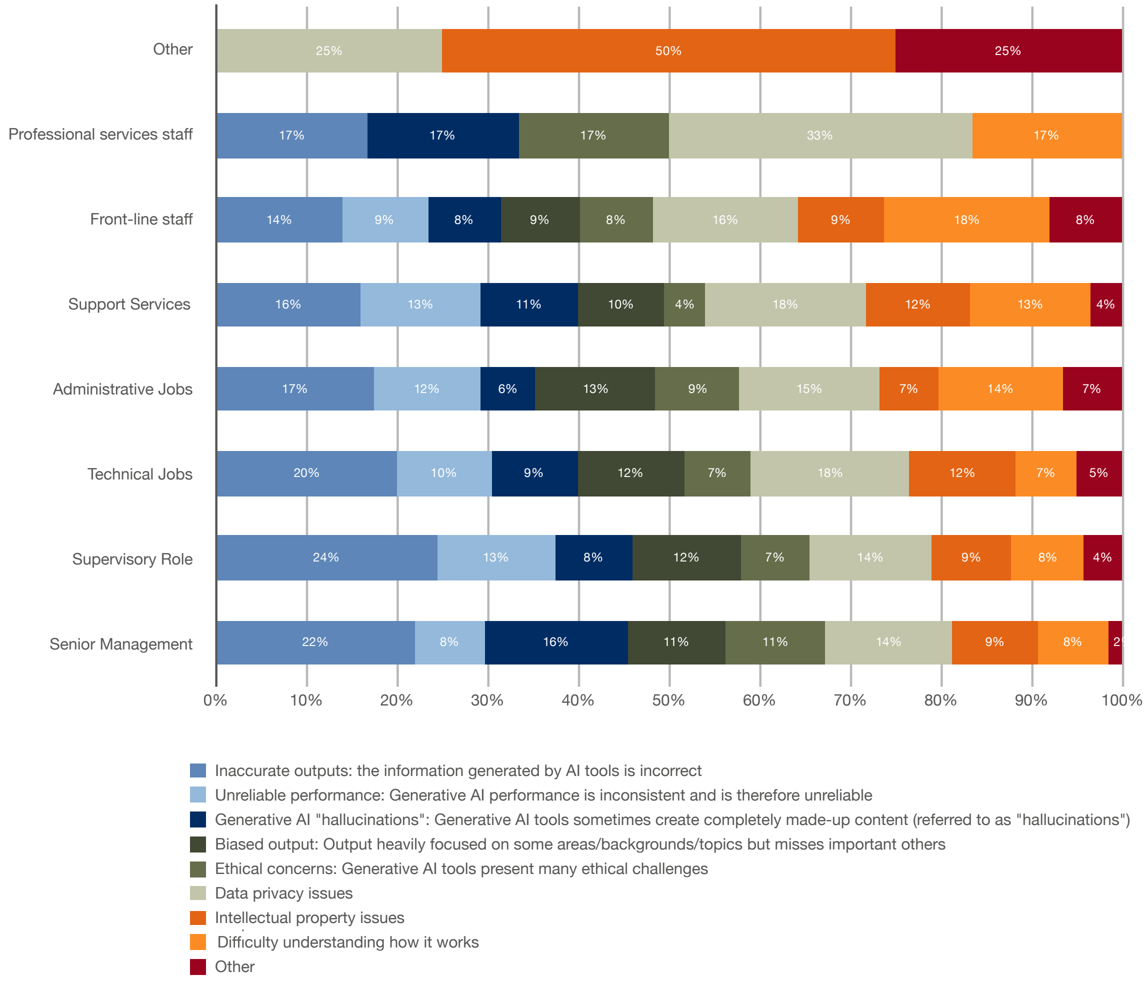
There is a variance in frequency of different issues reported as expertise increases



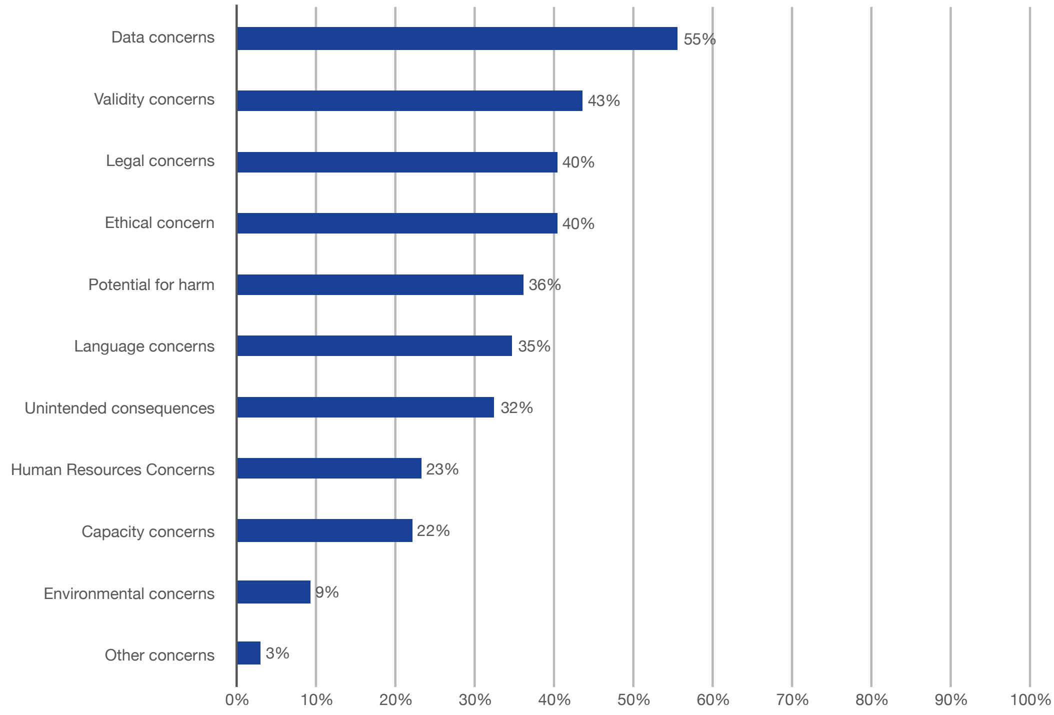
Users reporting difficulty understanding how gen AI tools work, by organizational role



Issues faced by respondents in different roles



Concerns: Do you have any concerns regarding using Generative AI applications (e.g. ChatGPT, Bard, etc.)?



Concerns Regarding Generative AI

Respondents identified several key concerns related to the use of generative AI applications, and concerns reported varied across roles and departments. Generally, data quality, availability, and representativeness emerged as the most significant issues, reported by over 50% of users. Concerns about the validity, legal implications, and ethical ramifications of generative AI followed closely, cited by more than 40% of respondents.

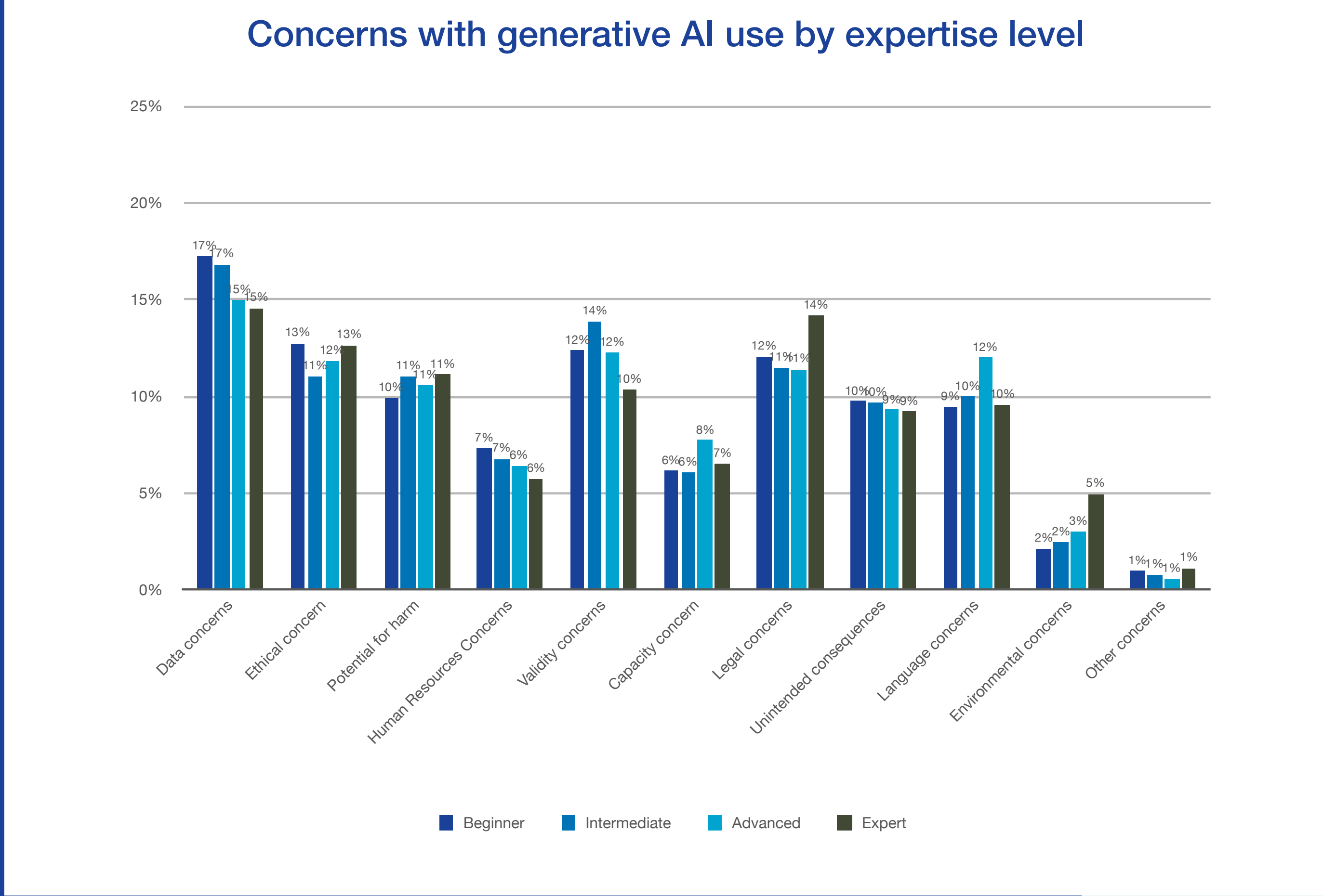
Interestingly, only about 23% of respondents expressed concerns about the potential impact of generative AI on employment or job security. However, employees in customer service, sales, legal, administrative, and front-line roles were more likely to report such concerns, indicating a greater perceived vulnerability to automation or augmentation in these areas.

The survey data revealed varying concerns across different roles and departments, reflecting the different accountabilities of employees in different roles. Research and operations departments were more likely to cite issues related to data availability and representativeness, while quality assurance departments were more concerned with ethical implications. Marketing and legal teams expressed greater worries about the potential for misinformation, and senior management and supervisory roles were more likely to raise legal concerns.

An important concern that was *not* recognized by most employees, was related to the environmental impact of generative AI technologies, indicating a general lack of awareness regarding the substantial energy consumption and associated environmental consequences of running these applications.

Specifically, less than 3.5% of senior management and 1.55% of supervisors identified environmental issues as a concern. Among users of generative AI, only 2% of beginners and intermediate users, 3% of advanced users, and 5% of experts expressed concern about environmental impacts.

Given the increasing importance of environmental sustainability goals for governments and businesses, however, it is crucial to educate employees, particularly leaders, about the significant environmental impacts of generative AI. This knowledge will empower them to make informed decisions and adopt sustainable practices while considering the use of this technology.



A. Job displacement concerns and generative AI

While most employees are at least somewhat concerned about the potential of generative AI to replace or significantly impact human jobs, a significant portion of respondents, approximately 38%, expressed no concern about this.

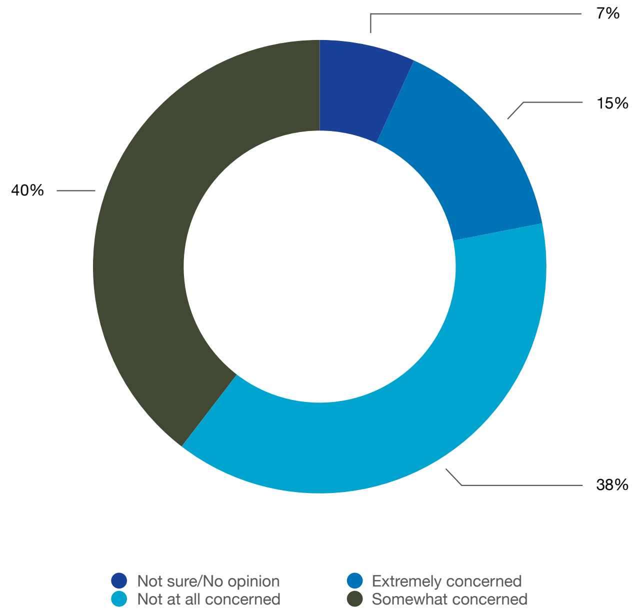
It is noteworthy that advanced and expert users, as well as individuals in senior organizational roles and with higher levels of education, were particularly *less* concerned. This may be attributed to their confidence in their ability to leverage generative AI to augment their productivity and maintain their relevance in the job market, which may cause them to not be concerned about the impact of generative AI on *their* own jobs. But it may also be attributed to their potential belief that generative AI may not as significantly affect the job market in the future as is predicted by the current generative AI hype cycle.

In general, higher levels of education correlated with lower levels of concern about job displacement.

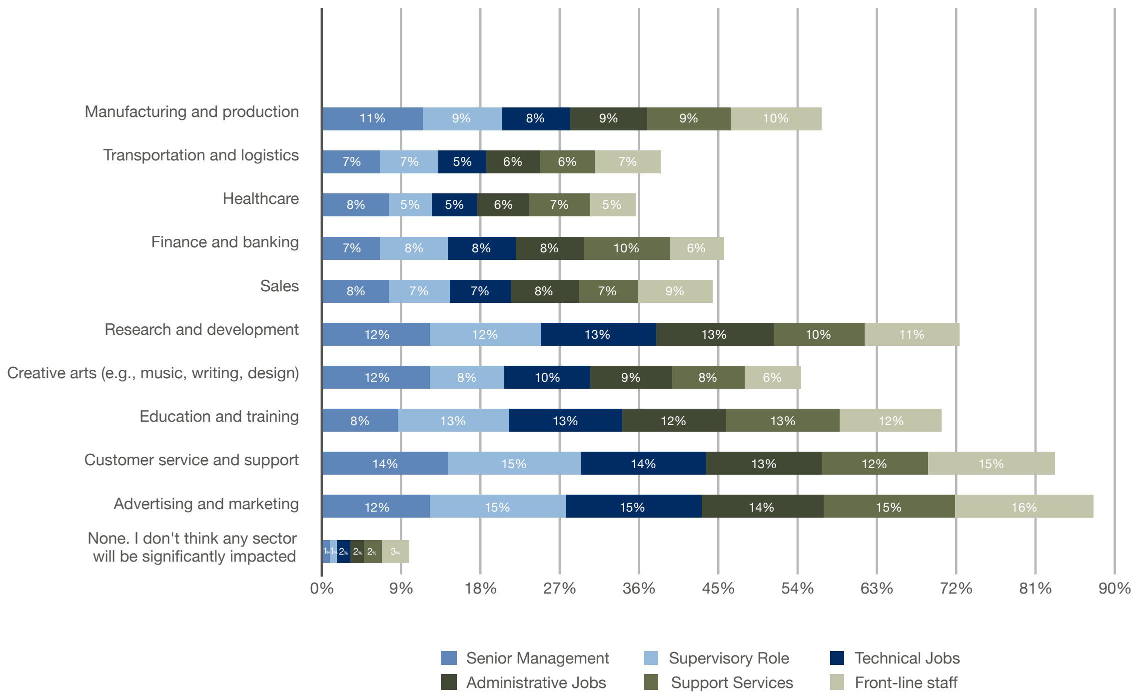
While over half of non-users expressed some concern about job loss due to generative AI adoption, the intensity of these concerns was moderate. Similar percentages of both users and non-users expressed concerns: 17% of non-users were extremely concerned, and 37% were somewhat concerned, comparable with 15% and 40% of users respectively.

When asked about the industries most likely to be impacted by generative AI, respondents identified advertising and marketing, customer service, and research and development as the top three sectors. The reasons for their specific choices of these industries needs further investigation.

Jobs and Generative AI: How concerned are you about the potential of Generative AI to replace or significantly alter human jobs in the near future?



Which sectors do you think will be most impacted by generative AI?



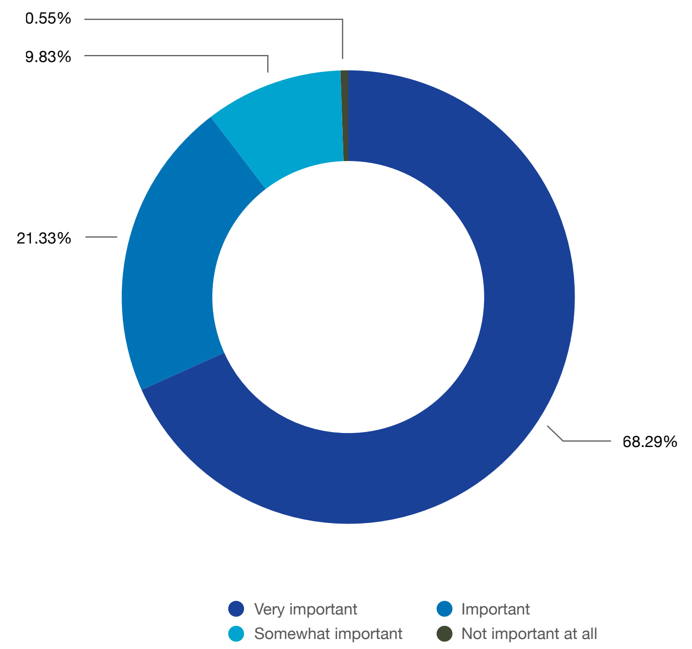
4.5 Skills and training related to generative AI

A vast majority of users (89.6%) of generative AI agree that it is important for government employees to develop skills to use generative AI tools effectively.[2]

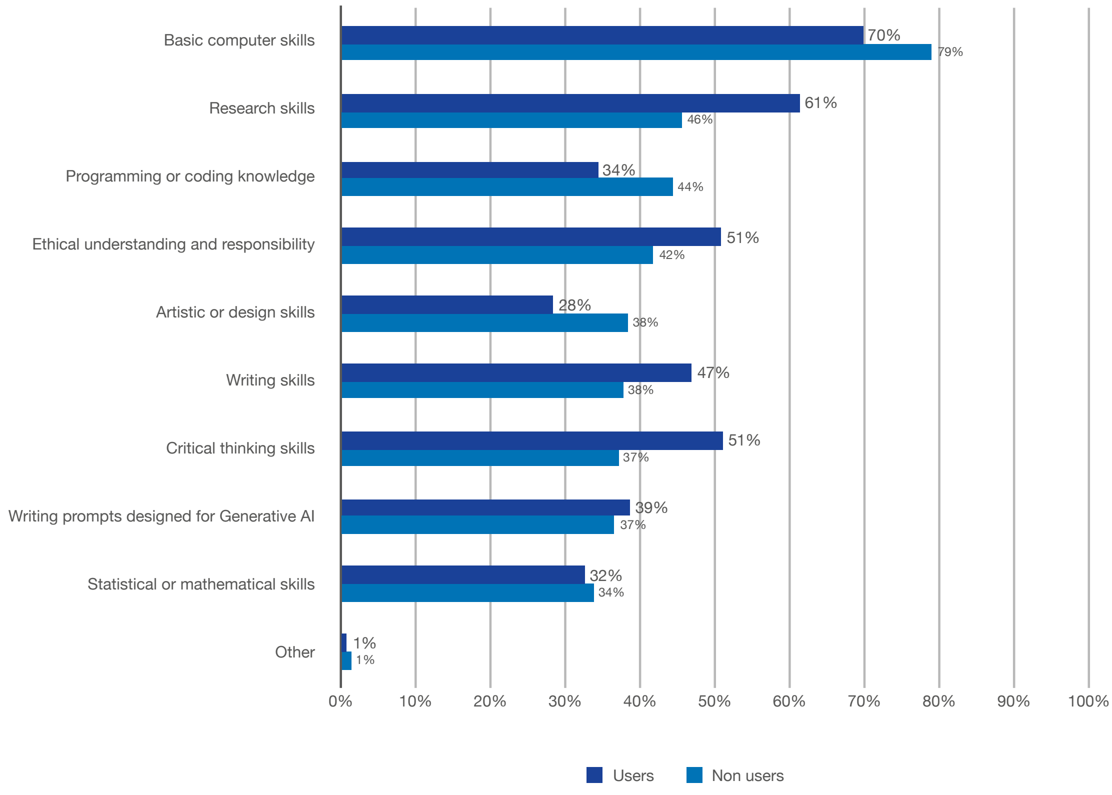
Interestingly, there's a notable discrepancy between user and non-user perceptions of essential skills. While both users and non-users agree that basic computer skills are essential to leverage generative AI tools, they differ on what other skills they deem as important.

Users of AI recognize that beyond basic computer skills, research skills, ethical understanding, writing, and critical thinking skills are all important to effectively leveraging generative AI. Non-users, on the other hand, think to a greater extent that programming or coding knowledge is important, with 44% of non-users believing this in comparison to only 34% of users. 38% of non-users also seem to think that artistic or design skills are important, in contrast with only 28% of users who think so. These discrepancies highlight the evolving nature of skill requirements as users progress in their understanding and application of generative AI.

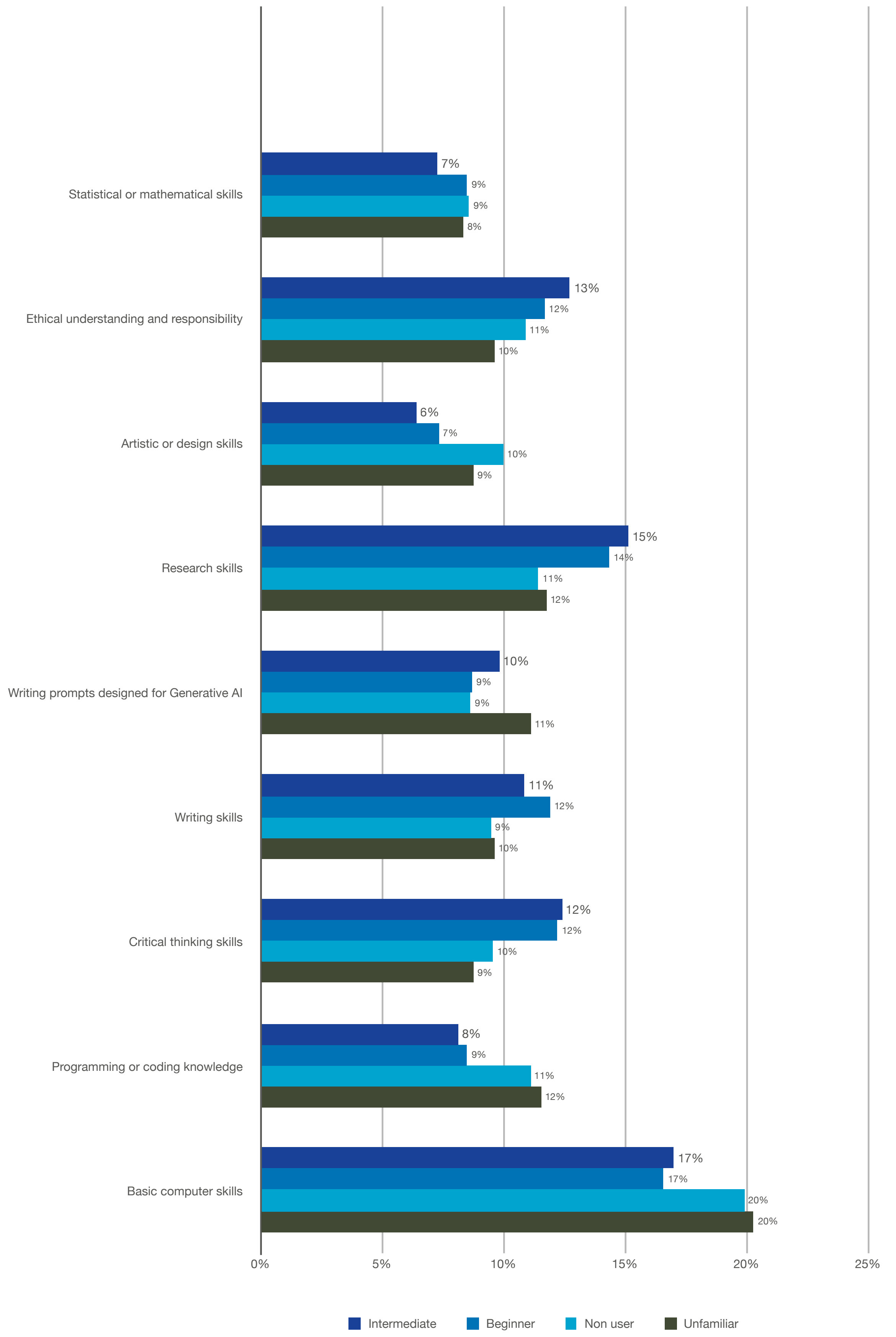
In your opinion, how important is it for government employees to develop skills in using Generative AI tools?



What do you think are the essential skills for effectively using generative AI tools?



What skills are essential to effectively use gen AI tools?



4.5.1 Managers' perceptions regarding generative AI skills and training

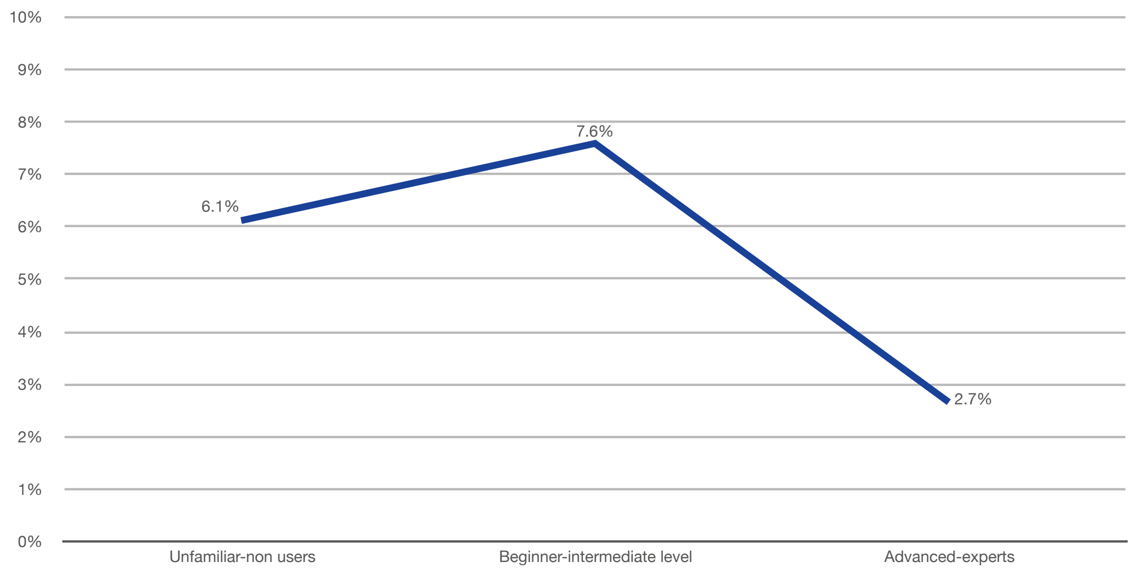
We surveyed managers, supervisors and senior leaders (henceforth simply "managers"), across expertise levels, to understand their opinion on skills, training and the degree to which they felt that different skills related to generative AI would be useful at their work.

A significant proportion of managers (64.38%) indicated a moderate level of confidence in the accuracy of gen AI outputs, while a substantial minority (19.93%) expressed high confidence. To mitigate the risks associated with overreliance on AI, it is imperative to sensitize all managers, including those with high confidence levels, to the potential pitfalls and inaccuracies of AI-generated content.

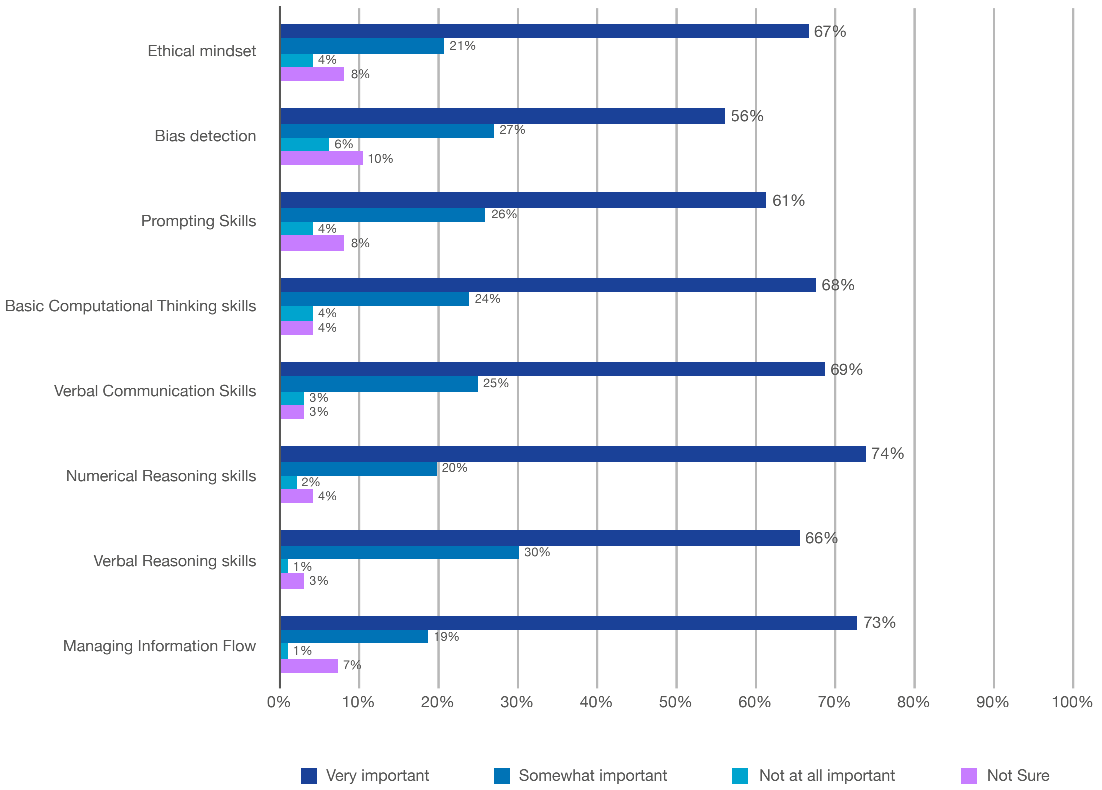
As managers transition from non-users to users and improve their expertise, they develop a more nuanced understanding of the skills required to effectively leverage generative AI and are less likely to report being "unsure" of skills requirements. Advanced and expert managers more frequently believe that skills like bias detection, prompting, and verbal reasoning are very important for the use of generative AI at work. This highlights the importance of first familiarizing managers with generative AI if they are to be expected to lead their team in the use of this technology. Alarmingly, more than half (57.42%) of managers who use generative AI are not aware of any ethical principles or guidelines for AI use, highlighting the need to also train managers on generative AI ethics.

Regardless of their expertise level, most managers (86%) agree that generative AI will have a positive or very positive impact on their work. Managers, both users and non-users of generative AI, also broadly concur on the relative importance of several generative AI skills. Further, most managers (85.2%) report time savings as a major benefit to leveraging generative AI in day-to-day tasks.

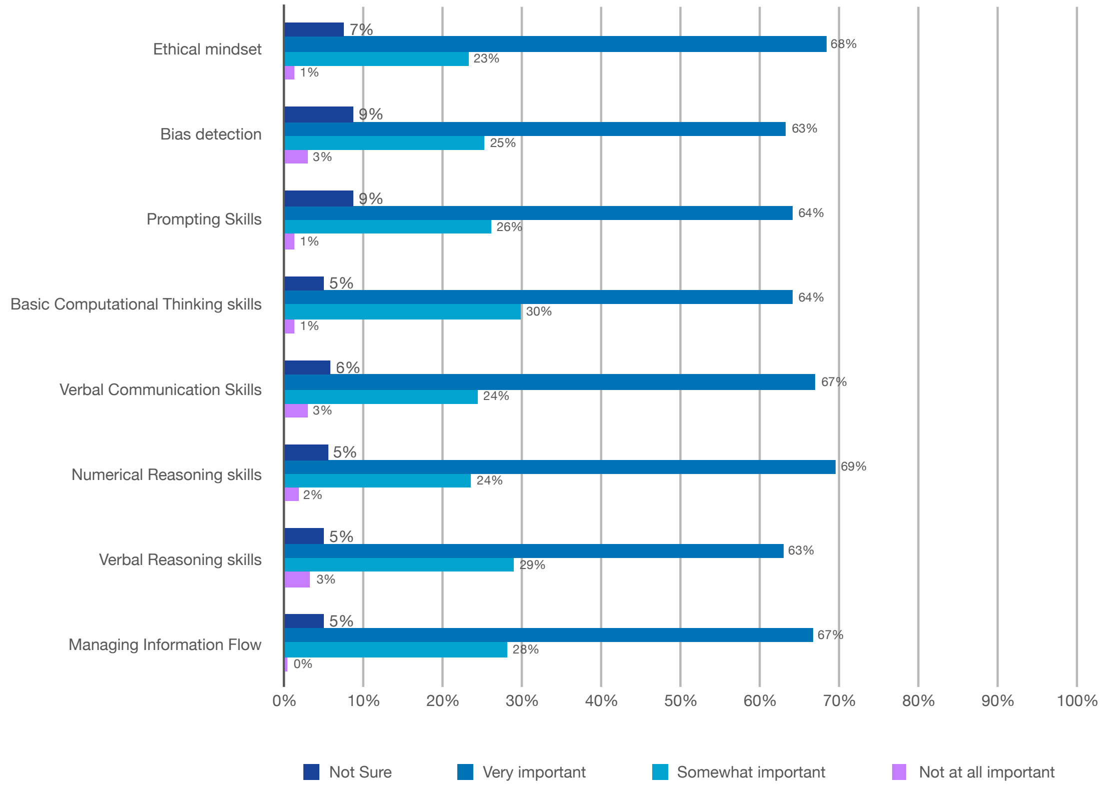
Percentage of supervisors and managers "unsure" about the relevance of different skills for the use of generative AI at work



Non user Managers: How would you rate the importance of following skills required for generative AI at work?



Managers who use gen AI: How would you rate the importance of following skills required for generative AI at work?

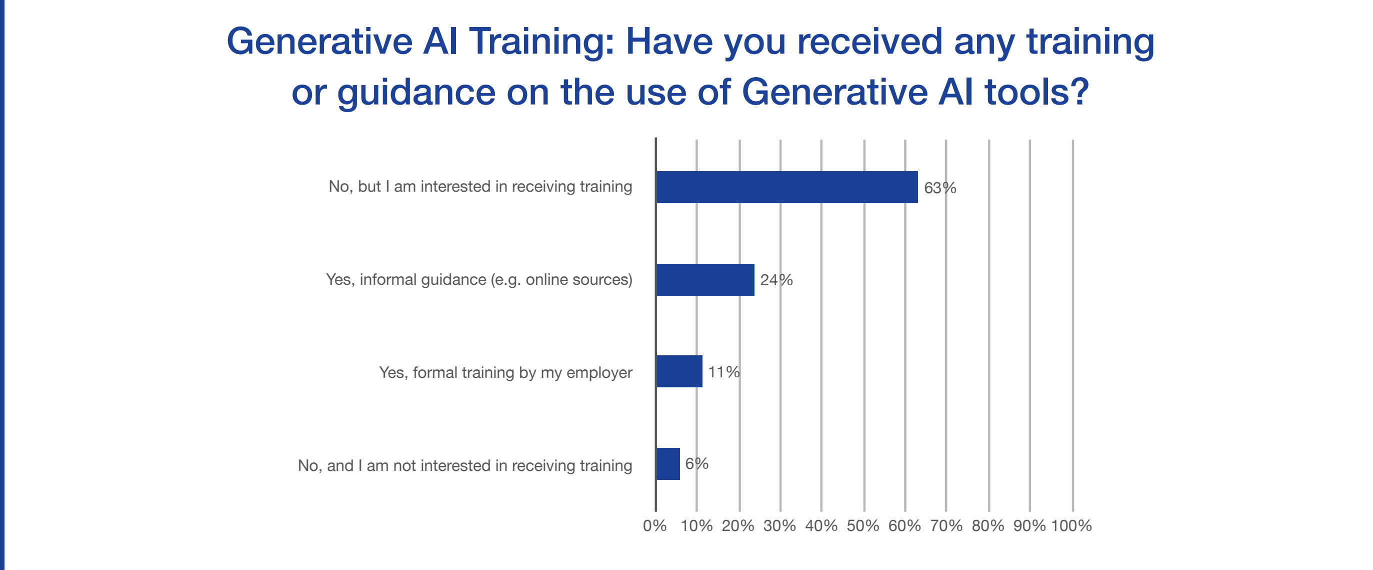


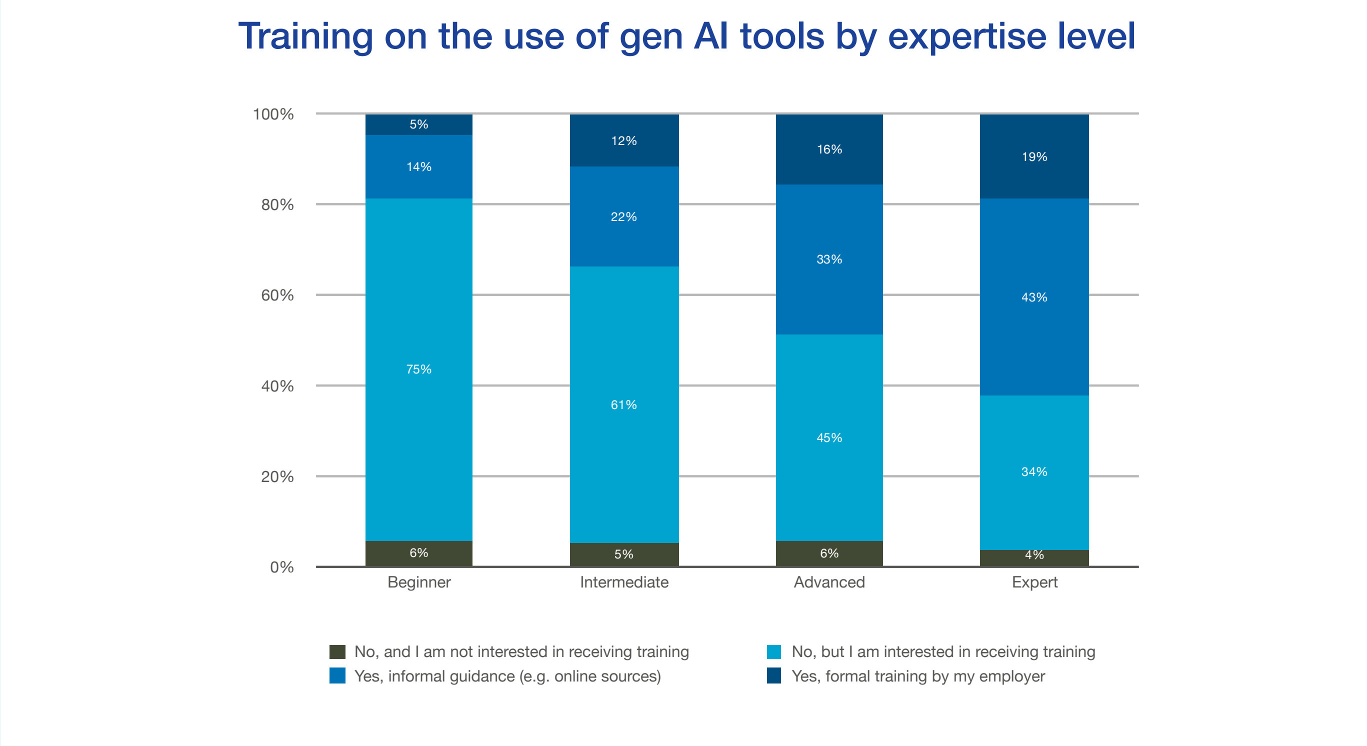
4.5.2 Training Needs and Gaps

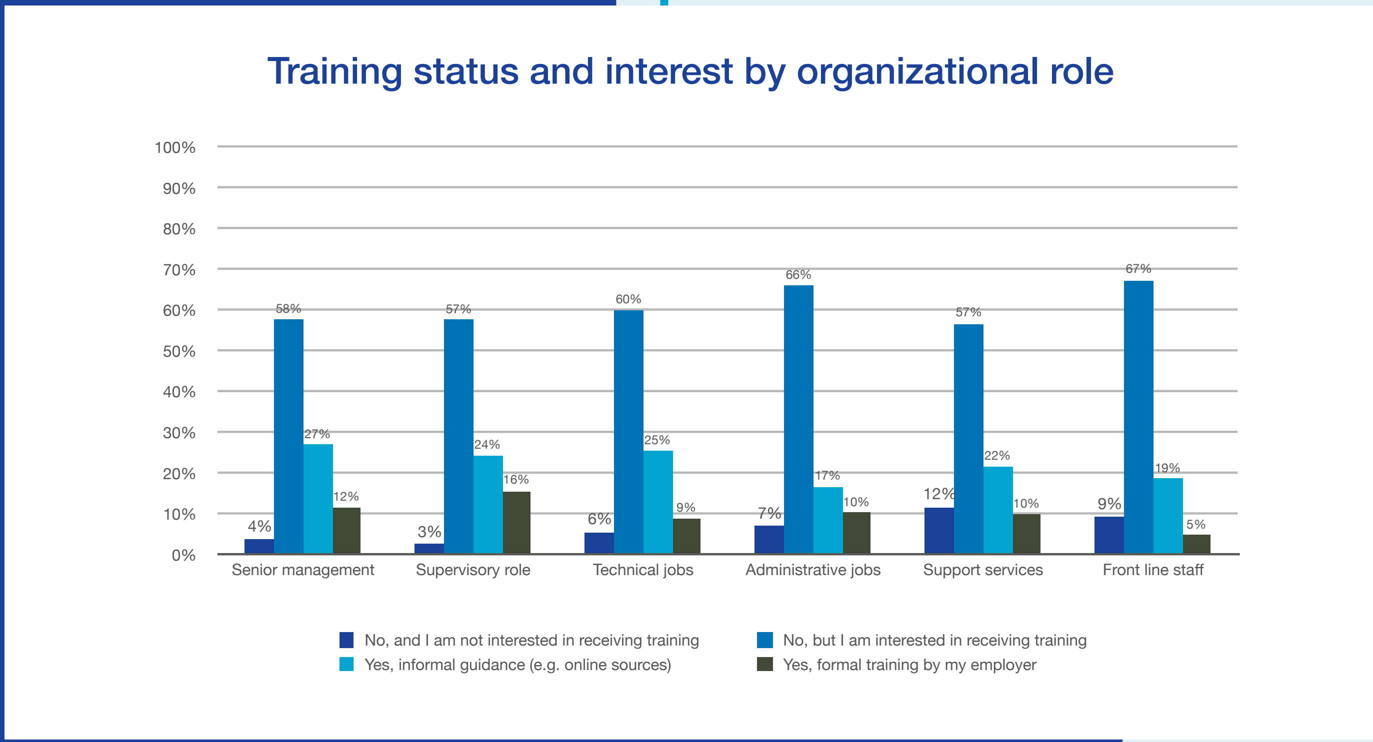
A significant proportion of current generative AI users (63.1%) have not received training but are eager to. Across all expertise levels, almost twice the proportion of respondents have sought informal training (24%) than have received formal employer-provided training (11%). As expertise increases, so does the likelihood of having received prior training, either informally on their own, or formally through their employer.

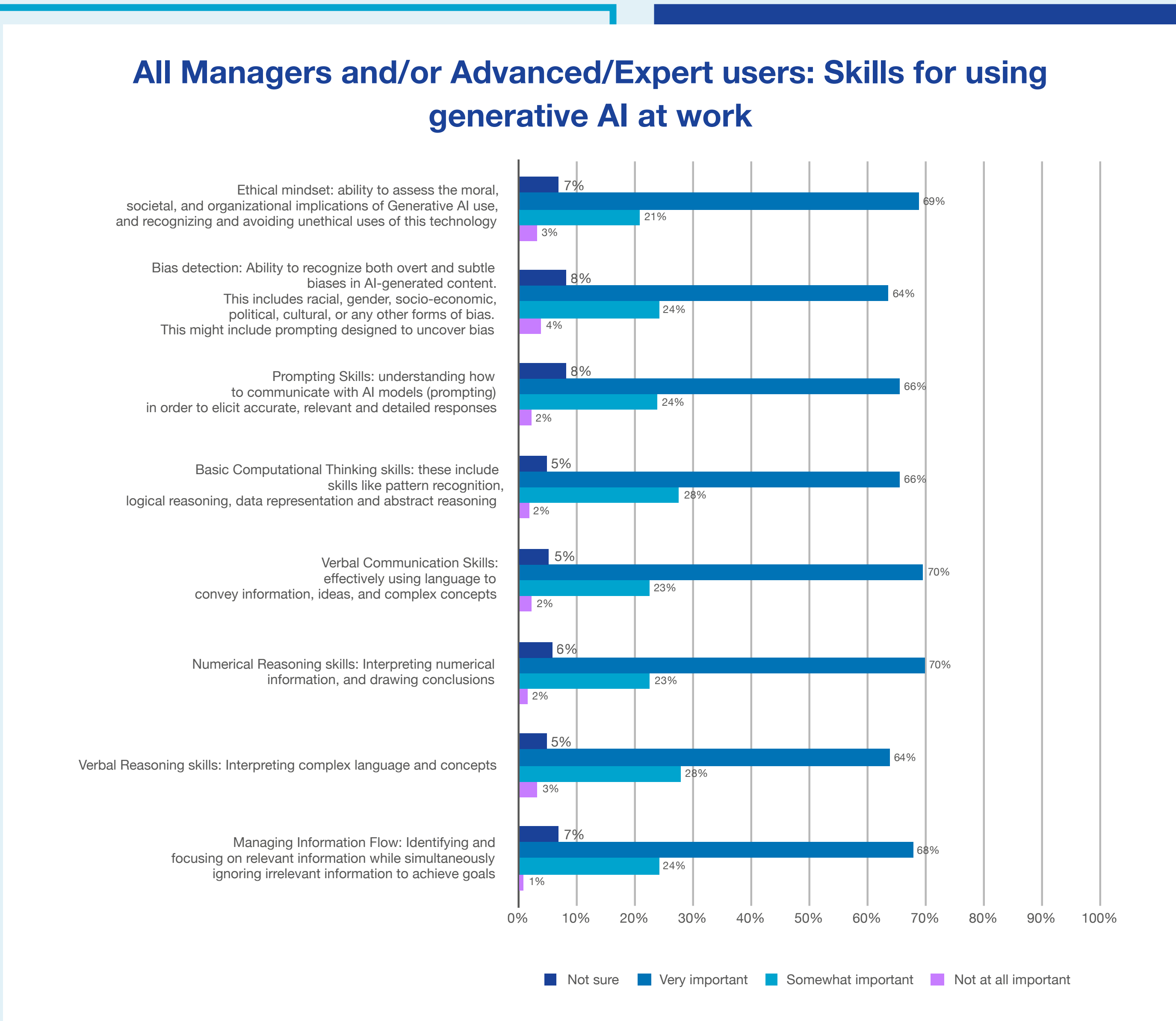
Across the board, there is a strong desire for training, with less than 6% of users expressing disinterest.

Front-line staff, support services staff, and administrative staff, roles particularly vulnerable to AI-driven automation or augmentation, notably exhibit a slightly higher level of disinterest in training (9.3%, 11.7%, and 7%, respectively) than respondents in other roles.






Training status and interest by organizational role
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
4%
58%
27%
12%
3%
57%
24%
16%
6%
60%
25%
9%
7%
66%
17%
10%
12%
57%
22%
10%
9%
67%
19%
5%
Senior management
Supervisory role
Technical jobs
Administrative jobs
Support services
Front line staff
No, and I am not interested in receiving training
No, but I am interested in receiving training
Yes, informal guidance (e.g. online sources)
Yes, formal training by my employer


All Managers and/or Advanced/Expert users: Skills for using generative AI at work
Ethical mindset: ability to assess the moral, societal, and organizational implications of Generative AI use, and recognizing and avoiding unethical uses of this technology
7%
69%
21%
3%
Bias detection: Ability to recognize both overt and subtle biases in AI-generated content. This includes racial, gender, socio-economic, political, cultural, or any other forms of bias. This might include prompting designed to uncover bias
8%
64%
24%
4%
Prompting Skills: understanding how to communicate with AI models (prompting) in order to elicit accurate, relevant and detailed responses
8%
66%
24%
2%
Basic Computational Thinking skills: these include skills like pattern recognition, logical reasoning, data representation and abstract reasoning
5%
66%
28%
2%
Verbal Communication Skills: effectively using language to convey information, ideas, and complex concepts
5%
70%
23%
2%
Numerical Reasoning skills: Interpreting numerical information, and drawing conclusions
6%
70%
23%
2%
Verbal Reasoning skills: Interpreting complex language and concepts
5%
64%
28%
3%
Managing Information Flow: Identifying and focusing on relevant information while simultaneously ignoring irrelevant information to achieve goals
7%
68%
24%
1%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Not sure
Very important
Somewhat important
Not at all important

4.6 Trust in generative AI

Analysis of survey data demonstrates that most users (63%), across diverse organizational roles, expertise levels, and departments, express moderate confidence in the accuracy of generative AI outputs. This suggests a widespread recognition of generative AI's inherent limitations regarding output reliability.

Advanced and expert users report "high" confidence in generative AI accuracy at twice the rate of their beginner and intermediate counterparts. This difference in reported confidence levels relative to expertise may reflect an enhanced ability to critically evaluate AI outputs among experienced users and potential confidence arising from familiarity with the technology and how to effectively use it and mitigate its risks.

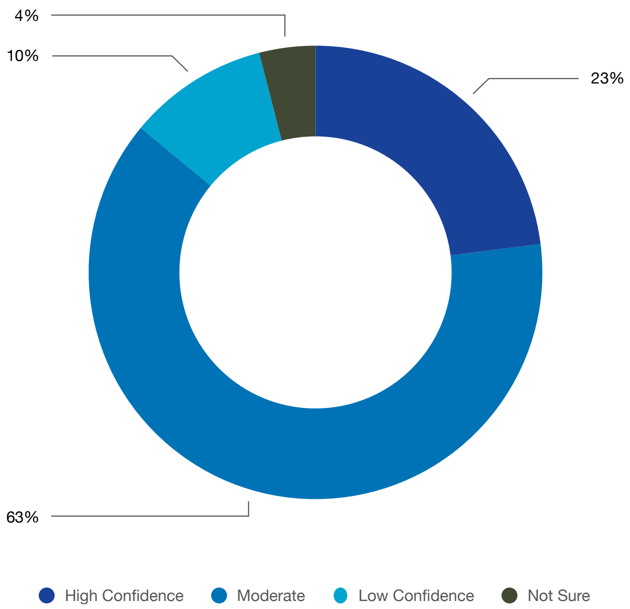
Analysis of survey data reveals that 23% of respondents across all organizational roles indicate "high" confidence in the accuracy of AI-generated outcomes. Notably, senior management personnel demonstrate above-average confidence levels, with approximately 27% expressing "high" confidence in generative AI outputs. The observation that more than a quarter of senior leadership maintains such strong confidence in generative AI accuracy indicates the openness of senior leadership to new technology and the overall acceptance of technological change. However, this does raise concerns, given the well-documented propensity of these systems to produce errors. These findings suggest a critical need to enhance awareness among executive decision-makers regarding the current limitations and potential risks of generative AI technologies, while continuing to encourage the adoption of these technologies.

Employees in technical and supervisory roles reported the highest levels of scepticism regarding AI output accuracy, with 67% and 65% respectively reporting "low" confidence in generated results. This suggests an awareness of generative AI's limitations among those in technically oriented roles.

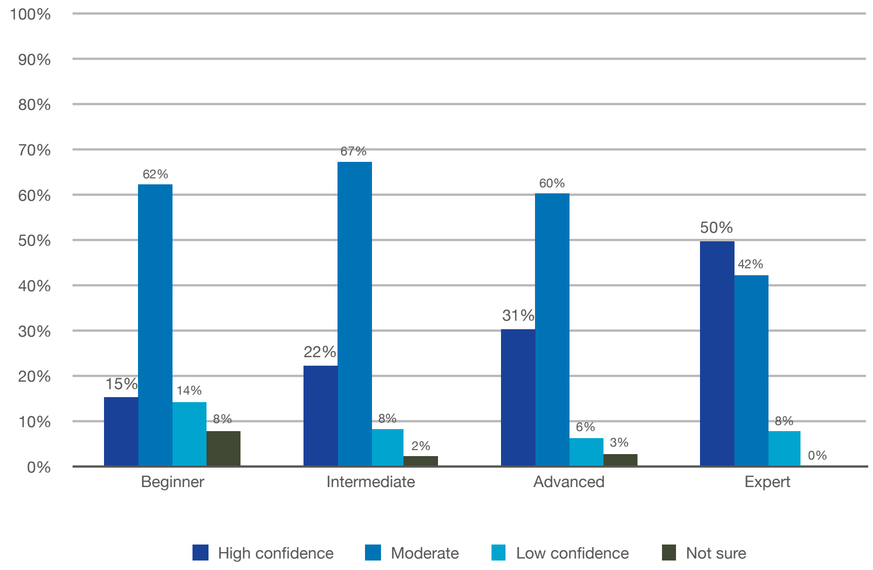
When analysing the data based on departmental affiliation, **survey results indicate that customer service and office administration staff expressed the highest confidence in AI-generated outputs, with over 34% reporting "high" confidence levels**. The legal department and executive office follow, with 28% of users indicating high confidence.

Given these varying confidence levels across departments, organizations should prioritize comprehensive training programs that help raise employee awareness regarding generative AI's flaws and potential inaccuracies. Such training is essential for developing institutional competency in critically evaluating AI outputs, particularly as organizations increase their reliance on these technologies.

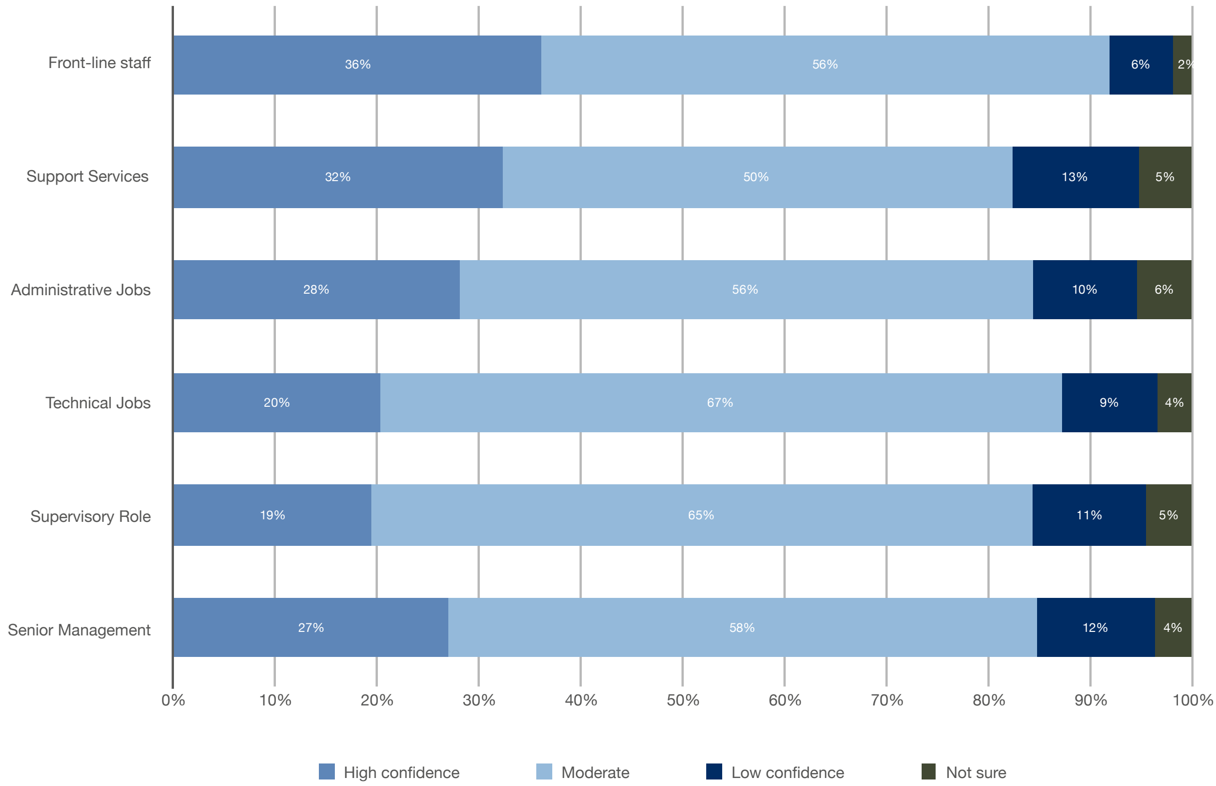
How confident are you in the accuracy of the outcomes generated by the Generative Artificial Intelligence applications that you use?



Level of confidence in accuracy of outcomes by gen AI applications by expertise level



Confidence in accuracy of the outcomes generated by the Gen AI applications by organizational role



4.7 Generative AI Ethics Awareness and perceptions

A significant proportion of generative AI users (59%) are unaware of specific ethical guidelines or principles related to AI. Among those who are aware, Dubai AI ethics and principles are the most recognized, followed by UAE AI ethics principles and guidelines.

Senior management and advanced/expert users demonstrate a higher level of awareness of AI ethics guidelines. 81.6% of senior management and 88.7% of advanced/expert users are aware of at least one ethical guideline for responsible generative AI use.

Most respondents (83%) believe that introducing AI ethics guidelines would have a positive impact on their work. This sentiment is particularly strong among senior management and supervisors, among whom 95% of senior management members and 85.7% of supervisors think that such an introduction will have a positive or very positive impact on their work.

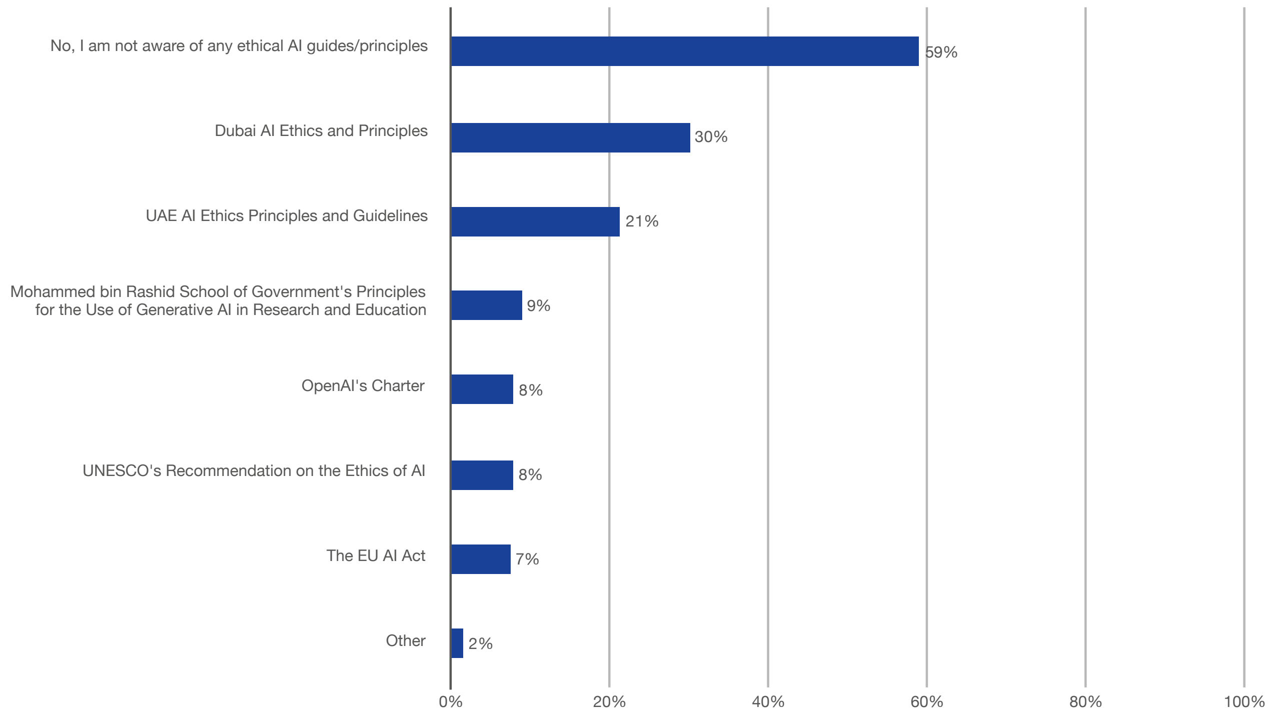
Regarding the responsibility for ensuring ethical AI use, most respondents (62%) believe that both employees and employers share this responsibility. Additionally, they emphasize the need for regulatory bodies to establish clear standards and guidelines.

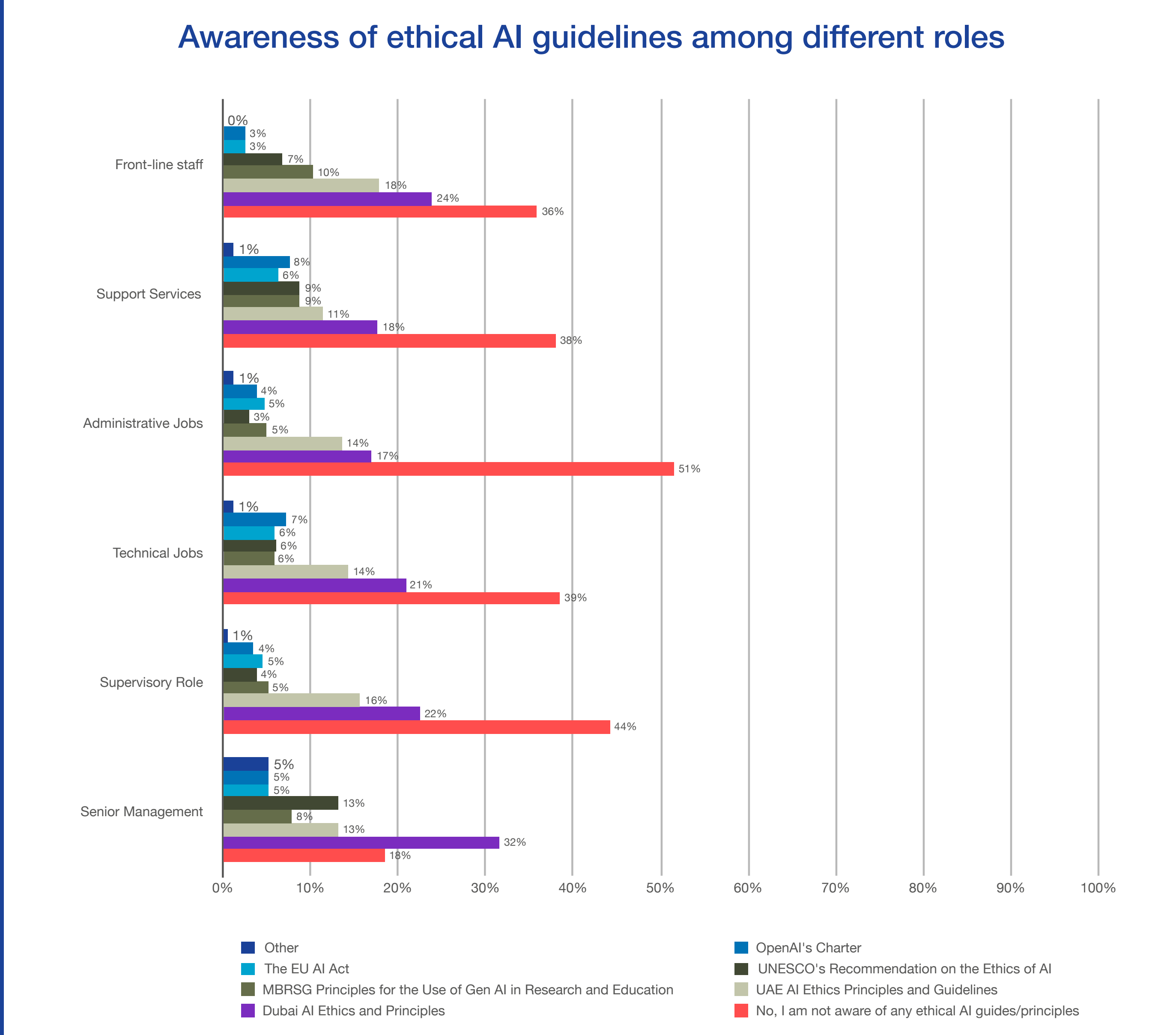
While many advanced and expert users consider themselves to be intermediate level in AI ethics experience, a significant minority (7-10%) express uncertainty about their knowledge in various AI ethics areas. This highlights the need for continued education and awareness initiatives, even among experienced users.

There is considerable uncertainty among users, particularly senior management and supervisors, regarding the ethical implications of replacing human tasks with AI, 32% of all users are unsure whether it is ethical human tasks with AI and this rises to 43% of respondents among the senior management and supervisors. This finding has important implications for the future of work and the potential impact of AI on employment.

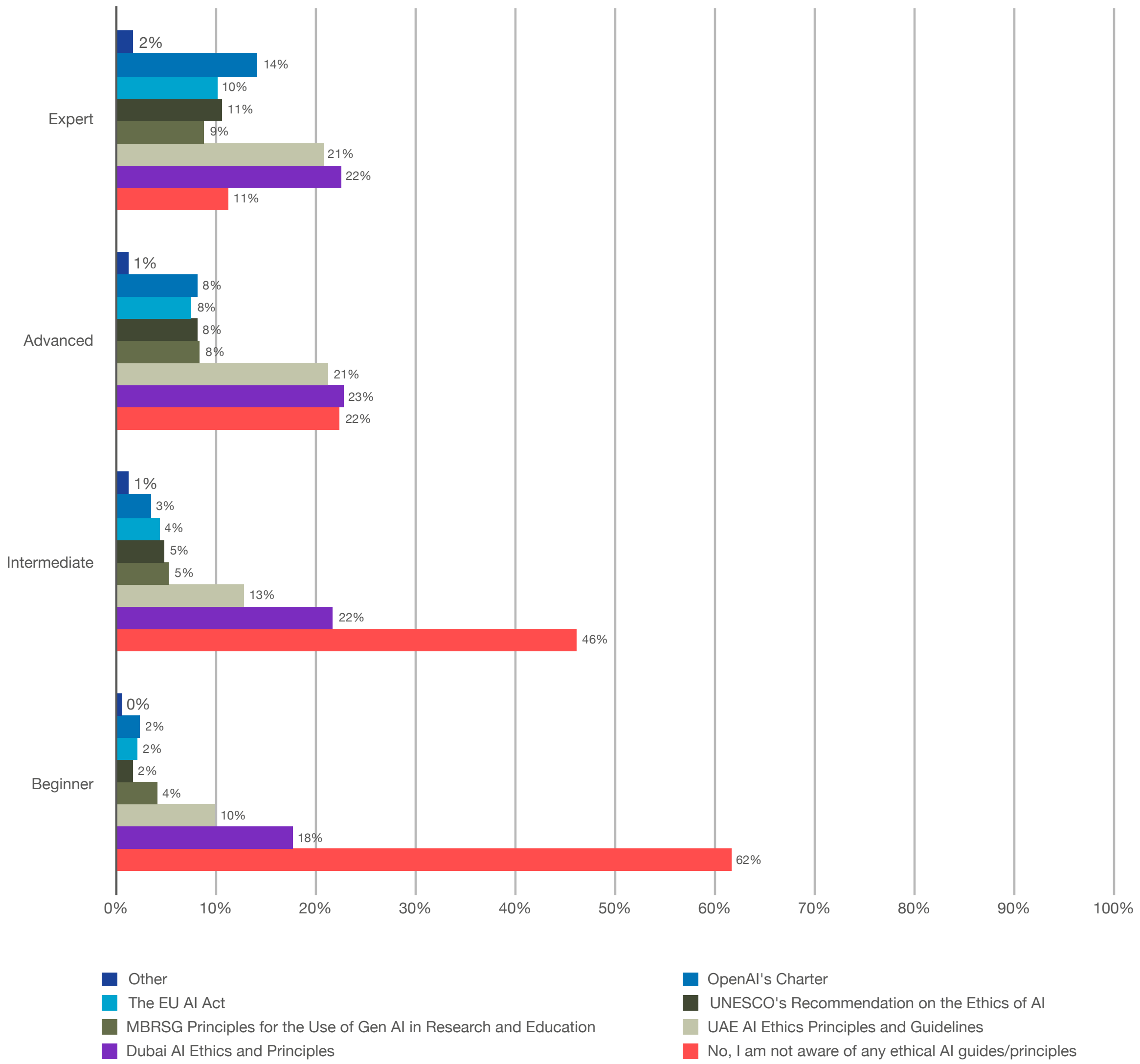
Views on AI ethics among Respondents in Senior Management

Are you aware of any of the following principles or guidelines regarding the ethical use of Generative AI tools?

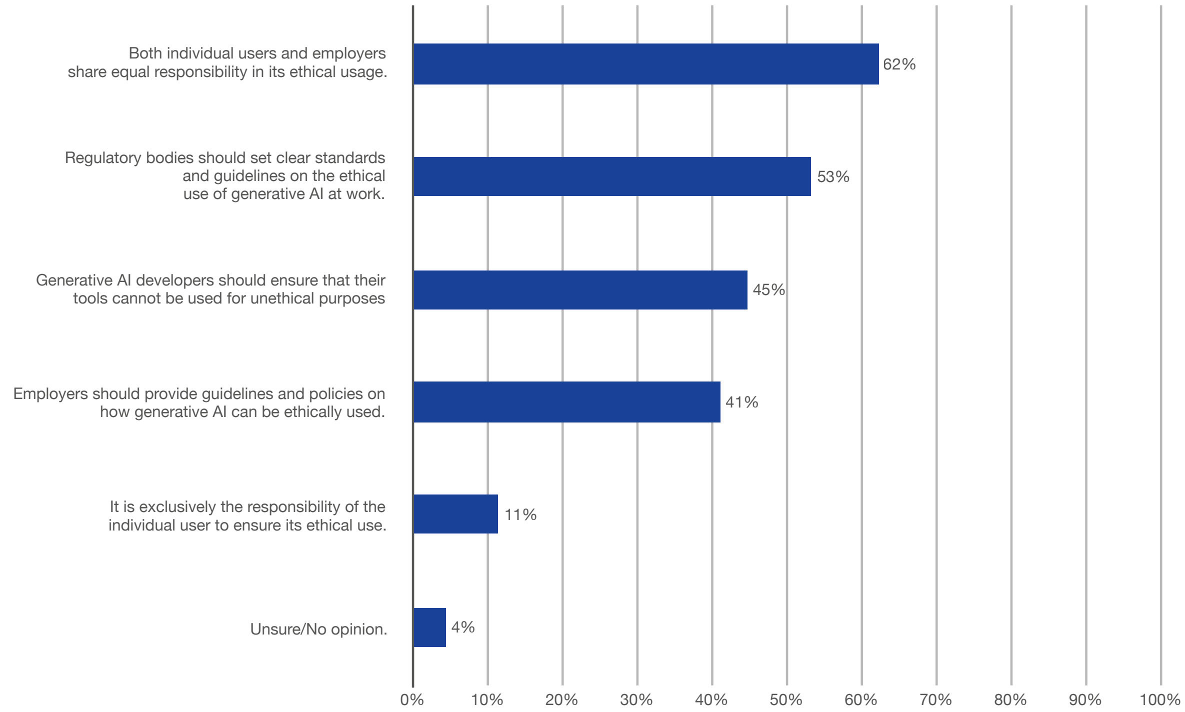



Awareness of ethical AI guidelines among different roles
Front-line staff
Support Services
Administrative Jobs
Technical Jobs
Supervisory Role
Senior Management
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Other
The EU AI Act
MBRSG Principles for the Use of Gen AI in Research and Education
Dubai AI Ethics and Principles
OpenAI's Charter
UNESCO's Recommendation on the Ethics of AI
UAE AI Ethics Principles and Guidelines
No, I am not aware of any ethical AI guides/principles

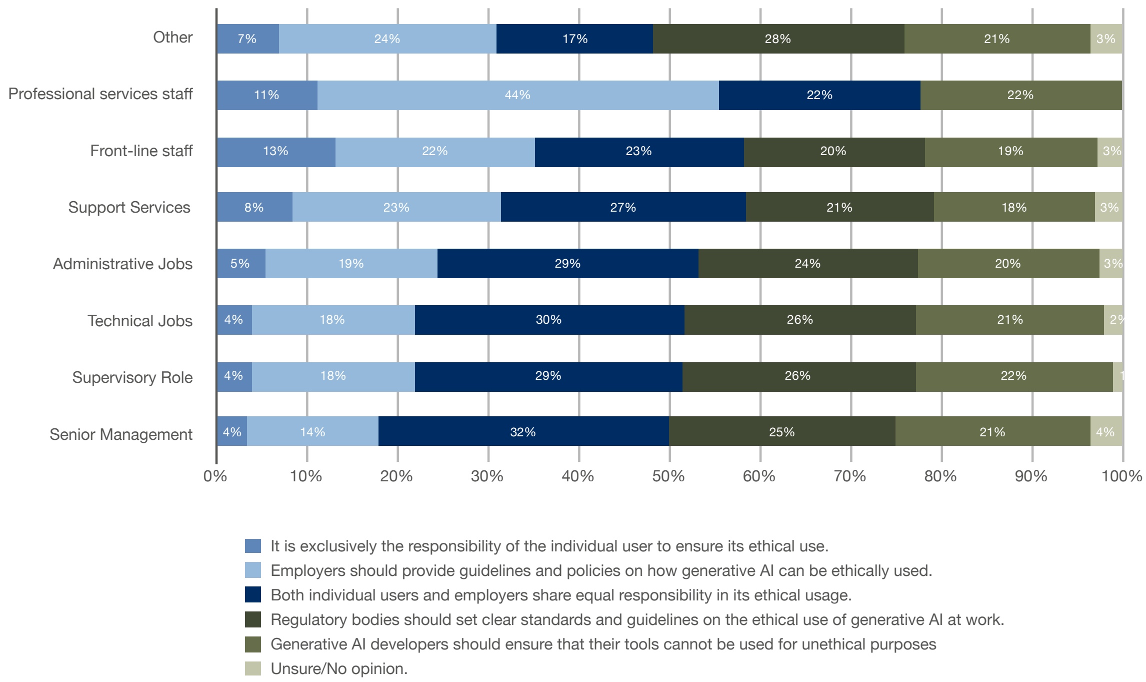
Awareness of AI ethics principles by level of expertise



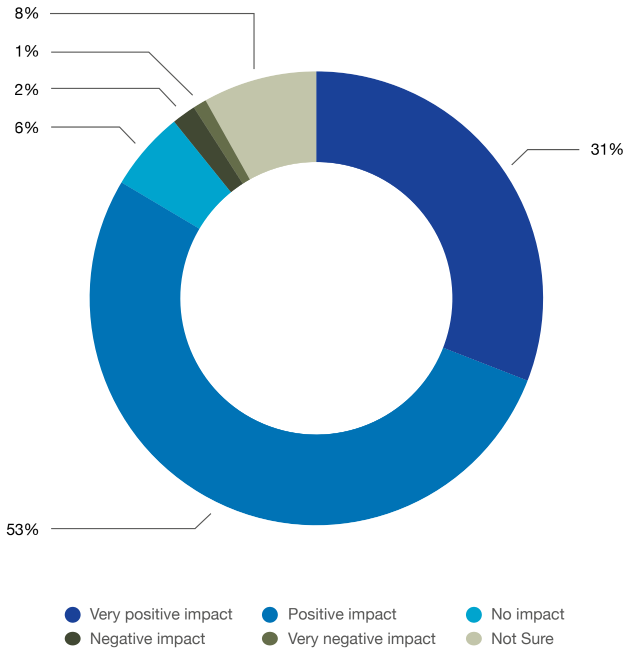
Whose responsibility to ensure ethical AI?



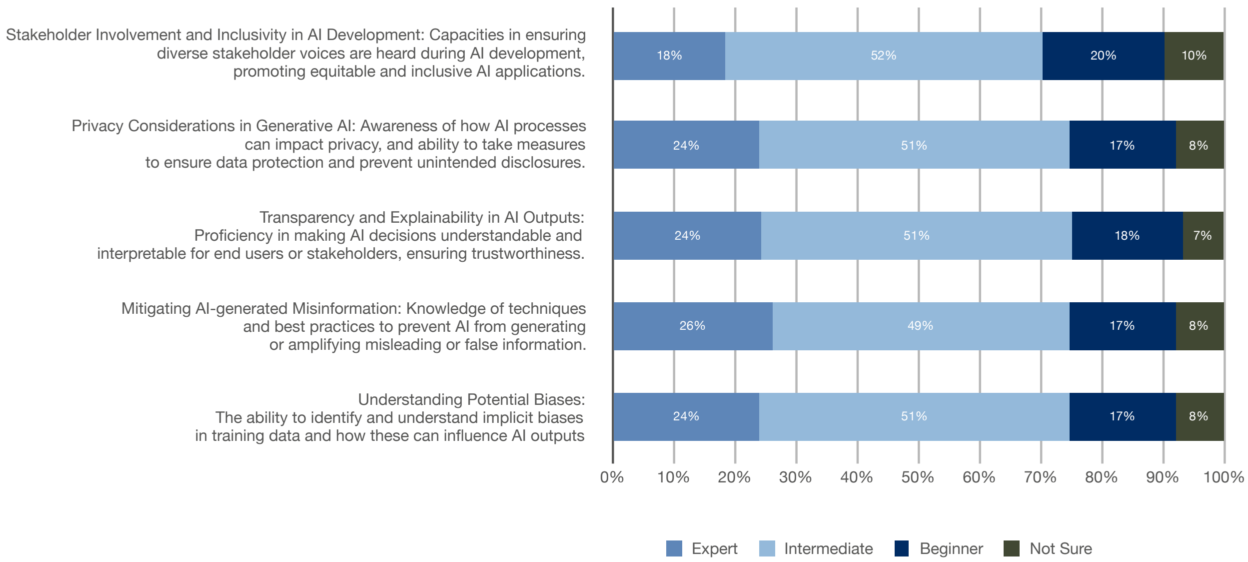
Opinion on whose responsibility the ethical use of gen AI is across roles



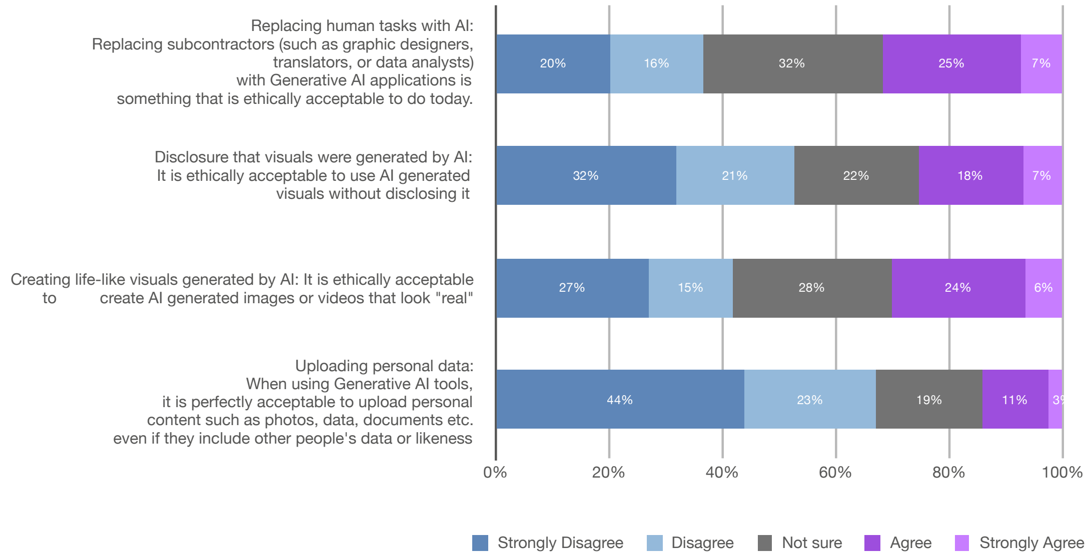
Impact of Generative AI Guidelines on your Work: If guidelines for the responsible use of generative AI technologies were to be introduced, what kind of impact do you think this would have on your work?



AI Ethics Expertise: Please rate your level of experience in the following areas related to AI ethics



What is your view on the following practices related to Generative AI?



4.8 Perceptions among non-users

Despite their current non-adoption, non-users of generative AI express significant interest in the technology. However, several key barriers hinder adoption:

- **Uncertainty about Starting:** Nearly half (44%) of non-users report uncertainty about how to begin using generative AI.
- **Perceived Lack of Relevance**: Approximately one-third of non-users are uncertain about the relevance and usefulness of generative AI to their specific work functions.
- **Limited Access to Information**: A significant portion of non-users lack access to information on the appropriate use of generative AI in their roles.

To address these barriers, tailored training programs can empower employees to understand the potential applications of generative AI and how to effectively leverage it in their work.

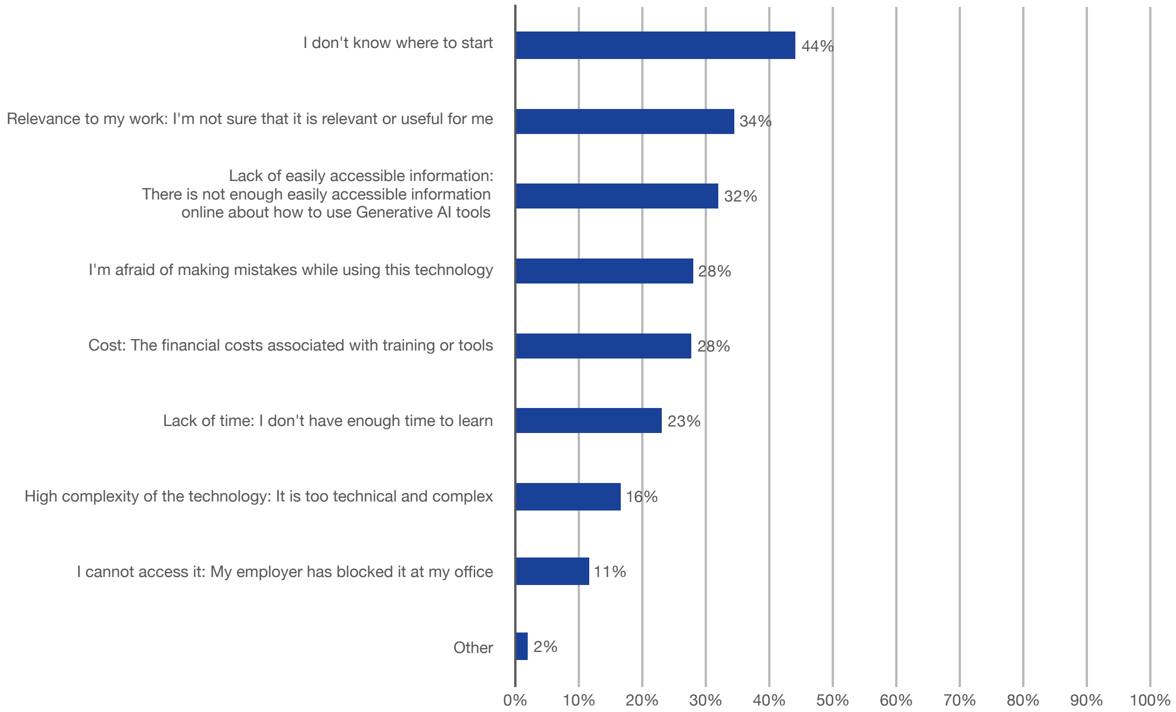
4.8.1 Concerns Regarding Generative AI among non-users

Non-users and those unfamiliar with generative AI harbour several concerns:

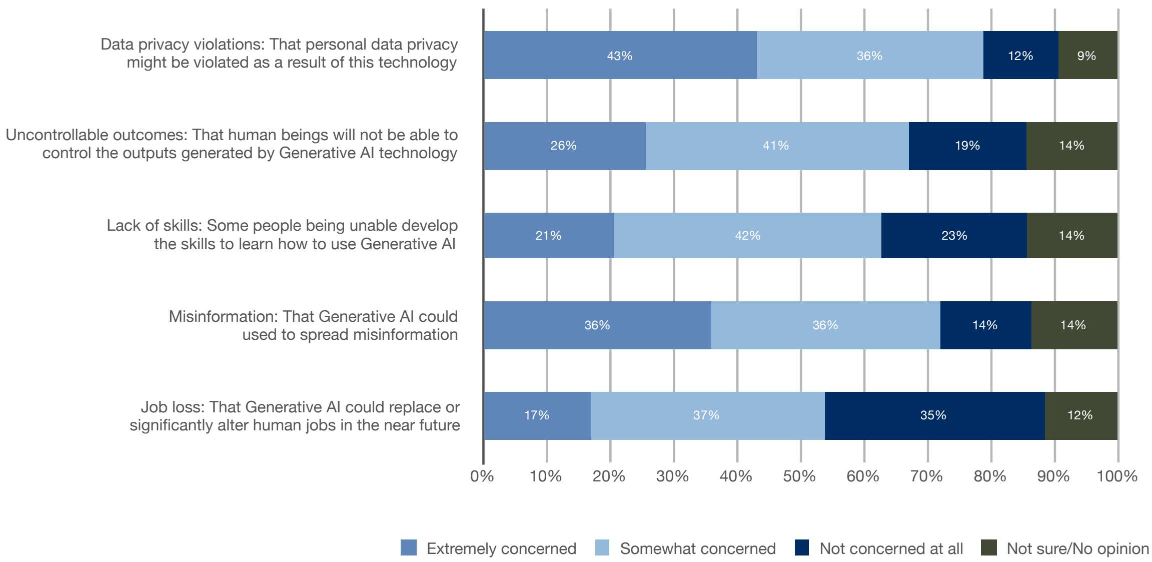
- **Data Privacy**: A majority (79%) are concerned about potential data privacy violations.
- **Misinformation:** 72% express concerns about the spread of misinformation.
- **Uncontrollable Outcomes**: 67% are worried about the potential for uncontrollable outcomes.
- **Skills Gap**: 63% cite a lack of necessary skills as a concern.
- **Job Loss**: 54% are concerned about job displacement.

Additionally, nearly half of non-users (44.8%) do not believe that generative AI is spreading rapidly.

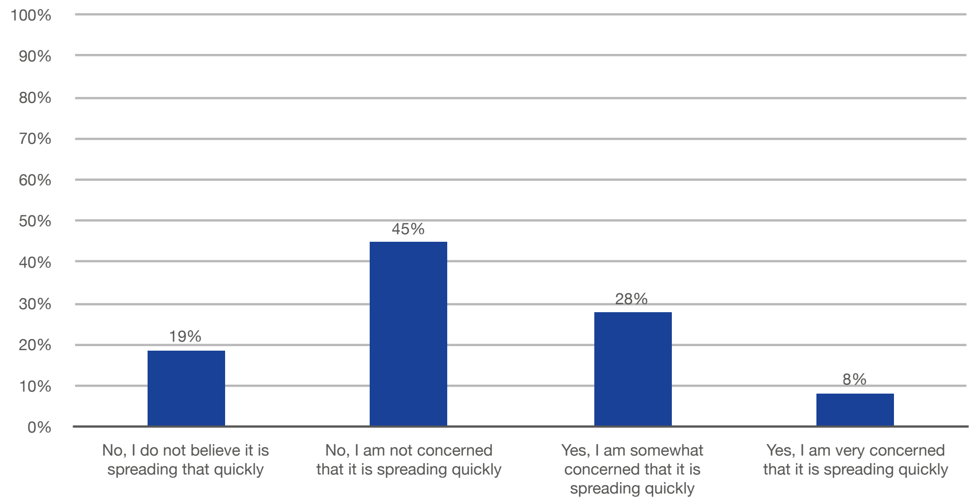
Non-users/Unfamiliar users: What do you feel are the main barriers preventing you from using generative AI tools?



Unfamiliar/Non users of gen AI: How concerned are you about the following things?



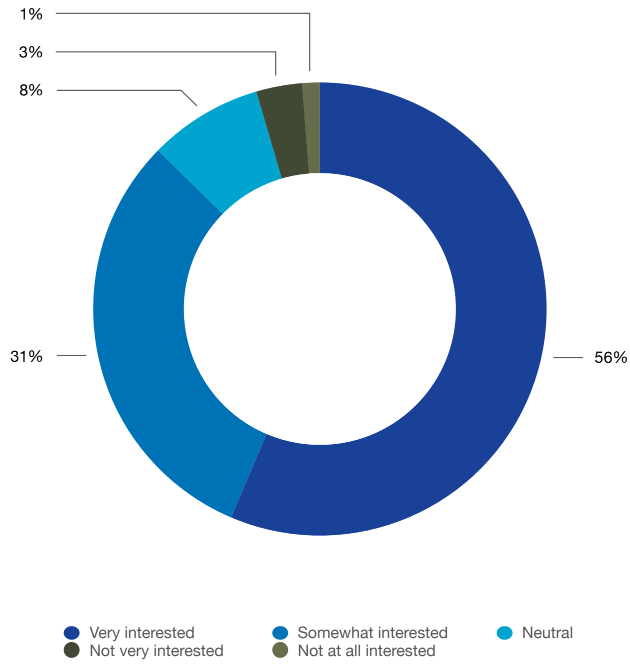
Non users/unfamiliar users: Are you concerned that the use of Generative AI tools is spreading so quickly?



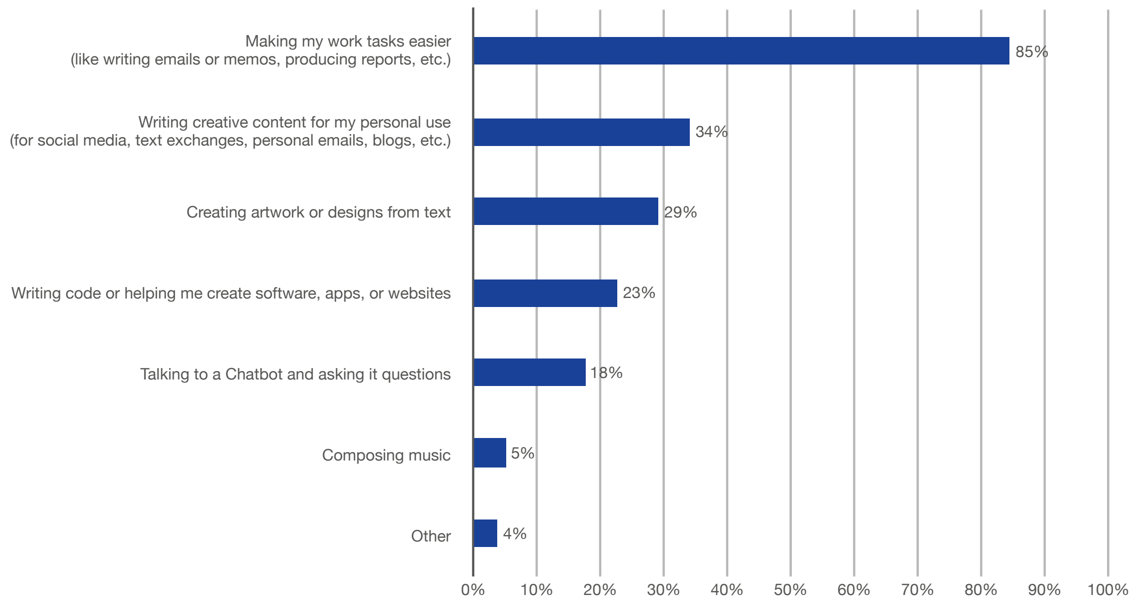
4.8.2 Interest in training amongst non-users

87.3% of non-users are at least somewhat interested in learning about generative AI applications and tools, particularly to help them make their work tasks easier. This suggests that if nonusers are given appropriate training, they will be willing to leverage AI for tasks at work.

Unfamiliar/nonusers: How interested are you in learning how to use Generative AI tools and applications?



Unfamiliar/nonusers: What aspects of using Generative AI interest you the most?



Labour Market Exposure Analysis

In this section, we analyse employee characteristics that can predict high occupational exposure to the automation impacts of generative AI, benchmarked on the capabilities of GPT-4. To obtain exposure estimates among government employees in Dubai, we leverage novel data from the survey outlined in the previous section, as well as overall public sector employment estimates in Dubai, by occupational role, as documented by the Dubai Government Human Resources Department.

We find, upon running regressions on the survey data among Dubai government employees, that the highest level of education, followed by the type of education specialization are the most important predictors of employee job exposure to automation. The greater the respondent's highest level of educational qualification, and the more quantitative their field of educational specialization, the lower is their estimated job exposure to automation due to gen AI. Less important, but significant nonetheless are, gender and age group, with females and younger people likelier to face job automation exposure to generative AI.

1. Literature Review

The ability of generative AI to augment and automate certain tasks at work has been well documented in recent years through employee surveys (Brynjolfsson et al, 2023) and explored by researchers across tasks, by occupational role, at the global, and regional levels (Gmyrek, Berg and Bescond, 2023; Pizzinelli et al., 2023). Because of their ability to augment certain work tasks and automate others, generative AI technologies differentially impact workers in different job roles. Findings from recent studies on the impact of generative AI on the labour market have shown that jobs composed mostly of routine tasks, such as clerical and administrative roles face the highest risk of automation and displacement.

This impact of generative AI is in line with findings exploring the impacts of earlier automation technologies on the labour market, which find that jobs composed of mostly of routine tasks were the ones most impacted by the automating effects of roboticization, computerization and other digital technologies, as routine tasks can be codified (Autor, 2015; Acemoglu and Restrepo, 2019). Although generative AI displays novel capabilities for interactivity, creativity and text generation which differentiates it, it has shown to have similar impacts as previous technologies (Autor, Levy and Murnane 2003), in that it (a) complements or augments the skills of workers doing novel tasks involving decision making, strategic thinking and abstract thinking, and (b) automates clerical or administrative tasks such as basic email responses, knowledge based direct retrieval of information, chatbot support etc.

While most research in the intersection of generative AI and the labour market have studied the extent of exposure of tasks and roles and estimated the aggregate proportion of individuals affected, few have explored the underlying characteristics of individuals which may predict whether they will occupy a role that is composed mostly of tasks at high risk of automation, rather than augmentation, by generative AI.

What factors might predispose someone to a job that is highly susceptible to automation, rather than one that can be enhanced by AI?

This is an important question because (a) it can inform choices that people make to skill and reskill themselves to move into less vulnerable occupations, and for policymakers tasked with reskilling vulnerable force and (b) it can highlight poorly explored connections between employee characteristics and composition of tasks at work, that we should strive to better understand.

In this section, we contribute to the body of literature that has strived, by focusing on employment exposure to the recently released GPT-4 class of large language models and by using detailed results from the survey conducted on generative AI use among Dubai government employees, which also collected data about employees' organizational roles, seniority, and base characteristics, such as gender, age group, and educational status.

Using local government data detailing public sector roles and descriptions, we map respondents' job roles to standardized ISCO-1 roles defined by the International Labor Organization (ILO). We then assign these each respondent an exposure score based on their occupational role, drawing on the global exposure estimates to GPT-4 obtained by Gmyrek et al. 2023, aggregated at the ISCO-1 level. We then regress the exposure scores on various respondent's level characteristics from the survey data, to identify the key employee-specific predictors of job exposure to generative AI, specifically to the Generative Pretrained transformer – 4 (GPT-4).

2. Methods and Data

2.1. Estimating exposure of jobs in the public sector to generative AI

We estimate the extent and type of exposure of public sector roles to generative AI, first at the Dubai government level, and then at the survey level.

First, we identify the percentage contribution of each of the ISCO-1 occupations to total employment in the public sector in the city of Dubai, by mapping local occupations to corresponding ISCO-1 codes. To aid with mapping and creation of local estimations, we utilize data regarding local employment classifications, structures, job roles, descriptions, tasks and estimates of the number of public sector employees in each occupational role, provided by the Dubai Government Human Resources Department (DGHR) . After mapping local roles to ISCO-1 roles, we apply the methodology and results of a previous ILO paper (Gmyrek et al., 2023). to assign the extent and type of exposure to GPT-4 by ISCO-1 occupational codes, and then aggregate this data to create jurisdiction level and survey level estimates.

Gmyrek et al. (2023) estimates the level and type of exposure of each of the tasks under each ISCO-4-digit occupations to generative AI, specifically GPT-4, which is then aggregated up to the ISCO-1 digit level in the following way:

Employment exposure estimates are created upon a data frame of 436 ISCO-08 occupations at the four-digit level, where each occupation is mapped to several tasks, between 4 and 14. The estimates are scores which range, for each occupation between 0 and 1, with 0 representing lowest exposure level and 1 representing the highest exposure level to generative AI technology. Each task is assigned a score, and the task level scores are aggregated to create job-level exposure estimates. Finally, the result from exposure estimates at the ISCO-4-digit level are aggregated and used to calculate the share of tasks with high and medium exposure in each ISCO-1 digit grouping. These estimates of the ratio of tasks with different levels of exposure at the ISCO-1 digit level are then calculated at the role level.

The composition of tasks, the number of tasks and the extent to which they are exposed to GPTs varies with occupation. To determine whether the type of exposure of a task is related to the automation or augmentation potential of generative AI, two principal characteristics of the task scores distribution are focused on, namely, the mean and standard deviation of task exposure scores.

Occupations are grouped based on the following combination of parameters related to the task exposure scores:

	Low Mean	High Mean
High SD	Augmentation potential	The big unknown
Low SD	Not affected	Automation Potential

Several jobs can be categorized, based on the distribution of their task exposure scores, into jobs with high potential to be automated, or augmented by generative AI. There is also a category of jobs, with tasks in general having low mean and low spread of exposure scores, which fall into the "unaffected" category. "The big unknown" category consists of jobs with high mean scores and high standard deviation of these scores; whether the augmentation or automation potential in the exposure to generative AI will dominate in this category of jobs depends on a) the evolution of GPT technologies and b) policy decisions and environment.

To ensure a clear distribution of occupations as having high automation and augmentation potential, Gmyrek et al. (2023) apply a formula focused on the extremes of the distribution. An occupation will be defined to have "Augmentation potential" if the following conditions are satisfied:

$0.4 > \mu_i$ and $\mu_i + \sigma_i > 0.5$

Similarly, an occupation is said to have "automation potential" if it fulfils these criteria:

$\mu_i > 0.6$ and $\mu_i — \sigma_i > 0.5$

Where μ_i and σ_i denote the mean and standard deviation of the task-level scores for a given occupation *i*, respectively.

The following table presents aggregate estimates of government employees for the emirate of Dubai, and at the survey level, classified into low and high exposure groups based on occupational codes mapped to ISCO-1.

Table 1: Classification employees into low/medium and high exposure groups

	Medium/Low exposure roles		**High exposure roles**		**Total number of employees (N) in the public sector**
	Number of employees (N)	% employees	Number of employees (N)	% employees	
State/City level	37,350	67	22,323	33	59,673
Survey level (Subset of city)	1,368	66.28	696	33.72	2,064

2.1.1 Limitations with the exposure mapping methodology:

At the jurisdiction level, there may be imperfect mapping of the locally defined, state level job-codes to the ISCO-1 level codes, due to incomplete or vague task descriptions of jobs. Some job classifications at the DGHR level were "department level" classifications rather than "role wise" classifications – in these cases, we mapped the function to the closest likely ISCO-1 occupational code after qualitative investigations and research. When mapping under uncertainties, we have made common sense and local investigation-based approximations, which was easy to do at the ISCO-1 level since it is a broad classification encompassing a broad range of specific jobs and tasks.

Given Dubai's uniquely high level of digital adoption, the 'public sector roles, and other specific factors, the findings and estimates of this research may not be directly applicable to the UAE as a whole or to a global context without significant adjustments.

Also, due to features unique to the nature of Dubai, including a general high level of digital adoption, the composition and responsibilities of its public sector roles, the conclusions and estimates reached for Dubai may not directly be extendible to the UAE level, or a global level comparison with significant revisions.

It is ideally desirable to create task level generative AI exposure estimates based on local jobs and tasks and have more granular ISCO job classification and employment data, beyond the 1-digit level, at the level of the local jurisdiction and the survey data, to create more precise, detailed estimates – however, we did not have access to such granular employment information.

2.2 Survey and regression design

Section III. of this report details the methodology, timeline and goals of the anonymous survey on generative AI use, perceptions and trends, disseminated between 2023 and 2024 among employees of various Dubai government entities. Data from this survey was used to inform the main estimates of this job exposure analysis.

It is important to note that our survey data covers only public sector employees, primarily in office-based jobs, so this excludes employees in armed forces, doing manual labour etc. – jobs which may have little or no exposure to generative AI at work.

Based on the organizational role reported by the respondent, and the mapping of the organizational roles in the survey to corresponding ISCO-1 digit level occupations, we estimate the respondent's level job exposure to GPT-4. Exposure is the dependent variable of interest in our regressions.

We introduce exposure scores extraneously to the survey data by defining two different exposure variables whose scores are assigned directly based on the respondent's organizational role and the ISCO-1 code based exposure for that role:

(1) "Binary Exposure" (EB), a binary variable taking two possible values, 0 and 1.

(2) "Mean Exposure" (EM) which takes continuous values between 1 and 3.

To define EB, we assign organizational roles with an aggregate high exposure to GPT-4 a score of 1, and roles with an aggregate low to medium exposure a score of 0. The advantage of defining exposure as a binary variable is that it's value 1 for an employee indicates high exposure, particularly to automation effects of gen AI, which is the adverse scenario of our specific interest, while the exposure value of 0 is assigned to all other cases, including those who are: (a) not affected by gen AI at all (b) exposed to low or medium extents or (b) whose tasks are primarily augmented by generative AI.

One potential issue with defining exposure a binary variable, however, that the realistic nature of exposure to generative AI is not binary or a "yes/no" function – it is a combination of exposure of different types (augmentation/automation) and extents for the various tasks that compose an occupation.

To address this drawback of exposure as a binary variable, a second, continuous, exposure score is also constructed, which we call "Mean exposure" (EM). It is calculated for each ISCO-1 occupational code and corresponding organizational role in the following way:

Mean exposure = $1z + 2x + 3y \in [1,3]$

where:

x = (Percentage of tasks with medium exposure to GPT-4) /100

y = (Percentage of tasks with high exposure to GPT-4)/100

z = $1 - x - y$ = (Percentage of tasks with low or no exposure to GPT-4)/100

The values x and y for each ISCO-1 occupation (mapped to each of the organizational roles in our survey) is obtained from the exposure values estimated by Gmyrek et al (2023).

By construction, mean exposure score takes on values between 1 and 3, where a value of 1 would indicate that 0% of the tasks in the role are exposed to GPT-4, as is the case for ISCO – 0-Armed Forces occupation, which is excluded in this analysis. On the other hand, an EM score of 3 would imply that 100% of the tasks in a role have high exposure to GPT-4. No occupation currently receives this score; the highest EM score received is by ISCO-04-Clerical support workers with a value of 2.06.

Note that the two measures of exposure, binary exposure (EB) and mean exposure (EM) are highly correlated as both measure the exposure of a respondent; they have a correlation coefficient of 0.9927.

Separate regressions are performed, first with (a) binary exposure (EB) and with (b) mean exposure (EM) as the dependent variable, and with a variety of respondent characteristics as regressors, to determine the most significant respondent characteristics that could robustly predict respondent exposure. When binary exposure is the dependent variable, we perform a binary logistic regression with the regressors, and when mean exposure is the dependent variable, we use a multi variable linear regression model.

We test the following respondent characteristics as independent variables in the regressions: *gender, age group, highest level of education obtained, and type of educational specialization obtained*

Among regressors, we encode gender, and type of educational specialization as categorical/dummy variables. We do this rather than treat these variables as continuous for the following reasons. Gender is not an ordinal variable, where 2 is greater than 1, moreover, the “interval” between 1 and 2 cannot be clearly defined or understood.

For type of educational specialization type: This variable has 3 possible values, classified by us as least, moderately and highly quantitative qualifications. These 3 classifications are obtained from grouping 14 different education specialization choices which respondents chose into 3 ordinal categories. The table containing occupations mapped to scores of educational specializations is presented in the appendix section.

Here again, the interval between 1, 2, 3, may not be “evenly” spaced, or “comparable” in a quantifiable way. So, we choose to discretize and dummy code this variable in the regressions. Age group on the other hand, has been defined as groups of 5 consecutive ages, in strictly increasing order. Buckets 1-6 have strictly equal interval sizes. Only the last bucket, with value 7 has all employees above the age of 51 which may result in a broader age grouping than the buckets 1-6. From summary statistics on the variable, we see that bucket 7 has a comparable number of respondents to other buckets. Assuming the unbounded nature of the last categorization will not significantly affect the interpretation of our regression results, we assume this variable to be continuous. Assuming age group to be continuous rather than a categorical dummy variable also reduces the number of predictors in our model, making it parsimonious, which is to our advantage.

Similarly, we also assume the highest level of education to be continuous. This is because this variable, which takes 5 possible values, is strictly ordinal, ranging from high school degree through post-doctoral degree, with each level being exactly one level greater than the previous. Therefore, the interval between 2 levels is exactly one degree level. Due to strict ordinality and comparability of interval sizes, we assume this variable to be continuous.

Although for model parsimony we chose the two selected variables above to continuous, and only two to be discrete, we do re-run the regression model assuming all variables as categorical (see appendix), as a robustness check.

The following table lists the independent and dependent variables used in the regressions along with their possible values.

Table 2: Variables used in the regressions

Variable	Var	Values	Type
Highest level of education	h_i	Discrete values 1-5; 1 = high school diploma, 5 = post-doctoral degree **Treated as a continuous variable in the regressions*	Independent variable
Educational specialization	s_i	Discrete values 1-3; 1 = Minimally quantitative degree, 3 = Highly quantitative degree **Encoded as a categorical variable in the regressions.*	Independent variable
Gender	g_i	Discrete values 1-2; 1 = female, 2 = male **Encoded as a categorical dummy variable in the regressions.*	Independent variable
Age group	a_i	Discrete values 1-7; 1 = ages 18-22; 7 = ages 51+ **Treated as a continuous variable in the regressions*	Independent variable
Exposure_mean	y_i^2	**Continuous; values Є [1,3];** 1 = 100% of job tasks are low/no exposure, 3 = 100% of job tasks are high exposure.	Dependent variable **Multivariable regression*
Exposure_binary	y_i^1	Discrete values 0 or 1; 0 if overall job exposure is low or medium, and 1 if overall job exposure is high	Dependent variable **Binary logistic regression*

3. Analysis

3.1 Regressions: Analysing determinants of exposure at the state level

We construct two measures of exposure – the binary and mean exposure scores- and for each measure, run a different type of regression, to identify which respondent characteristics significantly predict exposure. Using the binary exposure score a dependent variable we run a binary logistic regression. Secondly, using the mean exposure score, which is a continuous measure, we run a multiple linear regression model. We use the same set of independent variables for both regressions.

We first specify the following binary logistic regression model, where *i* indexes the respondent and is the binary variable for exposure to GPT-4, which takes value 0 if the respondent's ISCO-1 role has on average low or medium exposure, and value 1 if the role is highly exposed:

$$y_i^1 = \beta_0 + \beta_1 h_i + \beta_2 s_i + \beta_3 g_i + \beta_4 a_i + \epsilon_i \ldots (1)$$

With the components described as follows. denotes the respondent's highest level of education, denotes the degree of quantitative applications in their educational specialization, denotes gender, and denotes their age group.

Subsequently, we run another regression, this time a multiple linear regression, with a continuous dependent variable measuring exposure, called the mean exposure, and where *i,* once again, indexes the respondent i. takes values between 1 and 3, by averaging the proportion of low, medium and high exposure tasks in the ISCO-1 role of the respondent. The set of independent variables on the right-hand side remain the same as in (1) and our multiple linear regression specification is as follows:

$$y_i^2 = \beta_0 + \beta_1 h_i + \beta_2 s_i + \beta_3 g_i + \beta_4 a_i + \epsilon_i \ldots (2)$$

Results of the Regression are presented and discussed below.

4. Results and Discussion

Results of both the logistic and multivariable regression analyses show that the highest level of education, the type of educational specialization, gender and age group all help predict the extent of exposure to generative AI, with statistical significance. In particular, the highest level of education is the strongest predictor of exposure, followed by the type of education specialization. Gender and age group are, although significant, explain only a smaller portion of the variability in exposure level as compared to the level and type of educational qualification. Regression results are presented in the tables below.

Table 3a: Results of binary logistic regression

Exposure (Binary)	(1)	(2)	(3)	(4)
Highest level of education	-1.528***	-1.452***	-1.447***	-1.392***
Specialization Type				
2	-0.164	-0.201	-0.097	
3	-1.425***	-1.519***	-1.380***	
Gender				
2 (Male)	-0.633***			
Age group	-0.240***	-0.258***		
_cons	4.437***	4.055***	2.750***	2.045***
N	1157	1163	1170	1424
chi2	316.512	299.846	276.885	270.794
r2_p	0.226	0.213	0.196	0.150

Legend: * p<0.05; ** p<0.01; *** p<0.001. Panel (1) lists regression results using all regressors, highest level of education, educational specialization, gender and age group. (2) excludes gender, (3) excludes gender and age group, and (4) excludes all regressors besides highest level of educational specialization.

Table 3b: Results of Binary logistic regressions (odds ratios)

Binary Exposure score	(1)	(2)	(3)	(4)
Highest level of education	-1.528***	-1.452***	-1.447***	-1.392***
Specialization				
2	-0.164	-0.201	-0.097	
3	-1.425***	-1.519***	-1.380***	
Gender				
2	-0.633***			
Age group	-0.240***	-0.258***		
_cons	4.437***	4.055***	2.750***	2.045***
N	1157	1163	1170	1424
Chi2	316.512	299.846	276.885	270.794
R2_p	0.226	0.213	0.196	0.150

Legend: * p<0.05; ** p<0.01; *** p<0.001

Table 4: Results of multiple linear regression

Mean level of exposure	(1)	(2)	(3)	(4)
Highest level of education	-0.184***	-0.190***	-0.189***	-0.199***
Specialization Type				
2	-0.039	-0.024	-0.031	
3	-0.193***	-0.176***	-0.194***	
Gender				
2 (Male)	-0.065**	-0.078***		
Age group	-0.032***			
_cons	2.180***	2.037***	1.997***	1.926***
N	1157	1159	1170	1424
r2	0.226	0.211	0.201	0.169
r2_a	0.222	0.208	0.199	0.168

Legend: * p<0.05; ** p<0.01; *** p<0.001. Panel (1) lists regression results using all regressors, while panels (2)-(4) each omit one regressor consecutively from the regressions.

Highest level of education obtained

Highest level of education is the most important predictor of an employee's job exposure to generative AI. We find that each increase in the level of higher education, the odds that the employee is highly exposed (with a score of 1), decreases steeply by a factor of 0.78, from results of the binary logistic regression. From the multiple linear regression results, with exposure scores continually ranging between 1 and 3, we find that one level increase in the respondent's highest level of education predicts a decrease in the mean exposure score (EM) by 0.183.

Those with higher levels of education are less likely to be in roles with high automation exposure. They are in fact, likelier to be in roles in which most tasks are augmented by generative AI, as our survey results contain very few respondents whose jobs are unexposed to generative AI. Their productivity and earnings are thus predicted to increase with the advent of generative AI technology (Autor, 2022).

The observation that the level of educational qualification can help predict labour market exposure is corroborated by studies on previous waves of computerized automation. Autor et al., 2003 for instance, find that computerization of tasks in the last two decades of the 1900s contributed largely to rising demand for college educated labour as compared to non-college educated labour.

Type of educational specialization

The type of the respondent's educational qualification, denoted by a score ranging from 1 (least quantitative degree) to 3 (highly quantitative degree) is the second most important and significant determinant of exposure. Employees with more quantitative educational specializations are less likely to be exposed to automation effects of generative AI in their role.

The binary logistic regression shows that among types of educational specializations, while the category 2 of "moderately quantitative degree" does not statistically significantly differ from category 1 of "least quantitative degrees" in their effect on exposure, category 3 "highly quantitative degrees" are significantly more likely to decrease the likelihood of respondent exposure to GPT-4 than category 1. The odds of a respondent being exposed decreases by a factor of 0.76 if they have an educational specialization of category 3 rather than category 1, keeping other characteristics constant. Results of the multiple linear regression also affirm this result. The mean exposure score of a respondent having educational specialization of category 3 is likely to be lower by a factor of 0.192 than someone with specialization of category 1.

That more quantitative educational degrees predict decreased exposure to automation effects of generative AI is a somewhat puzzling result because generative AI as a technology is particularly good at several quantitative tasks such as programming and data analysis tasks (Berg and Gmyrek, 2023; Cheng, Li and Bing, 2023). However, successful prompting and implementation for these tasks requires a considerable level of skilful and experienced oversight, which may make these tasks more augmentative of labour rather than automative. So, while workers with quantitative specializations may be exposed to GPT-4, the technology might thus far only augment their capabilities, which may help explain why automation exposure is predicted to decrease in more quantitative educational specializations. Further explanation into this link, is however, needed.

Gender

Being male rather than female, is a significant but a weak predictor of exposure scores. Mean exposure measure is predicted to decrease by a factor of 0.065 if the respondent is male rather than female. The odds of exposure score being 1 decrease by 0.63 if the employee is male. This finding correlates with findings of gendered exposure effects using gender segregated employment data at the global level, where a greater share of females than males have been estimated in roles which are highly exposed to automation effects of generative AI,5 6. There is, however, insufficient research to explain why this gendered correlation might exist, and further investigation is needed to identify what the underlying causes may be.

From preliminary analyses on our survey data, some speculations for why gender may be a predictor of exposure, are based on the following observations:

- There is no significant difference between the genders in the highest level of education obtained, so this should not play a role in the gendered difference in exposure that is observed.
- There is a small but significant difference between genders in the type of education specialization, with the odds of a male having a more quantitative educational specialization being 0.22 higher than a female, on average. Thus, females having less quantitative educational specialization may explain a small part of the gendered difference in exposure. Note: The correlation between the education specialization and gender (0.13) is however, small enough to avoid the issue of multicollinearity in our main regression, as also observed through the VIF table (see appendix).
- In our data, females are on average, in a slightly lower age group than males. Since, as we will see below, increasing age group predicts lower exposure to generative AI, this may also be partly contributing to the increased gen AI exposure of females. Once again, the correlation (0.09) and VIF factors (see appendix) are low enough between gender and age group that inclusion of both these predictors don't cause multicollinearity in our main models.
- Other variables that are not measured in our survey data and beyond the scope of this analysis, such as cultural factors, differences in personal preferences of genders, and institutional factors may also contribute to the gendered outcomes of exposure, however, this needs to be explored separately.

Age group

Age group predicts even less of the variability in the exposure outcome than does gender, however, it does so with statistical significance, when age group is treated as a continuous variable, with 7 levels. With one level increase in age group (being five years older, on average), a respondent's mean exposure is predicted to decrease by a small factor of 0.035. Through logistic regression, we find that the odds of exposure score 1 decreasing by a factor of 0.22 for each level increase in age group.

When we re-run both types of regressions treating age group as a categorical variable as a robustness check (see appendix), we find that the difference in predicted exposure scores for every age group is not statistically significantly different from the exposure scores of the next consecutive age group. This may partly be due to smaller sample sizes in each of the 7 age group categories, and it may also be because while on aggregate, increase in age group predicts decrease in exposure, there is not a statistically significant difference of exposure between immediately consecutive age groups with gaps of a maximum of 10 years or less.

From preliminary analyses on our data, we see that those in higher age groups are predicted to have (a) higher levels of education (albeit with low collinearity and VIF scores thus avoiding multicollinearity in our main regressions) and (c) be in more senior organizational roles. Perhaps age grants the time for more employees to be promoted, and hence escape high-automation exposed roles, and gives them time to complete more advanced levels of education. Both are directly correlated with lower job role exposure. These cannot help us reach definitive conclusions however, as to why age group might significantly predict job exposure, and further research is needed on this front also.

4.1. Limitations

Some limitations to our approach and the subsequent conclusions we can make are as follows:

In predicting job exposure, we have considered only those possible respondent characteristics as potential predictors, about which we collected information during the survey. There may be other predictors – such as IQ of the individual – tied to individual capability, or a personal preference to routine tasks, which may have influenced both our predictors such as the respondent's specialization field and educational level, as well as the outcome variable, job exposure. We were, in the scope of this study, not able to obtain information to control for such confounding variables, and a separate study would be needed to address potential impacts of the same.

Further, one possible reason that highly educated workers or those holding more quantitative education specializations may be in less exposed roles, is that such roles may be relatively scarce in supply relative to the labour market demand for them. In this case, higher levels of education and more quantitative degrees could simply be market signals or filtering mechanisms to allow people to occupy these "safer" roles, instead of being indicative of the individual's underlying capabilities or skills. In this case, the results of our regressions may be confounded, and further exploration warranted.

Finally, given the rapid pace of evolution of generative AI technologies the introduction of several improved large language models in the past year alone, it is important to acknowledge that the findings of this paper are bound by a) the capabilities of the generative AI technology we benchmarked on, namely GPT-4, based on which the task and job wise exposure scores have been calculated, in 2023 and b) the survey results containing characteristics and roles of workers, and job classifications with descriptions, which was obtained between 2023-2024 from one local jurisdiction. Results may change with a bigger and more diverse sample size and may not be generalizable out of context. As the capabilities of large language models keep improving, even tasks which have been thus far predicted as "augmentable" by the technology, may be at risk of "automation", putting new categories of workers at risk.

5. Conclusion

The study finds, from regression analyses on the survey results, that lower levels of educational qualification and less quantitative fields of educational specialization are likely to predict high exposure to automation among Dubai government employees. That a higher highest level of education is the strongest predictor of reduced automation exposure is not surprising. Studies on labour impacts of historic waves of automation have shown a polarizing shift in occupational demand towards high paid professional, and low wage services (Autor et al. 2023), where high paid professionals are much more likely to be college educated and new occupations tended to increase demand for college educated rather than non-college educated workers.

With regards to the relationship between educational specializations classified as more “quantitative or analytical” and lower automation exposure, existing literature has less to offer, and this relationship can be explored in further research.

Being female and younger are also robustly predictive of greater automation exposure scores from our data, although to a smaller extent. The gendered effects of job exposure to automation adversely affecting a larger proportion of females are confirmed by global estimates which predict the same. However, the causes of such gendered effects to automation exposure need to be better understood and this requires further research.

Findings from this paper highlight the need for further research into the determinants of job exposure to automation by generative AI in general, and in the government of Dubai more specifically. If we assume that advanced degrees and quantitative specializations, are the *cause* of *some* new capabilities and interests in employees, that did not exist in them before, it is important to understand what these capabilities or skills are, which results in these employees being able to perform occupational tasks that are largely benefited or “augmented” by generative AI. How can such skills or abilities be effectively transferred to people in vulnerable roles so that they can be repositioned, reskilled or upskilled, quickly and effectively? Will there be enough demand in the roles that are augmented by generative AI, so that workers from highly automated occupations when reskilled, can also be accommodated in higher productivity roles the labour market? These dynamics must be studied for effective policy planning and labour reskilling decisions, as this new wave of rapid improvements in generative AI technology begins to leave its early footprints on the labour market.

Policy Implications and Recommendations

1. Implications

The findings from this survey and case study based analytical report reveal several implications that require attention from government leaders and those looking to successfully implement generative AI across their organizations. The following policy directions were developed based on the analysis of the findings of the study and fieldwork with chief AI officers across the government. While the following remains specific to the government of Dubai, they provide various opportunities for benchmarking and trend analysis at the wider government level in the UAE, and beyond.

The pressing need for comprehensive training programs for employees across Dubai government organizations: With over 60% of current users of generative AI lacking necessary training (but showing interest in receiving it), there is a clear and present need for at least basic training programs in prompt engineering, and generative AI risks and mitigation strategies. These programs must be tailored to different categories of employees from technical staff to administrative and front-line staff. Particular attention must be paid to departments that are most vulnerable to AI automation and augmentation like customer service and administrative departments like HR and finance. This kind of training can help employees to adapt and more effectively utilize this technology in their daily work. Employees should also be made aware of the less-known facts regarding generative AI technology, such as its adverse environmental impacts, of which less than 10% employees have currently expressed any concern.

Risk management emerges as another priority, particularly as it concerns data privacy, and assessment of GAI outputs. Organizations must develop robust protocols for categorizing and handling sensitive organizational data and establish clear procedures for verifying the accuracy and validity of generative AI generative content and analysis. This includes training employees in these skills and implementing “human in the loop” monitoring systems. This includes developing clearly defined accountability chains for AI-assisted decisions – here, employees should be encouraged to use these technologies and indicate where they have been used and the procedures employed to verify the accuracy and validity of outputs. Procedures must also be developed for how to handle errors, hallucinations, and inaccuracies.

Risk management includes the re-development of comprehensive ethics frameworks and guidelines that assist employees in understanding the ethical implications of generative AI technologies. This is important given that 59% of current generative AI users in our survey reported that they were unaware of any AI ethics guidelines. Such frameworks should offer practical guidance and be unified across Dubai government with specialized guidance for organizations that handle unique sensitive data. Integrating these ethical guidelines with existing governance frameworks, and training employees on them, is crucial to ensure consistent application.

With significant concerns emerging about job displacement due to AI automation and augmentation of existing roles, **organizations must develop clear communication and change management strategies that help employees to transition to an AI augmented workforce**. This includes developing career paths and growth opportunities that incorporate generative AI skills and reward employees who participate in AI skills training and certification. Organizations must create cultures of technological adaptation that encourage experimentation with generative AI technologies and upskilling in areas crucial to the organization.

Finally, **implementation of skills taxonomies and robust skill evaluation processes is crucial for long term adaptation and success**. Such a taxonomy should identify and evaluate current AI and generative AI skills ranging from analytical skills to computational skills and bias detection. This will help organizations to understand their current skill gaps and develop strategies to bridge them. Such taxonomies must be continually updated to reflect ongoing technological and skill development.

Bridging the generative AI skill gap in Dubai government will require collaboration and coordination from multiple government departments, both those leading the charge and those lagging behind. Organizations must take a whole-of-government approach to upskilling ensuring that employees across government have the opportunity to develop their skills while at the same time each organization must understand its unique needs and the skills required to meet them.

2. Potential Initiatives

1. **Taking a collaborative approach to generative AI implementation and upskilling:** Given the resource and expertise intensive nature of generative AI implementation across government a cooperation not competition approach is needed. Formal mechanisms can be developed for sharing technical expertise to enable the sharing of experiences, best practice, and resources. Regular forums should be established for sharing use-cases, implementation experiences, challenges, and solutions. This will create a shared knowledge ecosystem that will benefit all of Dubai Government ensuring that all departments, including smaller departments that might otherwise struggle to develop GAI capabilities, will benefit. Additionally, Dubai government entities, especially smaller ones, can explore collaborative procurement and licensing arrangements for AI tools and services, as well as for training and upskilling programs.

2. **Developing government wide skills taxonomies that can be tailored for each organization**: Led and coordinated by the central HR department, government entities across the government of Dubai can collectively develop standardized skills taxonomies that align with global and expert understandings of critical skills related to generative AI technology. The frameworks would aid in establishing clear proficiency levels aligned with role specific competency requirements and assessments. These frameworks should also include skills for advanced and technical users as well as for general users. These taxonomies will need to be regularly updated. These taxonomies can then be tailored to each organization will maintaining the core standardized framework.

3. **Developing skill assessment tool kits in the age of GAI:** There is a growing need for skill assessment tools that include role specific assessment criteria that align with the proficiency levels and skills needed for specific roles within an organization. These diagnostic tools will be available to organizations across the government of Dubai and can be tailored to suit an organization's needs. Having shared assessment tools and criteria will also assist the policymakers to continuously observe government wide trends related to skill attainment and skill gaps as new generative AI applications (among other digital tools) are introduced.

4. **Collaborating on upskilling efforts:** Developing government wide thematic training programs and certifications related to generative AI that allow employees from across government to share experiences and expertise. These training programs can reduce the burden on individual organizations to develop and fund training, while also ensuring that all employees have equal access to upskilling opportunities. Such programs can also ensure that different employment categories across government can receive training and develop skills that are aligned with their competency requirements based on the GAI skills taxonomy.

5. **Developing generative AI-at-work ethics guidelines:** Developing generative AI-at-work ethics guidelines that are based in the practical knowledge of how generative AI is being used within their organizations. Such guidelines will incorporate concerns related to data privacy, GAI biases, and how to establish robust monitoring and "human in the loop" mechanisms for GAI systems.

6. **Review existing data privacy guidelines to incorporate generative AI considerations**: Existing data privacy guidelines and policies would benefit from introducing measures to address risks presented by generative AI applications in government settings.

7. **Developing transparent change management priorities for an AI augmented workforce:** A comprehensive change management framework is needed within entities that clearly outlines organizational visions for AI/GAI integration. Such a framework should clearly communicate the way that organizational roles will transform, and at what pace, and how employees can develop their skills to fit their new roles.

Finally, given the nature of generative AI applications and the breakneck speed of development and exponential improvement in quality, growth in penetration and user adoption, and the expanding innovative use cases, it is important to highlight that the trends of using generative AI are also rapidly changing within government structures. The study is a first attempt to capture and explore the emerging trends at critical early stage of adoption of generative AI applications in government, and the impact of these applications on public sector employees' productivity, behaviours and their interaction with business processes and job tasks. It is important to continue observing the scope of change, expand data collection and expand deeper sectoral analysis to document the ever-changing dynamics of introducing this sociotechnical phenomenon rapidly transforming government operations. Such continuous assessment will be necessary to identify the emerging opportunities as well as address the ethical implications and risks.

Appendix

Part A: Survey (Part III) Appendix

Part B: Labour Market Exposure Analysis (Part IV) Appendix

Robustness Checks

I. Correlation check between independent variables used in the multiple linear regression

We perform the VIF test to check for issues of multicollinearity that may exist between the explanatory variables used in our regressions. Given that all the variation inflation factors are well below the threshold of 10, we don't have concerns about multicollinearity between the variables.

Variable	VIF	1/VIF
Highest level of education	1.02	0.985186
Specialization type		
2	2.12	0.471201
3	2.16	0.464
2. Gender	1.04	0.963466
Age group	1.04	0.960305
Mean VIF	1.47	

II. Hosmer–Lemeshow Test for the binary logistic regression model, evaluating goodness of fit

Results of the Hosmer-Lemeshow test are presented below:

Variable: Binary_Exposure

Number of observations = 1,157

Number of groups = 10

Hosmer–Lemeshow ***chi²*** *(8) = 4.18*

Prob > chi^2 = 0.8401

Given that the results of this test are statistically insignificant, our binary logistic regression model can be concluded to have goodness of fit.

III. Classification accuracy of binary logistic regression model

The logistic regression model more accurately predicts non-exposure as compared to exposure. False negative predictions for true exposed cases is high, at 50.3%. The model thus underestimates the likelihood of a person's role being exposed to GPT-4. Overall classification accuracy is 79.2%.

Classified	True D	True ~D	Total
+	168	71	239
-	170	748	918
Total	338	819	1157

Classified + if predicted Pr(D) >= .5
True D defined as exposure_01 != 0

Sensitivity	Pr(+| D)	49.70%
Specificity	Pr(-|~D)	91.33%
Positive predictive value	Pr(D| +)	70.29%
Negative predictive value	Pr(~D| -)	81.48%
False + rate for true ~D	Pr(+|~D)	8.67%
False - rate for true D	Pr(-| D)	50.30%
False + rate for classified +	Pr(~D| +)	29.71%
False - rate for classified -	Pr(D| -)	18.52%
Correctly classified		79.17%

Regressions: Assuming all regressors as categorical

Results for logistic regression model treating all regressors as categorical

Binary exposure score	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Highest level of education						
2	-2.045***	.2065449	-9.90	0.000	-2.450147	-1.640506
3	-3.031***	.2556705	-11.86	0.000	-3.532379	-2.530169
4	-4.955***	1.035615	-4.78	0.000	-6.985043	-2.925508
5	0	(empty)				
Specialization type						
2	-.134	.2142988	-0.62	0.533	-.5535314	.2865046
3	-1.380***	.2186564	-6.31	0.000	-1.808936	-.9518187
2.gender	-.718***	.1597733	-4.49	0.000	-1.030969	-.404669
Age group						
2	.158643	1.150627	0.14	0.890	-2.096545	2.413831
3	.0683337	1.141153	0.06	0.952	-2.168286	2.304953
4	-.2495022	1.138403	-0.22	0.827	-2.480731	1.981727
5	-.6648378	1.136594	-0.58	0.559	-2.892522	1.562846
6	-1.028333	1.141765	-0.90	0.368	-3.266151	1.209486
7	-.6948139	1.147571	-0.61	0.545	-2.944012	1.554384
_cons	2.597*	1.157487	2.24	0.025	.327927	4.865191

Legend: * p<0.05; ** p<0.01; *** p<0.001

Multivariate regression results treating all regressors as categorical

Mean exposure	Coefficient	Std. err.	t	P>|t|		Beta
Highest level of education						
2	-.357***	.0282132	-12.64	0.000		-.4670692
3	-.473***	.0310186	-15.26	0.000		-.5502496
4	-.543***	.0533093	-10.19	0.000		-.2867416
5	-.568***	.1197179	-4.74	0.000		-.1232877
specialization type						
2	-.025	.0297582	-0.84	0.401		-.0312302
3	-.166***	.0287615	-5.77	0.000		-.2174652
2.gender	-.089***	.0208276	-4.29	0.000		-.1126575
Age group						
2	.041	.1512745	0.27	0.788		.0291904
3	.020	.1498702	0.14	0.892		.0184156
4	-.050	.1493811	-0.34	0.737		-.0512946
5	-.097	.148913	-0.65	0.516		-.1109774
6	-.141	.1491802	-0.95	0.345		-.1475906
7	-.087	.1498772	-0.58	0.564		-.0768687
_cons	2.027***	.1513552	13.39	0.000		.

Legend: * p<0.05; ** p<0.01; *** p<0.001

Classification of educational specializations

The following are the classifications of different educational specializations by the general degree of analytical or quantitative study that the disciplines involve.

Educational Specialization selected by respondent	Classification of specialization	Description of specialization
Computer Science/IT	3	Very quantitative
Natural Sciences	3	Very quantitative
Engineering	3	Very quantitative
Data sciences	3	Very quantitative
Mathematics	3	Very quantitative
Accounting and finance	3	Very quantitative
Social sciences	2	Somewhat quantitative
Law	2	Somewhat quantitative
Management or business administration	2	Somewhat quantitative
Humanities	1	Minimally quantitative
Human Resources management	1	Minimally quantitative
Other	1	Minimally quantitative

Regressions – Detailed results

Binary logistic regression results: Predictors of exposure level (0 or 1)

Exposure_Binary	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Highest level of education	-1.52811	.1256542	-12.16	0.000	-1.7744	-1.2818
Specialization_type						
2	-.1636474	.2112513	-0.77	0.439	-.5777	.25040
3	-1.424565	.2140909	-6.65	0.000	-1.8442	-1.0050
2. Gender	-.6326843	.1552886	-4.07	0.000	-.9370	-.3283
Age group	-.2401072	.0520557	-4.61	0.000	-.3421	-.1381
_cons	4.436857	.4231026	10.49	0.000	3.6076	5.2661

Binary logistic regression: Odds Ratio

Exposure_Binary	Odds ratio	Std. err.	z	P>|z|	[95% conf. interval]	
Highest level of education	.2169452	.0272601	-12.16	0.000	.1695872	.2775282
Specialization_type						
2	.8490413	.1793611	-0.77	0.439	.5611919	1.284536
3	.2406132	.0515131	-6.65	0.000	.1581557	.3660614
2.gender	.5311641	.0824837	-4.07	0.000	.3917842	.7201295
Age group	.7865435	.0409441	-4.61	0.000	.7102527	.871029
_cons	84.50889	35.75593	10.49	0.000	36.87711	193.6636

Multiple linear regression: Predictors of mean exposure score, with standardized coefficients

Mean_Exposure	Coefficient	Std. err.	t	P>|t|	Beta
Highest level of education	-.1836298	.0127296	-14.43	0.000	-.3769521
Specialization_type					
2	-.0390272	.0302517	-1.29	0.197	-.0487453
3	-.1928026	.0290512	-6.64	0.000	-.2527009
2.Gender	-.0650655	.0209504	-3.11	0.002	-.0820649
Age group	-.0320331	.0068104	-4.70	0.000	-.1244917
_cons	2.179939	.0488428	44.63	0.000	.

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