BROOKINGS

AI IN THE INFORMATION SECTOR ADVANCING SOFTWARE, CUSTOMER SERVICE, AND DESIGN

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AUTHORS' NOTE

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Generative AI technologies have experienced incredible advances in recent years, which have brought on many interesting and useful applications across various industries. One broad industry that covers many different aspects of the economy is the information sector, which includes occupations such as customer service representatives, software developers, computer programmers, and graphic designers. Generative AI applications like ChatGPT and others have substantial applications across these occupations and have the potential to improve productivity in the sector but also pose significant risks of job displacement. As AI systems evolve, they have the potential to automate certain job functions, which could shift workforce demands and require new skill adaptations. This case study details how generative AI is being applied in specific occupations within the information sector by investigating relevant research and use cases. Due to the wide range of occupations within the information sector, we focus on three specific areas of the information sector: computer programming, customer service, and graphic design.

This case study is structured as follows: First, we provide an overview of the information sector. Second, we document the applications of generative AI in the information sector, specifically highlighting computer programming, customer service, and graphic design. Lastly, the third section concludes.

1. Overview of the information sector

The information sector is a service-providing industry that, according to the North American Industry Classification System (NAICS), is made up of establishments engaged in the following processes: "(a) producing and distributing information and cultural products, (b) providing the means to transmit or distribute these products as well as data or communications, and (c) processing data" ("Industries at a Glance: Information: NAICS 51" n.d.). There are approximately 371,000 business entities that operate in the information sector in the U.S. with some of the largest companies operating in the sector like AT&T, Meta Platforms, and Microsoft ("NAICS Code Description: 51 – Information" n.d.). This sector comprises several key components: publishing industries, which include software publishing as well as both traditional and internet-exclusive publishing; motion picture and sound recording industries; broadcasting industries, encompassing both traditional broadcasting and internet-only broadcasting; telecommunications industries; and web search portals, data processing industries, and information services industries ("NAICS Code Description: 51 – Information" n.d.).

The information sector encompasses a wide range of occupations across its subindustries. In publishing, roles include reporters, correspondents, and graphic designers. Telecommunications employs professionals such as electronics engineers and customer service representatives, while data processing and hosting services rely on computer programmers, software developers, and IT support specialists. Although the sector hosts diverse occupations, several have significant potential for AI to enhance worker productivity.

One framework of the information industry deconstructs the sector into three areas: create, move, and use information (Raphael 1989). The "create" area of the information sector is comprised of submarkets such as newspapers, periodicals, market research, libraries, and economic and financial data. The "move" subsector includes submarkets like television, radio,

FIGURE 1

Information subindustry contributions to total factor productivity growth

Publishing industries, except internet (includes software)

Motion picture and sound recording industries



Broadcasting and telecommunications

Data processing, internet publishing, and other information services



Note: Calculated using Domar weights and 3-year moving averages.

telephone services, and communication equipment. Finally, the "use" subsector involves transaction processing, consumer electronics, computer hardware, and electronic mail. A similar framework for grouping the sector's establishments separates them into three categories: "(1) those engaged in producing and distributing information and cultural products; (2) those that provide the means to transmit or distribute these products as well as data or communications; and (3) those that process data" ("Industries at a Glance: Information: NAICS 51" n.d.).

Productivity growth in the sector has remained mostly strong in recent decades. As seen in Figure 1 and Figure 2, the information sector experienced strong productivity growth in the mid-2000s, largely due to the strong productivity growth in the broadcasting and telecommunications subsector. From 1990 through 2010, data processing, internet publishing, and other information services didn't contribute much to productivity growth, except in 2004. Since 2020, the data processing, internet publishing, and other information services subsector has contributed to significant productivity growth within the broader information sector. The COVID-19 pandemic likely drove some of these gains by increasing reliance on digital tools and accelerating the transition of businesses to remote work and online platforms. Additionally, data processing services are inherently well-suited for remote work, enabling companies to reduce physical office expenses, and potentially benefit from improved workforce management systems, which may have boosted employee productivity.

FIGURE 2





2. Applications of AI in the information sector

Generative AI has broad applications in key occupations in the information sector such as computer programming, customer service, editors, and graphic designers. These occupations have seen the most innovation with generative-AI-powered tools such as GitHub copilot and Adobe Photoshop's Generative Fill. These applications of AI have the potential to improve productivity for information sector workers, leading to higher standards of living and wages in the long run.

2.1. COMPUTER PROGRAMMING

Al-assisted software development is a new technology powered by generative Al that can help coders become more productive. These assistants are integrated into the coding environment and offer intelligent code suggestions and auto-completion. Some examples of Al-assisted software development programs include GitHub Copilot, Amazon CodeWhisperer, and Replit Ghostwriter ("GitHub Copilot - Your Al pair programmer" n.d.; "What is CodeWhisperer?" n.d.; Masad et al. 2022).

These Al-assisted software development programs have been the subject of numerous case studies of the use of AI for computer coding. For example, Cui et al. (2024) find that software developers using GitHub Copilot complete 26.08% more tasks than software developers without the assistant. In addition, Peng et al. (2023) found that software developers using GitHub Copilot completed a task 55.8% faster than the control group that wasn't offered access to the program. Not only does this program make developers more productive but one GitHub-sponsored survey shows that it increases job satisfaction and enjoyment (Gao and GitHub Customer Research 2024). Specifically, 90% of developers found they were more fulfilled in their jobs when using GitHub Copilot. The same survey also found that AI-assisted software development programs are being rapidly adopted, with over 80% of participants successfully adopting GitHub Copilot. More than 50,000 organizations have adopted GitHub Copilot and approximately 30% of businesses in data processing, hosting, and related services (NAICS 518) had used AI in some capacity in the past two weeks as of late February 2025 (Nadella and Hood 2024).¹

GitHub copilot can also improve the pull request (PR) process of software development. A PR is a way for developers to propose changes to a codebase and get feedback from team members before merging the changes into the main project. GitHub Copilot for Pull Requests is a service intended to automate various developer tasks related to PR. This includes generating summaries of changes and helping team members review pull requests. Xiao et al. (2022) studied the impact of GitHub's Copilot for PRs and found that Copilot for PRs decreases the review time by 19.3 hours and increases the likelihood that PRs are merged by 57%.

Al can also help developers translate code from one language to another. While rule-based methods are common in this process, Al has been able to perform similar functions. An example of a neural machine translation (NMT) model is the Transcoder, a translation model developed by researchers at Meta Al, which produces correct code translations 25%-92% of the time, depending on coding languages (Lachaux et al. 2020). To achieve correct translation, human effort is needed to identify and fix errors in code translation. Weisz et al. (2022) estimated the effect of the Transcoder on software engineers' code translation performance, finding that despite incomplete or erroneous translation, participants aided by the outputs of the Transcoder produced code with fewer errors than when working without it.

AI and Large Language Models (LLMs) can also help with software maintenance such as program repair, code review, and debugging (Hou et al. 2024). Program repair is the process of identifying and fixing bugs or defects in software, which can be automated using LLMs. LLMs perform strongly in program repair and can generate patches for bugs and defects. They can also capture underlying semantics and dependencies in code. During code review, developers examine code to uncover errors, spot vulnerabilities, and address quality issues with the goal of making the code more maintainable, scalable, and readable, which LLMs can assist with. LLMs trained on massive code repositories can assist reviewers in comprehensively understanding code and enable more accurate detection of errors and issues. These models can also offer suggestions for code improvements or optimizations.

There are many additional applications of LLMs for software maintenance, including code clone detection, bug reproduction, duplicate bug report detection, logging, bug prediction, and many others. Code clones are samples of code that are identical and can have structural or semantic equivalence. A study by Sharma et al. (2022) used BERT, a transformer-based LLM, to identify code clone detection, finding a 21-24% increase in performance using BERT. In addition, LLMs can be used for bug reproduction: Feng and Chen (2023) introduce an LLM to extract Steps to Reproduce (S2R) from bug reports. Logging is the "systematic recording of events, messages, or information during the operation of a software application," which can be enhanced through the use of LLMs (Hou et al. 2024, 38).

2.2. CUSTOMER SERVICE

Another occupation in the information sector that can benefit from the use of generative AI is customer service representatives. Customer service is the assistance and support provided by a company before, during, and after they make a purchase or use a product or service (Ferraro et al. 2024). As of May 2023, there were approximately 2.8 million customer service representatives employed in the U.S., 124,600 of which come from the information sector ("Customer Service Representatives" 2024). The hourly median wage for customer service representatives in the information sector was \$22.33, above average for the for the overall occupation (\$19.08). Customer service representatives have a wide range of tasks such as keeping records of customer interactions or transactions, contacting customers to respond to inquiries, and providing information to customers about products or services ("43-4051.00 - Customer Service Representatives" 2025).

Al has been used in the customer service occupation for many years, but it has traditionally relied on predictive Al. There is a wide range of applications of predictive Al that are being used in the occupation, including pattern recognition, automated prevention, and smart resource allocation (Koundinya 2024). Al uses pattern recognition to identify common customer pain points or spot issues before they become widespread. In addition, Al can be used in customer service by implementing automatic preventative measures and triggering proactive support interventions. In addition, predictive Al can improve the allocation of resources such as staff attention by predicting support volume trends and optimizing staffing levels.

Even before the advent of generative AI, "chatbots" have been commonly used in customer service to help and complete routine tasks such as answering questions, providing guidance to customers, or providing product recommendations. These systems are conversational software systems capable of simulating human communication skills to interact with customers via chat (Misischia et al. 2022). These chatbots are extremely helpful to companies that are looking to provide personalized assistance to customer issues at a lower cost than humans. Chatbots are particularly useful for more routine requests from customers, allowing companies to focus worker attention on high-skill tasks. Chatbots can also be available 24/7 for customers, reducing response times and improving accessibility for customers. However, performance of

chatbots depends on several factors, such as the type of product (Ruan and Mezei 2022), purchase intentions of the consumer (Chen et al. 2023), or the type of firm (Xiao and Kumar 2021). For example, human customer service representatives tend to do better than AI chatbots when a product is experiential and AI chatbots perform better than humans when the product is functional (Ruan and Mezei 2022).

With the introduction of generative AI, the capabilities of chatbots have expanded, allowing for greater use in customer service occupations. Generative AI can create unique, new outputs that are similar to how a customer service representative would respond to customer needs and offer solutions. Generative AI can automatically generate replies to customer requests using resources that the AI has been trained on such as web links or knowledge bases. Further, using natural language processing, chatbots can analyze customer sentiment and identify customer needs.

Generative AI-powered chatbots can benefit workers and employers in many ways, boosting productivity. There is significant productivity for customer service representatives using generative AI. AI can be used as a personal assistant for customer service representatives, which can help with generating personalized replies to service inquiries. When trained on relevant data, generative AI models can deliver natural language responses by drawing on customer information, internal knowledge bases, and reliable third-party sources. The productivity benefits for customer service representatives have been documented as well. Brynjolfsson et al. (2023) find that access to an Al-based conversational assistant improves productivity, measured by issues resolved per hour, by 14% on average. Similar to other studies, within a given occupation, generative AI greatly improves the productivity of low-skilled and novice workers while having small effects on high-skilled, experienced workers.

There are several examples of state-of-the-art, generative AI-powered chatbots that are being used by companies today. These examples include IBM's Watson Assistant, Salesforce's Service Cloud Einstein, and Google's Dialogflow ("IBM watsonx Assistant Virtual Agent" n.d.; "Salesforce Einstein AI Solutions" n.d.; "Conversational Agents and Dialogflow" n.d.). IBM's Watson Assistant is a conversational AI that can communicate with customers to help boost productivity of customer service operations. This AI model can understand complex customer queries and enable customer self-service. An IBM-commissioned study on the effects of Watson Assistant found that chatbot-augmented customer service agents reduce interaction handle time by up to 30% (Forrester Consulting 2023).

While there are many benefits to integrating chatbots into customer services, there are also many drawbacks to the use of generative AI-powered chatbots. For example, data security risks can lead to customer confusion, dissatisfaction, or avoidance. Ferraro et al. (2024) highlight several key paradoxes of AI-enabled customer service: Chatbots can lead to customer isolation due to the lack of human interaction; chatbots' use of data can help businesses personalize customer service but may raise privacy concerns; and chatbots can lead to lost and/or damaged customer relationships if a customer becomes frustrated with a chatbot.

2.3. GRAPHIC DESIGNERS

Graphic designers create visual concepts or designs to convey ideas that engage, inform, and inspire consumers using computer software or by hand. They design layouts and production elements for various applications, including advertisements, brochures, magazines, and reports. In the U.S., there were approximately 212,720 graphic designers as of May 2023, with 23,280 coming from the information sector, accounting for around 10% of all graphic designers. The hourly median wage for graphic designers in the information sector is \$28.65, similar to the annual median wage for all graphic designers (\$28.32).²

New generative AI tools have been developed to improve the productive processes of graphic designers. Large-scale models such as OpenAI's DALL-E 2 or Midjourney are trained on millions of images to create new images from users' text inputs ("DALL-E 2" 2022; "Midjourney" n.d.). A particularly important generative AI model for graphic designers is Adobe's Firefly, a generative AI model trained on Adobe stock images, openly-licensed content, and content in the public domain ("Adobe Firefly" n.d.). This technology is useful to graphic designers because it is integrated into the Adobe suite of products like Adobe Express, Photoshop, and Illustrator, which many graphic designers use for their work. Adobe Firefly can not only create new images but can also be used to fill in graphics with new content using Generative Fill, allowing graphic designers to incorporate new ideas or images into existing visual media. According to Adobe, generative Al can make graphic designers more efficient by automating repetitive tasks, improving creativity by providing graphic designers with a brainstorming tool, and ensuring the accessibility of outputs ("Al for graphic designers: 3 major benefits" n.d.).

Generative AI tools like large-scale, text-to-image generation models (LTGMs) like DALL-E and Adobe Firefly have broad applicability in graphic design processes. One study by Ko et al. (2023) featured interviews with 28 visual artists covering 35 distinct visual art domains, including graphic design. This study found that LTGMs have a host of benefits that apply to graphic design. Specifically, LTGMs can help graphic designers find reference images for their creations, a crucial part of the creative process. LTGMs provide a quick and easy way for artists to create high-quality and unique reference images to use in their work. LTGMs can also help artists come up with ideas for images based on instructions or descriptions from supervisors, particularly if the directions are imprecise.

Al tools can be particularly useful during the ideation stages of graphic design, which is often the most difficult part of a graphic designer's design process. Graphic designers are often inspired in their work through the recombination of references-that is, taking elements from many different sources and bringing similar aspects together to create new designs (Choi et al. 2024). Generative AI can provide a diverse set of references for graphic designers to use in their work, streamlining the ideation process by reducing the time needed to search for references. Graphic designers can utilize generative AI to represent ideas as visual media quickly and easily using text prompting. Text prompting can provide graphic designers with a collaborative way to come up with new ideas. Choi et al. (2024) propose a generative AI system called CreativeConnect that helps graphic designers find useful aspects of reference images using keywords and can generate diverse recombination options with user-selected keywords. This model helps graphic designers come up with new ideas by recombining images in the early stages of ideation. This study found that CreativeConnect helped users become more productive when coming up with graphic design ideas. Users also perceived their ideas as more creative compared to the baseline.

While there are many potential benefits of using generative AI in graphic design, there are also several limitations to using the technology. In interviews with many artists, including some graphic designers, Ko et al. (2023) identified the challenges and limitations of LTGMs in assisting artists and graphic designers. First, artists and graphic designers found the predictability of LTGM outputs a burden, as it was unable to represent complex ideas and often directly matched the input text prompt when artists are looking for an abstract output. Another limitation some artists experienced was that text prompting restrained creativity. LTGMs pull information from the data they were trained on, making it difficult for artists and graphic designers to create novel or more abstract designs that are not similar to any of LTGMs training data. Another limitation was that LTGMs became a burden for some artists and graphic designers. Some respondents struggled with the use of text prompts to create images, as it was difficult to find an appropriate text prompt because of its open-ended nature.

Another point of uncertainty in Al's impact on graphic design is how it will affect the copyright and ownership of graphic designers' work. While there is still debate on whether Al-generated images are copyrightable, Copyright Registration Guidance from the Copyright Office and copyright proceedings indicate that the Copyright Office will likely not find human authorship where an Al program generates work in response to text prompts (Copyright Office, Library of Congress 2023). However, the issue of copyright protection of Al-generated work remains unsettled (Zirpoli 2023). Another unresolved issue is the issue of which party owns the materials generative Al creates. Companies may allocate ownership rights to either the company or its users via contract, like a company's terms of service. As it stands, OpenAl's Terms of Use assigns copyright to the user, but in a previous version, it was given to OpenAl ("Terms of Use" n.d.; Guadamuz 2022). Graphic designers' work will likely be impacted by future developments in copyright and ownership rights in the courts, which could impact the ability of the occupation to use generative Al in their work.

3. Conclusion

The integration of generative AI into the information sector offers transformative opportunities for occupations within the sector such as computer programmers, customer service representatives, and graphic designers. When integrated into the workflows of these occupations, these technologies can enhance productivity, streamline processes, and introduce creative tools that empower workers. From AI-assisted software development technologies like GitHub Copilot advancing software development to advanced AI-chatbots redefining customer service, in addition to tools like Adobe Firefly enabling new levels of creativity for graphic designers, the potential for generative AI in the information sector is vast.

Despite these opportunities, there remain significant headwinds to adopting and deploying generative AI in the information sector. Concerns over data privacy, job displacement, and limited reliability of models will need to be addressed, as it is critical to ensuring that generative AI is deployed ethically and effectively, complementing human effort rather than replacing it.

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Endnotes

1 Data is from the Census Bureau's Business Trends and Outlook Survey, Subsector (Buffington et al. 2023).2 Data is from the BLS's "Occupational Employment and Wage Statistics" (n.d.).