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In this issue:

- 4. Towards Adaptive Learning: A Review of Machine Learning on LMS Data**
Cindy Zhiling Tu, Northwest Missouri State University
Gary Yu Zhao, Northwest Missouri State University
Omar El-Gayar, Dakota State University
- 20. A Comparison of Large Language Models for Oncology Clinical Text Summarization**
Chiazam Izuchukwu, Georgia Southern University
Hayden Wimmer, Georgia Southern University
Carl Redman, University of San Diego
- 30. Stress and Driving Performance Evaluation through VR and Physiological Metrics: A Pilot Study**
Rehma Razzak, Kennesaw State University
Yi Li, Kennesaw State University
Estate Sokhadze, University of Louisville
Selena He, Kennesaw State University
- 52. A Comparison of Oversampling Methods for Predicting Credit Card Default with Logistic Regression**
Dara Tourt, Metropolitan State University
Queen E. Booker, Metropolitan State University
Carl Rebman, University of San Diego
Simon Jin, Metropolitan State University
- 64. Emergent Technologies Production in the US: Exploratory Analysis of Motivations and Adverse Factors**
Katarzyna Toskin, Southern Connecticut State University
Marko Jovic, Kennesaw State University

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Emergent Technologies Production in the US: Exploratory Analysis of Motivations and Adverse Factors

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Abstract

New technologies can provide substantial business opportunities, and many firms are currently working on adopting them in their organizations. Prior literature provides insight and guidance to help firms navigate the technology adoption process, but there is limited information about companies that supply or produce newer technologies in the US market. Therefore, this study analyzed the extent to which US firms produce or use emergent technologies, the motivating factors to do so, and the reasons that impede their progression. Findings reveal that the share of technology producers is proportional to the share of users based on each technology group. Additionally, a majority of US companies that produce technologies report upgrading of goods and services, expanding the range of goods and services, and increasing or maintaining market share as the top motivating factors for producing emergent technology or products/services that include such technology. Furthermore, the producers reported high costs as the top adverse reason for generating emergent technology. These findings provide new insight into firms that produce technologies and have direct implications for business strategists, as well as policymakers.

Keywords: Artificial intelligence, cloud-based, robotics, technology, innovation, adoption, production

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Emergent Technologies Production in the US: Exploratory Analysis of Motivations and Adverse Factors

Katarzyna Toskin and Marko Jocić

1. INTRODUCTION

A significant effort has been devoted to examining factors contributing to new technology adoption or impeding organizational progress toward innovation. More specifically, prior studies have investigated motivations and barriers to various firms' using or adopting emergent technologies (Bunte et al., 2021; Cubric, 2020). Some studies have also assessed the current adoption and use level of advanced technologies within US businesses (Acemoglu et al., 2022, 2024). However, the primary focus of these studies has been on the early adopters or technology users only. Little attention has been given to the producers or the suppliers of such technologies in the US market.

Therefore, the purpose of this study is to expand the current literature by investigating the share of US technology producers and users as well as motivations, and factors that adversely affect the production or usage of emergent technologies by US firms. This group provides a unique insight as it represents US companies that have already progressed through the initial phase of the technology adoption curve and possess hands-on experience creating and delivering innovative technologies to the market. Understanding such factors will not only shed new light on this group of companies but also provide understanding and a chance to address tech suppliers' motives, opportunities, and needs.

2. LITERATURE REVIEW

The main reason organizations adopt or use advanced technologies such as AI is to increase performance through improved operational efficiency (Bhalerao, Kumar, Kumar, & Pujari, 2022). Prior literature reports that about 29.5 % of Small and Medium-sized Enterprises (SMEs) were open to adopting AI applications (Bhalerao et al., 2022). More specific reasons include innovation, increased productivity and efficiency of business processes, reduced human error, improved decision-making, and predictive capabilities (Cubric, 2020). However, Acemoglu et al. (2022, 2024) noted that current adoption in US firms is still minimal, especially for AI, with

only 3.2% of companies using AI and only 2% of companies using robotics during the 2016–2018 time period. Although the low technology adoption rates have been highlighted in the current literature, along with the motivations and challenges, we know very little about US firms that produce or supply this technology.

The diffusion of innovation theory (Rogers, 1995) posits that adoption occurs after innovation is communicated in several phases through the social system. It consists of innovators, early adopters, early majority, late majority, and laggards, and it resembles an S-shaped distribution when the number of adopters from each category is mapped over time (Lai, 2017). Hall & Khan (2003) discussed the factors affecting technology diffusion. The authors highlighted that adoption is affected not only by demand but also by the suppliers of the new technology. The demand is primarily driven by the perceived benefits and the cost of adoption. On the other hand, the suppliers' role relates to addressing improvements of the new technology, which might initially be imperfect, and lowering the cost of new technologies over time (Rosenberg, 1972). Another important factor relates to "complementary inputs," which involves the suppliers' ability to offer training courses to upskill labor on the demand side (Hall & Khan, 2003). This information provision and knowledge transfer builds the firm's potential to use and ultimately adopt the new technology.

Considering that the adoption rate for AI and other emergent technologies within the US firms is still very low, we posit that this is in part due to the low share of supplying firms available in the US market. Hence, we form our first hypothesis as follows:

H1: The share of US firms that are suppliers is proportional to the share of adopters by each technology group.

Motivation to adopt emergent technologies can vary across companies and industries, but ultimately, the key reason for the adoption of innovative technology is to increase organizational performance (Hameed, Counsell, and Swift, 2012). Acemoglu et al. (2022)

estimated that the use of advanced technologies could lead to an 11.4% higher labor productivity because automation can replace manual labor and increase the efficiency of many internal processes. However, the motivations for companies that produce AI and other emergent technologies could be different primarily because selling or supplying innovative technology becomes part of the firm's value proposition. Hence, their business model is built around solving customers' problems with emergent technologies and establishing new customer segments and markets. As the motivations for producers of emergent technologies are likely to differ from technology adopters, we form our second hypothesis.

H2: The motivation of producers has a more strategic focus targeted externally towards the market, whereas users of emergent technologies focus on improving and upgrading internal processes.

The adoption of new technologies does not come without challenges. The most prominent adverse reasons identified by these firms were the lack of applicability and the high costs of deploying and integrating these technologies. Similar findings were reported by McElheran et al. (2024), who investigated the adoption and diffusion of technologies associated with AI, such as automated guided vehicles, machine learning, machine vision, natural language processing, and voice recognition. Their study revealed that fewer than 6 % of US firms utilized any of those technologies as of 2018.

Additionally, Cubric (2020) analyzed 30 published reviews involving AI adoption across various business sectors. The author reported that in addition to economic reasons such as high cost, AI adoption was negatively affected by technical and social aspects. Technical aspects included a lack of suitable data and limited reusability of models. Social reasons included a lack of expertise in this field, such as not understanding AI capabilities, which led to unrealistic expectations. Other social factors included stakeholder's perspective, distrust in the technology, fears related to its safety, and job insecurity. Similarly, Bunte et al. (2021) conducted interviews with 68 German companies and reported several challenges associated with the application of AI in SMEs. The reasons ranged from some participating companies feeling they were too small for AI to other companies evaluating the potential use of AI. Also, the lack of sufficient expertise, the extended amortization period, and the different

priorities for capital expenditures were listed as challenges. Additionally, some companies felt that AI did not offer enough potential for organizational improvements. To alleviate some of these challenges, further efforts have been made by formulating guidelines, solutions, and best practices to help organizations expedite the technology adoption process (Bunte et al., 2021; McKinsey, 2019). Due to the financial reasons being highlighted as the most prominent adverse factor impacting technology adopters, in our final hypothesis, we posit that cost is also one of the largest challenges facing suppliers.

H3: The adverse factors for technology producers are similar to adverse factors of technology adopters, with high cost being one of the primary reasons.

Considering the critical role of technology suppliers in the adoption and diffusion process, this study extends current research by investigating the motivations and barriers of companies that produce emerging technologies or use them for their goods or services. This specific subset of companies offers unique insight into the motivations and challenges due to their firsthand experience with these technologies in the US market, which might shed additional light on the diffusion process and low adoption rates of the advanced technologies among US firms.

3. METHOD

This study used the US Census Annual Business Survey (ABS) data collected in 2019 (United States Census Bureau, 2019) and reported on three years from 2016 - 2018. This is the latest data set available that contains valuable information about both technology users and producers. We used the surveys regarding the extent to which US firms produced and used emergent technologies, the motivations for doing so, and the factors that adversely impacted technology production or adoption.

The exact names of the data set used for production were titled Annual Business Survey: Technology Production in Employer Firms by 2-digit NAICS for the United States and States: 2018, Annual Business Survey: Motivation to Produce Technology of Employer Firms by Sex, Ethnicity, Race, Veteran Status, and Employment Size for the United States: 2018," and "Annual Business Survey: Factors Adversely Affecting Technology Production in Employer Firms by Sex, Ethnicity, Race, Veteran Status, and Employment Size for the United States: 2018."

For usage, the datasets were titled "Annual Business Survey: Extent of Technology Use of Employer Firms by Sex, Ethnicity, Race, Veteran Status, and Employment Size for the United States: 2018," "Annual Business Survey: Motivation for Technology Use of Employer Firms by Sex," and "Annual Business Survey: Factors Adversely Affecting Technology use in Employer Firms by 2-digit NAICS in the United States and States: 2018."

They contained information about firms with paid employees and receipts of \$1,000 or more grouped by industry using a 2-digit NAICS (North American Industry Classification System) code. The data set also included aggregate data for all sectors. Since the Census suppresses specific data to maintain confidentiality, only the aggregate-level data (totals) were available for analysis.

Measures

The ABS survey captured information about the following five technology groups:

- Artificial Intelligence
- Cloud-based
- Robotics
- Specialized Software
- Specialized Equipment

In the technology production part of the survey, the participants were asked whether their business sold one of the technologies or sold goods or services that included one of such technologies. The choices provided for respondents included yes, no, or don't know. Those participants who answered no or don't know were asked to skip the Motivations section and progress to the end of the survey to answer the questions regarding "Factors Adversely Affecting Technology Production." Otherwise, the participants who responded yes were directed to the next section, which captured the factors that motivated the technology production in these firms.

For the technology adoption portion of the survey, the participants were asked to what extent their business used one of the technologies in production processes for goods or services. The response options included: did not use, tested but did not use in production or service, low use, moderate use, high use, and don't know. Those participants who answered that they did not use, tested but did not use in production or service, or didn't know were asked to skip the Motivations section and progress directly to the "Factors Adversely Affecting

Technology Adoption and Utilization" section. Responses with all forms of usage levels (i.e., low, moderate, and high) were counted towards the yes category to compute the technology usage metrics.

Table 1 lists the total number of employer firms that participated in each part of the production survey (dataset) broken down by technology group.

Technology Group	Production	Motivation*	Adverse Factors
Artificial Intelligence	4,740,855	43,515	4,872,086
Cloud-Based	4,771,077	290,800	4,836,407
Robotics	4,771,494	28,758	4,814,035
Specialized Equipment	4,771,936	204,661	4,825,232
Specialized Software	4,740,229	340,577	4,825,607

* The sample size is smaller because it applies only to firms that indicated they were producing the technology, thus filtering out non-producers.

Table 1: Total Number of Firms Reporting in the Production Survey by Technology Group

Table 2 provides the sample sizes for employer firms that participated in each part of the extent of use survey broken down by technology group.

Technology Group	Extent of Use	Motivation*	Adverse Factors
Artificial Intelligence	4,750,687	141,731	4,743,443
Cloud-Based	4,784,033	1,550,716	4,731,659
Robotics	4,785,415	88,657	4,748,446
Specialized Equipment	4,785,419	855,657	4,751,574
Specialized Software	4,750,559	1,821,368	4,733,331

* Sample size is smaller as it applies only to firms that indicated they were using the technology, thus filtering out non-users.

Table 2: Total Number of Firms Reporting in the Usage Survey by Technology Group

4. FINDINGS

The data was analyzed using Tableau Desktop version 22.2.0 and Microsoft Excel 365 software. We begin by reporting the breakdown of firms that produced, did not produce, or did not know whether they produced the corresponding technology in Table 3. The data shows that most businesses did not produce any of the emergent technologies or goods/services that included those technologies during the survey period. From the subset of companies that did produce the technology, specialized software represented the largest percentage (3.9), followed by cloud-based computing (3.2), specialized equipment (2.3), AI (0.4), and Robotics (0.3).

Technology Group	Yes	No	Don't know
Artificial Intelligence	19,789 (0.4)	4,470,228 (94.3)	250,838 (5.3)
Cloud-Based	152,386 (3.2)	4,356,220 (91.3)	262,471 (5.5)
Robotics	15,071 (0.3)	4,520,639 (94.7)	235,784 (4.9)
Specialized Equipment	108,675 (2.3)	4,393,931 (92.1)	269,330 (5.6)
Specialized Software	185,315 (3.9)	4,296,562 (90.6)	258,352 (5.5)

Table 3: Number of Firms Responding to Technology Production Questions by Technology Group (percentage of firms in parenthesis)

We then analyzed the number of firms that used each technology group in Table 4. We find that specialized software is the most used, followed by cloud-based technologies, specialized equipment, AI, and robotics. The share of firms using and producing, as well as their order in terms of size, is proportionate to one another, hence providing supporting evidence for hypothesis 1.

Technology Group	Yes	No	Don't know
Artificial Intelligence	141,731 (3)	4,336,113 (91.3)	251,786 (5.3)
Cloud-Based	1,550,716 (32.4)	2,931,192 (61.3)	264,342 (5.5)
Robotics	88,657 (1.9)	4,517,555 (94.4)	170,601 (4.9)
Specialized Equipment	855,657 (17.9)	3,658,991 (76.5)	256,238 (5.4)
Specialized Software	1,821,368 (38.3)	2,641,604 (55.6)	262,673 (5.5)

Table 4: Number of Firms Responding to Technology Usage Questions by Technology Group (percentage of firms in parenthesis)

We then compute a ratio of users to producers

for each technology group. We find the highest ratio (10.1) for cloud-based computing, followed by specialized software (9.8), specialized equipment (7.8), AI (7.5), and robotics (6.3). Higher numbers indicate greater demand for this technology relative to producers, whereas lower numbers indicate higher competition for producers of that technology.

Technology Group	Users	Producers	Ratio of Users to Producers
Artificial Intelligence	141,731 (3)	19,789 (0.4)	7.5
Cloud-Based	1,550,716 (32.4)	152,386 (3.2)	10.1
Robotics	88,657 (1.9)	15,071 (0.3)	6.3
Specialized Equipment	855,657 (17.9)	108,675 (2.3)	7.8
Specialized Software	1,821,368 (38.3)	185,315 (3.9)	9.8

Table 5: Ratio of Users to Producers by Technology Group

To gain additional insight regarding the industries in which these technologies were produced, we provide the number of firms for each industry sector (by NAICS Code) and Technology Group in Table 6, posted in the Appendix (due to space limitations). The data shows that the largest sector that produces specialized software, specialized equipment, cloud computing, and AI is "Professional, scientific, and technical services." The largest sector that produces robotics is Manufacturing.

Next, we report the motivating factors for firms that produced the technologies in Figure 1. Using the highlighted table approach to emphasize the magnitude of each factor, we note that the foremost motivating factor across all technology groups was to upgrade goods and services. The second most important reason across the board was to expand the range of goods and services. The third top reason was different for AI with adapting existing products to new markets (at 41.2%). The third reason for all remaining technology groups included increasing or maintaining market share. Adopting standards and accreditation was the least reported factor, followed by "Some other reason".

	Artificial Intelligence	Cloud-Based	Robotics	Specialized Equipment	Specialized Software
Upgrade goods or services	56.50	50.70	45.40	52.50	50.80
Expand the range of goods or services	54.70	42.60	41.80	44.90	39.20
adapting existing products to new markets	41.20	27.30	32.70	25.50	24.30
Increase or maintain market share	36.10	30.40	35.00	31.20	29.70
Adopt standards and accreditation	16.50	18.40	12.40	14.70	16.90
Some other reason	14.80	21.50	23.50	19.50	22.90

Figure 1: Percentage of Firms by Motivation to Produce Technology Group

Subsequently, we report the motivating factors for firms that use the technologies in Figure 2. Using the same approach, we note that the foremost motivating factor was improving the quality or reliability of processes or methods, followed by upgrading outdated processes or methods. These results provide some support for hypothesis 2.

	Artificial Intelligence	Cloud-Based	Robotics	Specialized Equipment	Specialized Software
To improve quality or reliability of processes or methods	49.30	49.20	45.20	51.10	50.90
To upgrade outdated processes or methods	37.10	43.30	32.60	38.60	43.40
To automate tasks performed by labor	27.50	15.60	40.20	20.50	19.80
To expand the range of goods or services	23.80	14.10	24.40	25.60	15.30
Some other reason	18.20	23.50	21.10	17.80	19.40
To adopt standards and accreditation	11.70	10.40	8.60	10.90	11.90

Figure 2: Percentage of Firms by Motivation to Use Technology Group

Finally, we report factors adversely affecting technology production in Figure 3 and technology usage in Figure 4. These figures demonstrate that most respondents reported that no factors adversely affected the technology production or usage or that the technology did not apply to their business. However, the specific adverse factors for both users and

producers included technology being too expensive, which provides support for hypothesis 3.

	Artificial Intelligence	Cloud-Based	Robotics	Specialized Equipment	Specialized Software
No factors adversely affect..	43.90	52.40	43.20	48.80	53.50
Technology not applicable to thi..	48.80	38.60	50.10	43.50	38.00
Technology was too expensive	5.50	5.40	5.40	5.80	6.00
Lacked access to capital	0.90	0.90	0.70	1.20	1.10
Concerns regarding safety..	0.60	2.00	0.40	0.50	0.80
Technology was not mature	1.10	0.70	0.60	0.40	0.50
Lacked access to required human ..	0.70	0.70	0.50	0.60	0.80
Laws and regulations	0.40	0.60	0.30	0.40	0.60
Lacked access to required data	0.50	0.50	0.30	0.30	0.40
Required data not reliable	0.30	0.30	0.20	0.20	0.20

Figure 3: Factors Adversely Affecting Technology Production by Technology Group

	Artificial Intelligence	Cloud-Based	Robotics	Specialized Equipment	Specialized Software
No factors adversely affected the adoption of this technology	43.10	55.30	43.30	50.70	57.90
Technology not applicable to this business	46.60	31.00	48.00	38.50	29.60
Technology was too expensive	7.70	7.00	7.20	7.90	8.50
Concerns regarding safety and security (physical security and/or cyber security)	1.10	4.20	0.50	0.60	1.40
Lacked access to capital	1.50	1.40	1.00	1.80	1.60
Technology was not mature	2.10	1.10	0.90	0.60	0.80
Laws and regulations	0.80	1.00	0.30	0.60	1.00
Lacked access to required human capital and talent	1.20	1.00	0.70	0.70	1.00
Lacked access to required data	0.90	0.80	0.40	0.50	0.70
Required data not reliable	0.50	0.50	0.30	0.30	0.40

Figure 4: Factors Adversely Affecting Technology Usage by Technology Group

Additionally, for AI, respondents noted that the technology was not mature, whereas, for cloud computing, the concerns regarding safety and

security were more prevalent. The percentage was more evenly distributed among the remaining factors for robotics, specialized equipment, and specialized software.

5. DISCUSSION AND CONCLUSION

This study explored the prevalence of US firms producing and using technology, factors motivating technology production or usage, and reasons hindering their progress among US firms.

Our first hypothesis investigated the proportions of US firm adopters to producers. Data shows that shares of adopters of emergent tech groups are proportionate to shares of producers. For example, the AI share of users was ranked as the second smallest category, which matched the order of AI producers, who also ranked as the second smallest share. Hence, we found supporting evidence for our first hypothesis. This finding, therefore, raises an important point regarding the role suppliers play in the diffusion of the innovation process. The ratio of users to producers offers insights into the technology groups that are more saturated with competition, like robotics, which has the lowest ratio, versus cloud-based computing, which has the highest ratio and thus less competition.

Our second hypothesis looked at the motivations of producers when compared to users, investigating their scope and reach. The results reveal that the majority of firms that produce emergent technologies do so to upgrade their goods or services and expand their range of goods or services. However, one key distinction between users and producers was that producers also focused on increasing market share and adapting existing products to new markets. These reasons demonstrate that companies that supply or produce technology focus on more strategic business reasons, whereas the companies that only use emergent technologies do so at an operational level and to gain efficiency through internal processes. Hence, it provides at least partial support to our second hypothesis.

Our last hypothesis looked at the adverse factors of producers, highlighting cost as the primary challenge for producers. This hypothesis was met based on data analyzed for this study. When the "technology non-applicable to this business" and "No factors adversely affecting the adoption..." were excluded from the sample, the main adverse reason for both users and producers was financial in nature, with both

groups selecting technology as too expensive as the key adverse reason. This factor emphasizes that technology has been and continues to be one of the most expensive units within the organization. It is multifaceted and accounts for infrastructure, data, application development, security, and production support, to name a few. According to Bell's law, a new computer class is created each decade, imposing constant change and improvement (Bell, 2008). This ongoing change contributes to increased costs not only due to the need for new and improved hardware and software but also human resources and continuous upskilling and knowledge-sharing initiatives. Such factors might be compounded for suppliers who also focus on sales, marketing, customer service, and support.

This paper has important implications for both business strategy and policymaking. For businesses, the findings underscore the importance of innovation and technological advancement as critical drivers for competitiveness and market expansion. Firms that invest in producing new technologies are more likely to secure a stronger position in the market by continually improving their offerings and exploring new market opportunities. This strategic approach not only helps retain existing customers but also attracts new ones by meeting their evolving needs with advanced products and services.

From a policymaking perspective, the study highlights the need for supportive measures that encourage technology production. Government incentives, such as tax breaks, grants, and subsidies for research and development, can play a crucial role in fostering innovation. Additionally, creating a favorable regulatory environment that simplifies the process of bringing new technologies to market can significantly boost the efforts of firms engaged in technological production. Policymakers should also consider investing in education and training programs to build a skilled workforce capable of supporting high-tech industries (Acemoglu & Restrepo, 2019).

However, the study also points to several factors that may hinder the progress of technology-producing firms. These include high research and development costs, regulatory challenges, and a shortage of skilled labor. Addressing these barriers is essential for sustaining innovation. Firms must find ways to manage R&D expenses, perhaps through collaborations and partnerships that share the financial burden and risks associated with innovation. Furthermore,

engaging with regulatory bodies to streamline processes and reduce bureaucratic delays can facilitate faster commercialization of new technologies (Cordes et al., 2022).

Moreover, this study highlights the importance of technology suppliers and their role in innovation diffusion. Their ability to share information about innovation through the social system influences the adoption of that technology (Hall & Khan, 2003). With such a slight prevalence of technology suppliers observed in the US market today, it is rational to conclude that this might be one of the reasons the adoption rate is still very low. Similarly, Dar et al. (2024) found that information intervention directed at suppliers increased the adoption of farming modernization in agriculture. Hence, supporting and investing in technology suppliers might help facilitate and expedite user adoption.

While this study provides valuable insights, it is not without limitations. One significant limitation is the scope and timeframe of the data, which may not fully capture the diverse landscape of technology production across different industries and regions today. Future research could benefit from more refined measures and questions to capture the technology categories and motivations more clearly (Zolas et al., 2020). Additionally, more recent longitudinal studies could provide deeper insights into technology production trends and impacts on firm performance and market dynamics. Studies assessing the reach and level of information propagation by advanced technology suppliers could reveal opportunities for intervention and further support. Finally, comparative studies involving firms from different countries could offer a more comprehensive understanding of global trends in technology production and how the US compares to other innovators like Europe (e.g., Eurostat, 2024).

In conclusion, this study sheds light on the strategic importance of technology production for firms and the factors influencing their ability to innovate. By addressing the identified challenges and leveraging the motivating factors, firms can better navigate the complex landscape of technological advancement and secure a competitive edge in the market. Policymakers, in turn, must create an enabling environment that supports sustained innovation and technological growth.

6. REFERENCES

Acemoglu, D., Anderson, G. W., Beede, D. N.,

Buffington, C., Childress, E. E., Dinlersoz, E., ... & Zolas, N. (2024). Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey*. National Bureau of Economic Research

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., ... & Zolas, N. (2022). Automation and the workforce: A firm-level view from the 2019 Annual Business Survey (No. w30659). National Bureau of Economic Research.

Acemoglu, D. & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor *Journal of Economic Perspectives*—Volume 33, Number 2—Spring 2019—Pages 3–30.

Bell, G. (2008). Bell's law for the birth and death of computer classes. *Communications of the ACM*, 51(1), 86-94.

Bhalerao, K., Kumar, A., Kumar, A., & Pujari, P. (2022). A study of barriers and benefits of artificial intelligence adoption in small and medium enterprise. *Academy of Marketing Studies Journal*, 26, 1-6.

Bunte, A., Richter, F., & Diovisalvi, R. (2021). Why It is Hard to Find AI in SMEs: A Survey from the Practice and How to Promote It. In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021)* (pp. 614-620). SCITEPRESS Science and Technology Publications, Lda.

Cordes, J., Dudley, S., & Washington, L. (2022) Regulatory Compliance Burdens: Literature Review and Synthesis, The George Washington University Regulatory Studies Center. Retrieved from: https://regulatorystudies.columbian.gwu.edu/sites/g/files/zaxdzs4751/files/2022-10/regulatory_compliance_burdens_litreview_synthesis_finalweb.pdf

Cubic, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society*, 62, 101257.

Dar, M. H., De Janvry, A., Emerick, K., Sadoulet, E., & Wiseman, E. (2024). Private input suppliers as information agents for technology adoption in agriculture. *American Economic Journal: Applied Economics*, 16(2), 219-248.

Eurostat (2024). Community innovation survey. Retrieved from: <https://ec.europa.eu/eurostat/web/microdat>

- a/community-innovation-survey
- Hall, B. H., & Khan, B. (2003). Adoption of new technology,
https://www.nber.org/system/files/working_papers/w9730/w9730.pdf
- Hameed, M. A., Counsell, S., & Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, 29(3), 358-390.
- Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, 14(1), 21-38.
- McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2), 375-415.
- McKinsey (2019). How Artificial Intelligence will transform Nordic businesses,
<https://www.mckinsey.com/featured-insights/artificial-intelligence/how-artificial-intelligence-will-transform-nordicbusinesses>.
- Rogers, E.M. (1995). *Diffusion of Innovations*. 4th ed., New York: The Free Press
- Rosenberg, Nathan (1972). "Factors Affecting the Diffusion of Technology." *Explorations in Economic History*, Vol. 10(1), pp. 3-33. Reprinted in Rosenberg, N. (1976), *Perspectives on Technology*, Cambridge: Cambridge University Press, pp. 189-212.
- United States Census Bureau (2019), Annual Business Survey,
<https://data.census.gov/cedsci/table?q=technology>
- Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D., Buffington, C., Goldschlag, N., Foster, L. & Dinlersoz, E. (2020). Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey, NBER Working Paper No. 28290, JEL No. M15,O3,O47,O51

**Appendix A.
Additional Table**

Meaning of NAICS Code	Artificial Intelligence	Cloud-Based	Robotics	Specialized Equipment	Specialized Software
Professional, scientific, and technical services	8148	60691	2786	18265	66944
Health care and social assistance	1573	14298	1192	13635	18362
Retail trade	1823	10556	1771	10839	13437
Wholesale trade	1377	7960	2356	12629	11401
Manufacturing	833	3630	3050	14116	9400
Construction	1198	7892	752	10242	9501
Other services (except public administration)(663)	649	5672	N/A	9604	8672
Administrative and support and waste management and remediation services	984	7020	837	6688	8747
Information	1328	10436	347	2145	9366
Finance and insurance(662)	803	8437	186	1304	9709
Accommodation and food services	749	5876	756	4258	6871
Real estate and rental and leasing	309	5155	189	1513	6646
Transportation and warehousing(661)	194	2345	107	2172	2620
Educational services	94	2255	179	731	2649
Arts, entertainment, and recreation	107	1188	181	1317	2171
Management of companies and enterprises	184	818	157	804	1131
Mining, quarrying, and oil and gas extraction	5	49	4	359	293
Agriculture, forestry, fishing and hunting(660)	N/A	210	N/A	132	172
Utilities	7	16	8	58	49
Industries not classified	N/A	N/A	N/A	N/A	104
Grand Total	20365	154504	14858	110811	188245

Note: Rows with N/A indicate that the number was unavailable in the data set for those records.

Table 6: Number of Firms Producing Technology by Industry Sector and Technology Group