The limits of user innovation: MD inventors and potential substitute inventions*

Colleen Cunningham† David Hall‡ Ryan Cooper§

Abstract

Expert users play a crucial role in driving innovation due to their unique perspectives and specialized knowledge. However, user motives, such as concerns about substitution, may influence the types of technologies they invent. We explore these ideas in the context of physician (or MD) inventors and medical inventions. We measure potentially substituting inventions as those leveraging AI applied to MD-performed tasks. We find MD inventors are more likely than non-MDs to incorporate AI into their inventions for non-MD tasks but less likely to do so for tasks performed by MDs, especially those within the MD's specialty. In supplementary analyses, we examine mechanisms relating to technology substitution, knowledge, task complexity and risk. Our results provide evidence that expert user inventors direct invention away from potential substitutes.

Keywords: User Innovation, Expertise; Technology Aversion Medical Invention; Artificial Intelligence

*We thank seminar participants at Brigham Young University, New York University, University of Washington, University of Utah, Women in Strategy and Entrepreneurship, and 2022 Academy of Management conference, 2024 SMS Washington DC conference, and 2024 Crete workshop on Innovation & Entrepreneurship for their helpful feedback.

†University of Utah, colleen.cunningham@eccles.utah.edu

‡Independent Researcher, dave22hall@gmail.com

§University of Arkansas, ryanlewiscooper@gmail.com

1 Introduction

Users are an important source of invention (Urban and von Hippel, 1988; Cohen *et al.*, 2000; Gambardella *et al.*, 2017). They see problems that non-users do not (Lüthje *et al.*, 2005), and they have tacit knowledge that is not easily obtained by or transferred to others (Von Hippel, 1994; von Hippel, 1998). Further, expert user inventors have specialized knowledge which can result in more useful and novel inventions (Chatterji and Fabrizio, 2012, 2014).

However, like all inventors, expert users will also have limits in what they ultimately invent (Nelson, 2008; Fleming and Sorenson, 2004; Singh and Fleming, 2009). While experience and expertise likely inform the problems expert users seek to solve (Chatterji and Fabrizio, 2012; Agarwal and Shah, 2014), user motives also likely influence their choice of technological solutions. Expert user innovators may ignore, whether explicitly or implicitly, technologies that could potentially substitute for their expertise (Lüthje *et al.*, 2005). A simple reason for this aversion would be a form of "technological anxiety" (Mokyr *et al.*, 2015) whereby expert users fear that such technologies will negatively impact demand for their expertise. Beyond pure role substitution, there are more nuanced mechanisms which may underpin expert user inventor avoidance of potentially substituting technologies. They may be blind to or skeptical about the viability of technologies to address the complex issues experts are trained to solve (Shane and Venkataraman, 2000; Tripsas and Gavetti, 2000; Gaube *et al.*, 2021). Furthermore, experts are indoctrinated with professional norms (Ding, 2011; American Medical Association, 1848) and attuned to technology-related legal risks (Galasso and Luo, 2022) which may cause them to more heavily weigh the downside of technologies they may ultimately use.

Collectively, such reasoning suggests expert users will be less likely to generate inventions that potentially substitute for their expertise. If true, this tendency suggests a limit to expert user value in firm innovation collaborations, which are both common (Arora *et al.*, 2016) and a potential source of value (Gambardella *et al.*, 2017; von Hippel *et al.*, 2012; Chatterji and Fabrizio, 2014). In this paper, we aim to provide some empirical evidence of the phenomenon and explore, to the best our data allow, evidence consistent (or inconsistent) with the related but nuanced mechanisms that could drive such patterns.

Our context is medical invention and physician (MD) inventors, prototypical expert user inventors (Chatterji and Fabrizio, 2012, 2014; Katila *et al.*, 2017; Smith and Shah, 2013; Pahnke *et al.*, 2015). We focus on how being an expert user affects the type of inventions invented, examining the application of artificial intelligence (AI) technologies to medical invention.

We focus on AI for several reasons. Increasingly, AI has the potential to perform non-routine tasks that may substitute for or augment professional expertise (Brynjolfsson and Mitchell, 2017; Brynjolfsson *et al.*, 2018; Felten *et al.*, 2021; Jia *et al.*, 2024), in areas from medical image recognition (Li *et al.*, 2022) to creative tasks (Koivisto and Grassini, 2023). Yet, AI-based decision-making has historically lacked several features—including the ability to explain and be accountable for decisions (Brynjolfsson and Mitchell, 2017)—which may increase expert user skepticism about its broad usefulness. Further, AI represents a large technological shift (Acemoglu and Restrepo, 2019; Trajtenberg, 2018), with the potential to create systemic disruption and change and thereby lower the value of certain domains of expertise, which may increase expert users' aversion towards it. To measure potential substitutability, we focus on AI inventions used in MD-performed tasks compared with those for non-MD-performed tasks.[1]

Our sample includes all firm medical device patents from 2006-2015 linkable to medical tasks. We delineate inventions as to whether they have an MD inventor; we separately delineate them as to whether they incorporate AI technology. Example AI inventions range from technologies for regulating and automating cardiopulmonary resuscitation (CPR) (e.g. patent no. 8870797 and 9149411) to those for improving radiographic image quality (8520920) to those which automates the incorporation of user feedback to manage electrical stimulation

[1] Like all indirect measures of potential substitutes, AI is imperfect. Separating out inventions by task performer (MD vs not) helps us to ensure our results are not just about aversion to AI. However, to provide robustness, we supplement our AI-based analyses by using tool inventions (compared to therapeutic or prosthetic) as another measure of potential substituting invention (see Appendix Table A1).

therapy (8996123). We further separate inventions relating to MD-performed tasks (e.g. Laparoscopy, Angioplasty) from those relating to non-MD-performed tasks (performed by nurses, technicians or other health professionals, e.g. Mammography, Immunization). We then estimate the relationship among MD inventors, MD task-related inventions and AI.

As a baseline, consistent with the logic that users' knowledge and motives direct inventive activity, we find that MD inventors disproportionately invent for MD tasks. Moreover, aligned with prior work (Chatterji and Fabrizio, 2016), we find that MD's medical inventions are more highly cited and novel than non-MD's medical inventions.

Turning to AI invention, we find MD inventors are less likely than non-MDs to incorporate AI into inventions for MD tasks, while they are more likely to do so when inventing for non-MD tasks. The negative relationship is driven by inventions that fall within the MD's own specialty (e.g. cardiovascular surgeons and cardiac inventions). Notably, the negative pattern does not exist for AI inventions within the MD's specialty but for non-MD tasks, suggesting the core results are not simply technological knowledge gaps or general AI aversion. Additional analyses examine mechanisms of technological anxiety (via invention use, firm type, and task value), knowledge gaps (inventing team, inventor experience, and geographic and specialty AI proclivity), task complexity (task fixed effects and specialization) and invention risk. The collective evidence is consistent with direct or indirect technological anxiety explaining, at least in part, why MDs inventors appear to avoid AI in inventing for tasks MDs perform.

Our paper makes two main contributions. First, we examine the important issue of the direction of user invention, focusing on a key potentially substituting technology, AI. While the risk of technology substituting for labor has historically been highest for low-skill workers performing routine tasks (Autor *et al.*, 1998), and a significant amount of recent work has focused on AI as a complement to high-skilled workers (Choudhury *et al.*, 2020; Jia *et al.*, 2024), a defining characteristic of more recent advancements in AI has been mastery of expert tasks. This development may lead to perceptions that substitution is increasingly likely. Our results are suggestive that "technological anxiety" relating to AI may inhibit some AI-based inventive activity. As MD inventors are associated with higher value invention, this aversion may constrain the usefulness of such inventions. While our results show evidence of aversion to potential substitutes by expert user inventors, we leave estimation of welfare implications to future work.

Second, we provide evidence of a limiting factor for firms in collaborating with expert users in invention. The common view is that such collaborations provide value to firms, especially in new technology areas or for novel technology (Chatterji and Fabrizio, 2014). However, we find expert user inventors may avoid technologies when they have the potential to substitute for their expertise. As such, collaboration might lead to an "AI divide" in invention across firms akin to that which exists in AI adoption (McElheran *et al.*, 2024). Thus, an important strategic challenge implied by our findings is how firms should best collaborate with expert user inventors to access the associated benefits, while also navigating their limits.

2 Background: The Direction of (User) Invention

2.1 The process of inventive search

Invention is a cumulative, recombinant, problem-driven search process (Arts and Fleming, 2018; Nelson and Winter, 1982; Arthur, 2007). It involves the generation and selection of ideas, and the ongoing re-use of inventive knowledge in subsequent inventions (Singh and Fleming, 2009). At an individual level, would-be inventors follow idiosyncratic search paths (Nelson, 2008). What is ultimately invented depends on an inventor's knowledge and expertise (Gruber *et al.*, 2013), which shapes what ideas they generate and select (Arts and Fleming, 2018; Singh and Fleming, 2009). Variation in experience among firms also shapes the direction of invention. Incumbent firms tend to have both market power and experience with existing technologies, which can lead them to incrementally invent (Henderson, 1993). Like incumbent firms, expert user inventors' power and expertise are often aligned with existing technology. Importantly, inventors—including expert users—are motivated by profiting from their inventions via commercialization.

2.2 Expert user inventors and the limits of user invention

Expert user inventors hold tacit knowledge about how inventions are used (Von Hippel, 1994; Cohen *et al.*, 2000) and have insight into current and future demand that can complement the more supply-side knowledge of firms (Schweisfurth, 2017; Lüthje *et al.*, 2005). Building from these factors, corporate inventive activity involving expert users is, on average, of higher quality and novelty (Chatterji and Fabrizio, 2014, 2012; Schweisfurth, 2017).

2.2.1 Limits to user innovation

While collaborating with expert users has benefits for firms, it may also have some limits. Specifically, expect users may avoid technologies that potentially substitute *for them*, for several interrelated reasons. At a base level, they may anticipate a loss of value of their main role (Goldin and Katz, 1998; Mokyr *et al.*, 2015). Even barring technological anxiety (i.e., fear of expertise devaluation), experts may be blind to or skeptical about such technology given the complexity of expert-performed tasks. Or, given their professional responsibilities and liabilities, expert users may be more attuned to the risks of potentially substituting technology, and thus less likely to invent such technologies in the first place.

Technological anxiety: New technologies can complement or substitute for the knowledge and skills of workers (Autor, 2015; Frey and Osborne, 2017; Brynjolfsson *et al.*, 2018). History provides many examples of occupations fundamentally altered by new technology, from the seismic impact of mechanization and automation on domestic production in the early 19th century (Mokyr *et al.*, 2015) to localized shifts in users' occupational roles from CT scanners in the 1980s (Barley, 1986; Black *et al.*, 2004). Even when new technologies initially complement occupations, they may still evolve to disrupt them. For instance, technologies may commoditize core tasks and thus facilitate entry, or improvements in complements may undermine the value of core tasks (Adner and Lieberman, 2021).

Recent technological advances in AI have made it possible for machines to perform advanced tasks previously performed by highly skilled humans, sometimes even surpassing human performance (Brown and Sandholm, 2018; He *et al.*, 2015; Silver *et al.*, 2017) and substituting for experts in team production (Teodoridis, 2018). AI may therefore be perceived as a potential, even if partial, substitute by experts. Even if a particular expert user inventor does not fear (or care about) potential substitution for themselves, it may affect their technology selection in evaluating demand by other expert users. Overall, expert users may be deterred from inventing technologies that could be perceived as potential substitutes (Christensen and Raynor, 2003; Henderson, 2006) due to fear of substitution for their main occupation.

Technological blindspots or skepticism: Research on technology *adoption* finds expert users may not adopt certain technologies because they do not see them as applicable to their jobs (Shane and Venkataraman, 2000). There are two related reasons. The first is *blindspots*: experts may not consider certain technologies as related to or useful for their tasks (Orlikowski and Gash, 1994; Bijker, 1997; Tripsas and Gavetti, 2000), favoring more familiar solutions over novel ones (Berg, 2016; Tripsas and Gavetti, 2000). The second reason is *skepticism*: even if an expert recognizes the potential of a new technology and its applicability to their job, if it is positioned as a potential substitute, they may not believe it will be "up to the task", i.e., their standard of performance (Gaube *et al.*, 2021; Lebovitz *et al.*, 2022; Nelson and Irwin, 2014) and thus not adopt it. Like technology adoption, blindspots and skepticism likely also extend to expert users' *invention* choice. They may forgo certain technologies when inventing for tasks they perform because of blindspots or skepticism.

Technological risk: New technologies frequently introduce new ethical and legal concerns (Wright and Schultz, 2018) that can inhibit innovation (Munoko *et al.*, 2020; Galasso and Luo, 2022). The ethical issues can be significant (Verbeek, 2006), in fields from accounting (Munoko *et al.*, 2020) and finance (Buchanan, 2019), to medicine (Smith *et al.*, 2005; Sutton and Sharma, 2021). Examples of relevant issues for AI in medicine include access to data (i.e., using patient medical data without explicit consent), and accountability for AI-influenced decisions and outcomes. Further litigation risk is salient for MDs and can direct medical innovation (Galasso and Luo, 2022). In general, expert users can be wary of black-box solutions, preferring to understand the processes underlying their tools to ensure proper application and accuracy of the associated results, for which they are often held accountable (Anthony, 2021; Lebovitz *et al.*, 2022).

Expert user inventors—like MDs—are likely to be especially attuned to the issues surrounding unproven technologies, including the costs associated with convincing various stakeholders—including their peers—that such issues are adequately addressed. MDs may therefore avoid new, unproven technologies when inventing for MD tasks.

2.3 Empirical implications: The direction of user invention

In sum, expert user inventors develop inventions that leverage their knowledge and which they are likely to use, avoiding areas in which they have little experience (Lüthje *et al.*, 2005; von Hippel, 1998). We argue they also tend to avoid potentially substitute technologies. The reason may be "technological anxiety" or fear of substitution, or task complexity (i.e., technology may be perceived as an unviable substitute for expert tasks, especially by those who perform said tasks), or because unproven technologies pose especially high risks when used for expert tasks.

Our main empirical investigations explore these ideas for MD inventors, MD-performed tasks, and AI-infused medical inventions. As a baseline we examine whether MDs are more likely to generate inventions for MD-performed tasks, to validate the fundamental idea that knowledge and user motives drive invention. Our main analyses examine whether MDs are less likely to generate AI inventions for MD-performed tasks. We provide supplementary analyses to examine if our core results are driven by "technological anxiety," if a lack of access to knowledge plays a role, and if task complexity and invention risk appear to drive, at least partially, the patterns we observe.

3 Empirical Context and Data

We study these ideas using data on U.S. medical device inventions from 2006-2015, inclusive. This is an ideal setting for our study for several reasons. First, patents are used extensively for medical inventions (Cohen *et al.*, 2000; Arora *et al.*, 2016), making patent data an appropriate approach to observing inventive activity. Second, MDs, who are frequently the users of medical inventions, often play an important role in the invention process (Chatterji and Fabrizio, 2014). Third, as discussed above, medical inventions increasingly leverage AI to facilitate various tasks performed by healthcare providers, and the importance of AI in medicine has grown in recent years (i.e., during our study period and beyond). Our time window includes substantial AI inventive activity, but also high levels of uncertainty as to how AI will augment medical tasks.

3.1 AI in Medicine and Medical Invention

While first conceptualized in the 1950s, AI has only become broadly used in inventions in the past 20 years (OECD, 2019; USPTO, 2020). AI technologies "can learn to solve complex problems, make predictions or undertake tasks that require human-like sensing (such as vision, speech, and touch), perception, cognition, planning, learning, communication, or physical action" (National Institute of Standards and Technology, 2019).

AI applied to medical invention has the potential to drastically change health care practice, as a tool for diagnosis (Smith *et al.*, 2020; Park *et al.*, 2023), prediction of possible therapeutic outcomes (van den Oever *et al.*, 2020; Joshi *et al.*, 2021) as well as through various robotic applications (Beasley, 2012; Silvera-Tawil, 2024). While popular attention has focused on radiology (Barragán-Montero *et al.*, 2021; Cau *et al.*, 2021; Shen *et al.*, 2021), many other areas have seen increased potential application of AI, including cardiology (Ledzinski and

Grzesk, 2023), gastroenterology (Parsa *et al.*, 2021), oncology (Liao *et al.*, 2023; Elkhader and Elemento, 2021), ophthalmology (Prabhakar *et al.*, 2021), pathology (Baxi *et al.*, 2022), respiratory medicine (Liang *et al.*, 2022), surgery (Joshi *et al.*, 2021; El Hechi *et al.*, 2021), and telemedicine (Gorincour *et al.*, 2021). A common theme in health care research is whether AI is a complement (Itchhaporia, 2020; Kaul *et al.*, 2020; Parsa *et al.*, 2021) or a substitute to practitioners, with some concern about the suitability of AI as a substitute for expert tasks (Moyo *et al.*, 2019; Valikodath *et al.*, 2021; Botwe *et al.*, 2021).

3.2 Data

Our unit of analysis is a medical invention, i.e., a medical device patent linked to a medical task. Constructing our analytical data set involves several key steps. First, we link medical patents to medical tasks, differentiating tasks performed by MDs from those performed by other healthcare providers (including technicians and nurses). Second, to identify expert user inventions, we link in U.S. physician registry data via inventor information. Third, we use USPTO data to identify AI patents. Finally, we link inventions to medical device product markets, which allows us to identify if the invention is in the "same specialty" as the MD inventor. We describe each step in detail below.

These steps mean our sample is restricted to patented inventions with linkable medical tasks, with at least one inventor located in the U.S., for which we have AI information, and which are linkable to medical device product markets. We further restrict our analyses to patents with firm assignees, excluding patents granted to individuals, government agencies, and universities, as the motives underlying such inventive activity are likely not as uniformly economic.

3.3 Medical task-related patents

We begin constructing our sample by collecting all granted patents, 2006-2015 inclusive, from PatentsView.org. We then link patents with a classification potentially relevant to medical invention to medical tasks.[2]

Healthcare providers such as MDs, nurses, and medical technicians perform various tasks (or procedures) as a part of providing health services to patients. Technologies facilitate the performance of many tasks. For example, consider atherectomy, a minimally invasive surgical procedure to remove plaque buildup within the walls of an artery. Various inventions have been developed to aid MDs performing this task: one device uses a laser to ablate the plaque buildup in the artery (Dippel *et al.*, 2015); another uses a blade that scrapes the inner wall of the artery (Topol *et al.*, 1993); and, yet another uses a grinding wheel that breaks down the buildup as it rotates within the artery (Gupta *et al.*, 2019). Our analysis focuses only on patents for technologies—such as those listed above—used in medical tasks.

3.3.1 Medical Text Indexer

To link patents to medical tasks, we used the Medical Text Indexer (MTI), a machine learning algorithm developed by the National Library of Medicine. The MTI draws on the most comprehensive dictionary of medical terminology available, the Unified Medical Language System (UMLS), which includes the population of tasks performed by healthcare providers.[3] We apply the MTI algorithm to patent titles and abstract text to generate our sample of medical patents.[4]

Of the medical patents we input into the MTI, 30.7% are matched to medical tasks. Inspection of the unmatched patents indicates they are for devices not associated with a particular medical task (e.g. hospital bed software, patent number 5787528), or they are

[2]This includes patents with the following CPCs: Of A61 (Medical or Veterinary Science): A61B, A61C, A61F, A61H, A61J, A61K, A61L, A61M, and A91N (*excluding* A61D (Veterinary), A61G (Medical Transport), A61P (Therapeutic Chemicals), A61Q (Cosmetics)); and G01N 33/48-33/98 (physical/chemical/other analysis of biological materials). We included patents assigned *any* of those classes for potential medical task linkage. See www.uspto.gov/web/patents/classification/cpc/html/cpc.html for more info on CPC.

[3]The MTI was initially developed to facilitate medical publication indexing for databases such as MEDLINE. It combines traditional feature engineering approaches such as bag-of-words with more sophisticated approaches such as n-grams, noun phrases, and related publications (Jimeno Yepes *et al.*, 2015). Further, various types of learning models within the algorithm have been tested and evaluated against each other to significantly improve the performance of the text classification (Jimeno Yepes *et al.*, 2015). Additional details on the algorithm as well as a web interface for accessing it can be found at https://ii.nlm.nih.gov/MTI/.

[4]This process links medical inventions to the tasks or procedures for which they are used. Our analysis does not include any patents directly granted for medical tasks.

pharmaceutical patents. We use the medical task-linked patents as our core sample.

3.3.2 Linking medical tasks to provider type

To categorize tasks, we employed 12 subject matter experts (nine medical residents and three 4th-year medical students). For each medical task, our experts were asked: 1) their level of familiarity with the task, 2) what type of provider is most likely to perform the task (MD, nurse, or technician), 3) whether the task is diagnostic, therapeutic, or laboratory, and 4) if the task is (mostly) limited to the hospital. We split the full list of medical tasks into blocks of 200, and each block was coded by (at least) two separate experts. We aggregate expert responses based on their (self-determined) level of familiarity with the task and their seniority. Some tasks are more general than others: to ensure the quality of the data we asked respondents to indicate whether the activity was too vague to provide meaningful responses (e.g. "Diagnostic Tests, Routine"), and exclude vague tasks from the analysis. Our final sample covers inventions associated with 834 medical tasks. Examples of several tasks and their associated categorizations are listed in Table 1.

[Insert Table 1 Here]

3.4 MD Inventors

Our second data step was to identify MD inventors. To do so, we use the National Plan & Provider Enumeration System (NPPES) National Provider Identifier (NPI) registry. The NPI registry contains all practicing physicians in the U.S., as any transaction that falls under the Health Insurance Portability and Accountability Act of 1996 (HIPAA) must include an NPI for the provider. Other researchers have also used these data to identify U.S. MDs (Gottlieb *et al.*, 2020; Zhang and Yang, 2022).

We restrict the NPPES data to providers with Medical Doctor credentials and match inventors using first and last name and location (city and state). Patents include inventor location, and NPPES data includes both the address of the business practice and the mailing address of the MD. We include matches of inventor address to either the business address or mailing address.[5] In addition to allowing us to identify MDs, the NPPES data includes medical specialty of the MDs.

3.5 Artificial Intelligence

To identify if a given invention includes AI technology, we used the USPTO classification (USPTO, 2020). Using a supervised machine learning algorithm, the USPTO flags patents for AI technology using any of eight component technologies: natural language processing, machine learning, knowledge processing, speech, vision, AI hardware, planning and control, and evolutionary computation. As detailed in Table 2 the main categories in our sample of AI medical inventions are: vision (56%), knowledge processing (42%), and planning and control (30%) (note that a patent can be assigned to more than one AI type). We use an "Any AI" flag to identify AI inventions.[6]

[Insert Table 2 Here]

3.6 Medical product markets

Our final main dataset construction step involves linking inventions to medical product markets. Identifying the product markets of our invention sample is important for two reasons: (1) to account for market characteristics in our analyses, given that the suitability and expected profitability of AI will vary across different markets, and (2) to be able to link MD inventor-inventions to within the same specialty or different specialty areas. Notably, we also use the market link to identify the invention purpose, which we then group into tool (diagnostic, monitoring, surgical) vs therapeutic/prosthetic, with tool inventions for MD tasks as an additional measure of potential substitutes.

[5] Because we use a U.S. registry, we necessarily drop patents from non-U.S. inventors.

[6] We also run the main analyses separately for each AI type category, and find consistent results across all categories; see Appendix Table A3.

To link patents to potential markets, we adapted the Algorithmic Links with Probabilities (ALP) method developed by Lybbert and Zolas (2014). We used ALP to link detailed patent classes to medical product markets.[7] To define product markets, we use regulatory categories defined by the Code of Federal Regulations and the U.S. Food and Drug Administration (FDA) which developed 1,700 different classifications of medical devices grouped into 16 medical specialities.[8] We use specialties as broad "market" controls. We then hand-linked MD inventor specialties (in the NPPES data) to these product-market derived specialties to determine if the invention was in the "same specialty" as the inventing MD.

This linkage also enabled our proxy measure for risk. The FDA has three classes into which it assigns medical devices based on regulatory controls they deem necessary to ensure device safety and efficacy. Class III devices are considered of highest risk to patient and/or users and are thus subject to the highest regulatory scrutiny pre-market. We categorize inventions linked to FDA Class III devices as higher risk.

4 Analysis and Results

4.1 Key variables

Our final sample is 48,797 patent-medical tasks (or inventions) associated with 38,203 patents.[9] We cluster all standard errors at the patent level. In our main analyses, we predict

[7]The ALP process involves 3 broad steps: (1) identifying 3-5 keywords for each market (which we did using machine learning, research assistant checks, and leveraging the UMLS metathesaurus for medical synonyms), (2) searching for those keywords in patents and aggregating counts to patent class level, and (3) creating probabilistic linkages between patent classes and product markets. One example: the CFR code *§ 870.2100 Cardiovascular blood flowmeter* is matched to patent classes (CPC) *A61B8/06 Measuring blood flow* with weight of 0.932 and *A61B8/02 Measuring pulse or heart rate* with weight of 0.068. We use these weights to select the CFR and associated specialty, e.g., Cardiovascular for the prior example, that best matches the primary patent class of each patent.

[8]https://www.fda.gov/medical-devices/overview-device-regulation/classify-your-medical-device

[9]Sample steps: (1) ˜67,000 patents linked are to medical tasks using MTI; (2) ˜52,000 with a U.S. inventor (necessary for MD linkage); (3) ˜42,000 with firm assignee; (4) 39,264 with matched to AI data (representing 50,170 patent-tasks). Full fixed effect models include device-linked variables, leading to the final sample numbers in the main text. Approximately 40% of the patents are associated with more than one task. For example, patent 7225964 is a surgical stapler used in laparoscopic procedures. This patent links with the task "Surgical Stapling" and with the task "Laparoscopy".

whether the invention is an *AI patent*, and our key explanatory variables are *MD inventor* which is defined as a patent with an MD listed as inventor, and *MD task*, which is defined as the associated task is performed by MDs. Before the main analyses, we first predict if an MD inventor's inventions are associated with an *MD task*, the relative quality of MD inventor-inventions, measured using *patent citations* which is the number of (logged) citations the patent received in the 3 years following grant, and the relative *patent novelty* of MD inventor-inventions, or how dissimilar a patent is to the patents it cites, using the measures developed by Kuhn *et al.* (2020).[10]

All analyses take into account important task-, invention- and patent-based factors, typically as fixed effects. First, at the task level, we classify each by *task type* into *diagnostic*, *therapeutic*, or *laboratory*, and *task location* as *hospital*, *non-hospital*, or *equally likely* to be performed at either. Second, at the invention level, we categorize into *invention specialty* categories, including *cardiovascular*, *obstetric and gynecological*, and 14 others which align with medical specialties (see Table 3 for a full list and associated shares); and into *invention purpose* categories, including *diagnostic*, *monitoring*, *prosthetic*, *surgical*, and *therapeutic*. Notably, while task type and invention purpose categories correlate, they do not perfectly align (i.e., you can have a diagnostic invention associated with a therapeutic task), allowing us to include both as fixed effects. Third, we include patent *year* and *group* fixed effects.[11] In quality outcome regressions, we include the count of *claims* on the patent, and the *number of inventors*, as these are likely to be related to quality and possibly the presence of a MD inventor.

We include several mechanism-focused analyses aimed at further understanding the specific conditions that drive (or mitigate) the relationship between MD inventors and AI inventions for MD tasks. These analyses involve additional variable construction.

First, we build a measure of *same specialty* using the MD specialty categories from NPPES and the specialty categories of the invention. We distinguish MD-inventor inventions into

[10] We use the Kuhn-Younge-Marco patent citation similarity data available via iiindex.org. To construct our measure, we calculate a mean similarity score for a patent: novelty=1-mean(similarity).

[11] As 86% of our sample have CPC A61 as their main group, we use two groups: A61 and non-A61.

those in the *same specialty* and those outside the MD-inventor specialty. Second, we separate out *therapeutic and prosthetic (TP)* inventions from *tools*, i.e., diagnostic, monitoring or surgical inventions, as it is more likely that tools are substitutes for MDs. Third, we categorize the firm assignee as either *established firm* or *startup*, as startup-associated inventors are potentially more motivated by invention performance (or less concerned with technological anxiety). Fourth, we include analysis of *task value*, measured using the revenues of a (FTE) full-time-equivalent physician to the hospital system for a given specialty, as the downside of substitution would be more significant for higher value tasks. Fifth, we look at measures of inventor access to knowledge, including *MD inventing experience*, *Solo inventors* versus teams, and the degree of AI-related knowledge available both in the local geographic area (or CBSA) as *local AI supply*, and in the related product area as *specialty AI proclivity.* Sixth, we employ two analyses to explore whether or not the AI-related patterns we observe are down to MDs selecting out of AI-related inventing for more complex tasks. We re-run our main analysis including task-level fixed effects. Then, we try to measure task complexity using an imperfect proxy: whether it is a *specialist* or *generalist* task, based on the number of departments that perform the procedure. Seventh, we measure invention risk, using the FDA device classification (Class III = 1) which is intended as a measure of riskiness of device use. Finally, we explore whether quality-based selection by MD inventors drives our results, using patent citations and novelty (described above) as measures of quality.

4.2 Descriptive Statistics

Table 3 includes variable descriptions and some descriptive information for our key variables: 10.4% of the inventions in our sample have AI technology; 5.4% of all inventions have an *MD inventor*, and; the majority of the inventions in our sample, 63.7%, are associated with *MD tasks.* There are no dominant specialties, types, or purposes.

[Insert Table 3 Here]

4.3 Main Results

Before exploring AI invention, we first examine in Table 4 if MD inventions tend to correspond to their knowledge and motives, and if MDs generate higher quality inventions on average compared to non-MDs. All regressions in the paper are linear models and include fixed effects to control for year, patent group, invention specialty and purpose, and task type and location, to ensure we are comparing observably similar inventions. We find that MDs on average are 3.6 percentage points (*pp*, p=0.000) or 5.6% more likely to generate inventions associated with MD tasks than non-MD inventors. MD inventors' inventions receive more forward citations, a commonly used measure of invention quality (increase of 0.059 (p=0.002) or 12.7%) and are more novel (increase of 0.015 (p=0.000) or 2.2%). These results align with prior work on expert users and provide evidence that collaborating with MD inventors potentially has benefits for their firms.

[Insert Table 4 Here]

Table 5 provides our first set of main results predicting AI invention. We do not find evidence that MD inventors, on average, are less likely to generate AI patents (Columns 1 and 3). When we split out inventions linked to MD tasks from those linked to other tasks (Columns 2 and 4), we find that MD inventors are less likely to generate AI inventions for MD tasks, by 3.7 *pp* (p=0.016), and significantly more likely than non-MD inventors to generate AI inventions for non-MD tasks, by 4.4 *pp* (p=0.005). Finding a positive relationship for non-MD tasks provides some suggestive evidence that it is not knowledge (or lack of access or general aversion to AI) driving our results.

[Insert Table 5 Here]

4.3.1 Technological anxiety mechanism

Table 6 splits MD inventor-inventions into two categories: those within the MDs *same specialty* (e.g., cardiac surgeons and cardiology inventions), and those outside their specialty.

This analysis provides a finer examination of the technological anxiety (or threat of substitution) mechanism for the results in Table 5. First, we use the full sample (columns 1-2), with the reference group as non-MD inventor inventions. We find the negative results are driven by MDs inventing for MD tasks within their same specialty (β=-0.092 p=0.007). The result is not apparent for MDs inventing for MD tasks outside their specialty (β=-0.016 p=0.331), again suggesting it isn't simply knowledge gaps or general aversion. Results using only the MD inventor sub-sample (columns 3-4) confirm the full sample results, although with less precision (β=-0.057 for Same specialty X MD task, p=0.117). Overall, splitting out same specialty inventions provides additional evidence that potential substitution is a factor driving disproportionately lower rates of AI invention by MDs for MD tasks.

[Insert Table 6 Here]

To provide additional evidence relating to technological anxiety, we re-ran the Table 5 main results, splitting the inventions by three factors influencing the level of technological anxiety, in Table 7. First, we investigate if our results vary by *invention purpose*, a measure built using our link from patent classes to medical device product markets (described above). We use FDA product market aggregations[12] to categorize inventions into two purposes: therapeutic/prosthetic (TP) and tools (diagnostic, monitoring and surgical). Our motivating logic for this split is that TP inventions are more likely to complement MDs whereas tool inventions are more likely to be potential substitutes, at least in part. If the substitution mechanism is driving the results, the negative interaction between MD inventor and MD task on AI should be more pronounced among tools. Correspondingly, in columns 1-2, we find that the results are stronger among tool inventions, with a decrease of 6.0 *pp* (p=0.018) and an insignificant interaction for TP device inventions (β=-0.008 p=0.630). Note that for these and all split sample results, we also ran fully interacted models (with triple interactions) and report associated Tables in the appendix. For this analysis, the triple interaction provides

[12]See www.ecfr.gov/current/title-21/chapter-I/subchapter-H, Parts 860-892. Each specialty area (Part) has Subparts relating to purposes. In turn, Subparts are aggregations of product markets.

evidence of a significant difference between TP and tools (Table A5 (p=0.073)).[13]

[Insert Table 7 Here]

Next, we explore differences across firm types, in columns 3 and 4. Our rationale is that inventors who are more focused on invention profits may weigh the threat of potential substitution less in their invention choices. Further, those inventing with startups are likely to be more focused on invention profits compared to those inventing with established firms. Here, we see that a clear negative relationship between MD inventors inventing for MD tasks and AI is not apparent among startup firms (β=-0.013 p=0.549) but is sizable and significant for established firms ((β=-0.053 p=0.009). Although the difference is not significant in the triple-interacted model (Table A6, p=0.148), these results provide additional evidence consistent with potential substitution: when MD inventors plausibly care more about profiting from the invention, they seemingly do not avoid AI technologies when inventing for MD tasks.

Our last analysis examining technological anxiety varies the value of technological substitution by looking at the relative pecuniary value of associated tasks. To do so, we use medical specialty level measures of hospital revenues per FTE physician.[14] If technological anxiety is driving our results, we would the results to most pronounced in specialties where there is more to lose from substitution (i.e., with higher task values). Correspondingly, we find the main results are driven by specialties with relatively higher task values, with a decrease of 10.2 *pp* (p=0.001), whereas there is no evidence of a negative relationship for lower value specialties (β=-0.006 p=0.730). The difference is significant in the triple-interacted model (p=0.011).[15]

[13] Notably, in supplementary analyses, we also consider tools as an outcome in place of AI. We replicate the Table 6 results in the Appendix, and find, as in our AI results, that MD inventors are less likely to invent potential substitutes, measured as tools applied to their own specialty.

[14] Source: AMN Healthcare 2019 Physician Inpatient/Outpatient Revenue Survey: www.amnhealthcare.com/amn-insights/surveys

[15] We also ran analyses splitting out *hospital*-performed tasks from other tasks, and found the results are driven by hospital tasks. While broadly consistent with the specialty-based value analyses (i.e., if we consider hospital tasks to be a rough proxy for higher task value), hospital tasks likely also differ in terms of other important dimensions, including task complexity and legal risks. Thus, we include these analyses in the Appendix (Table A4).

4.3.2 Knowledge gap mechanism

A key implicit assumption underpinning the mechanisms we elaborate in section 2.2 is that inventors are similarly able to leverage AI for their medical inventions, whether those inventors are MDs (or not) and whether the inventions are for MD tasks (or not). An alternative explanation is that gaps in access to knowledge explain the differences we observe.

To more directly investigate whether lack of access to AI knowledge may be driving the results, we looked at four sources of variation in the availability of knowledge. The first two relate to inventor knowledge: (1) inventor experience, where we might expect inexperienced inventors to be less able to incorporate cutting edge knowledge (like AI) into their inventions, and (2) inventing team, where, if knowledge gaps were behind our main results, we would expect the results to be more prevalent for solo (MD) inventors. We also examine if the availability of knowledge in the inventors' environment is also a potential contributing factor to our main results, examining both (3) proximate geographic AI supply; and (4) the AI-ness of the invention specialty category.

Our analyses based on inventor experience (Table 8) is inconsistent with knowledge gaps driving our results. On the contrary, experienced MD inventors drive the negative MD inventor X MD task interaction (β=-0.049 p=0.004), whereas inexperienced MD inventors—who more plausibly lack the inventing-related knowledge to search and select broadly across all technologies—are no less likely to invent AI for MD tasks than non-MDs or for non-MD tasks (β=0.017 p=0.606).[16]

[Insert Table 8 Here]

The rest of our analyses of knowledge gaps are in Table 9. First, we examine inventing teams, splitting out solo inventors from teams. While the composition of the inventing team is likely endogenous to technological choice, this analysis suggests our main findings are not

[16] We further broke out MD inventing experience into AI and non-AI in Appendix Table A2. Inconsistent with knowledge gaps, it is MD inventors *with* AI experience that drive the negative results for MD tasks (and the postive results for non-MD tasks).

driven by solo (MD) inventors, who plausibly lack AI expertise. Contrary to knowledge gap explanations, inventing teams (column 1) have a stronger negative interaction (β=-0.040 p=0.015) than solo inventors (column 2) (β=-0.026 p=0.504), though the difference is not significant in the triple-interaction (Table A8 (p=0.671)).

Beyond the focal inventor and team, knowledge gaps in the surrounding environment may limit the technological choices of inventors. Thus, we also examine "supply" type measures of AI knowledge to see if a gap in knowledge access drives our main results. That is, it could be that the technological choices of MD inventors inventing for MD tasks simply reflect their knowledge environment which could be (relatively) lacking in feasible AI technologies. However, columns 3-5 of Table 9 do not provide conclusive evidence in that regard. We find the negative relationship between MD task inventions and the use of AI for MD inventors is seemingly larger in low AI supply areas (column 3) and in specialties with relatively less AI patenting activity (column 5); however, neither difference is significant (in the fully interacted model triple-interactions, Table A9 (p=0.624) and Table A11 (p=0.823), respectively).

[Insert Table 9 Here]

4.3.3 Task complexity mechanism

Our next set of analyses explore the idea that our results be underpinned by task complexity. That is, perhaps MD tasks—at least certain ones—are too complex to be substituted by technology and MDs are best positioned to determine that. To investigate the task complexity mechanism, we performed two sets of analysis.

First, we re-ran the main results including task fixed effects, in Table 10. Notably, including task fixed effects means we cannot estimate the MD task coefficient. We find the same pattern of results as in our main analysis when including task fixed effects: MD inventor X MD task has a negative and significant relationship with AI invention, (β=-0.032 p=0.032).

[Insert Table 10 Here]

We also ran analysis with a proxy for task complexity, specifically noting if the task is specialized (i.e., only performed by 1 or 2 areas) or more general. Our presumption is that specialized tasks are more complex and thus less amenable to technological substitution, and this feature of particular tasks may be something MDs are more attuned to for MD tasks compared to others. If task complexity is driving the results, then we'd expect specialized tasks to drive the core patterns. However, in Table 11, we find that both specialized tasks and general tasks have a negative coefficient for MD inventor X MD task: general is β=-0.038 (p=0.032) and specialized is β=-0.049 (p=0.097), and the difference is not significant in the triple-interacted model (Table A11, p=0.748) .

[Insert Table 11 Here]

4.3.4 Invention risk mechanism

Our penultimate set of analyses look at invention risk to explore the idea that the apparent aversion to AI for MD task-related inventions by MD inventors might be because such types of inventions could be riskier, with MD inventors more sensitive to such risk in their invention choices for MD tasks than non-MD inventors. Using FDA regulatory classes, and flagging device class III as *risky*, we find, instead, that the negative interaction of MD inventors and MD tasks is driven by the less risky device categories. MDs are 4.3 *pp* less likely to invent AI technologies for MD tasks for lower risk devices (p=0.007), but are 5.8 *pp* more likely to invent AI technology for MD tasks for high risk devices (p=0.090). Invention risk is positively associated with AI invention by MDs for MD tasks.

[Insert Table 12 Here]

4.3.5 Selection mechanism

A major remaining issue with interpreting the above results as relating to technology anxiety is that we use realized invention outcomes to infer choice determinants. Instead, it may be that MDs make performance-based choices, selecting AI only when it is likely to outperform other technologies. If their ability to select for quality is strongest for MD task-related inventions (i.e., those most aligned with their expertise—a plausible assumption), then quality-related selection would be consistent with fewer AI inventions for MD tasks by MDs. In other words, they may be more selective. To further investigate this explanation, we explore the relationship between performance and AI inventions, across inventor and task types in Table 13. If MDs were making technology decisions based on quality, we should observe that MD inventor inventions with AI related to MD tasks are of higher realized quality than other MD inventions. However, while MD inventor inventions have higher forward cites and novelty (per Table 4), and even more so for those with AI, there is no additional quality bump associated with those for MD tasks. In contrast, the coefficients for MD inventors inventing AI for MD tasks are negative, β=-0.129 for patent citations (logged) and β=-0.006 for novelty, though statistically insignificant (p=0.312 and p=0.712 respectively). In short, these results are inconsistent with quality selection driving the decreases in MDs inventing AI devices for MD tasks.

[Insert Table 13 Here]

5 Discussion & Conclusion

In this paper we examine when and why expert users pursue, or do not pursue, certain types of inventions. Much of the literature on user innovation emphasizes the complementarities between user knowledge and the development of useful technologies with corporate partners, which leads to user-collaboration innovations being highly valuable and differentiated. We focus on a situation in which user knowledge and new technology may partially serve as substitutes. We suggest, and find supportive evidence, that expert users may be less likely invent technologies if and when they may potentially substitute for their unique expertise. The balance of the evidence is consistent with some version of "technological anxiety" driving, at least in part, MD inventor choices.

Our analyses of course have several limitations. First, while we include controls aimed at comparing otherwise similar inventions by vintage, technology areas, product markets, and associated task characteristics, and include various tests of mechanisms, our analyses are fundamentally correlational. Thus, while we can provide suggestive evidence in support of certain mechanisms, we cannot claim causality. Second, measuring potential substitutability is a fraught exercise; AI applied to MD tasks–while justifiable based on recent and current AI discussions–is not a perfect measure. Finally, our analyses stop short of providing estimates of the performance impact of physician-inventor, own-task AI aversion for firms that collaborate with MDs in invention. We leave this to future research.

Our results provide some necessary caveats to the user innovation literature and extend the literature on AI and labour to highlight the indirect, potentially negative effects of potential or perceived substitution on the generation of new technologies. Specifically, users in an industry can shape the technologies used in practice not just via adoption choices, but also because, when users are themselves an important source of invention, their choices will also shape which technologies are developed and thus available to adopt. Finally, our paper has managerial implications. Our results suggest partnering with users in corporate invention is not a panacea to improve innovation outcomes. Instead, user involvement may shape—for better or worse—the type of inventions produced by the firm.

References

Acemoglu, D. and Restrepo, P. 2019. The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand. Technical Report w25682, National Bureau of Economic Research.

Adner, R. and Lieberman, M. 2021. Disruption Through Complements. *Strategy Science*, 6(1):91–109.

Agarwal, R. and Shah, S. K. 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research Policy*, 43(7):1109–1133.

American Medical Association 1848. *Code Of Ethics Of The American Medical Association*. Creative Media Partners, LLC. Google-Books-ID: gGDJswEACAAJ.

Anthony, C. 2021. When Knowledge Work and Analytical Technologies Collide: The Practices and Consequences of Black Boxing Algorithmic Technologies. *Administrative Science Quarterly*, 66(4):1173–1212.

Arora, A., Cohen, W. M., and Walsh, J. P. 2016. The acquisition and commercialization of invention in American manufacturing: Incidence and impact. *Research Policy*, 45(6):1113–1128.

Arthur, W. B. 2007. The structure of invention. *Research Policy*, 36(2):274–287.

Arts, S. and Fleming, L. 2018. Paradise of Novelty—Or Loss of Human Capital? Exploring New Fields and Inventive Output. *Organization Science*, 29(6):1074–1092. Publisher: INFORMS.

Autor, D. H. 2015. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3):3–30.

Autor, D. H., Katz, L. F., and Krueger, A. B. 1998. Computing Inequality: Have Computers Changed the Labor Market?*. *The Quarterly Journal of Economics*, 113(4):1169–1213.

Barley, S. R. 1986. Technology as an occasion for structuring: evidence from observations of CT scanners and the social order of radiology departments. *Administrative Science Quarterly*, 31(1):78–108.

Barragán-Montero, A., Javaid, U., Valdés, G., Nguyen, D., Desbordes, P., Macq, B., Willems, S., Vandewinckele, L., Holmström, M., Löfman, F., Michiels, S., Souris, K., Sterpin, E., and Lee, J. A. 2021. Artificial intelligence and machine learning for medical imaging: A technology review. *Physica Medica*, 83:242–256.

Baxi, V., Edwards, R., Montalto, M., and Saha, S. 2022. Digital pathology and artificial intelligence in translational medicine and clinical practice. *Modern Pathology*, 35(1):23–32. Publisher: Nature Publishing Group.

Beasley, R. A. 2012. Medical Robots: Current Systems and Research Directions. *Journal of Robotics*, 2012(1):401613. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1155/2012/401613.

Berg, J. M. 2016. Balancing on the Creative Highwire: Forecasting the Success of Novel Ideas in Organizations. *Administrative Science Quarterly*, 61(3):433–468. Publisher: SAGE Publications Inc.

Bijker, W. E. 1997. *Of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change*. MIT Press.

Black, L. J., Carlile, P. R., and Repenning, N. P. 2004. A Dynamic Theory of Expertise and Occupational Boundaries in New Technology Implementation: Building on Barley's Study of CT Scanning. *Administrative Science Quarterly*, 49(4):572–607.

Botwe, B., Akudjedu, T., Antwi, W., Rockson, P., Mkoloma, S., Balogun, E., Elshami, W., Bwambale, J., Barare, C., Mdletshe, S., Yao, B., and Arkoh, S. 2021. The integration of artificial intelligence in medical imaging practice: Perspectives of African radiographers. *Radiography*, 27(3):861–866.

Brown, N. and Sandholm, T. 2018. Superhuman AI for heads-up no-limit poker: Libratus beats top professionals. *Science*, 359(6374):418–424. Publisher: American Association for the Advancement of Science Section: Research Article.

Brynjolfsson, E. and Mitchell, T. 2017. What can machine learning do? Workforce implications.

Science, 358(6370):1530–1534. Publisher: American Association for the Advancement of Science Section: Policy Forum.

Brynjolfsson, E., Mitchell, T., and Rock, D. 2018. What Can Machines Learn, and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings*, 108:43–47.

Buchanan, B. G. 2019. Artificial intelligence in finance. Technical report, Zenodo.

Cau, R., Flanders, A., Mannelli, L., Politi, C., Faa, G., Suri, J. S., and Saba, L. 2021. Artificial intelligence in computed tomography plaque characterization: A review. *European Journal of Radiology*, 140:109767.

Chatterji, A. K. and Fabrizio, K. 2012. How Do Product Users Influence Corporate Invention? *Organization Science*, 23(4):971–987.

Chatterji, A. K. and Fabrizio, K. R. 2014. Using users: When does external knowledge enhance corporate product innovation? *Strategic Management Journal*, 35(10):1427–1445.

Chatterji, A. K. and Fabrizio, K. R. 2016. Does the market for ideas influence the rate and direction of innovative activity? Evidence from the medical device industry. *Strategic Management Journal*, 37(3):447–465.

Choudhury, P., Starr, E., and Agarwal, R. 2020. Machine learning and human capital complementarities: Experimental evidence on bias mitigation. *Strategic Management Journal*, 41(8):1381–1411.

Christensen, C. M. and Raynor, M. E. 2003. *The Innovator's Solution: Creating and Sustaining Successful Growth*. Harvard Business School Press. Google-Books-ID: ZUsn9uIgkAUC.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). Working Paper, National Bureau of Economic Research.

Ding, W. W. 2011. The Impact of Founders' Professional-Education Background on the Adoption of Open Science by For-Profit Biotechnology Firms. *Management Science*, 57(2):257–273.

Dippel, E. J., Makam, P., Kovach, R., George, J. C., Patlola, R., Metzger, D. C., Mena-Hurtado, C., Beasley, R., Soukas, P., Colon-Hernandez, P. J., Stark, M. A., and Walker, C. 2015. Randomized Controlled Study of Excimer Laser Atherectomy for Treatment of Femoropopliteal In-Stent Restenosis: Initial Results From the EXCITE ISR Trial (EXCImer Laser Randomized Controlled Study for Treatment of FemoropopliTEal In-Stent Restenosis). *JACC: Cardiovascular Interventions*, 8(1, Part A):92–101.

El Hechi, M., Ward, T. M., An, G. C., Maurer, L. R., El Moheb, M., Tsoulfas, G., and Kaafarani, H. M. 2021. Artificial Intelligence, Machine Learning, and Surgical Science: Reality Versus Hype. *Journal of Surgical Research*, 264:A1–A9.

Elkhader, J. and Elemento, O. 2021. Artificial intelligence in oncology: From bench to clinic. *Seminars in Cancer Biology*, page S1044579X21001140.

Felten, E., Raj, M., and Seamans, R. 2021. Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.3286.

Fleming, L. and Sorenson, O. 2004. Science as a Map in Technological Search. *Strategic Management Journal*, 25(8/9):909–928.

Frey, C. B. and Osborne, M. A. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Galasso, A. and Luo, H. 2022. When Does Product Liability Risk Chill Innovation? Evidence from Medical Implants. *American Economic Journal: Economic Policy*, 14(2):366–401.

Gambardella, A., Raasch, C., and von Hippel, E. 2017. The User Innovation Paradigm: Impacts on Markets and Welfare. *Management Science*, 63(5):1450–1468.

Gaube, S., Suresh, H., Raue, M., Merritt, A., Berkowitz, S. J., Lermer, E., Coughlin, J. F., Guttag, J. V., Colak, E., and Ghassemi, M. 2021. Do as AI say: susceptibility in deployment of clinical decision-aids. *npj Digital Medicine*, 4(1):1–8. Number: 1 Publisher: Nature Publishing Group.

Goldin, C. and Katz, L. F. 1998. The Origins of Technology-Skill Complementarity. *The Quarterly Journal of Economics*, 113(3):693–732. Publisher: Oxford University Press.

Gorincour, G., Monneuse, O., Ben Cheikh, A., Avondo, J., Chaillot, P.-F., Journe, C., Youssof, E., Lecomte, J.-C., and Thomson, V. 2021. Management of abdominal emergencies in adults using telemedicine and artificial intelligence. *Journal of Visceral Surgery*, 158(3):S26–S31.

Gottlieb, J., Polyakova, M., Rinz, K., Shiplett, H., and Udavola, V. 2020. Who Values Human Capitalists' Human Capital? Healthcare Spending and Physician Earnings. Technical Report CES 20-23, U.S. Census Bureau. Section: Government.

Gruber, M., Harhoff, D., and Hoisl, K. 2013. Knowledge Recombination Across Technological Boundaries: Scientists vs. Engineers. *Management Science*, 59(4):837–851. Publisher: INFORMS.

Gupta, T., Weinreich, M., Greenberg, M., Colombo, A., and Latib, A. 2019. Rotational Atherectomy: A Contemporary Appraisal. *Interventional Cardiology Review*, 14(3):182–189.

He, K., Zhang, X., Ren, S., and Sun, J. 2015. Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification. *Proceedings of the IEEE International Conference on Computer Vision*, pages 1026–1034.

Henderson, R. 1993. Underinvestment and Incompetence as Responses to Radical Innovation: Evidence from the Photolithographic Alignment Equipment Industry. *The RAND Journal of Economics*, 24(2):248–270.

Henderson, R. 2006. The Innovator's Dilemma as a Problem of Organizational Competence. *Journal of Product Innovation Management*, 23(1):5–11. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-5885.2005.00175.x.

Itchhaporia, D. 2020. Artificial intelligence in cardiology. *Trends in Cardiovascular Medicine*.

Jia, N., Luo, X., Fang, Z., and Liao, C. 2024. When and How Artificial Intelligence Augments Employee Creativity. *Academy of Management Journal*, 67(1):5–32. Publisher: Academy of Management.

Jimeno Yepes, A. J., Plaza, L., Carrillo-de Albornoz, J., Mork, J. G., and Aronson, A. R. 2015. Feature engineering for MEDLINE citation categorization with MeSH. *BMC Bioinformatics*, 16:113.

Joshi, R. S., Lau, D., and Ames, C. P. 2021. Artificial intelligence for adult spinal deformity: Current state and future directions. *The Spine Journal*, pages 1–9.

Katila, R., Thatchenkery, S., Christensen, M. Q., and Zenios, S. 2017. Is There a Doctor in the House? Expert Product Users, Organizational Roles, and Innovation. *Academy of Management Journal*, 60(6):2415–2437.

Kaul, V., Enslin, S., and Gross, S. A. 2020. History of artificial intelligence in medicine. *Gastrointestinal Endoscopy*, 92(4):807–812.

Koivisto, M. and Grassini, S. 2023. Best humans still outperform artificial intelligence in a creative divergent thinking task. *Scientific Reports*, 13(1):13601. Number: 1 Publisher: Nature Publishing Group.

Kuhn, J., Younge, K., and Marco, A. 2020. Patent citations reexamined. *The RAND Journal of Economics*, 51(1):109–132. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12307.

Lebovitz, S., Lifshitz-Assaf, H., and Levina, N. 2022. To Engage or Not to Engage with AI for Critical Judgments: How Professionals Deal with Opacity When Using AI for Medical Diagnosis. *Organization Science*, 33(1):126–148. Publisher: INFORMS.

Ledzinski, L. and Grzesk, G. 2023. Artificial Intelligence Technologies in Cardiology. *Journal of Cardiovascular Development and Disease*, 10(5):202. Number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

Li, M.-D., Huang, Z.-R., Shan, Q.-Y., Chen, S.-L., Zhang, N., Hu, H.-T., and Wang, W. 2022. Performance and comparison of artificial intelligence and human experts in the detection and classification of colonic polyps. *BMC Gastroenterology*, 22:517.

Liang, S., Ma, J., Wang, G., Shao, J., Li, J., Deng, H., Wang, C., and Li, W. 2022. The Application of Artificial Intelligence in the Diagnosis and Drug Resistance Prediction of Pulmonary Tuberculosis. *Frontiers in Medicine*, 9:935080.

Liao, J., Li, X., Gan, Y., Han, S., Rong, P., Wang, W., Li, W., and Zhou, L. 2023. Artificial intelligence assists precision medicine in cancer treatment. *Frontiers in Oncology*, 12:998222.

Lybbert, T. J. and Zolas, N. J. 2014. Getting patents and economic data to speak to each other: An 'Algorithmic Links with Probabilities' approach for joint analyses of patenting and economic activity. *Research Policy*, 43(3):530–542.

Lüthje, C., Herstatt, C., and von Hippel, E. 2005. User-innovators and "local" information: The case of mountain biking. *Research Policy*, 34(6):951–965.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., and Zolas, N. 2024. AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2):375–415. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12576.

Mokyr, J., Vickers, C., and Ziebarth, N. L. 2015. The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives*, 29(3):31–50.

Moyo, E., Cashell, A., Chhin, V., Divanbeigi, L., Hill, C., Hyvarinen, R., Ishmail, N., Li, W., Morley, L., Roussos, J., Shessel, A., Velec, M., and Rosewall, T. 2019. Increased Automation and Artificial Intelligence in Radiation Therapy Clinical Practice: A Qualitative Exploration of Radiation Therapist Perceptions. *Journal of Medical Imaging and Radiation Sciences*, 50(2):S11.

Munoko, I., Brown-Liburd, H. L., and Vasarhelyi, M. 2020. The Ethical Implications of Using Artificial Intelligence in Auditing. *Journal of Business Ethics*, 167(2):209–234.

National Institute of Standards and Technology 2019. U.S. LEADERSHIP IN AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools. Technical report, U.S. Department of Commerce.

Nelson, A. J. and Irwin, J. 2014. "Defining What We Do—All Over Again": Occupational Identity, Technological Change, and the Librarian/Internet-Search Relationship. *Academy of Management Journal*, 57(3):892–928. Publisher: Academy of Management.

Nelson, R. R. 2008. Bounded rationality, cognitive maps, and trial and error learning. *Journal of Economic Behavior & Organization*, 67(1):78–89.

Nelson, R. R. and Winter, S. G. 1982. *An Evolutionary Theory of Economic Change*. Belknap Press, Cambridge, Mass.

OECD 2019. *Artificial Intelligence in Society*. OECD.

Orlikowski, W. J. and Gash, D. C. 1994. Technological frames: making sense of information technology in organizations. *ACM Transactions on Information Systems*, 12(2):174–207.

Pahnke, E. C., Katila, R., and Eisenhardt, K. M. 2015. Who Takes You to the Dance? How Partners' Institutional Logics Influence Innovation in Young Firms. *Administrative Science Quarterly*, page 0001839215592913.

Park, S. H., Han, K., Jang, H. Y., Park, J. E., Lee, J.-G., Kim, D. W., and Choi, J. 2023. Methods for Clinical Evaluation of Artificial Intelligence Algorithms for Medical Diagnosis. *Radiology*, 306(1):20–31. Publisher: Radiological Society of North America.

Parsa, N., Rex, D. K., and Byrne, M. F. 2021. Colorectal polyp characterization with standard endoscopy: Will Artificial Intelligence succeed where human eyes failed? *Best Practice & Research Clinical Gastroenterology*, 52-53:101736.

Prabhakar, B., Singh, R. K., and Yadav, K. S. 2021. Artificial intelligence (AI) impacting diagnosis of glaucoma and understanding the regulatory aspects of AI-based software as medical device.

Computerized Medical Imaging and Graphics, 87:101818.
Schweisfurth, T. G. 2017. Comparing internal and external lead users as sources of innovation. *Research Policy*, 46(1):238–248.
Shane, S. and Venkataraman, S. 2000. The Promise of Entrepreneurship as a Field of Research. *Academy of Management Review*, 25(1):217–226.
Shen, Y.-T., Chen, L., Yue, W.-W., and Xu, H.-X. 2021. Artificial intelligence in ultrasound. *European Journal of Radiology*, 139:109717.
Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., van den Driessche, G., Graepel, T., and Hassabis, D. 2017. Mastering the game of Go without human knowledge. *Nature*, 550(7676):354–359.
Silvera-Tawil, D. 2024. Robotics in Healthcare: A Survey. *SN Computer Science*, 5(1):189.
Singh, J. and Fleming, L. 2009. Lone Inventors as Sources of Breakthroughs: Myth or Reality? *Management Science*, 56(1):41–56.
Smith, K. G., Collins, C. J., and Clark, K. D. 2005. Existing Knowledge, Knowledge Creation Capability, and the Rate of New Product Introduction in High-Technology Firms. *Academy of Management Journal*, 48(2):346–357.
Smith, K. P., Wang, H., Durant, T. J., Mathison, B. A., Sharp, S. E., Kirby, J. E., Long, S. W., and Rhoads, D. D. 2020. Applications of Artificial Intelligence in Clinical Microbiology Diagnostic Testing. *Clinical Microbiology Newsletter*, 42(8):61–70.
Smith, S. W. and Shah, S. K. 2013. Do Innovative Users Generate More Useful Insights? An Analysis of Corporate Venture Capital Investments in the Medical Device industry. *Strategic Entrepreneurship Journal*, 7(2):151–167.
Sutton, R. A. and Sharma, P. 2021. Overcoming barriers to implementation of artificial intelligence in gastroenterology. *Best Practice & Research Clinical Gastroenterology*, 52-53:101732.
Teodoridis, F. 2018. Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise. *Management Science*, 64(8):3625–3648.
Topol, E. J., Leya, F., Pinkerton, C. A., Whitlow, P. L., Hofling, B., Simonton, C. A., Masden, R. R., Serruys, P. W., Leon, M. B., Williams, D. O., King, S. B., Mark, D. B., Isner, J. M., Holmes, D. R., Ellis, S. G., Lee, K. L., Keeler, G. P., Berdan, L. G., Hinohara, T., and Califf, R. M. 1993. A Comparison of Directional Atherectomy with Coronary Angioplasty in Patients with Coronary Artery Disease. *New England Journal of Medicine*, 329(4):221–227.
Trajtenberg, M. 2018. AI as the next GPT: a Political-Economy Perspective. Working Paper 24245, National Bureau of Economic Research. Series: Working Paper Series.
Tripsas, M. and Gavetti, G. 2000. Capabilities, cognition, and inertia: evidence from digital imaging. *Strategic Management Journal*, 21(10-11):1147–1161.
Urban, G. L. and von Hippel, E. 1988. Lead User Analyses for the Development of New Industrial Products. *Management Science*, 34(5):569–582.
USPTO 2020. Inventing AI: Tracing the diffusion of artificial intelligence with U.S. patents. Office of the Chief Economist 5.
Valikodath, N. G., Al-Khaled, T., Cole, E., Ting, D. S., Tu, E. Y., Campbell, J. P., Chiang, M. F., Hallak, J. A., and Chan, R. P. 2021. Evaluation of pediatric ophthalmologists' perspectives of artificial intelligence in ophthalmology. *Journal of American Association for Pediatric Ophthalmology and Strabismus*.
van den Oever, L., Vonder, M., van Assen, M., van Ooijen, P., de Bock, G., Xie, X., and Vliegenthart, R. 2020. Application of artificial intelligence in cardiac CT: From basics to clinical practice. *European Journal of Radiology*, 128:108969.
Verbeek, P.-P. 2006. Materializing Morality: Design Ethics and Technological Mediation. *Science,*

Technology, & Human Values, 31(3):361–380. Publisher: SAGE Publications Inc.

Von Hippel, E. 1994. "Sticky information" and the locus of problem solving: Implications for innovation. *Management Science*, 40(4):429.

von Hippel, E. 1998. Economics of Product Development by Users: The Impact of “Sticky” Local Information. *Management Science*, 44(5):629–644.

von Hippel, E., de Jong, J. P. J., and Flowers, S. 2012. Comparing Business and Household Sector Innovation in Consumer Products: Findings from a Representative Study in the United Kingdom. *Management Science*, 58(9):1669–1681.

Wright, S. A. and Schultz, A. E. 2018. The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, 61(6):823–832.

Zhang, Y. and Yang, W. 2022. Breakthrough invention and problem complexity: Evidence from a quasi-experiment. *Strategic Management Journal*, 43(12):2510–2544. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.3431.

Tables

Table 1: Medical task examples

Task	**Provider**	**Task Purpose**
Spinal Fusion	Medical Doctor	Therapeutic
Laparoscopy	Medical Doctor	Diagnostic
Platelet Transfusion	Nurse	Therapeutic
Blood Specimen Collection	Nurse	Diagnostic
Magnetic Resonance Imaging	Technician	Diagnostic
Glucose Tolerance Test	Technician	Laboratory

Table 2: Types of AI patents

	Mean	SD
AI: vision	0.56	0.50
AI: knowledge processing	0.42	0.49
AI: planning and control	0.31	0.46
AI: machine learning	0.18	0.38
AI: hardware	0.12	0.32
AI: evolutionary computing	0.03	0.16
AI: speech	0.01	0.11
AI: natural language processing	0.01	0.10
Observations	5175	

Note: AI Patents can be >1 type.

Table 3: Description of key variables

	Mean	SD
MD inventor	0.05	0.23
MD task	0.64	0.48
AI	0.10	0.31
Invention specialty		
Toxicology device	0.09	0.28
Hema/Pathology device	0.07	0.25
Immuno/Microbio device	0.06	0.23
Anesthesiology device	0.07	0.26
Cardiovascular device	0.19	0.39
Dental device	0.03	0.18
Ear/Nose/Throat device	0.07	0.26
Gastro/Uro device	0.11	0.32
General and Plastic Surgery device	0.13	0.34
General Hospital device	0.06	0.24
Neurological device	0.15	0.35
ObGyn device	0.07	0.26
Ophthalmic device	0.08	0.27
Orthopaedic device	0.06	0.24
Physical Med device	0.03	0.18
Radiology device	0.11	0.32
Invention purpose		
Diagnostic device	0.39	0.49
Monitoring device	0.14	0.34
Prosthetic device	0.25	0.43
Surgical device	0.30	0.46
Therapeutic device	0.23	0.42
Misc device	0.05	0.22
Task type		
Diagnostic Procedure	0.26	0.44
Laboratory Procedure	0.08	0.27
Therapeutic/Preventative Procedure	0.66	0.48
Task location		
Hospital task	0.56	0.50
Non-hospital task	0.09	0.29
Equally likely task location	0.34	0.48
Patent info		
N of inventors	3.11	2.11
N claims	18.76	11.08
Forward cites (3-yr, logged)	0.47	0.78
Novelty	0.70	0.13
Observations	42055	

Table 4: MD invention and performance

	(1) MD task	(2) Patent cits	(3) Novelty
MD inventor	0.036	0.059	0.015
	(0.008)	(0.019)	(0.003)
	[0.000]	[0.002]	[0.000]
Observations	48797	48797	42055
Year FE	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes
Invention purpose FE	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes
Pat qual controls		Yes	Yes
R2	0.355	0.056	0.036

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 5: MD inventors and MD tasks on AI invention

	(1)	(2)	(3)	(4)
MD inventor	-0.007	0.023	0.015	0.044
	(0.007)	(0.017)	(0.007)	(0.015)
	[0.320]	[0.173]	[0.029]	[0.005]
MD task		-0.060		-0.030
		(0.003)		(0.004)
		[0.000]		[0.000]
MD inventor X MD task		-0.034		-0.037
		(0.016)		(0.015)
		[0.040]		[0.016]
Observations	50170	50170	48797	48797
Year FE	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes
Invention specialty FE			Yes	Yes
Invention purpose FE			Yes	Yes
Task type FE			Yes	Yes
Task location FE			Yes	Yes
R2	0.011	0.020	0.137	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 6: MD inventors (different vs same specialty) and MD tasks on AI invention

	(1)	(2)	(3)	(4)
MD inventor	0.018	0.030		
	(0.008)	(0.016)		
	[0.026]	[0.070]		
MD inventor (same)	0.013	0.082		
	(0.013)	(0.035)		
	[0.339]	[0.018]		
MD task	-0.031	-0.030	-0.078	-0.062
	(0.004)	(0.004)	(0.018)	(0.020)
	[0.000]	[0.000]	[0.000]	[0.002]
MD inventor X MD task		-0.016		
		(0.016)		
		[0.331]		
MD inventor (same) X MD task		-0.092		
		(0.034)		
		[0.007]		
Same specialty			-0.008	0.036
			(0.019)	(0.040)
			[0.669]	[0.373]
Same specialty X MD task				-0.057
				(0.036)
				[0.117]
Observations	48797	48797	2646	2646
Year FE	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes	Yes
Invention purpose FE	Yes	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes	Yes
R2	0.139	0.139	0.209	0.210

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 7: Substitution mechanisms: Invention purpose, Firm Type, Task Value (by specialty)

	Invention Purpose		Firm Type		Task Value	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ther/Prost	Tool	Startup	EstFirm	LowValue	HighValue
MD inventor	0.018	0.060	0.025	0.062	0.022	0.098
	(0.017)	(0.025)	(0.022)	(0.020)	(0.017)	(0.031)
	[0.282]	[0.018]	[0.271]	[0.003]	[0.197]	[0.002]
MD task	-0.005	-0.048	-0.032	-0.029	-0.030	-0.039
	(0.005)	(0.006)	(0.008)	(0.004)	(0.005)	(0.008)
	[0.248]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
MD inventor X MD task	-0.008	-0.060	-0.013	-0.053	-0.006	-0.102
	(0.017)	(0.025)	(0.022)	(0.020)	(0.018)	(0.030)
	[0.630]	[0.018]	[0.549]	[0.009]	[0.730]	[0.001]
Observations	22460	26337	10083	38714	33055	15742
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes	Yes	Yes	Yes
Invention purpose FE	No	No	Yes	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.063	0.166	0.131	0.142	0.144	0.148

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 8: Knowledge mechanism: MD inventor experience

	(1)	(2)
MD inventor (inexp)	0.010	-0.003
	(0.016)	(0.032)
	[0.557]	[0.923]
MD inventor (exp)	0.018	0.054
	(0.008)	(0.017)
	[0.019]	[0.002]
MD task	-0.031	-0.030
	(0.004)	(0.004)
	[0.000]	[0.000]
MD inventor (inexp) X MD task		0.017
		(0.033)
		[0.606]
MD inventor (exp) X MD task		-0.049
		(0.017)
		[0.004]
Observations	48797	48797
Year FE	Yes	Yes
Patent group FE	Yes	Yes
Invention specialty FE	Yes	Yes
Invention purpose FE	Yes	Yes
Task type FE	Yes	Yes
Task location FE	Yes	Yes
R2	0.139	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 9: Knowledge mechanism: Inventing team, local AI supply, specialy AI proclivity

	Inventing team		Local supply		Specialty	
	(1) Team	(2) Solo	(3) LowAI	(4) HighAI	(5) LowAI	(6) HighAI
MD inventor	0.044	0.037	0.057	0.026	0.042	0.003
	(0.017)	(0.038)	(0.017)	(0.042)	(0.018)	(0.032)
	[0.008]	[0.335]	[0.001]	[0.530]	[0.016]	[0.921]
MD task	-0.030	-0.026	-0.027	-0.034	-0.030	-0.022
	(0.004)	(0.008)	(0.004)	(0.009)	(0.004)	(0.008)
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.004]
MD inventor X MD task	-0.040	-0.026	-0.047	-0.026	-0.030	-0.018
	(0.017)	(0.039)	(0.017)	(0.039)	(0.018)	(0.031)
	[0.015]	[0.504]	[0.007]	[0.512]	[0.091]	[0.553]
Observations	37829	10968	38049	8073	35497	13300
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes	Yes	No	No
Invention purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.143	0.130	0.135	0.147	0.113	0.116

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 10: Task complexity mechanism: including Task FE

	(1)	(2)
MD inventor	0.035	0.042
	(0.015)	(0.015)
	[0.017]	[0.005]
MD inventor X MD task	-0.029	-0.032
	(0.015)	(0.015)
	[0.049]	[0.032]
Observations	50052	48674
Year FE	Yes	Yes
Patent group FE	Yes	Yes
Task FE	Yes	Yes
Invention specialty FE		Yes
Invention purpose FE		Yes
R2	0.192	0.211

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 11: Task complexity mechanism: specialized vs general tasks

	(1) General tasks	(2) Specialized tasks
MD inventor	0.045	0.053
	(0.016)	(0.030)
	[0.005]	[0.078]
MD task	-0.013	-0.005
	(0.004)	(0.011)
	[0.003]	[0.664]
MD inventor X MD task	-0.038	-0.049
	(0.018)	(0.030)
	[0.032]	[0.097]
Observations	30151	18646
Year FE	Yes	Yes
Patent group FE	Yes	Yes
Invention specialty FE	Yes	Yes
Invention purpose FE	Yes	Yes
Task type FE	Yes	Yes
Task location FE	Yes	Yes
R2	0.108	0.182

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 12: Invention risk mechanism: FDA medical device class

	(1) Low risk	(2) High risk
MD inventor	0.055	-0.072
	(0.016)	(0.034)
	[0.001]	[0.032]
MD task	-0.031	-0.017
	(0.004)	(0.020)
	[0.000]	[0.419]
MD inventor X MD task	-0.043	0.058
	(0.016)	(0.034)
	[0.007]	[0.090]
Observations	44935	3862
Year FE	Yes	Yes
Patent group FE	Yes	Yes
Invention specialty FE	Yes	Yes
Invention purpose FE	Yes	Yes
Task type FE	Yes	Yes
Task location FE	Yes	Yes
R2	0.149	0.102

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table 13: Selection mechanism: MD inventors, MD tasks, AI and performance

	(1) Patent cits	(2) Patent cits	(3) Novelty	(4) Novelty
MD inventor	0.034	0.065	0.013	0.011
	(0.020)	(0.032)	(0.003)	(0.007)
	[0.080]	[0.042]	[0.000]	[0.112]
AI	0.063	0.063	-0.002	-0.006
	(0.015)	(0.017)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.419]	[0.106]
MD inventor X AI	0.261	0.320	0.030	0.033
	(0.079)	(0.108)	(0.010)	(0.014)
	[0.001]	[0.003]	[0.003]	[0.023]
MD task		0.060		-0.011
		(0.009)		(0.002)
		[0.000]		[0.000]
MD inventor X MD task		-0.044		0.003
		(0.036)		(0.008)
		[0.213]		[0.739]
AI X MD task		0.007		0.006
		(0.024)		(0.004)
		[0.778]		[0.154]
MD inventor X MD task X AI		-0.129		-0.006
		(0.128)		(0.017)
		[0.312]		[0.712]
Observations	48797	48797	42055	42055
Year FE	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes	Yes
Invention purpose FE	Yes	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes	Yes
Pat qual controls	Yes	Yes	Yes	Yes
R2	0.057	0.058	0.036	0.037

Robust SEs in parentheses (clustered by patent); p-values in brackets

Appendix

Table A1: Alternative DV: MD inventors and MD tasks on device purpose (tool)

	(1)	(2)	(3)	(4)	(5)	(6)
MD inventor	0.033	-0.078	-0.053			
	(0.014)	(0.026)	(0.024)			
	[0.018]	[0.003]	[0.029]			
MD inventor (same)	-0.096	0.018	-0.089			
	(0.022)	(0.041)	(0.038)			
	[0.000]	[0.650]	[0.019]			
MD task	0.033	0.030	0.028	0.101	0.184	0.120
	(0.005)	(0.005)	(0.005)	(0.024)	(0.028)	(0.031)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
MD inventor X MD task		0.152	0.096			
		(0.029)	(0.026)			
		[0.000]	[0.000]			
MD inventor (same) X MD task		-0.149	-0.050			
		(0.045)	(0.043)			
		[0.001]	[0.243]			
Same specialty				-0.137	0.092	-0.048
				(0.026)	(0.048)	(0.050)
				[0.000]	[0.056]	[0.333]
Same specialty X MD task					-0.302	-0.143
					(0.052)	(0.053)
					[0.000]	[0.007]
Observations	48797	48797	48797	2646	2646	2646
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes	Yes	Yes
Invention specialty FE			Yes			Yes
Task type FE			Yes			Yes
Task location FE			Yes			Yes
R2	0.004	0.005	0.269	0.030	0.044	0.261

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A2: Knowledge mechanism: MD inventors AI experience

	(1)	(2)
MD inventor (inexp)	0.009	-0.004
	(0.016)	(0.032)
	[0.571]	[0.903]
MD inventor (exp noAI)	-0.034	-0.035
	(0.005)	(0.012)
	[0.000]	[0.003]
MD inventor (exp AI)	0.175	0.253
	(0.024)	(0.043)
	[0.000]	[0.000]
MD task	-0.031	-0.030
	(0.004)	(0.004)
	[0.000]	[0.000]
MD inventor (inexp) X MD task		0.017
		(0.033)
		[0.592]
MD inventor (exp noAI) X MD task		0.001
		(0.012)
		[0.925]
MD inventor (exp AI) X MD task		-0.115
		(0.043)
		[0.007]
Observations	48797	48797
Year FE	Yes	Yes
Patent group FE	Yes	Yes
Invention specialty FE	Yes	Yes
Invention purpose FE	Yes	Yes
Task type FE	Yes	Yes
Task location FE	Yes	Yes
R2	0.142	0.143

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A3: Types of AI: MD inventors and MD tasks on AI invention

	(1) Any	(2) Vision	(3) Know	(4) Plan	(5) ML	(6) Hard	(7) Speech	(8) Evo	(9) NLP
MD inventor	0.044	0.038	0.028	0.021	0.016	0.031	0.000	0.001	0.002
	(0.015)	(0.014)	(0.012)	(0.011)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
	[0.005]	[0.005]	[0.020]	[0.053]	[0.068]	[0.001]	[0.994]	[0.670]	[0.532]
MD task	-0.030	-0.015	-0.015	-0.014	-0.005	-0.001	-0.002	-0.000	-0.000
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.266]	[0.007]	[0.603]	[0.577]
MD inventor X MD task	-0.037	-0.034	-0.035	-0.024	-0.012	-0.032	-0.001	-0.002	0.001
	(0.015)	(0.013)	(0.012)	(0.011)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
	[0.016]	[0.009]	[0.004]	[0.026]	[0.195]	[0.000]	[0.853]	[0.491]	[0.720]
Observations	48797	48797	48797	48797	48797	48797	48797	48797	48797
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invention purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Task location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.139	0.152	0.058	0.033	0.030	0.029	0.006	0.003	0.003

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A4: Task Location: MD inventors, MD tasks on AI invention

	(1) Non-hosp	(2) Hosp	(3) All
MD inventor	0.016	0.127	0.014
	(0.016)	(0.030)	(0.016)
	[0.309]	[0.000]	[0.390]
MD task	-0.033	-0.029	-0.033
	(0.005)	(0.006)	(0.005)
	[0.000]	[0.000]	[0.000]
MD inventor X MD task	-0.012	-0.118	-0.011
	(0.020)	(0.029)	(0.020)
	[0.557]	[0.000]	[0.571]
Hospital task			-0.002
			(0.006)
			[0.792]
MD inv X Hosp task			0.112
			(0.031)
			[0.000]
MD task X Hosp task			0.014
			(0.008)
			[0.074]
MD inv X MD task X Hosp task			-0.106
			(0.034)
			[0.002]
Observations	21320	27477	48797
Year FE	Yes	Yes	Yes
Patent group FE	Yes	Yes	Yes
Invention specialty FE	Yes	Yes	Yes
Invention purpose FE	Yes	Yes	Yes
Task type FE	Yes	Yes	Yes
Task location FE	No	No	No
R2	0.146	0.113	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets

Fully interacted models

For each of the split sample models of Table 7, Table 9, Table 11, Table 12, we include below the fully interacted models, with the triple interactions referenced in the paper.

Table A5: Substitution mechanism: invention purpose (therapy/prosthetic vs tool)

	(1)
MD inventor	0.027
	(0.017)
	[0.112]
MD task	-0.009
	(0.005)
	[0.058]
MD inventor X MD task	-0.008
	(0.017)
	[0.614]
Tool device	0.074
	(0.006)
	[0.000]
MD inv X Tool dev	0.036
	(0.031)
	[0.251]
MD task X Tool dev	-0.043
	(0.006)
	[0.000]
MD inv X MD task X Tool	-0.056
	(0.031)
	[0.073]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	No
Task type FE	Yes
Task location FE	Yes
R2	0.131

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A6: Substitution mechanism: established firms vs startups

	(1)
MD inventor	0.060
	(0.020)
	[0.003]
MD task	-0.030
	(0.004)
	[0.000]
MD inventor X MD task	-0.053
	(0.020)
	[0.009]
Startup	-0.019
	(0.007)
	[0.006]
MD inv X Startup	-0.036
	(0.030)
	[0.238]
MD task X Startup	0.001
	(0.007)
	[0.919]
MD inv X MD task X Startup	0.043
	(0.030)
	[0.148]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A7: Substitution mechanism: task value (by device speciality FTE revenues)

	(1)
MD inventor	0.024
	(0.017)
	[0.161]
MD task	-0.024
	(0.004)
	[0.000]
MD inventor X MD task	-0.007
	(0.018)
	[0.673]
High value	0.031
	(0.013)
	[0.018]
MD inv X High Value	0.072
	(0.036)
	[0.048]
MD task X High Value	-0.024
	(0.007)
	[0.001]
MD inv X MD task X High Value	-0.092
	(0.036)
	[0.011]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A8: Knowledge mechanism: solo inventor vs inventing team

	(1)
MD inventor	0.043
	(0.017)
	[0.010]
MD task	-0.031
	(0.004)
	[0.000]
MD inventor X MD task	-0.040
	(0.017)
	[0.016]
Solo inventor	-0.029
	(0.007)
	[0.000]
MD inv X Solo inv	-0.004
	(0.041)
	[0.920]
MD task X Solo inv	0.006
	(0.007)
	[0.391]
MD inv X MD task X Solo inv	0.018
	(0.041)
	[0.671]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.140

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A9: Knowledge mechanism: local AI supply (by CBSA-level)

	(1)
MD inventor	0.057
	(0.017)
	[0.001]
MD task	-0.028
	(0.004)
	[0.000]
MD inventor X MD task	-0.047
	(0.017)
	[0.007]
High AI area	0.003
	(0.009)
	[0.740]
MD inv X High AI	-0.038
	(0.046)
	[0.411]
MD task X High AI	-0.004
	(0.009)
	[0.644]
MD inv X MD task X High AI	0.021
	(0.044)
	[0.624]
Observations	46122
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.136

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A10: Knowledge mechanism: AI proclivity (by invention specialty)

	(1)
MD inventor	0.041
	(0.018)
	[0.020]
MD task	-0.029
	(0.004)
	[0.000]
MD inventor X MD task	-0.029
	(0.018)
	[0.101]
High AI dev cat	0.006
	(0.007)
	[0.413]
MD inv X High AI	-0.038
	(0.037)
	[0.304]
MD task X High AI	0.008
	(0.008)
	[0.281]
MD inv X MD task X High AI	0.008
	(0.036)
	[0.823]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	No
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.112

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A11: Task complexity mechanism: specialized vs general tasks

	(1)
MD inventor	0.045
	(0.016)
	[0.005]
MD task	-0.017
	(0.004)
	[0.000]
MD inventor X MD task	-0.035
	(0.018)
	[0.047]
Specialist task	0.044
	(0.006)
	[0.000]
MD inv X Spec task	0.001
	(0.032)
	[0.986]
MD task X Spec task	-0.033
	(0.007)
	[0.000]
MD inv X MD task X Spec task	-0.011
	(0.034)
	[0.748]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.140

Robust SEs in parentheses (clustered by patent); p-values in brackets

Table A12: Invention risk mechanism: FDA medical device class

	(1)
MD inventor	0.053
	(0.016)
	[0.001]
MD task	-0.031
	(0.004)
	[0.000]
MD inventor X MD task	-0.041
	(0.016)
	[0.010]
High risk device	-0.005
	(0.015)
	[0.762]
MD inv X High risk	-0.167
	(0.037)
	[0.000]
MD task X High risk	0.029
	(0.016)
	[0.066]
MD inv X MD task X High	0.117
	(0.038)
	[0.002]
Observations	48797
Year FE	Yes
Patent group FE	Yes
Invention specialty FE	Yes
Invention purpose FE	Yes
Task type FE	Yes
Task location FE	Yes
R2	0.139

Robust SEs in parentheses (clustered by patent); p-values in brackets