

Adoption Patterns of Generative Artificial Intelligence in Healthcare Occupations: Cross-Sectional Study of User Interactions with Claude

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Submitted to: Journal of Medical Internet Research
on: March 13, 2025

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Abstract

Background: Generative artificial intelligence (GenAI) systems like Anthropic's Claude and OpenAI's ChatGPT are rapidly being adopted in various sectors, including healthcare, offering potential benefits for clinical support, administrative efficiency, and patient information access. However, real-world adoption patterns and the extent to which GenAI is used for healthcare-related tasks remain poorly understood, distinct from performance benchmarks in controlled settings. Understanding these organic usage patterns is key for assessing GenAI's impact on healthcare delivery and patient-provider dynamics.

Objective: To quantify the real-world frequency and scope of healthcare-related tasks performed using Anthropic's Claude GenAI. We sought to: (1) measure the proportion of Claude interactions related to healthcare tasks versus other domains; (2) identify specific healthcare occupations (per O*NET classifications) with high associated interaction volumes; (3) assess the breadth of task adoption within roles using a "digital adoption rate"; and (4) interpret these findings considering the inherent ambiguity regarding user identity (professionals vs. public) in the data.

Methods: We performed a cross-sectional analysis of over four million anonymized user conversations with Claude (free and pro subscribers) from December 2024 to January 2025, using a publicly available dataset from Anthropic's "Economic Index" research. Interactions were pre-classified by Anthropic's proprietary Clio model into standardized occupational tasks mapped to the U.S. Department of Labor's O*NET database. The dataset did not allow differentiation between healthcare professionals and the general public as users. We focused on interactions mapped to O*NET Healthcare Practitioners and Technical Occupations. Main outcomes included the proportion of interactions per healthcare occupation, the overall healthcare interaction share versus other categories, and the digital adoption rate (distinct tasks performed via GenAI / total possible tasks per occupation).

Results: Healthcare-related tasks accounted for 2.58% of total GenAI analyzed conversations, significantly lower than domains like Computing (37.22%). Within healthcare, interaction frequency varied notably by role. Occupations emphasizing patient education and guidance exhibited the highest shares, including Dietitians and Nutritionists (6.61% of healthcare conversations), Nurse Practitioners (5.63%), Music Therapists (4.54%), and Clinical Nurse Specialists (4.53%). Digital adoption rates (task breadth) ranged widely across top healthcare roles (13.33%-65%), averaging 16.92%, below the global average (21.13%). Medical Records and Health Information Technician tasks had the highest adoption rate (65%).

Conclusions: GenAI tools are being adopted for a measurable subset of healthcare-related tasks, with usage concentrated in specific, often patient-facing roles. The critical limitation of user anonymity prevents definitively concluding whether this reveals primarily patient information-seeking (potentially driven by access needs) or professional workflow assistance. This ambiguity

necessitates caution when interpreting current GenAI adoption. Our findings emphasize the urgent need for strategies addressing potential impacts on clinical workflows, patient decision-making, information quality, and health equity. Future research must aim to differentiate user types, while stakeholders should develop targeted guidance for both safe patient use and responsible professional integration.

(JMIR Preprints 13/03/2025:73918)

DOI: <https://doi.org/10.2196/preprints.73918>

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Conclusions:

GenAI tools are being adopted for a measurable subset of healthcare-related tasks, with usage concentrated in specific, often patient-facing roles. The critical limitation of user anonymity prevents definitively concluding whether this reveals primarily patient information-seeking (potentially driven by access needs) or professional workflow assistance. This ambiguity necessitates caution when interpreting current GenAI adoption. Our findings emphasize the urgent need for strategies addressing potential impacts on clinical workflows, patient decision-making, information quality, and health equity. Future research must aim to differentiate user types, while stakeholders should develop targeted guidance for both safe patient use and responsible professional integration.

Keywords: Communication, Humans, Artificial Intelligence, Language, Machine Learning, Self-Management, Information Seeking Behavior, Outcome Assessment / Health Care, Referral and Consultation, Patient Care, Workflow, Patient Participation, Health Literacy



Introduction

Generative Artificial Intelligence (GenAI) systems, developed by organizations such as Anthropic (Claude), OpenAI (ChatGPT), Google (Gemini), Microsoft (Copilot), and Meta (Llama), represent a significant technological shift, and are rapidly being adopted in diverse sectors globally at unprecedented speed [1]. Healthcare stands as a domain where GenAI holds considerable transformative potential. Proposed applications range from enhancing clinical decision-making support [2, 3] and potentially automating high-skilled cognitive tasks distinct from previous software capabilities [4] to streamlining burdensome administrative workflows and empowering patients with more accessible, tailored health information [2, 3]. The rapid proliferation and increasing sophistication of these tools necessitate a clear understanding of their current role and impact within the healthcare ecosystem.

Initial research has begun to explore the capabilities of GenAI in healthcare contexts, often demonstrating performance on par with, or even exceeding, human clinicians on specific, well-defined tasks such as diagnostic reasoning or medical knowledge recall [5-7]. For instance, studies have compared GenAI outputs to physician performance in complex diagnostic challenges [6] and clinical reasoning assessments [5]. Furthermore, user trust plays a critical role in the adoption of these AI tools [8], adding another layer to understanding real-world uptake. However, these studies typically occur in controlled or experimental settings, focusing on benchmark performance rather than quantifying the extent and nature of GenAI's spontaneous, real-world application across the breadth of healthcare activities.

Consequently, a significant gap exists between understanding GenAI's potential capabilities and characterizing its actual adoption patterns and usage frequency for healthcare-related tasks by both professionals and the public. Studies have confirmed this rapid adoption is occurring across the economy [1, 9], highlighting the urgency of understanding its domain-specific implications. Such widespread availability and adoption of GenAI tools raises many questions about their real-world integration [10]. As individuals increasingly turn to free and widely available GenAI models, how frequently are these interactions related to healthcare? Are certain clinical roles or types of healthcare tasks seeing disproportionately high engagement via GenAI? Given these questions, we sought to move beyond capability assessment and provide empirical data on the current landscape of GenAI usage for tasks associated with healthcare occupations.

Using Anthropic's foundational "Economic Index" research which provided a broad overview of AI usage across various economic sectors [11], this cross-sectional study aimed to conduct a more focused analysis specifically within the healthcare domain. Leveraging the same large-scale, anonymized dataset of user interactions with Claude, our primary objectives were: (1) to quantify the overall proportion of GenAI interactions dedicated to tasks associated with healthcare occupations, as defined by the U.S. Department of Labor's [12] O*NET database [13]; (2) to identify which specific healthcare roles exhibit the highest frequency of associated task interactions; (3) to introduce and assess a novel metric, the "digital adoption rate," representing the breadth of GenAI adoption within these roles based on the variety of distinct occupational tasks performed using the AI; and (4) to contextualize healthcare-related usage by comparing it to usage patterns across other major occupational sectors.

Methods

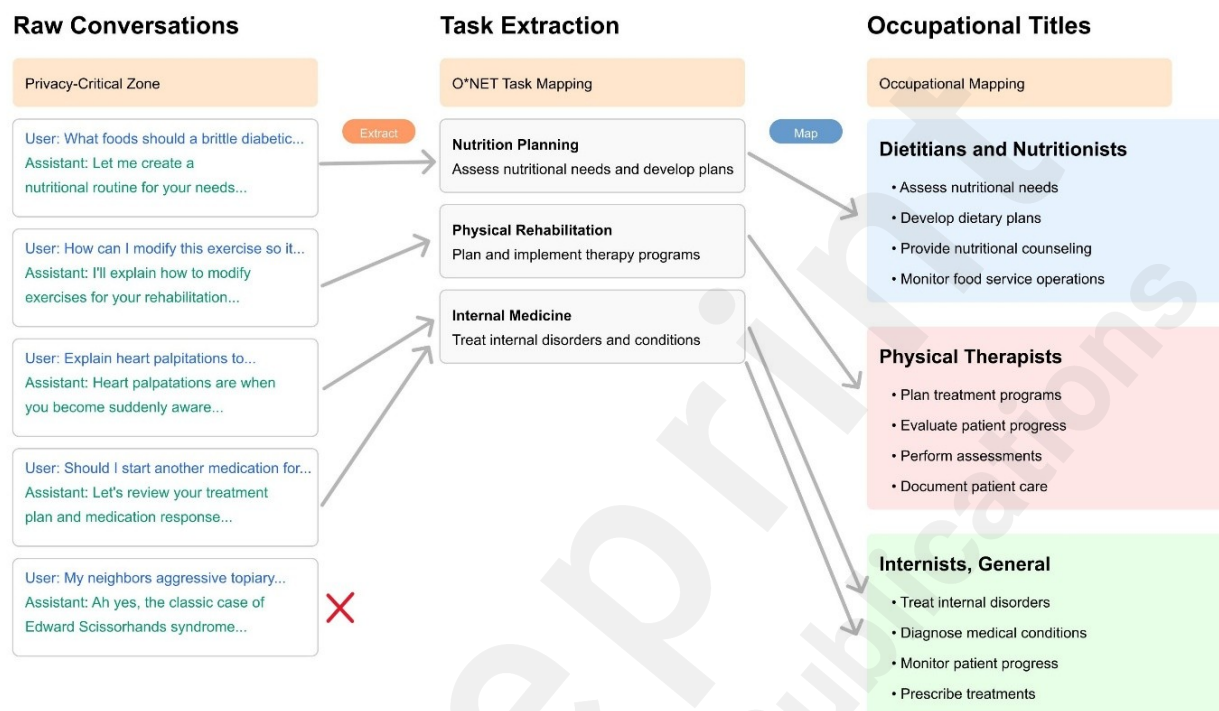
Data Source and Study Design

We leveraged a publicly available, privacy-preserving aggregated dataset derived from over 4 million anonymized conversations with Claude from free and pro subscribers, released as part of Anthropic's "Economic Index" research [11]. This dataset reflects a broad spectrum of real-world user interactions, offering an ecologically valid basis for examining GenAI engagement with professional tasks.

Occupational Task Mapping

Our analysis utilized the pre-mapped dataset created and open-sourced by Anthropic, which contains

conversations already mapped to standardized occupational tasks as defined by the U.S. Department of Labor's O*NET database. Anthropic's team used their proprietary Clio model[14] to create these mappings and validated them through manual review. Specifically, they used hand-validation to across 150 examples for their task hierarchy classifications, finding that 86% of conversations were judged as correctly assigned at the base O*NET task level, 91.3% at the middle level, and 95.3% at the top level of their hierarchical framework[11]. We focused our analysis specifically on the subset of this dataset related to tasks and occupations within the healthcare domain. **Figure 1** illustrates the Clio mapping methodology that underpins the dataset we utilized.



Metrics and Outcomes

- Occupation-Specific GenAI Usage:** We computed the proportion of total GenAI conversations attributable to each O*NET Healthcare Practitioners and Technical Occupation.
- Global Occupational Categories:** We compared healthcare's share of GenAI usage against other occupational categories (e.g., computing, arts/media, education) to contextualize overall representation.
- Digital Adoption Rate:** We calculated the ratio of distinct tasks performed with GenAI to total distinct potential tasks for each occupation. For instance, if an occupation had 20 potential tasks in the O*NET database and 5 of them appeared in GenAI conversations, the adoption rate was 25%. This analysis was conducted for the top 25 Healthcare Practitioners and Technical Occupations.

Statistical Analysis

Descriptive statistics summarized GenAI usage proportions and adoption rates. We used simple comparisons (e.g., ratio of usage in healthcare vs other categories) to maximize interpretability while highlighting relative differences. All analyses were performed in R[15].

Ethical Considerations

Our Office of Responsible Research Practices has determined that our study does not qualify as human subjects research requiring review as no identifiable personal data were included in the dataset; all conversations were pre-anonymized and aggregated, and the data was made [public](#) by Anthropic on February 10, 2025[16].

Results

Overall Healthcare Usage

Tasks mapped to Healthcare Practitioners and Technical Occupations collectively represented 2.58% of all GenAI conversations (**Table 1, Multimedia Appendix Figure 1**). In contrast, computing-related fields accounted for 37.22%, followed by arts/media (10.28%) and education (9.33%).

Table 1

Occupational Categories	Global Percentage (%)
Computer and Mathematical	37.22%
Arts, Design, Entertainment, Sports, and Media	10.28%
Educational Instruction and Library	9.33%
Office and Administrative Support	7.87%
Life, Physical, and Social Science	6.38%
Business and Financial Operations	5.93%
Architecture and Engineering	4.51%
Management	4.48%
Production	2.93%
Healthcare Practitioners and Technical	2.58%
Sales and Related	2.27%
Community and Social Service	2.07%
Legal	0.90%
Installation, Maintenance, and Repair	0.72%
Food Preparation and Serving Related	0.53%
Personal Care and Service	0.46%
Construction and Extraction	0.42%
Protective Service	0.38%
Transportation and Material Moving	0.28%
Healthcare Support	0.27%
Building and Grounds Cleaning and Maintenance	0.10%
Farming, Fishing, and Forestry	0.07%

Within-Healthcare Breakdown

In the top 25 list of Healthcare Practitioners and Technical Occupations by GenAI conversation share, Dietitians and Nutritionists (6.61%), Nurse Practitioners (5.63%), Music Therapists (4.54%), and Clinical Nurse Specialists (4.53%) had the highest usage (**Table 2, Multimedia Appendix Figure 2**). Meanwhile, other occupations such as Pediatricians (1.38%) and Internists (1.29%) had more modest representation.

Table 2

Top 25 Healthcare Practitioners and Technical Occupations	Healthcare Percentage (Global Percentage)
Dietitians and Nutritionists	6.61% (0.17%)
Nurse Practitioners	5.63% (0.15%)
Music Therapists	4.54% (0.12%)
Clinical Nurse Specialists	4.53% (0.12%)
Radiologists	4.16% (0.11%)
Exercise Physiologists	3.91% (0.10%)
Respiratory Therapists	3.86% (0.10%)
Medical Records and Health Information Technicians	3.74% (0.10%)

Critical Care Nurses	3.03% (0.08%)
Medical and Clinical Laboratory Technicians	2.98% (0.08%)
Genetic Counselors	2.83% (0.07%)
Pharmacists	2.75% (0.07%)
Nuclear Medicine Physicians	2.54% (0.07%)
Pathologists	2.52% (0.07%)
Advanced Practice Psychiatric Nurses	2.43% (0.06%)
Art Therapists	2.42% (0.06%)
Allergists and Immunologists	2.25% (0.06%)
Dietetic Technicians	2.08% (0.05%)
Nurse Midwives	1.89% (0.05%)
Medical and Clinical Laboratory Technologists	1.88% (0.05%)
Physical Therapists	1.75% (0.05%)
Naturopathic Physicians	1.69% (0.04%)
Acute Care Nurses	1.55% (0.04%)
Pediatricians, General	1.38% (0.04%)
Internists, General	1.29% (0.03%)

Adoption Rates

Digital adoption rates for top healthcare occupations ranged from 13.33% to 65%, with an average of 16.92%, compared to a global task adoption rate of 21.13% (**Table 3, Multimedia Appendix Figure 3**). Medical Records and Health Information Technicians (65%), Nurse Midwives (50%), and Pediatricians (43.75%) had the highest task adoption rate.

Table 3

Top 25 Healthcare Practitioners and Technical Occupation Adoption Rates	Adoption Rate (Affected Tasks/Total Tasks)
Medical Records and Health Information Technicians	65.00% (13/20)
Nurse Midwives	50.00% (10/20)
Pediatricians, General	43.75% (7/16)
Nurse Practitioners	37.04% (10/27)
Dietitians and Nutritionists	34.78% (8/23)
Dietetic Technicians	33.33% (4/12)
Exercise Physiologists	32.00% (8/25)
Internists, General	31.58% (6/19)
Genetic Counselors	31.58% (6/19)
Clinical Nurse Specialists	31.03% (9/29)
Pharmacists	30.00% (6/20)
Radiologists	27.59% (8/29)
Music Therapists	26.67% (8/30)
Pathologists	26.32% (5/19)
Acute Care Nurses	25.93% (7/27)
Physical Therapists	25.00% (6/24)
Naturopathic Physicians	25.00% (5/20)
Medical and Clinical Laboratory Technologists	25.00% (4/16)
Allergists and Immunologists	25.00% (4/16)
Advanced Practice Psychiatric Nurses	25.00% (6/24)

Art Therapists	24.00% (6/25)
Critical Care Nurses	17.24% (5/29)
Nuclear Medicine Physicians	15.38% (4/26)
Respiratory Therapists	13.64% (3/22)
Medical and Clinical Laboratory Technicians	13.33% (2/15)
Healthcare Occupational Average = 16.92%	
Global Occupational Average = 21.13%	

Discussion

Interpreting GenAI Usage Patterns in Healthcare Tasks through Multiple Perspectives

Our analysis reveals significant GenAI interaction volume related to healthcare tasks, yet concentrated within specific roles, particularly those involving substantial patient interaction, education, and guidance (e.g., Dietitians, Nurse Practitioners, Therapists). These findings point towards an emerging, complex integration of GenAI into the healthcare ecosystem. However, the anonymized nature of the data necessitates considering multiple interpretations regarding who is driving this usage and why.

Interpretation 1: Patient-Driven Information Seeking and Self-Management

One plausible interpretation is that the observed patterns reflect significant usage by the public. Patients may be turning to GenAI like Claude for accessible health information, clarification of medical terminology, lifestyle advice, or even emotional support related to health concerns, tasks commonly associated with roles like dietitians or nurse practitioners. Such information-seeking behavior aligns with pre-existing trends of patients consulting "Dr. Google" [17] and reflects a potential desire for readily available information [18]. Observed patterns among ChatGPT users seeking health information who tend to be younger, report poorer health status, and utilize transient care settings more often [19] may further point to this behavior, particularly when timely access to healthcare professionals is limited [20]. If patients are indeed primary users, this trend could signify a shift towards greater patient engagement and potential empowerment through readily accessible, personalized information. However, this interpretation also carries significant risks: the potential for consuming misinformation or AI "hallucinations," leading to misguided self-management decisions, delayed consultation with qualified professionals, or increased health anxiety [18], risks highlighted in studies examining user trust and reliance on chatbots for health advice [8]. The accessibility that drives usage could simultaneously introduce harm if not accompanied by subject matter expertise, digital health literacy, and critical appraisal skills.

Interpretation 2: Professional Workflow Assistance and Efficiency

Alternatively, the concentration of usage in these roles could indicate adoption by healthcare professionals themselves. Dietitians, Nurse Practitioners, Clinical Nurse Specialists, and others might be leveraging GenAI to enhance their workflow – drafting patient education materials, summarizing complex information, exploring differential diagnoses, generating notes, or even staying abreast of new research relevant to patient counseling, potentially automating specific cognitive tasks previously resistant to software automation [4]. From this perspective, GenAI acts as an efficiency tool, potentially helping overloaded professionals manage demanding workloads within a strained healthcare system. Indeed, workers in exposed occupations often perceive substantial productivity potential in GenAI tools like ChatGPT [9]. This interpretation suggests a pathway towards augmenting professional capabilities, potentially improving the consistency or breadth of patient communication. Yet, risks also exist here, including over-reliance on AI outputs potentially containing inaccuracies or biases, deskilling in core communication or critical thinking tasks through cognitive offloading, and the ethical implications of using AI to generate content for patient care without adequate oversight or personalization.

The Underlying Influence of Healthcare System Pressures

Regardless of whether patients or professionals are the primary users, the observed patterns may also indicate broader systemic issues within healthcare. When professional support is not easily or quickly accessible, individuals (both patients and potentially time-pressed professionals) are likely to turn to readily available tools like GenAI. Findings that users seeking health information from ChatGPT tend to report poorer health and greater use of transient care settings lend credence to this possibility [19]. This suggests that GenAI adoption in healthcare contexts might be partially driven by unmet needs and access gaps within the current system. Furthermore, even when productivity benefits are perceived, adoption can be hindered by factors like employer restrictions or the need for training [9]. This "compensatory" use stresses the importance for healthcare systems to adapt, not just by integrating AI safely, but by addressing the root causes that might drive patients or professionals towards potentially unverified AI tools out of necessity.

Implications for the Patient-Provider Dynamic and Information Hierarchy

The convergence of these possibilities, patients potentially arriving at appointments armed with AI-generated information, and/or professionals using GenAI to prepare for those encounters, points towards a fundamental reshaping of information hierarchies and the patient-provider relationship. The dynamic shifts from a traditionally asymmetric information flow to one where both parties may engage with AI-derived knowledge, demanding new communication strategies, enhanced critical appraisal skills from both sides, and a shared understanding of GenAI's current capabilities and limitations [7]. This is particularly relevant as a significant portion of patients report acting on AI-generated health information, such as changing medications or seeking referrals, often subsequently discussing the AI output with their physicians [19]. Addressing the potential for GenAI to exacerbate existing health inequities based on digital access or literacy is also paramount.

Future Directions

Healthcare organizations and regulatory bodies should develop comprehensive frameworks for responsible AI integration. This includes creating evidence-based guidelines for clinical practice integration and establishing rigorous standards for AI-generated health information accuracy. Ethical considerations surrounding data privacy, training bias, and the potential for exacerbating health inequities must also be central to any framework for responsible GenAI integration. Future research should investigate whether using GenAI translates into improved health outcomes and how shifts in digital literacy affect patient engagement. Importantly, developing methodologies to better differentiate between professional and lay user interactions with health-related GenAI queries will be essential for accurately interpreting adoption trends and tailoring interventions at scale.

Limitations

First, we relied on anonymized, aggregated conversations and thus information on user credentials and demographics is not available. Second, the mapping from conversation text to occupational tasks may be imperfect, particularly when laypersons seek professional-grade information. Third, our cross-sectional design offers a single snapshot in time rather than longitudinal trends. Fourth, data from conversations were limited to Claude since Anthropic is the only company that has open-sourced data for analysis. The demographics of Claude users, along with the reasons why users engage with Claude may or may not be representative across other GenAI tools which could fundamentally bias patterns. Finally, we do not know what users did with the information they received from GenAI or how this impacted health outcomes. Future analyses should account for ongoing changes in GenAI capabilities and usage patterns.

Conclusion

Generative AI is making tangible inroads into healthcare-related tasks, yet its adoption appears selective, with high interaction volumes associated with patient-facing roles like dietitians and nurse practitioners. Our analysis, based on interactions with Claude, highlights this emerging pattern but calls attention to a critical ambiguity: whether this usage is primarily driven by patients seeking information and navigating access challenges, or by professionals seeking workflow efficiencies, or a combination thereof.

Regardless of the primary user, this integration demands immediate attention. The observed patterns necessitate a shift beyond simply acknowledging GenAI's potential towards proactive strategies. Future research must prioritize understanding who is using these tools for healthcare tasks and why, potentially employing methods that can better infer user intent or role. Concurrently, stakeholders, including clinicians, educators, developers, and policymakers, must develop distinct guidance: resources promoting digital health literacy and critical appraisal for patients, alongside evidence-based best practices for safe and effective integration into professional clinical workflows. Addressing how systemic healthcare pressures might be influencing this adoption is also crucial. Ensuring GenAI enhances, rather than compromises, healthcare delivery requires targeted action now to shape its responsible use before patterns solidify.

Acknowledgements

We used GenAI (OpenAI's ChatGPT o3-mini) to improve the conciseness and clarity of our manuscript to meet word count recommendations. We take full responsibility for the integrity of the content generated.

Author Contributions

GA conceptualized the study, designed and directed the manuscript, conducted formal analysis, created visualizations, and led all writing and revisions. JC contributed to the conceptualization, writing, and reviewing of the manuscript. ES critically reviewed and edited writing, and designed visualizations. CCQY contributed to the conceptualization, writing, and reviewing of the manuscript. CEQ provided overall supervision, conceptualization, and reviewed the manuscript.

Conflicts of Interest

We, the authors, have no financial or personal disclosures to declare.

Abbreviations

GenAI: Generative Artificial Intelligence

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Figure Titles and Captions

Figure 1. Framework for Mapping GenAI Conversations to O*NET Tasks and Occupational Categories

Table 2/Multimedia Appendix Figure 1. Global Percentage of GenAI Conversations by Occupational Categories

Table 3/Multimedia Appendix Figure 2. Top 25 Healthcare Practitioners and Technical Occupational Titles by GenAI Conversation Share

Caption: Values in parentheses show each occupation's share of total global GenAI conversations, while the primary percentage represents the share within the healthcare practitioner group.

Table 4/Multimedia Appendix Figure 3. GenAI Task Adoption Rate for Top 25 Healthcare Practitioners & Technical Occupations

Caption: Values show each occupation's adoption rate as a percentage of possible tasks (total adopted tasks/total available tasks), with the raw task counts shown in parentheses.

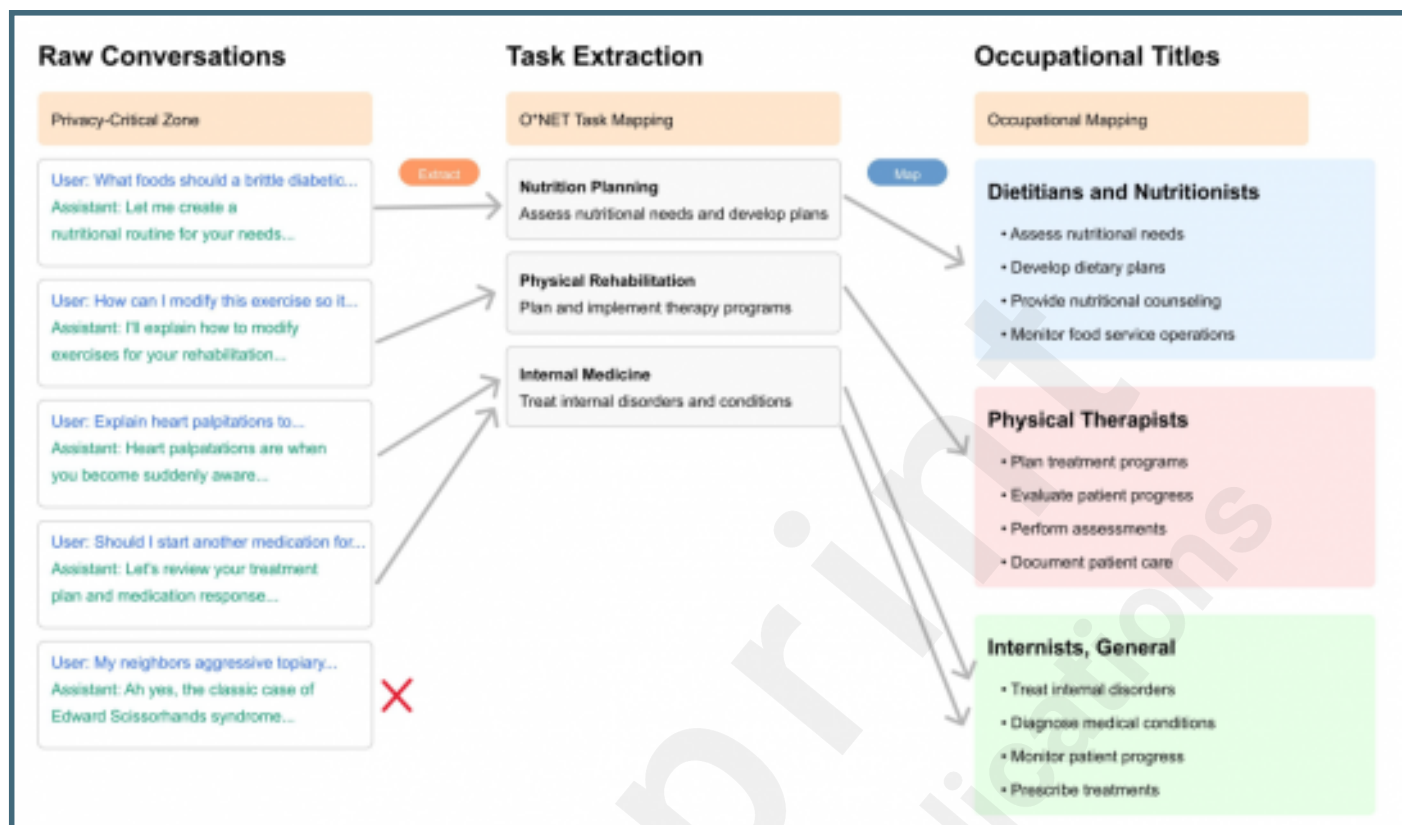
Supplementary Files

Untitled.

URL: <http://asset.jmir.pub/assets/fc9a6046e15883207153d282e74151ef.docx>

Figures

Framework for Mapping GenAI Conversations to O*NET Tasks and Occupational Categories.



Multimedia Appendixes

Global Percentage of GenAI Conversations by Occupational Categories.

URL: <http://asset.jmir.pub/assets/e4da48f9de574ee021aabe24cf702d00.png>

Top 25 Healthcare Practitioners and Technical Occupational Titles by GenAI Conversation Share. Values in parentheses show each occupation's share of total global GenAI conversations, while the primary percentage represents the share within the healthcare practitioner group.

URL: <http://asset.jmir.pub/assets/1321f6e19866761e904f57d82bcb7cc6.png>

GenAI Task Adoption Rate for Top 25 Healthcare Practitioners & Technical Occupations. Values show each occupation's adoption rate as a percentage of possible tasks (total adopted tasks/total available tasks), with the raw task counts shown in parentheses.

URL: <http://asset.jmir.pub/assets/24e46e9dbc42cfbdcb46bfc73c0e4906.png>