What is a Clinical Co-Pilot

A definition and overview of different companies in this space

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Introduction

In the ever-changing landscape of technology and business, the term *'Co-pilot'* has evolved from its original meaning in the aviation space, where it described the second in command assisting the pilot and providing situational awareness.

The concept *'Co-pilot'* has seamlessly integrated into the business world, represented by its recent adoption in various sectors as a symbol of a smart assistant or companion. For example, Microsoft's introduction of their AI Copilot, designed to enhance user efficiency through features like sentence auto-completion or smart inboxes.

This growth in the term *'Co-pilot'* is largely fuelled by the recent advancements in AI, particularly in generative AI technologies. The excitement around these *'AI Co-pilot'* hinges on their potential to significantly boost productivity and efficiency within organisations.

The healthcare sector, facing the growing challenge of escalating patient demand, complexity of care and an increasingly overstretched, cognitively overloaded and burnt-out clinical workforce, is no exception to this trend. Faced with a shortfall of over 14.5 million healthcare workers by 2030 [1] and the ageing baby boomer generation approaching the age where they require substantial healthcare, global healthcare systems are under immense strain. This issue was highlighted during the COVID-19 pandemic.

As a result, there are two ways to address this, (A) make the healthcare system more efficient so that more patients can be treated with the same resources – “supply” or (B) reduce demand through earlier intervention & prevention – “demand”.

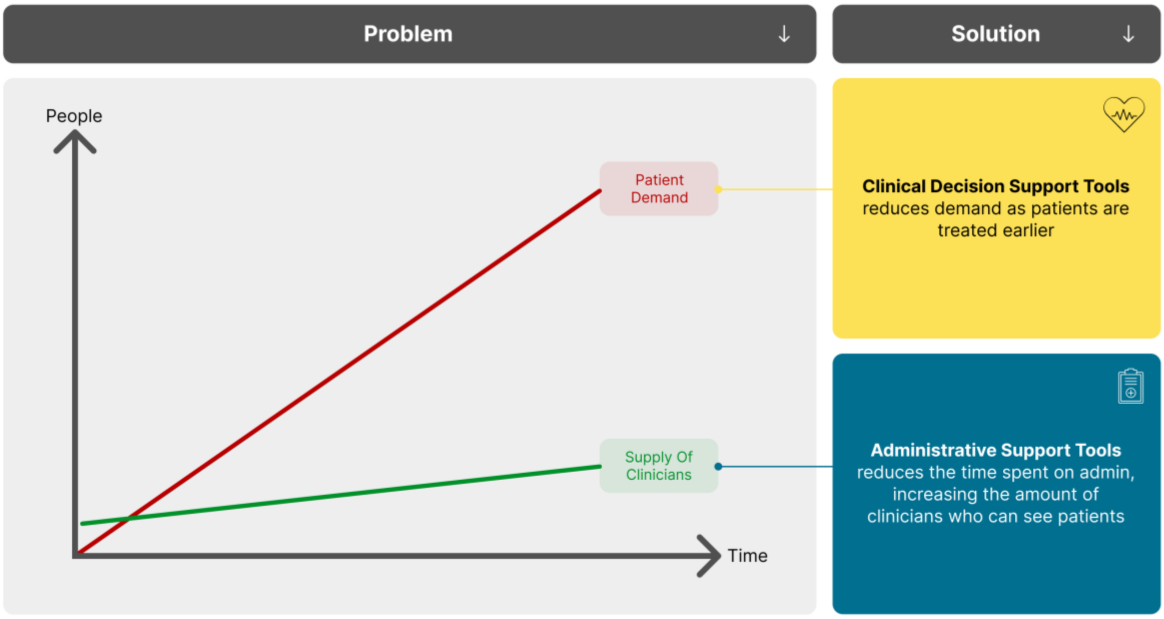

Figure 1 Growing healthcare gap due to increase in healthcare demand and growing staff shortages.

In both areas the term *'Clinical Co-pilot'* is gaining traction, reflecting a broad spectrum of applications. On the “supply” side, an increasing number of AI-powered tools are entering the market to support clinicians with administrative tasks so that they can spend sufficient time with patients. On the “demand” side, a wide variety of tools are centred around supporting clinicians to make earlier and better decisions that reduce the pressure on the healthcare system.

In response to the rapidly growing use of the term *'Clinical Co-pilot'* to describe a wide variety of applications, we attempt to provide a standardised definition and market overview of the *'Clinical Co-pilot'* space. As well as some initial thoughts on the future and its potential impact on healthcare.

To the best of our knowledge, this is the first attempt at both defining the term *'Clinical Co-pilot'* and provide a first market map, we therefore strongly encourage feedback and suggestions for inclusion or corrections in our definition and categorisation.

Why healthcare needs 'clinical co-pilots'

The evolution of national healthcare systems over the past 75 to 100 years has necessitated a significant shift towards standardised care. This shift was marked by the development of rules-based protocols for clinical workflows, which were eventually embedded into electronic systems in the 70's and 80's. These systems were initially designed to aid healthcare teams in delivering uniform (and billable) care, as well as supporting clinicians with situation awareness by surfacing relevant and timely information. However, the stringent evidence requirements needed to modify these clinical protocols have inadvertently led these electronic systems to become a major contributing factor to staff burnout [2].

The rapid digital transformation within healthcare is triggering a massive growth in healthcare data, estimated to grow at more than 36% annually [3]. This exacerbates the pressure on clinicians, who now face the task of navigating through an expanding amount of complex, often silo'ed data. The considerable cognitive load, brought on by the sheer amount of complex information required for patient care, is compounded by the often cumbersome and inefficient user interfaces of existing electronic systems, as well as the need to switch between multiple interfaces and systems. This escalation in complexity not only makes the clinicians' tasks more challenging and reactive but also contributes to increasing instances of burnout [4] [5]. Further, the growing need for coding and overall documentation means that clinicians spend up to 50% of their time interacting with these systems [6].

These trends are further exacerbated by an aging population, frequently facing multiple, complex health conditions, as highlighted in Figure 1 above. It therefore becomes critical that tools are developed that support clinicians with situational awareness – more time to focus on the patient and understand what is going on. This breaks down into two key areas, tools that:

1. **Reduce administrative burden**— helping clinicians spend more/ sufficient time with patients, therefore making them more efficient. This improves the "supply" curve in Figure 1.
2. **Improve clinical decision-making** supporting clinicians analyse, understand and act on complex clinical data, therefore enabling more effective and efficient clinical decision-making. This improves the "demand" curve in Figure 1.

Categorisation of 'clinical co-pilots'

While the scope of healthcare and clinical research presents numerous opportunities for augmentation by a *'Co-pilot'*, our focus for defining a *'Clinical Co-pilot'* is specifically within clinical settings. Consequently, we delineate our definition by excluding *'Co-pilot'* applications related to patient behaviour, clinical trials, drug development or broader research activities. This exclusion is based on the premise that these areas, while integral to the broader healthcare landscape, do not directly assist clinicians in their day-to-day patient care activities.

Our emphasis is therefore on *'Clinical Co-pilots'* that provide immediate, practical support to clinicians in their routine patient care responsibilities. Considering the varying interpretations of the term *'Clinical Co-pilots'*, we categorise them broadly into two types: (1) those that aid with administrative tasks, and (2) those that support clinical decision-making.

We then divide these two categories further into "core jobs to be done" for each.

For **reducing administrative burden**, these are:

- Supporting patient interactions;
- Aiding with surfacing and understanding information;
- Helping with administrative tasks, not related to either of the above.

For **supporting clinical decision-making**, these are:

- Earlier diagnosis, such as early warning systems or patient triage tools;
- Better diagnosis / prognosis;
- Aiding treatment decisions.

Regulatory bodies are actively reevaluating their criteria for what constitutes a medical device in the realm of AI-enabled tools and clinical decision support software, with guidance evolving at a rapid pace [7]. Given the inherent risks associated with supporting clinical decision-making (CDS) — it is often necessary for such technologies to be regulated as medical devices. For example, as class 2a or higher Software-as-a-Medical Device (SaMD) under EU MDR or class II under the FDA [8].

For simplicity of defining *'Clinical Co-pilots'* we will operate under the assumption that applications primarily focused on reducing administrative burdens are less likely to be regulated as medical devices, whereas those that provide support in clinical decision-making are more likely to fall under such regulatory frameworks.

The above division therefore not only clarifies the functions of *'Clinical Co-pilots'* but also delineates which ones are likely to require regulation as medical devices. As this is a rapidly evolving field, it will be interesting to follow this field, especially in light of the EU's recent AI act [9]

Clinical co-pilots that reduce administrative burden

Supporting patient interactions

The swift advancements in speech recognition solutions, and increasingly sophisticated Natural Language Processing (NLP) and Generative AI techniques have catalysed the emergence of numerous companies focusing on streamlining the patient-physician dialogue. These applications primarily revolve around recording and transcribing interactions between healthcare professionals and their patients, aiding in the overall documentation process and storing of information into Electronic Health Records (EHRs). Some of these companies include industry veteran Nuance Communications or new entrants such as Nabla, Corti, Tortus, AWS Healthscribe or Abridge.

Increasingly these companies are augmenting this *'Clinical Co-pilot'* with advanced AI models to identify key information and actions like prescription details, billing information or the ordering of tests, thereby further enhancing clinician workflows. These are sometimes described as Large Action Models or agentic models [10], with the potential to take on increasingly complex support tasks, such as navigating complex EHR systems and clinical workflows. In the near-term full automation is unlikely due to the high-risk nature of, for example, ordering an incorrect prescription and the associated liability. It will be interesting to follow how regulators will define and ultimately regulate these tools.

Another powerful application of a *'Clinical Co-pilot'* in this space is better support patient communication by aggregating, summarising and translating complex medical jargon into understandable summaries for patients. This represents a significant stride in engaging and informing patients about their treatment and addresses a key challenge of poor medication adherence due to misunderstandings.

Additionally, recent years have witnessed a surge in virtual assistant and chatbot-based symptom checkers. These tools conduct preliminary consultations, guiding patients through initial assessments before handing over to human medical professionals. Similarly, chatbots are being developed to assist patients during their healthcare journey, supporting them with background information, appointment reminders, support suggestions, as well as creating communities of "patients like me". Given the potentially high-risk nature of some these virtual assessments, it will be intriguing to observe their acceptance and integration within the healthcare landscape, both by patients and clinicians. This development poses a question about the future role and regulation of such *'Clinical Co-pilots'* in patient care.

Aiding with surfacing and understanding information

Clinicians are increasingly burdened by the complexity of clinical information systems, the fragmented nature of healthcare data, and the rapid growth of clinical knowledge, guidelines, and protocols. This complexity necessitates considerable time spent in searching for, gathering, and synthesising information before, during and after patient consultations. *'Clinical Co-pilots'* are being developed that leverage advanced AI, NLP, and efficient search technologies to streamline information management. These tools support clinicians to surface, aggregate, and interpret patient information, clinical guidelines, or the wider scientific literature. Often, they incorporate error checking tools such as checking prescriptions or allergies against clinical guidelines, which are especially powerful in elderly patients taking different medications for a variety of conditions. Others assist in deciphering complex clinical guidelines and patient referral pathways.

Another powerful use case is the development of medical chatbots that analyse medical and scientific literature to provide clinicians with the latest clinical information critical for current best practices. Examples include Medwise.ai, July or Clinomic. These platforms deliver swift, guideline-directed answers to clinical queries at the point of care and are reshaping the way clinicians' access and use medical information.

Administrative Support

The final category are tasks that are not directly related to a patient interaction or surfacing patient or treatment related information. Clinicians are often burdened with non-clinical administrative tasks, occupying up to 50% [6] of their time on activities like sending letters or other patient information material, booking appointments, handling prescriptions or medical billing. To address this, a variety of *'Clinical Co-pilots'* are being developed, aiming to support the workload of clinical teams and refocus their attention on patient care, thereby enhancing efficiency. These tools include systems designed to optimise appointment scheduling, particularly for complex tests and procedures, and to streamline communication across the healthcare spectrum, from referrals to specialists. A good example is xWave who support communication with and from radiologist or AbTrace from the UK.

Other applications offer assistance with tasks like auto-drafting and updating non-patient-related clinical notes, generating reports, and managing patient follow-ups, tests, or prescription refills. A good example is with Regard. Smart inbox assistants are another innovation, capable of identifying urgent patient cases, automating responses, and facilitating patient coding within clinical systems. eConsult are innovating in this space. These assistants are pivotal in automating mundane tasks such as data entry, scheduling, and prescription management, and they play a crucial role in ensuring accuracy and compliance in medical billing and coding. This not only speeds up the reimbursement process but also significantly reduces billing errors.

Additionally, some of these *'Clinical Co-pilots'* are equipped to handle large-scale administrative tasks, including organising events, conferences, or training sessions, with responsibilities extending to venue selection, attendee registration, and logistics coordination. All of these represent a huge step in reducing the administrative load on clinicians, allowing them to dedicate more time and resources to direct patient care.

Clinical co-pilots that support clinical decision-making

The second primary category of *'Clinical Co-pilots'* focuses on aiding clinicians in critical decision-making processes, such as prioritising patients, assisting in diagnoses, and determining optimal treatments. These tools play a key role in enabling clinicians to make earlier or more accurate decisions, which can lead to patients spending less time in clinical settings or requiring fewer healthcare resources. Therefore, making clinicians both more effective and efficient. Given the potential risks involved, these types of *'Clinical Co-pilots'* applications are subject to stringent medical device regulations.

To understand the specific functions and applications of these *'Clinical Co-pilots'*, we have categorised them in three main groups, each aligning with a distinct phase of the broader context of patient care and a high-level clinical workflow. The first group assists with identifying which patients may require clinical attention (e.g. pre-diagnosis). The second group is focused on supporting the diagnostic process itself. The third group aids in determining the best treatment, which may include supporting discharge decisions.

Pre-diagnostic decision support

The first category primarily includes risk stratification and early warning systems for health deteriorations. These tools are pivotal in triaging patients, enabling healthcare providers to concentrate on those who require urgent care and facilitate earlier diagnosis and intervention, thereby ultimately enabling better patient outcomes.

Risk stratification tools utilise data-driven algorithms to analyse various data points such as medical history, clinical measurements, wearables data, demographic information, and sometimes also non-health related data points such as social determinants. By assessing this data, these tools stratify individuals into different risk groups. For example, they can identify patients at high risk for chronic diseases or adverse events such as exacerbations of COPD or high risk of falls in care homes. A key application area is to use these tools to classify patients in primary care or emergency care rooms to triage patients more effectively. Solutions such as eConsult's eTriage tool can help to ensure that patients are seen by the right person at the right time in the right clinical setting. Similar solutions are being developed to stratify backlogs and waitlists, such as c2.Ai.

A big interest is to identify patients with a high likelihood of hospitalisations or re-admission to enable early intervention or delayed discharge. Risk stratification tools are increasingly being incorporated into virtual wards and remote patient monitoring solutions, therefore enhancing both their scope and effectiveness. Finally, other tools, working in collaboration with pharma companies, mine healthcare data to identify patients at risk of rare diseases.

Early Warning Systems (EWS) for health deterioration are another crucial aspect of this category. These systems monitor a variety of clinical data points and other health indicators to detect early signs of health deteriorations. These were originally developed for critical care settings to support early detection of sepsis, due to high clinical acuity level and the high data fidelity. A wide range of early warning scores have been developed for different clinical settings, patients or conditions, noticeably early warning systems for acute kidney injury (Google Streams, Gendius), post operative surgical site infections (HealthPlus.ai) or post operative delirium (Pipra).

The integration of wearable technology shows immense potential in EWS, for example Apple Watch atrial defibrillation feature, although challenges like data quality, regulatory approval and differential diagnosis remain.

Considering the complexity of healthcare data and its multimodal nature – i.e. images, clinical notes, prescriptions, bloods, genetics etc an exciting area to watch is that of multimodal biomedical AI [11]. This approach mirrors how a clinician tries to build an understanding of a patient, by reviewing the various patient data points available. By integrating diverse AI algorithms to analyse this multifaceted healthcare data, this approach delivers higher levels of accuracy than would be achieved by analysing isolated data types, like single images, facilitating a more thorough and nuanced understanding of patient health. Players such as Bayesian Health or Sanome are taking such a multimodal biomedical AI approach to achieve ever higher degrees of accuracy in a variety of different clinical settings and conditions.

The application of *'Clinical Co-pilots'* for risk stratification and early warning systems, represents a hugely exciting area in clinical AI, as it holds the promise of enabling proactive healthcare by identifying patient deteriorations earlier and facilitating timelier interventions. Especially to support overstretched clinicians focus on their limited resources where it matters the most. A key feature of these systems will be their ability to explain the reasoning behind their alerts or classifications, to build trust and adoption. With the advent of increasingly digitised and interoperable healthcare systems, combined with powerful multimodal AI-tools shows enormous potential to alleviate burden on the healthcare system. Although challenges such as regulatory approval, reimbursement and generalisability need to be overcome.

Diagnostic Decision Support

The second category of *'Clinical Co-pilots'* that facilitate clinical decision-making focuses on supporting clinicians in the diagnostic process. These tools come into play to support with determining the patient's condition by either offering diagnostic support or by suggesting which additional tests could be conducted. This is where they sometimes overlap with 'Clinical co-pilots' that support administrative tasks.

One of the primary functions of these “diagnostic decision support” *'Clinical Co-pilots'* is to assist in differential diagnosis. In situations where the clinician may not have a clear initial diagnosis, these tools suggest possible conditions based on the patient's symptoms, aiding the clinician in considering a range of potential diagnoses. Companies like Knidian and Glass Health are notable players in this space.

Another aspect is target diagnosis, where the clinician has a suspected diagnosis in mind but seeks a second opinion to validate their hypothesis. By employing a co-pilot, diverse perspectives and specialist opinions become more readily available, or at the very least, accessible more quickly. For example, a General Practitioner may leverage specialist AI support for advice on complex areas such as radiology and cardiology, fields outside their expertise, thereby saving time and enhancing diagnostic accuracy.

A key aspect of these co-pilots is their use of AI technologies, which can analyse medical data, images, and other relevant information at a significantly faster rate than humans. These technologies provide insights, identify patterns, and offer diagnostic recommendations and precision diagnostics. The processing power of these AI tools adds remarkable speed to the diagnostic support process.

State-of-the-art AI technology now enables rapid and precise diagnoses. Computer vision techniques are employed to analyse medical imaging, including X-rays, MRIs, ultrasounds, and CT scans. This leads to faster diagnosis, significantly improving patient outcomes. Additionally, some tools go beyond clinician-initiated diagnosis by suggesting alternative diagnoses, treatments, or tests, thereby expanding the scope of clinical decision-making. Key companies involved in this area include Ibex, Gleamer, Paige.ai, Praxium, and others.

Overall, this category represents a significant advancement in diagnostic processes, leveraging AI's capabilities to augment the clinician's expertise in making informed, precise diagnoses, and ensuring a more efficient and effective approach to patient care.

Treatment Decision Support

The final category of decision support *'Clinical Co-pilots'* focuses on assisting clinicians in providing the most effective treatment for patients. This encompasses a range of treatments including adjustments in clinical settings, such as modifying the level of care acuity or facilitating earlier discharges, drug therapies, and surgical interventions.

These solutions optimise care management based on the patient's diagnosis and treatment need. They may assist in determining the appropriate specialty for referral or the necessary additional tests for monitoring the patient's condition. Often, these solutions overlap with *'Clinical Co-pilots'* designed for administrative support, reflecting their multifaceted nature. Similarly, there is overlap between companies that support diagnostic decision-making and then extending toward treatment recommendations, such as companies like DemDx and Glass Health, who use AI to simplify clinical pathways and support clinicians with deciding what the next best step in the treatment pathway us.

Another key aspect of this category is to support clinicians with deciding to change acuity levels in hospitals, for example when to step a patient down from intensive care into general wards or when to discharge a patient from hospital. Companies such as Signal1 or Recare have developed AI platforms to support the discharge process. With hospitals being the most expensive clinical setting and many of them operating at or above capacity, there is growing pressure to discharge patients safely from hospital earlier. We are therefore seeing a growth in risk stratification and early warning system *'Clinical Co-pilots'* being added to these applications to enhance the clinical decision-making process. Companies in this space include Bayesian Health or Sanome.

Treatment decision support also includes tools for better precision drug prescription. Some of the first applications of clinical decision-support tools were knowledge-based system that flag drug counterindications or potential allergy risks. With polypharmacy a growing problem, especially in elderly patients, sophisticated system that help clinicians with providing the right treatment and dosage becomes paramount. An example is Cherub which supports primary care providers with monitoring drug prescriptions and identify potential risks. Other *'Clinical Co-pilots'* help with determining the most suitable treatment regime for a patient based on their genetic or epigenetic profile. This area ultimately extends to precision medicine. Related to this is the field of companion diagnostics and we will likely see companion diagnostics increasingly being incorporated into *'Clinical Co-pilots'.*

Overall, this category plays an indispensable role, in enhancing the quality of patient care by supporting clinicians in making informed treatment decisions, thereby contributing to improved patient outcomes and efficiency in healthcare delivery.

Market Map

Figure 2 shows a market map of key players operating in the different categories described above. It is important to note that several companies do not describe themselves directly as a *'Clinical Co-pilot'* and some have been selected to illustrate the category. Especially, diagnostic decision-support tools, which technically could include any diagnostics provider.

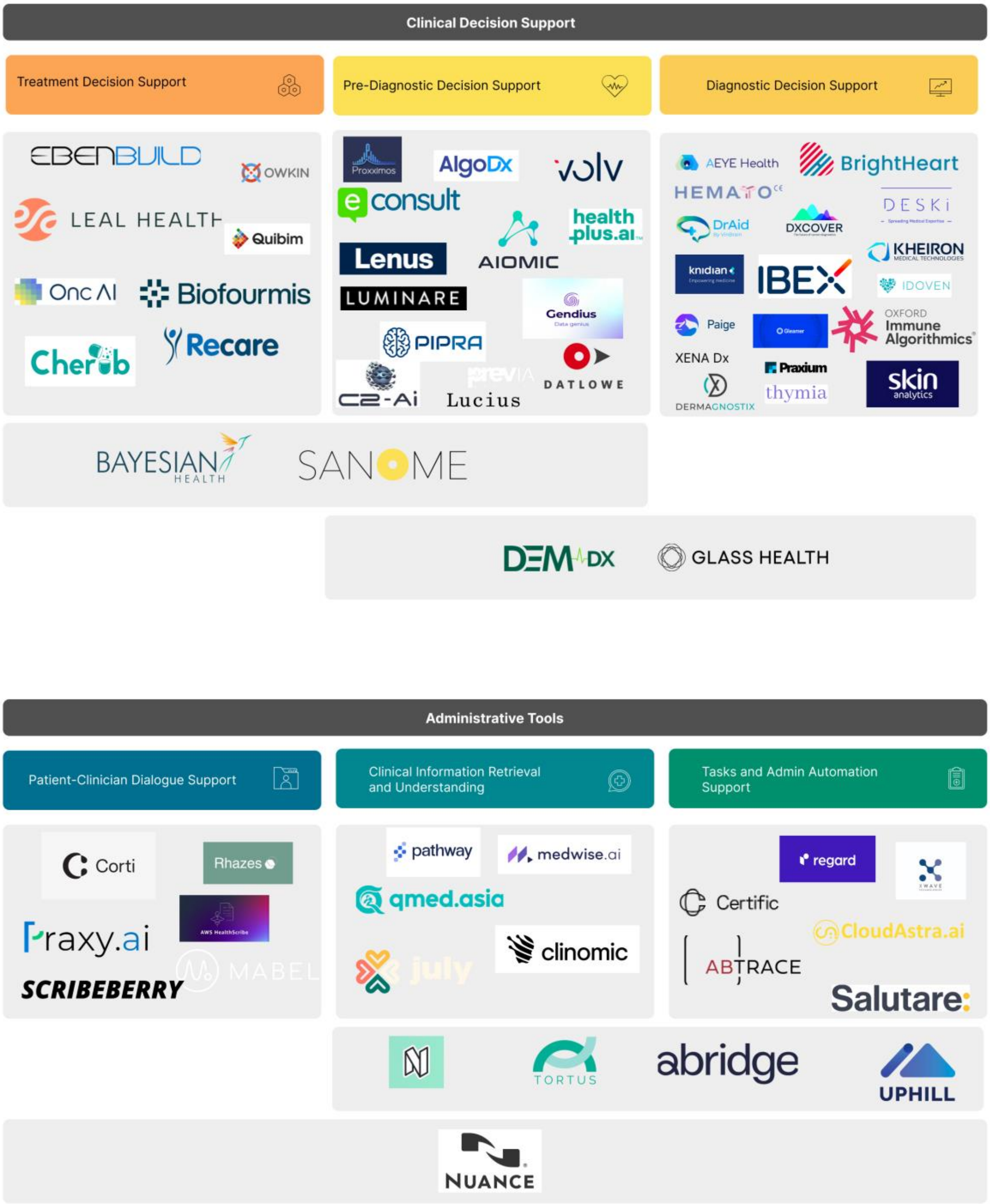

Figure 2 - Market map for the two main categories and their respective three subcategories. Companies that cover two or more categories are listed in separate columns. So far, no company identified that covers both Clinical Decision Support and Administrative Support tools

Discussion and Outlook

The integration of *'Clinical Co-pilots'* in healthcare represents a transformative leap towards addressing the increase in demand but limited increase of supply of clinicians. As healthcare systems continue to digitise, the flood of novel digital data will unlock a plethora of opportunities for developing tools aimed at alleviating the supply-demand conundrum. *'Clinical Co-pilots'* will be instrumental in aiding clinicians with both decision-making and administrative tasks, thereby reducing burnout and enhancing the quality of patient care.

The growing frustration among staff, stemming from the cognitive overload of processing vast amounts of information and contending with outdated legacy IT systems, is starkly contrasted with the user-friendly and seamless experience of modern personal device applications. It is therefore not surprising to see huge demand for *'Clinical Co-pilots'* that simplify administrative tasks and demonstrate tangible time-saving benefits.

For these types of *'Clinical Co-pilots'* lower regulatory barriers to entry make it easier and faster to innovate and we expect a proliferation of solutions in the near term. However, with more players entering this market, a critical challenge will be preserving value generation and avoiding commoditisation, especially as AI models become ubiquitous—a trend previously observed in the enterprise software industry. Companies are responding to by enhancing feature functionalities and diversifying across various sub-categories.

Meanwhile, *'Clinical Co-pilots'* that support clinical decision-making face higher entry barriers due to their regulation as medical devices, therefore we expect to see fewer companies building in this space. The longer development cycles and regulatory hurdles offer strong defensive moats but often lead to strong verticalisation due to the regulatory need to clarify and evidence their intended use. Companies are starting to respond to this challenge by starting to simplify the key decision support by focusing on the high-level questions first – which patients to focus on.

As the role of *'Clinical Co-pilots'* in healthcare becomes more pronounced, there is an increasing need for regulatory frameworks to evolve in tandem. Future healthcare systems require robust regulations to ensure the responsible and ethical implementation of AI technologies, focusing on patient safety and data integrity. An interesting aspect to observe will be how regulators delineate between solutions regulated as medical devices and those that are not. The FDA recently issued guidance on its definition of clinical decision support systems [12] and it is a rapidly evolving space.

Analogues to the aviation co-pilot's role of providing situational awareness, a key task for *'Clinical Co-pilots'* providers, will be the seamlessly integration into existing clinical IT infrastructures and workflows. A prevalent barrier to the adoption of new healthcare technologies is often increase in steps a clinician needs to undertake to surface the relevant information, such as logging into another programme or 'yet another dashboard' [13]. With EHR providers often the main operating system in healthcare, it will be interesting to monitor how various EHR providers facilitate third-party solution integration and build business models around these. First examples of this include the EPIC developer portal or next generation EHR providers like PatientSource or NerveCentre in the UK, which pursue an API-first strategy and are designed for interoperability with diverse technologies. Looking to the future, the development of sophisticated multimodal biomedical AI tools capable of grasping the nuances of human health is set to provide deeper insights, empowering clinicians to make more efficient and effective decisions, thereby easing the strain on healthcare systems. It's likely that we will witness companies bridging the gap between the two categories of *'Clinical Co-pilots'*, using data and insights from both to develop solutions that not only enhance clinician efficiency but also improve decision-making.

Given the complexity and diversity of clinical tasks, we expect the future landscape to be marked by a variety of *'Clinical Co-pilots'* approaches, each addressing different aspects of healthcare and beyond. Covering areas from clinical research, drug development and clinical trials, as well as increasingly embedded in the daily lives of people, allowing them to decide when, how and where they will want to receive care. This evolution, along with the growing availability of detailed personal healthcare data sets the stage for the creation of "human digital twins". These will be intricately linked with *'Clinical Co-pilots'*, thereby paving the way for truly personalised, precision medicine. This prospect highlights the transformative potential of *'Clinical Co-pilots'* in reshaping healthcare delivery and optimising patient outcomes.

Conclusion

The COVID-19 pandemic starkly highlighted the vulnerabilities of global healthcare systems, with patient demand nearly overwhelming available clinical resources. As the baby boomer generation enters later stages of life, the ensuing demand in healthcare will undoubtedly place further strain on these systems. In this context, *'Clinical Co-pilots'* emerge not merely as tools but as essential allies in healthcare delivery. We firmly believe that *'Clinical Co-pilots'* will be pivotal in supporting clinicians with both decision-making and administrative tasks, thereby alleviating clinician burnout, and substantially enhancing the quality of patient care. These innovations represent a significant step towards more efficient, effective, and patient-centric healthcare, addressing the challenges of today and preparing for the demands of tomorrow.

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