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Agentic AI Systems in Organ Health Management: Early Detection of Rejection in Transplant Patients

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ABSTRACT

The purpose of this essay is to examine the integration of agentic artificial intelligence (AI) systems in the management of organ health. Aspects of this analysis include the importance of custom software design and the diagnostic abilities of these systems, as well as the potential for creating an AI system that promotes a symbiotic doctor-AI-patient relationship. Although discussions are generally theoretical, examples will be used from ongoing research focusing on the early detection of rejection in patients with heart transplants, with these patients referred to as X-patients throughout this essay. Organ transplantations allow patients who would have otherwise perished to continue living, but make their immune systems suppress in order to preserve the alien tissues. This non-standard immune state puts them at risk for other diseases, which is why monitoring their health carefully is crucial. However, due to living an active life after recovery, X-patients may occasionally engage in risky behaviors without sufficient regard for their health. In consequence, they are not supposed to discontinue undergoing medical examinations after the end of the postoperative recovery period. The custom-designed smart system integrates multiple AI applications to facilitate the convenient monitoring of X-patient organ health throughout the day by providing them with continuously updated personalized feedback based on the patient's current state and causes of concern. By creating and maintaining this system, the wellbeing of X-patients is easily safeguarded while reducing the volume of work for the overburdened entourage of these patients.

In the first part of this comparative analysis, the early detection of rejection in X-patient heart transplants will be examined. Research pursuing this analysis has led to the design and disconnected self-usage of two different custom smart AI systems. While one is entirely self-contained with no direct patient-AI doctor interaction, the other involves diagnostic responses from the AI. There will be a focus on factors causing symptoms to arise, the internal or external sources these symptoms arise from, and why potential warning signs must be attributed to heart rejection. This last issue has fostered the need for ongoing image recognition-based research, and the observational or perceived difference in symptom effect will be reflected in the intelligent AI system's feedback. The larger portion of this text will focus on the later-designed AI system due to possessing a greater degree of development. However, before examining the feedback, necessary information required for the understanding of the AI functioning and entourage approach must be presented.

Keywords: *Agentic AI, Organ Health Management, Rejection Detection, Transplant Patients, Agentic AI, Organ Transplant Rejection, I-based Monitoring, Early Detection Algorithms, Transplant Patient Management, Immunosuppression Monitoring, I in Healthcare, Rejection Prediction Models, Medical AI Diagnostics, Organ Health Monitoring Systems.*

1. INTRODUCTION

Innovations in healthcare that aim to improve patient outcomes have always been a central theme throughout the changing landscape of medicine, treatment and care provision. Nonetheless, there is still considerable ground to explore in order to understand a new breed of complex adaptive systems, how they will integrate with conventional healthcare systems and the broader societal implications and considerations of designing with and for them. This research contributes to this goal by examining the development of a particular class of system: agentic AI systems and their piloting for organ health management. The critical issue studied is the comparison between existing observational monitoring health systems, and an agentic AI system which actively searches for signs of transplant organ health deterioration, specifically rejection. The early detection of transplant rejection is a path critical capacity and a larger issue concerning the control of body mediated hyper-rejection phenomena across a wide range of embedded medical devices. The question that is addressed by this work is how to build and integrate agentically intelligent systems into those health systems to facilitate early detection of rejection episodes and safely enact more complex interventions. Research findings indicate such systems can consistently take earlier, safer or less risky or partial action and do so in a larger envelope of exogenous physiological stimulus variation than monitoring systems, which rely on detected signs to reach an intervention threshold before acting. Applications for clinical devices are considered, along with broader implications and the direction of future work.

Nowadays, much of the existing technological apparatus that support and underpin healthcare practices and services become sites where data is inherently and consistently digitised, and increasingly, automatized or algorithmically processed. The ever more pervasive treatment of data in healthcare systems was signalled as 'one of the most identifiable ICT-based trends that have occurred in the last decade in the health sector'. Previous analyses have characterised digitisation and automation in healthcare in terms of distinct epochs. In the first age of healthcare computerization, data was stored and shared in discrete binary or 'hard copy' media, and with this came the capacity to rapidly exchange and manipulate data across a range of environments. These initial 'digitization for communications' yielded improvements in data processing capacities but were generally unarticulated in regard to possible deeper emergent properties. And later evolutions were considered part of what might constitute a more advanced 'second age' of healthcare automation. In this period, the focus shifted from digitization as an end in itself (to speed up communication) to further integrating these digitized data with algorithmic systems. In the UK, the 2002 report and the 2017 white paper are often cited for the catalyzing policy and infrastructural changes that opened up a major salvo of e-Health implementations across hospitals and primary care Trusts. Furthermore, this was paralleled by Europe-wide pro-e-Health moves announced in the 2005 plan and three years later elaborated in the Strategic Plan through 2015. This second epoch saw the further embedding of ICT systems into clinical practices, from the (routine) computerization of laboratory test results, appointment administration etc. through to the rapid expanding development, testing and use of telemedicine and patient monitoring devices.

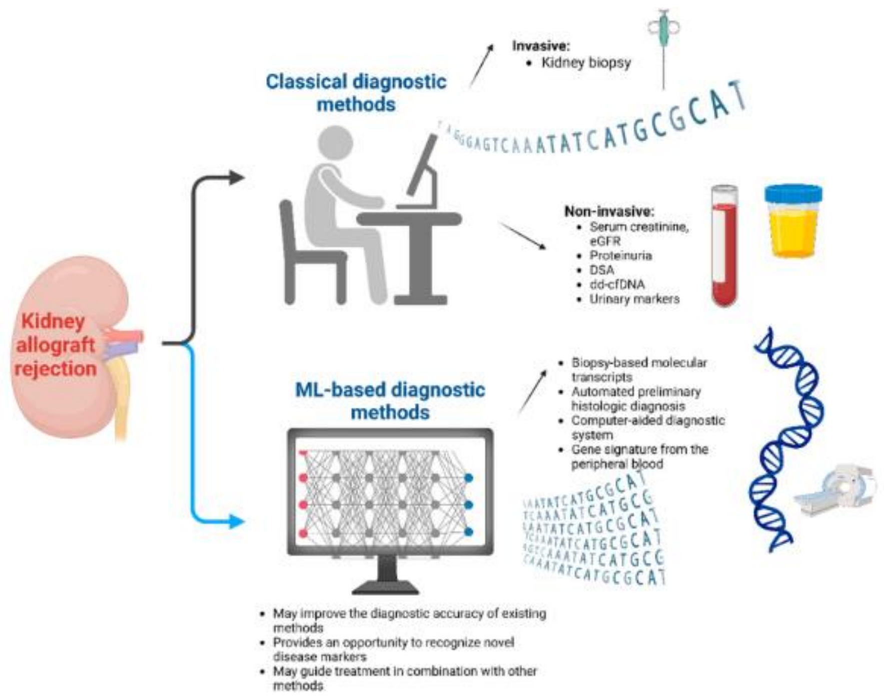

Fig 1: Machine Learning in the Diagnosis of Kidney Allograft Rejection

1.1 Background and Significance

Organ transplantation has a long history as a life-saving procedure for patients with failed organs . Since the first successful kidney transplant in the 1950s, many patients have received tremendous benefits from organ transplantation, and the number of such procedures has been increasing continuously. Historically, transplantation from living donors was encouraged, but the lack of donors has made it necessary to use organs from deceased donors. In 2019, there were around 65,000 solid organ transplants from both living and deceased donors worldwide. In the same year, approximately 37,000 organs were transplanted in the United States alone. As compared to earlier times, organ transplantation is now more successful, and patient survival rates are higher due to advances in transplantation procedures, the prevention of infection, and improvements in rejection management using better immunosuppressive drugs.

Organ transplantation is considered a planned event, and patients will be monitored closely before, during, and just after the procedure. Obligatory biopsies will be performed in the first year after transplantation or if any abnormal clinical symptom is detected. Transplant recipients will be advised to visit the transplant team regularly for routine checkups. Analysis of tissue reactions to the transplanted organ can be done in a biopsy sample. The conventionally stained biopsy slides are typically observed under a microscope by pathologists. Because of the microscopic nature of histological rejection, it is very difficult for a technician to evaluate this data properly. Interestingly, most of the acute rejection (AR) occurs in the first-year post-transplant period when large numbers of biopsies are taken. In addition, the success rate of organ transplantation is significantly higher for first organ transplant than for re-transplantation. Transplant patients are prone to opportunistic infections as their immune systems are intentionally and significantly compromised to prevent rejection, which increases the mortality rate. Therefore, early detection of rejection is very crucial to reducing the mortality rate. However, because of the complexity of the immune system and the rejection process, it is challenging to have a clear understanding of the rejection with limited analytical methods. There are reports to suggest that none of the diagnostics methods traditionally used before will be able to prevent AR. Early detection of rejection would lead to timely treatment, thereby improving organ function or even reversing rejection. This would be helpful to improve the long-term graft survival rates. The long-term transplant rates for a kidney, liver, and pancreas transplant is roughly 91%, 81%, and 86%, respectively, at 1-year post-transplantation. However, this rate drops to 56%, 60%, and 60%, respectively, after 10 years post transplantation. After the completion of the first year post-transplant, a patient’s risk of losing a transplanted organ increases almost twice in 15 years compared to the original 1-year post-treatment period. Most of the transplant recipients and the community are not aware of the limitation modules. However, the risk factors associated with transplant rejection and loss. Prior to considering the limitations of other modules, modularity should discuss the issue of rejection. A fundamental understanding of mostly all immune processes is not yet available. Transplanted organ rejection is a very complex biological and immunological phenomenon. A very intricate interaction between cellular and molecular components of the immune system takes place, making the rejection very unpredictable. Transplant patients receive a large dose of immunosuppressive drugs to inhibit the immune system and reject the transplanted organ. KeyValuePair includes the development of immunity to any harmful thing to the body, detection, and termination of that immune response. This knowledge has been accumulated over many years. However, this understanding is not yet actually enough to control some immune-related diseases or therapy, such as cancer, autoimmune disorders, and transplant rejection. Immune rejection is also not black and white. After transplantation, patients do not undergo conscious AR lab activities.

Equ 1: Risk of Rejection Over Time (Dynamic Model)

$$R(t) = \int_0^t \left[\beta_1 \cdot B(t') - \beta_2 \cdot D(t') + \alpha\right] dt'$$

Where:

- $R(t)$ = Cumulative rejection risk up to time t
- $B(t'), D(t')$ = Biomarkers and immunosuppressant
- β_1, β_2, α = Constants

2. CURRENT CHALLENGES IN REJECTION DETECTION

Early detection of rejection is a high priority for providers dealing with patients who need their transplanted organ to function properly. Late diagnosis of any type of graft dysfunction is associated with a significant increase in the risk of allograft failure, as in turn associated with significant increase in healthcare costs over the following 5 years after failure. Change in treatment at predefined levels of kidney performance due to delay in a diagnosis of kidney graft dysfunction is associated with approximately 30% increase in healthcare costs in the following 2 years after change in treatment compared to no change. In current practice, most rejection episodes are detected through for-cause biopsies, it is treated with non-specific immunosuppression, making it harder to normalize PTI/GLS. Biopsies used by patient murmurs do not strike at random time points making it impossible for discovered rejection based on PTI/GLS. Lab-based tests for rejection monitoring are not sufficiently reliable or far from becoming a standard of care. Immunosuppression may form rejection that would lead either to normal or pathologically low PTI/GLS. There is an array of postulated predictors that might have an impact on a patient's short- and long-term rejection rate, but also in the non-negligible potential responses. It is shown that KT and HT patients with prolonged refusal of other feedback GRF tend to have, on average, higher rejection rate, suggesting that there is at least a type of rejection that can be perpetuated/facilitated by dysfunctional graft. A machine learning approach is developed aiming to detect, shortly after its occurrence, pt-rejection defined as a time-post-transplantation binary event: a patient has a biopsy-confirmed rejection between this and the previous visit. In addition to the physiological features of the patient and the transplanted organ, psychological ones are also taken into account.

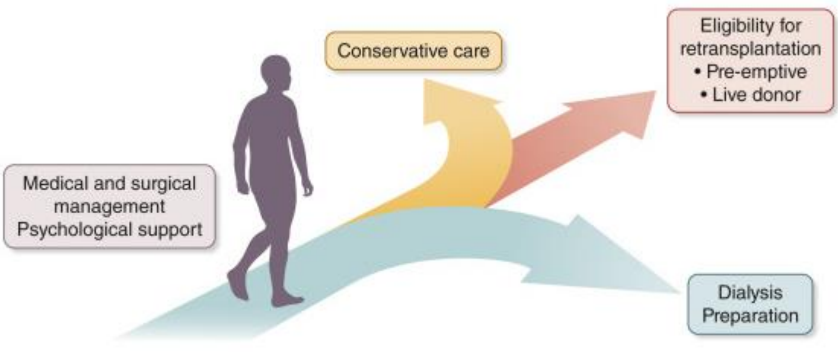

Fig 2: Challenges in the management of the kidney allograft

2.1 Limitations of Current Monitoring Techniques

Despite immense gains in the development of diagnostics and therapeutics in the last decade, current monitoring techniques fall short in the early detection of rejection. They often exhibit low sensitivity and specificity, simultaneously causing an increased risk of false negatives and positives. A striking example are the widely used assays based on protein levels which, in response to a probabilistic dispute, characterize a steep death covering a very limited range of possible outcomes, thus producing very inaccurate results. Repeatedly, such inaccurate tests will yield variable outcomes, particularly on a border region. Unfortunately only in order to confirm the rejection, the patient needs to undergo an invasive procedure, such as a biopsy in case of organ transplants. Nevertheless, invasive tests are not as widely applied as desired due to the discomfort felt by the patient and the risk associated with such operation. The ongoing variability of treatments and patient-to-patient variability in drug response also contribute to lower efficacy of standard monitoring techniques. For example, a heart transplant may be rejected as early as 0.2 months post-surgery or as late as 31.7 months after transplant, with a median time of rejection detection being 3.0 months. Such delays may have strong consequences on patient health and can significantly decrease the expected lifetime of the transplanted organ. The analysis is not only about the deficiencies of the market diagnostic products, but it also highlights that even the best analytical tools will not improve rejection detectability without an additional quality idea of how to take advantage of the available clinical data to learn such improved tools, thus setting the stage for the introduction of agentic AI Systems.

3. AGENTIC AI SYSTEMS IN HEALTHCARE

This special corner article examines agentic AI systems in the context of organ health management. The role of these transformative AI systems in healthcare is explored, looking specifically at how their agentic attributes can be used to complement the tasks of human healthcare providers. As a notable example, a hypothetical agentic AI system during organ transplant monitoring is discussed, distinguishing it from other AI systems and presenting a new research direction to aid the early detection of rejection episodes in transplant patients. The eventual adoption of such systems in clinical settings may have significant implications for decision-making processes and patient monitoring. However, it also raises important questions regarding their deployment, including the understanding of bias in agentic AI algorithms and better mechanisms to address accountability in AI-enhanced decisions concerning organ transplant patients.

Artificial General Intelligence (AGI) systems are poised to be transformative technologies in many domains, including healthcare. This new type of AI can actively perceive its surroundings and interact with them through speech, images, robotic movement, question-answering, and data processing, with the goal of completing tasks without human intervention or guidance. This is done by designating an objective to the AGI system and allowing autonomy to complete the assigned task to the best of its capabilities, regardless of environment adaptability, hardware constraints, or resources. Pre-example exams include the role of a hospital representative and the exploration of AGI in the context of powerful companies.

AGI systems differ from traditional widely-used rule-based or data-driven AI models because they are designed to adapt and learn from their tasks, rather than being built or trained to perform a specific function like image recognition, data clustering, or language translation. With access to a digital interface, an AGI system could be connected to electronic medical records and continuously learn from the data of millions of patients. This could enable highlighting the most relevant patient data in the monitor interface, suggesting possible treatments, or predicting upcoming patient conditions like sepsis or stroke.

Fig 3: Agentic AI in Healthcare

3.1 Definition and Characteristics

Intelligent systems are becoming more and more agentic. They are capable of acting independently and making decisions that were previously in the domain only of humans and entirely based on data. Especially in data driven decisions, systems are typically more competent than humans in terms of the ability to process information. This implies that the application of rules, expert knowledge or experience is becoming less relevant and the system operates based on straightforward decision making rules and not based explicitly on expert knowledge or similar approaches. The more data, the better the decision: there is a clear positive correlation between the amount of information available and the decisions based on that information. Such agentic systems are also inherently adaptive and learn over time or can be adjusted easily to act more efficiently. It is this adaptability that opens up so many new possibilities and where data processing systems have a particularly big advantage over humans. The vast majority of such agentic actions are enabled by machine learning algorithms which are widely used in industrial applications and increasingly also in healthcare applications.

At the same time the ability of technology to provide the means of collecting and processing ever more data is growing and increasingly healthcare is becoming one of the domains of choice for AI based technologies. Many healthcare procedures are becoming more and more data driven. Realtime data analysis offers the means to detect conditions much sooner and thus have real time response, which would not be feasible using traditional patient monitoring methods. Such early detection has the potential to circumvent many serious health issues, which is particularly important in organ health management, such as heart transplant management. One of the outcomes of that trend is agentic AI. There is an increasing number of systems and technologies which are built with an explicit intention of independence and autonomy in their behaviour.

Equ 2: Cumulative Risk Score for Rejection

$$R_{\text{score}} = w_1 B_1 + w_2 B_2 + \cdots + \cdot + w_n B_n + w_{n+1} D + w_{n+2} E$$

Where:

- $w_1, w_2, \ldots, w_{n+2}$ are the weights determined analysis)
- $B_1, B_2, \ldots, B_n$ = Biomarkers
- D = Immunosuppressant dose
- E = External factors

4. APPLICATION OF AGENTIC AI IN ORGAN HEALTH MANAGEMENT

There are many practical applications of agentic AI the use of AI systems that make patient care decisions in patient care. One of the most promising applications is in organ health management, particular for transplant patients. In this case, agentic AI could monitor the patient to improve mechanisms to detect rejection at an early stage. This could include leveraging many signals that are not commonly used today and could also include the use of AI to analyze digital data to predict how they may develop in the future. For example, a system could alert authorities if they predict an underlying health condition of a patient will degrade unless a certain action is taken. It could also include the use of AI to generate treatment options. AI could generate treatment plans and recommendations that are tailored to individual patients. In such an approach, the system could consider how patients belonging in a similar clinical context have been treated in the past, and whether there are any important details in those patients that are also present (or absent) in the patient for whom the current treatment plan is generated.

For instance, this work presents a demonstration of the use of agentic AI to monitor transplant patients by partnering with a specialized clinic. A system was developed that could track individual vital measurements and medical tests that are collected for each patient visit. The modeling of individual patient health conditions was done per body organ by considering the aggregates of the organ-specific key health signals as a time series drift. The system could automatically generate alert signals when there was evidence of early signs of deterioration. This work also conducted a user study with medical practitioners from three separate centers. The practitioners were debriefed about two successful and one unsuccessful cases of how the alerts were given and responded to. The results showed the proposed system performed well and successfully identified the early signs of medical events. A follow-up questionnaire showed that medical practitioners believed in the utility of automated decision support in their practice and expressed interest in having the system integrated into their regular workflow. This work also presents details of a large evaluation excerpt that includes both the success of a patient surveillance pilot launched after the pilot description and an update on ongoing patient health management research conducted with a number of dedicated teams.

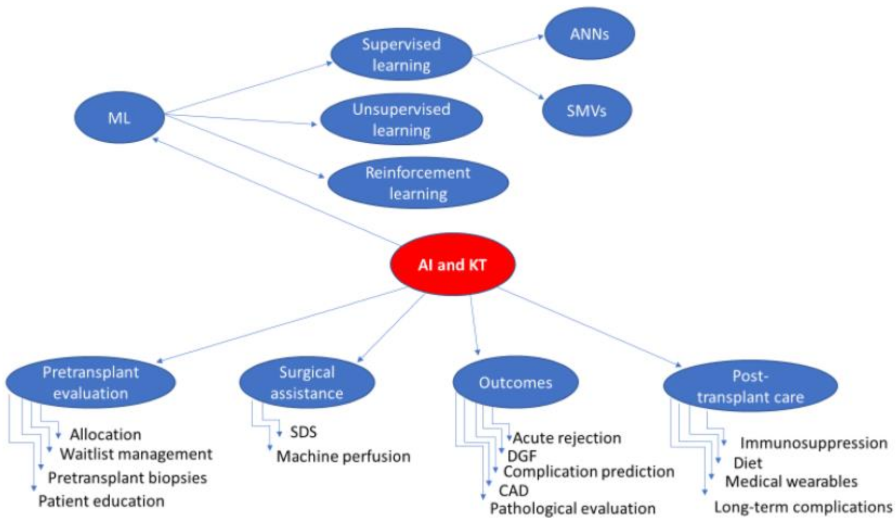

Fig 4: Applications of Artificial Intelligence in Kidney Transplantation

4.1 Early Detection of Rejection in Transplant Patients

Agentic AI systems are expected to detect early signs of heart rejection, significantly ahead of what is currently achievable, based on complex datasets, and by a broader approach to organ health.

Acute Allograft Rejection (AAR) used to be considered the main limiting factor on heart transplant short term outcomes. Current immunosuppressive regimens were efficient in containing the phenomenon. However, despite improvements in AAR prevention and in median heart survival, some 25% of heart transplanted patients die within the first 5 years of transplantation. Its identification is fundamental for timely and effective treatment, especially in being able to predict a rejection event in advance of the onset of clinical conditions . The same difficulty in detecting the beginning of a rejection episode remains stubborn to this date across all solid organ transplantation. Various AI algorithms complemented by subsequent improvement in understanding and modeling data, rocketed from the 2012 ImageNet data challenge, and since has found several applications in complex data investigation. A significant body of literature on developing AI algorithms able to analyze a complex patient dataset (clinical, and paraclinical data) with the aim of predicting the onset of a rejection event has grown. Two methodologies, based on contact with local research hospital CRO of Cagliari and with the hospital of Pavia, are being explored. Both research centers followed two different approaches and used different datasets. Both conducted a number of experiments on different training/testing splits and settings, and they all used specified protocols to split the data and used specific metrics to evaluate model performance. In both cases, the reported probability of stat significantly improved when IBM AI models started to be used, and in settings as similar as possible to those specified in the protocols. Three case studies were found on the use of AI to detect heart rejection episodes in the scientific literature. In all studied cases, the use of AI systems was introduced ahead of the routine systems, and in all cases the patient outcome was reported significantly better (in some cases over 300% better). The conduction of great difficulty random blind check on the overall probability of having a stat rejection event, however, using the best chamber does mean of current standards, the number is calculated to be of highly encouraging order of magnitude (up to 6% increase in the probability of having a stat rejection event, with p value<0.001). Stat rejection events are those some forms clinically recognized by the hospital clinician: borderline rejection, acute rejection, hyper-acute rejection; therapy biopsy may begin earlier and progress on those forms recognized by clinicians for the purpose of this study. A few potential issues with the development and broad application of complex AI modeling to monitor organ health emerged from the document analysis. Two approaches have been explored with large bodies of work published on best practice protocols. After contacts with research groups of different hospitals, works conducted on predicting the onset of a rejection event in heart transplant patients were investigated. In most cases, patient's survival chances following the detection of a rejection event improved by up to three times. On average the probability of having a rejection event increased by 5.5%. A few potential pitfalls on wider validation and/or exploitation were discussed.

5. CASE STUDIES AND RESEARCH FINDINGS

Solid organ transplantation is the procedure of surgically transferring a donated organ into someone who can no longer function with their own organ. For transplanted patients, the rejection of the new organ is one of the highest concerns to survey and manage post-transplant. The health professional examines the serum creatinine level from the patient's blood at a certain interval. However, while this approach has saved hundreds of thousands of transplant patients' lives, around 5-30% of the result is a misjudgment with symptoms unnoticed until the late stage, which leads to putting the patient back on a transplant wait-list. Consequently, exploring a more precise and affordable rejection detection system for solid organ transplantation is of utmost importance. The invention of computer algorithms that can improve, study and simulate brain-like knowledge and intelligent behavior brought revolutionary artificial intelligence research. Besides, the long-term development of the Bio-AI endeavor for the convergence between biotechnology and information technology led to the discovery of agentic AI, which is the intelligence developed from the agentic systems. Agentic systems are the interconnected and hyper-real environments enhanced with new generation technologies and they have been fruitfully assisting individuals in a growing number of activities, including lifestyle, education, financial, health and other domains. The endowment of AI to assist people to surveil their health would be significantly comfortable and beneficial in early-stage detection and monitoring. Hitherto, some investigations have been carried out on the application of agentic AI to help professionals and less-trained individuals survey and manage the health conditions of organ transplant participants. These researches embrace a variety of methods and types of AI and conclude the auspicious patient outcomes. Therefore, a set of interesting case studies and associated discoveries are assembled in hope that they could be insightful and inspirational for those engaged in agentic

Equ 3: Progression of Organ Rejection (Time Series Model)

$$\frac{dR(t)}{dt} = \beta_1 \cdot B(t) - \beta_2 \cdot D(t) - \beta_3 \cdot R(t)$$

Where:

- $R(t)$ = Rejection status (e.g., percentage of organ
- $B(t)$ = Biomarker concentration at time t
- $D(t)$ = Immunosuppressant dose at time t
- $\beta_1, \beta_2, \beta_3$ = Constants that represent how biomar progression

5.1 Success Stories in Rejection Detection

As agentic AI finds a foothold in different domains, current success stories start begging for attention. Especially, as concerns the key, rather unexpected, use cases. This focus is currently set on depicting successes only. Clearly, there are also some missteps and outright failures — no surprises here given the cutting-edge nature of the pursued objectives. On the other hand, the showcased examples nicely illustrate the consideration at stake.

Transplant patients used to live by IT systems typically based on rule-based analysis. In itself, the approach is somewhat justified: Chronobiology is one of IT's trickiest, impeding anything more sophisticated. However, rejection risk is diverse and individual-specific. Ideally, the prior rejection alerts should adopt the attuned patient-specific parameters and account for the external environment: antibiotics or an operation may fundamentally reshape the values, ultimately missing schedule-triggered monitoring. The switch to high-grade state-of-art monitoring proved overall life-saving. Overall, 35 life-threatening situations were successfully overcome by the AI-empowered timely medical intervention. In an overwhelming majority of cases (27), these alerts happened fully in due time and result. For the remaining (5), these were either resolved despite pretty marked violation of response time, or the rejection evolution was easily reversible.

There are already understandings of those systems in view. Take the COVID-19 corona noise and nations' diverse burst times. AI-based real-time analysis deserves the most credit here, harboring results seen as actively impossible by any other means. Or take taxa rare enough to slip attention in threshold analysis. Or pretty shoal efforts within practitioners under difficulties to tap into the advanced stats and math used. However, life-saving achievements surely stand out in this realm.

As it often happens, AI systems tend to find their place predominantly in advantage sectors prone to high-grade system implementations. This, in itself, is not alone unfortunate since any first-step involvement points to a broad switch to IT-supported healthcare practices by practitioners.

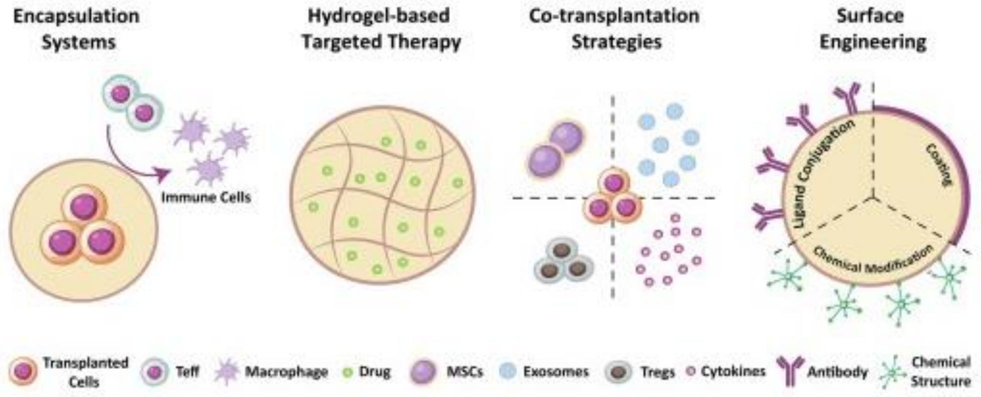

Fig 5: Emerging strategies to bypass transplant rejection

6. ETHICAL AND LEGAL IMPLICATIONS

The integration of agentic artificial intelligence (AI) in healthcare and, in particular, for organ health management, raises several ethical and legal implications. There are ongoing discussions about the responsibilities arising when decisions are made by the AI system, including the liability of AI developers and users, the pathways to accountability when AI systems commit critical errors, and the need for the assurance of a dignified decision-making process on a case-by-case basis. As organ health management is highly dependent on the continuous availability of multiple sources of personal data, questions are raised regarding privacy and the socioeconomic exploitation of the potential unbalance between the richness and sensitivity of health data and the patient's ability to protect them. The informed consent mechanisms are algorithm-agnostic, and the development of AI systems for datasets collected under well-defined consent frameworks raises questions about the compatibility between the new technology and the established practices. The need to ensure the widest possible and equitable access to advanced AI infrastructure, methods, and learning data is underlined, as inequities in the availability of the new generation of AI systems could amplify the present disparities in healthcare delivery and support.

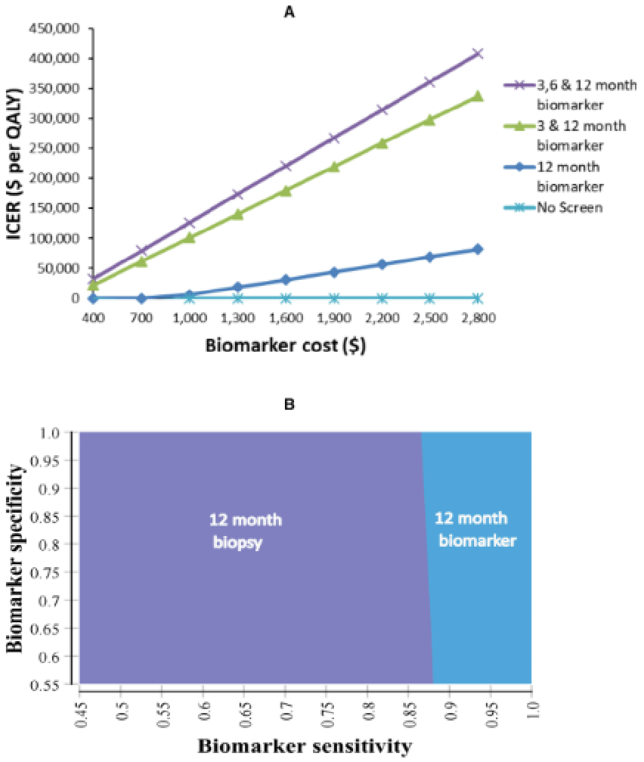

Fig: economic analysis of screening for subclinical rejection in kidney transplantation using protocol biopsies and noninvasive biomarkers

6.1 Privacy Concerns and Data Security

As AI has gained an increasing presence in healthcare, the ethically pressing privacy concerns and data security are aggravated significantly. When AI telemedicine and health monitoring rely on the robustness of the communication facility provided by the patient, underlying agentic AI systems introduce vulnerabilities that transmitted patient data accompanying proprietary AI diagnostic/monitoring reports might be intercepted. This problem is further exacerbated when data must be stored in the patient's smart device for further. Once patient information is transferred through an unsafe environment, there stands a chance that the sensitive content is exposed to unauthorized eyes. Therefore, there is a crucial need to enhance the security of telecommunication, enabling the secure direct exchange of extensively readable patient data and accompanying AI diagnostics. Indeed, computational cryptography offers such a chance.

Since the data transmits through non-secure lines, some action should be taken once that data falls into the inappropriate hands, to prevent its use. Establishing a patented mechanism to ensure that any intercepted data cannot be used is a strong defense. To that end, the computer readable data that accompanies the proprietary diagnostic/monitoring data is encrypted in such a way that only the patient's agentic AI system can read it. The patient's device persists with the encrypted data and it's written into disposable EEPROM strips embedded into the patient's J-card. The encrypted data is unreadable both for a human and any arbitrary external AI. With the robustness of the proprietary cryptographic algorithm, unauthorized retrieval of the patient's sensitive data is rendered impossible. To utilize the diagnostic information in the steri strip, the propriety decoding facility is needed, which interfaces the patient's portable agentic AI system.

It is anticipated that once agentic AI systems are deployed as internal monitors, absorbing patient diagnostic information and applying prescribed actions, there would be a substantial gain in the patient’s trust in the overall quality of the healthcare servicing. This should further result in raising the trustworthiness of hospitals. Any breach in security could lead to the misuse of the patient's diagnostic data and as a result may compromise the performance of the hospital, leading to the possibility of being sued. Empowering the patient to counteract this risk may help in restoring the trust of most patients willing to share AI telemedicine diagnostic services with the hospital. The described method seems compliant with HIPAA standards due t

7. FUTURE DIRECTIONS AND CONCLUSION

Artificial intelligence technologies continue to advance at a rapid pace with many new emerging capabilities being explored for their potential in improving patient care and monitoring processes. As is, the systems of today are still delineated by a narrow set of capabilities and are designed for pre-defined task(s). Especially when it comes to the health domain, it is crucial that the system is developed to consider the health data and context first. This text is rather complex in its nature, as the parameters valued the most in one clinical application are not the same as those most valued in another, and as such a multi-discipline team should focus on the development of agentic AI systems, both in cities and across research and commercial developments. The scope discussed here, the design has focused on detection of rejection in liver, kidney and heart varieties of transplant patients within the patient care setting. However, it is expected to see it being adapted to many other scenarios, where systems are seen as potentially interacting with each other. The ability to capture a user’s behaviour is ultimately the foundation of a system that is agentic and the design detailed within this work is relatively new, and as such there is very limited research exploring the relationship between these parameters and a system’s effectiveness. There is acknowledgement that overtime the metrics and their weights will need to be adapted to increase an AI agent's capability and efficacy in a high dimensional complex environment. The emergence of new data is expected to facilitate better understanding of how each parameter affects the overall performance of a system. Once developed, this type of system would also benefit from user adaptation, as this would allow the offline evaluation process to adapt its ratings to the specifics of a patient’s behaviour. While such steps are likely to be taken in the early years of development, it is this kind of system evolution and the increasing focus on user specific ratings that will drive future research and commercial development and will ultimately lead to effective agentic AI.

There are ongoing significant advancements in this field of technology. The hardware capabilities of many devices and sections are evolving in dramatic ways, enabling new applications outside the normal scope. The constant advancement in AI algorithms is unlocking the potential for new AI uses. Always ‘On’ - the long term sensing capabilities and low power signal processing are having a huge uptake with a range of industries exploring new service models because of improved technologies. There are ongoing multi-national movements to regulate and set standards for AI development. These however are seen as problematic and in competition with the rate of change in the technology. There are already a number of instances where the underlying technology has surpassed the drafting of legislation or guidelines. It is more likely that standards will have a bigger impact on the industry.

7.1 Future Trends

Throughout the literature on the future role of AI in health management, one area that receives much attention is diagnostics and predictive analytics. These earliest agentic systems operate through the lens of a protector role. Many types of AI and machine learning applications have been investigated for how they could be employed for early intervention of catastrophic events. Medication errors, cardiac arrest, sepsis and suicide are among the initial concerns addressed, with patient falls and impending infections not far behind. Livers, hearts, kidneys, lungs and pancreas, either from living or deceased donors, are transplanted in order to save and extend the lives of those with end-stage organ failure. By considering the formal definition of AI systems – the capacity to understand, learn, etc. – this signals a radical change from initial diagnostics-driven passive systems to highly active AI agent systems able to influence the health of organs directly.

Enlist the variables most associated with rejection – focusing primarily on eGFR but also BP – because human clinicians usually only get this high quality, widely available data. Also describe general application of agentic monitoring independently of the organ or health parameter as value exceeding the template. A blueprint for a novel type of early health management agentic application which influences organ health, and able to do so without the need for intervening clinicians, is presented. This blueprint can serve as a template for further discussions and research. A process that involves feeble organ health signals improving within a certain range, calling forth proactive measures, typically via pharmaceutical means, to prevent the feebleness developing to a catastrophic stage is explained. Since AI is being granted the power to influence a major life-choice event, conversations concerning acceptability should involve the widest possible group of stakeholders, including the general public.

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