Artificial Intelligence – A New Frontier for Rehabilitation

By Linda Winterbottom

How to best use and integrate Artificial Intelligence (AI) into claims environments is currently on the minds of Australian life insurers. No longer an "if" but a "when," many insurers are currently considering how Ai can best be leveraged to enhance the customer experience and increase efficiencies by automating routine tasks and processes. And this is likely to gather momentum in the coming years.

RGA anticipates AI could also have a transformative impact on the rehabilitation ecosystem. Life insurers may benefit from an awareness of its potential benefits and limitations, and the risks that could derail its successful implementation.

Understanding the essence of rehabilitation

Ask a rehabilitation professional what the essence of rehabilitation is, and the answer will probably be something like this: "A person-centered approach where we seek to understand an individual's specific needs so we can intervene with the right services at the right time in order to support them back to their life roles following illness or injury."

Fundamental to the rehabilitation model is the premise that every individual undergoing the process is different. While recovery from a medical condition usually follows a certain trajectory, it is often an individual's underlying motivations and biopsychosocial ecosystem (i.e., their personal, work, family, social, and environmental circumstances) that are the true determinants of successful recovery and their ability to return to work. It is this person-centeredness – the human-to-human connection – that is at the heart of what rehabilitation professionals do.

Rehabilitation professionals therefore often struggle to fathom how a machine can outperform a human in what is a fundamentally human activity. However, we suggest the more useful question to ask is: how can AI enable a rehabilitation professional to spend more time directly working with customers and less time on necessary ancillary administrative tasks?
For example:

- How can AI be leveraged to help more efficiently identify the customers who will best benefit from rehabilitation?
- Can AI support more effective implementation of rehabilitation interventions that achieve superior outcomes by more accurately tailoring the support to the needs of the individual, including their unique biopsychosocial circumstances?

AI's demonstrated benefits in diagnostics, treatment, and recovery

AI has enhanced a myriad of capabilities in diagnostics, treatment, and recovery, such as:

Diagnostics

- AI has facilitated analysis of vast datasets, enabling identification of patterns that can yield more precise diagnoses and personalised treatment plans.[1]
- AI-powered imaging techniques have enhanced detection of anomalies and are providing valuable insights into various neurological, cardiovascular, and cancer related conditions.[2]

Therapeutic care and recovery

- AI algorithms are already powering robots and exoskeletons that are helping patients with physical, neurological, and spinal deficits regain their balance, coordination, and strength by predicting and adapting to their movements.
- Wearable devices equipped with AI-driven biometric sensors monitor vital signs, providing real-time health data to individuals and their allied health professionals. In addition, AI-equipped wireless motion sensor trackers are being used to analyse the quality of movements performed when undertaking rehabilitation exercises.[3, 4]

- Immersive AI-driven technologies such as virtual reality (VR), augmented reality (AR), and gamification (i.e., active video games) assist individuals, particularly those recovering from strokes, musculoskeletal conditions, and spinal injuries, in their strengthening and healing by providing gamified incentives for improvements.[3, 4]

Mental health

- AI-supported chatbots and virtual mental health assistants are providing on-demand therapeutic support.[5]
- Machine learning, predictive analytics, natural language processing, and sentiment analysis are used to detect subtle changes in how individuals interact verbally in order to identify the potential onset of certain mental health conditions and develop personalised treatment plans.[6]
- VR is showing promise as a tool to treat trauma- and anxiety-based mental health conditions.[7]

While not within the scope of this paper, it should be noted that ethical concerns have been raised with the use of AI in mental health care, given the increased risks that may arise with this vulnerable population.[8]

AI in vocational and occupational rehabilitation

Vocational and occupational rehabilitation service providers are also exploring ways to integrate AI into their service offerings and day-to-day practices.

The reliance on wearables and wireless sensors to track progress and understand effort is now commonplace in physical and work conditioning programs. Machine learning and predictive analytics are also being used to refine and optimise performance and health metrics.

VR/AR is proving useful as well, giving individuals a way to practice real-life skills such as mimicking the performing of activities of daily living or the functions required of their occupational duties, or new job skill development and training.[9]

AI-driven assistive technologies that support disabled individuals in the workplace are also seeing exponential growth and are changing how work disability is viewed. Two examples are: Microsoft's *Seeing AI* app, a smartphone app that verbally describes environments to individuals with a vision impairment; and Google's *Project Euphonia*, which translates and interprets unclear speech (common with individuals recovering from stroke or neurological disorders).[10]

Also gathering momentum, although not yet widely adopted by occupational rehabilitation providers in Australia, is AI's ability to support transitions into new careers and the obtaining of new employment. Careerbots (such as IBM's Watson Career Coach) are providing job search guidance and real-time feedback on interview skills and job vacancies, allowing individuals to assess their work skills and interests and determine work for which they may be suited without the need for career counsellor assistance.[10, 11]

Generative AI solutions such as ChatGPT are also creating professional-looking resumes and cover letters, which can then be utilised (with some user input) for job applications. While still in the embryonic stage, AI is reinventing how career counselling is performed as well, allowing greater client autonomy as well as access to support at very little cost.

> The transformative impact AI is having in vocational and occupational rehabilitation is unlikely to stop at individual and service provider levels. It may also have clear and significant potential to reshape and reimagine entire rehabilitation operations within the life insurance industry, which will give rehabilitation experts the time and space to do what they do best.

From analysing complex medical data from various sources to identifying cases deemed suitable for vocational rehabilitation, and even offering guidance on the most effective treatment and rehabilitation interventions to achieve optimal return-to-work (RTW) outcomes, AI has already proven that it can outperform humans both in time and accuracy and that it is easily scalable. Add to this AI's ability to perform routine administrative tasks, and it is not difficult to see that opportunities for efficiencies will abound should rehabilitation teams within the life insurance industry embrace and work alongside AI technology to refine and renew their day-to-day operations, harnessing its power to enhance current practice.

Limitations, risks

While the benefits and possibilities of AI are impossible to ignore, they do not come without limitations and potential risks.

The human-centric nature of rehabilitation necessitates careful consideration of individual variability and unique customer needs, including value plurality (i.e., different customers possess differing values and priorities that may influence their engagement). AI algorithms should be designed to adapt to diverse rehabilitation contexts and respond to the nuances of each individual.[12]

The difficulty is that the historical rehabilitation datasets on which models are currently trained are not likely to have had such variables recorded. This means a high probability exists that the datasets may contain significant conscious and unconscious biases as well as inaccurate and incomplete information. Training an algorithm using data with these flaws can lead not only to incorrect and inaccurate modelling, but can also risk perpetuation of existing biases, resulting in unintentional discrimination and financial and reputational consequences.[13]

Ensuring customer privacy, data security, and informed consent are also paramount. Developers of AI systems for rehabilitation need to establish robust safeguards to protect sensitive health data, and there must be transparency around how AI is used to manage claims (either from a case management or rehabilitation perspective) to engender and maintain trust with customers. Similarly, rehabilitation decisions often involve complex human factors, so it is essential for AI systems to provide transparent insights into their decision-making processes.[14]

Finally, the collaborative nature of rehabilitation involves extensive human interaction. While AI can enhance efficiency, it should be viewed as a supportive tool rather than a replacement for human expertise. Striking the right balance between AI assistance and human intervention is crucial to maintaining the personalised and empathetic care that is integral to successful outcomes and customer satisfaction.[15]

AI in practice

Case Study 1: Use of AI to identify claims suitable for vocational rehabilitation support

It may be surprising to learn that AI technology has been used since 1991 to automate the screening and identification of cases suitable for vocational rehabilitation.[16]

That year, In response to funding cuts, New York State's Department of Social Services Office of Disability Determination (ODD), together with the state's Department of Education Office of Vocational and Educational Services for Individuals with Disabilities (VESID), developed, piloted, and deployed DISXPERT. This intelligent rules-based technology system, intended to refer members of the Social Security Disability Insurance (SSDI) program for vocational rehabilitation services, was not only successful at in identifying cases suitable for such referrals. For vocational services, it also did so with greater precision and objectivity than human rehabilitation subject matter experts (SMEs), and at greater speed and with lower associated costs.[16]

DISXPERT's knowledge base was created using a combination of empirical research findings of the factors that predict successful vocational rehabilitation outcomes. A machine learning approach was used to analyse the statistical data of 9,000 cases to discern among factors that positively contributed to a RTW outcome, and the rules-based system created from a review of 225 cases by subject matter experts.[16]

Notably, at the time DISXPERT was piloted, results showed it accurately identified 93% of the cases that would benefit from rehabilitation intervention.

DISXPERT was piloted at a single site for a nine-month period, during which it the system screened and assessed a total of 12,431 cases. Its progress was closely tracked. During the testing process, two changes were made to improve DISXPERT's efficiency. In the first, the rules used for orthopedic disabilities were modified to more closely match the thinking of the vocational rehabilitation counselors. In the second, modifications to the rules were made in response to a new disability coding scheme from the U.S. Social Security Administration. Using the new coding scheme allowed DISXPERT to more clearly delineate disability cases.[16]

Upon completion of the pilot, its accuracy and performance were validated by comparing the decisions it provided on 200 cases with those reached by each of the SMEs on their manual review of the same cases. Results of this validation showed the determinations by DISXPERT and the SMEs aligned in 198 of the 200 cases, reflecting an overall agreement rate of 99%.[16]

Following the rollout of the DISXPERT intelligent screening system to all district offices in New York State from 1992 onwards, benefits continued to be realised. The offices saw a significant increase in productivity (more cases screened for rehabilitation suitability with less staff), reduced time to reach decisions, an 80% decline in the drop-out rate of participants who commenced vocational rehabilitation programs, and enhanced training opportunities for junior staff on how decisions and determinations were reached.[16]

> As one of the primary functions of case managers and rehabilitation consultants in the life insurance industry is the identification of claimants who would benefit from rehabilitation intervention, this case study presents a blueprint for how life insurers might leverage AI capabilities to realise similar gains.

Case Study 2: Use of AI to predict timespans of work disability and guide optimal rehabilitation strategies

Developed in Hong Kong in response to the increasing demand for private occupational rehabilitation programs available for injured workers experiencing long delays accessing rehabilitation services in the public system, the city's Smart Work Injury Management (SWIM) System 1.0 was developed and piloted in 2021.[17]

The objectives of SWIM 1.0 were to enhance the traditional prediction of disability duration, identify the likely RTW trajectory, and provide guidance to case managers and other stakeholders regarding what would be the most appropriate medical care and rehabilitation interventions to achieve optimal results, based on the cases' characteristics and complexities. Using a combination of machine learning (using 90,154 work injury records as static data and 15,515 work injury cases as dynamic data) and a rules-based system derived from case manager self-experience, the model was trained to analyse the outcome of each of the cases, including whether a return to work occurred, number of days off work, percentage of those with permanent disability, case costs, and determination of any legal disputes.

In simple terms, once a new case was received or queried, SWIM 1.0 was trained to collect the static data, search for the 50 most similar cases to find the possible strategies and interventions previously used, and then analyse the dynamic pathway these cases took and the various outcomes achieved. Using this data, SWIM 1.0 would then provide output to the case manager on a dashboard, indicating whether this new case required high-level management (HLM), the dates HLM should commence (if required), recommendations of case and rehabilitation strategies, and interventions to achieve the optimal result. The dashboard also sought to aid the case manager's decision-making process by highlighting the differences in terms of recovery and return-to-work, ongoing disability, and case costs should the case continue to be managed normally as opposed to 'high level'.[17]

While the methods used to evaluate the results of SWIM 1.0 are beyond the scope of this paper, the authors did report findings supporting that that their system outperformed humans when predicting disability duration, with estimations of a minimum 30% improvement in prediction error (human prediction average error = 154.857 days compared to the SWIM 1.0 average error = 107.447 days) and again in predicting permanent disability levels.

> Acknowledging the limitations in relying mostly on static data (and some dynamic data), the authors have signalled their intention to update the model in the future (SWIM 2.0) so that incoming dynamic data can be analysed and factored into real-time adjustments.

It will also incorporate cutting-edge technology such as QR codes, apps, and other technologies to enhance communication and data collection between stakeholders.

Way forward

As subject matter experts, we rehabilitation professionals need to approach integrating AI into our recommendations and referrals with a healthy curiosity while maintaining a keen awareness of its limitations and risks.

The best way forward is for rehabilitation professionals to be active participants:

- Provide your technical expertise to assist in the development of any rehabilitation rules-based systems aimed at enhancing the machine learning algorithm.
- Be proactive in identifying and articulating potential biases in datasets and request to be part of the testing environment.
- Keep abreast of medical, rehabilitation, and labour market advancements and where relevant, provide this feedback to developers to ensure the output of any intelligent system remains relevant and accurate.
- Rehabilitation professionals should also be part of the testing environment, as they can provide perspective along with their input.

AI integration into the rehabilitation landscape is here to stay. As a rehabilitation professional, I find this new world fascinating and exciting, and believe the possibilities are limitless. Where do you stand?

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