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Identifying Quality and Safety Learning Opportunities Through EHR Data Analytics in Musculoskeletal Practice

Melinda Wassell

drmelinda.wassell@gmail.com

RMIT University

Henry Pollard

Durban University of Technology

Kerryn Butler-Henderson

Charles Sturt University

Karin Verspoor

RMIT University

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Abstract

Background

Electronic health records (EHRs) collect real-world clinical data that can objectively measure clinical outcomes and deliver personalized learning opportunities for clinicians when analyzed. Current safety principles and the learning health system framework recognize that proactive analysis of routine practice data, rather than only monitoring adverse events, is fundamental to the continuous improvement of patient and clinician outcomes. The aim was to assess musculoskeletal clinicians' use of an EHR and identify areas of potential clinical improvement by comparing data entry variability with clinical outcomes.

Methods

A retrospective observational study was conducted on EHR data from an Australian occupational healthcare organization employing chiropractors, physiotherapists, and osteopaths from 2014–2021. Data were restricted to food manufacturing industries to control for patient population variability, and clinicians with fewer than 100 complaints were excluded. The primary outcome was treatments to release (TTR). Variables were selected based on a literature review of predictors of work-related musculoskeletal disorder outcomes.

Results

Data from 46,539 complaints and 52 clinicians were analyzed. Meaningful variation was identified across all variables examined, consistent with the presence of learning opportunities within routine clinical data. Mean TTR ranged from 1.02 to 5.16 across clinicians, with body region and mechanism of injury associated with variation in recovery length. Obstacles to recovery documentation varied widely across clinicians, from 1.9% to 85.4%, while psychosocial factors ranged from 0% to 20.4%. Prognosis accuracy was consistent across all experience levels, with clinicians consistently overestimating recovery length, offering insights into opportunities for clinician development.

Conclusions

Clinical EHR data contains meaningful information that supports the identification of learning opportunities for clinicians, to inform feedback discussions on clinician skills, biases, and EHR training. Clinical quality measurement as part of routine clinical governance is a significant safety improvement for patients, who deserve care from clinicians who have access to objective EHR data, not solely self-assessed competence.

Background

A clinician may determine that an injured worker's shoulder pain will never fully resolve, and they will require ongoing treatment to remain in their role on the production line, while another clinician fully resolves the same condition and returns the worker to full duties. Both patients might report high satisfaction if expectations were appropriately set, yet their clinical outcomes are vastly different. Measuring clinical performance in terms of patient outcomes is challenging, so, how do we know if we are providing high-quality care? Objective structured clinical exams (OSCEs) for students assess performance at a single point in time [1]. Patient-reported outcome measures (PROMs) provide patient-centric data, while satisfaction scores provide limited detail on the efficacy of care. What we fail to do well is measure the quality of clinical care in terms of efficiency and long-term health outcomes. Once graduated, musculoskeletal (MSK) clinicians have little ability to objectively assess their performance, with continuing professional development relying on subjective self-assessment through learning journals rather than objective data.

Electronic health records (EHRs) collect data on every patient encounter, revealing patterns in practice by identifying where outcomes vary between clinicians, and where targeted learning might improve results. Providing clinicians with feedback on their clinical data can improve both outcomes and data capture [2–4]. As health systems adopt value-based care models [5] that link outcome measurement to clinical and cost improvement [6], the ability to analyze clinical EHR data becomes increasingly important. With MSK conditions affecting more than 1.63 billion people globally as the second leading cause of non-fatal disability [7], the consequences of variation in quality of care extend beyond pain, but to prolonged recovery, unnecessary recurrence, and personal, economic, and social costs [8]. Delivering high-quality MSK care is a patient safety imperative. Yet despite the volume of data MSK clinicians collect, there is little evidence that routine EHR can identify or inform clinical practice variation or clinician development, whether due to infrastructure, culture, capability, or methods.

The gap has broader implications for patient safety. The World Federation of Chiropractic (WFC) Global Patient Safety Task Force has called on the profession to embrace the World Health Organization (WHO) Global Patient Safety Action Plan framework [9], and to collect, analyze, and publish transparent, high-quality safety data to function as a learning profession through proactive learning [10]. Research into patient safety culture in chiropractic found that the profession has focused extensively on traditional safety methods, such as reactive adverse-event documentation, with limited infrastructure for proactive performance monitoring [10].

In modern safety methods, the Safety-II principles recognize that safety is present in everyday work that goes well [11], viewing safety as an active presence and appreciating that healthcare clinicians often work to ensure their patients receive safe, high-quality care. This requires analyzing clinical data to identify what's working and where targeted learning could improve outcomes. In healthcare, Safety-II principles are integrated via the learning health system. The learning health system is a concept in which data flows through a continuous cycle. Clinical practice generates data, which is analyzed to generate

knowledge that feeds back to improve practice. The WHO's objectives recognize that maintaining clinician competency through lifelong learning is critical to patient safety. In the learning health system, real-world EHR data can be used for analytics, enabling identification of variations across clinicians that may indicate knowledge gaps or training opportunities to build a learning culture.

The aim was to assess clinicians' use of an EHR to identify potential learning opportunities by comparing variability in data entry with clinical outcomes. A learning opportunity is defined as a pattern identified within EHR data that, has the potential to prompt reflection, inform clinical decision-making, or support practice improvement. Learning opportunities do not imply substandard care, rather, they represent signals within aggregated data that may warrant further investigation and discussion. As a proof-of-concept analysis, this analysis does not intend to definitively determine whether findings represent true training needs, as understanding the meaning behind the data requires discussions with clinicians. Rather, the intent is to provide a practical methodology for medical educators and organizational leaders to reuse clinical EHR data for continuous quality improvement, recognizing that each organization will have different use cases and applications.

Methods

The data source

An organization operating nationally across Australia employs chiropractors, physiotherapists, and osteopaths who provide on-site care to injured workers. They operate a value-based care model with closely monitored outcomes, clinician KPIs, and governance processes ensuring quality of clinical care. Clinical outcomes data is reused for reporting to both clinicians and clients. Previous data quality analyses of the EHR show that the data are appropriate for predicting outcomes of care [12], yet indicate variability in how clinicians enter data into the EHR [13], leading to the hypothesis that analyzing patterns in relevant EHR fields would reveal learning opportunities.

The EHR dataset includes 58571 patient complaints (care plans) from 20663 unique patients and data from 67 chiropractors, physiotherapists, and osteopaths. All records available for analysis were included. Data from July 2014 to November 2021 were analyzed, although the obstacles to recovery variables were added to the EHR during this period, limiting analysis of these variables from January 2018. The dates represent those between large EHR upgrades, which would impact data availability and analysis. Clinicians work across a range of industries, predominantly manufacturing. Therefore, to control for case-mix variability across industries, the analysis was restricted to food manufacturing, the most common industry in the dataset. Clinicians rotate workplaces around every six months and typically work across multiple sites weekly, reducing the influence of worksite-specific injury and cultural factors on individual clinician data. Patients’ appointments are not assigned to specific clinicians. On occasion, a clinician may refer a complex case to another clinician, although most commonly, there is only one clinician working at a site at a time. The dataset contains mostly structured variables regarding patients’ complaints, examinations, care plans, treatment notes, and medical history. For example, aggravating

and relieving factors, onset mechanisms, and treatment modalities are selected from lists rather than entered as free text. The generalizability [14] and quality of the data [12] have been outlined in previous studies.

The analysis

Variables were selected based on a literature review of predictors of work-related MSK disorder outcomes and consultation with senior clinicians as EHR subject matter experts. While harmonized quality indicators do not yet exist for MSK practice, the selected metrics align with quality indicator frameworks [15, 16] and map to the process and outcome domains of the Donabedian structure-process-outcome framework for quality indicators [17]. Mapping of the EHR variables to QI frameworks is outlined in Supplementary Material 1 [18–24]. As the EHR data had already been used to report clinical outcomes to workplaces and clinicians, deep insights were available from subject matter experts. Hypotheses were developed on expected usage patterns and their relationship to outcomes before analysis commenced.

Although the EHR includes key tests and PROMs, these fields are non-mandatory and have high missingness, making them unsuitable for this analysis. The primary outcome was treatments to release (TTR) which is the number of visits until a patient is released from care, defined as complaint resolution or ability to self-manage. TTR is monitored within the organization under established governance processes, and the metric used here includes any reinjury or recurrence within six months. Patients may also exit care through referral, employment cessation, or other attrition, and whilst this would make interesting inter-clinician analysis, these reasons are not available for research analysis; it was estimated internally at 1% of care plans. It is possible there is variability between clinicians that could be uncovered in the analysis of patients exiting care. Clinicians with fewer than 100 complaints were excluded as likely new or untrained. Confidence intervals were t-distribution derived. Any missing data is reported in tables and excluded, but because mandatory data collection is required, this is rare. Analysis of data quality relating to plausibility, conformance, completeness, and extrinsic factors such as governance, timing, accessibility, interoperability, and technical platform is reported in prior work [12]. Any grouping of data for graphs was chosen to avoid having a single clinician in a group.

As the aim of the paper is to assess EHR data for learning opportunities, the analysis was conducted in Excel and Tableau. Tableau was used as the visualizations provide easy-to-understand representations of the data that are likely more useful for clinical leaders and educators than more technical statistical software. As this is only an initial analysis, many factors underlie each data point, meaning a more technical software tool may be less effective at demonstrating the opportunities the EHR data could provide.

The variables

Treatments to release by body region

The EHR captures 28 specific body regions, grouped into 7 larger body areas. The larger body area was used for analysis. The clinician's average TTR was compared by body region. When reporting clinician averages, clinicians with fewer than 10 records per body region were excluded to provide more accurate averages.

Recurrence of conditions – Reopened care plans

A recurring care plan is one that has been released and reopened due to returning symptoms. It was hypothesized that clinicians may release patients at different points depending on their understanding of the condition — for example, resolving local pain without addressing the underlying mechanical load may precipitate recurrence. Recurrence was calculated as the proportion of reopened care plans relative to total care plans. For clarity, the TTR metric included all reopened care plans, thus the total number of visits for a complaint, where for this analysis, if the complaint was released from care then returned, these are considered as separate.

Mechanism of injury

Mechanism of injury is captured across five coded subcategories of traumatic, repetitive overuse, static/postural, exertional, or nothing specific. Four non-traumatic subcategories map to SafeWork Australia's 'body stressing' category. Repetitive overuse indicates that symptoms occur from cumulative mechanical loading during repeated task performance. Exertional causes refer to symptoms that begin with a discrete physical effort without a clear traumatic event. A static/postural cause describes symptoms attributed to sustained or awkward postures. A traumatic cause indicates symptoms following an identifiable traumatic incident. Nothing specific indicates that no clear mechanism could be identified. The hypothesis was that if clinicians do not correctly understand the mechanism of injury, they may miss critical questions in the patient interview and treatment options, and fail to resolve conditions as quickly as if they had better information to inform their clinical decisions. Percentage usage of each subcategory was compared across clinicians; those with fewer than 10 records per subcategory were excluded.

Obstacles to Recovery

The organization captures structured data relating to any perceived obstacles to recovery for patients. They are documented by treating clinicians at any point in the care plan using a structured field within the EHR, allowing selection of one or more complicating factors. Each factor was assigned to one of 9 categories: Medical History, Physical, Psychosocial, Compliance and Communication, Workplace, Injury, Job, Health, Outside Work Physical Activity, with around 10 individual factors in each category. These categories span biopsychosocial, occupational, and patient engagement domains. These factors are predominantly those shown in the literature to predict outcomes for WMSDs [25], as well as those

identified by clinicians within the organization as trends. The literature shows that psychosocial factors significantly impact recovery from injury [26, 27].

Prognosis

Clinicians record the expected number of treatments needed to release a patient at the initial visit. This is captured as a mandatory structured field in the EHR at the point of first consultation, before the clinical outcome is known. Accuracy was assessed by comparing this initial estimate against the actual number of treatments recorded at the point of release from care. It was hypothesized that clinicians become more accurate at recording prognosis over time; therefore, clinicians were grouped by length of service to report the expected versus actual treatments to release. The groupings were not decided by the researchers and were already present in the dataset as they were used for internal analysis and clinical governance. Existing quality indicators require prognosis to be documented, and that sessions be in agreement with prognosis [28], yet no validated quality indicators currently measure prognosis accuracy as a computable metric as this EHR can achieve.

Additional treatment variables, including the number of modalities used and the number of structures treated across a care plan, were considered and reported as means. However, these variables were not compared against treatments to release, as they were identified as potential confounders, as both are expected to increase as care plan length increases, reflecting clinician attempts to identify underlying causes of patient conditions rather than serving as independent predictors.

Learning Health System Framing

The analytical approach in this study is grounded in the learning health system framework. Friedman describes this cycle in terms of three information flows: performance-to-data (P2D), data-to-knowledge (D2K), and knowledge-to-performance (K2P) [29]. Our study methods address the P2D and D2K phases of this cycle (Fig. 1), using routinely collected EHR data as the raw material for descriptive analysis and visualization.

Results

There were 46539 patient complaint records analyzed for 52 clinicians across 64 workplaces in the food manufacturing industries. The mean body regions treated per complaint is 2.11 (CI 2.10–2.20), clinician range of 1.25–3.23. The mean number of joints documented as treated per complaint was 2.42 (CI 2.14–2.70), clinician range of 0.95–7.01. No missing data were present for body region, treatments to release, prognosis, reopened care plan, or mechanism of injury variables. Obstacles to recovery recording varied by practitioner, and missingness was reported as is, with no discussion with users to

determine missing at/not at random status. No demographic information, including sex and profession (chiropractor, physiotherapist, osteopath), was available for reporting due to privacy requirements.

Figure 2 demonstrates that the elbow and lower arm are the most common regions treated (23.14%), with hips and upper leg the least (3.62%). Shoulder and elbow region complaints required, on average, more treatments than other body regions (3.89), with the upper back requiring the least (2.92). The figures reflect the types of manual work involving upper-body effort in the food industry. Individual clinician variability ranged from an average of 0.24 treatments in the knee to 6.52 in the elbow. During a patient consult, if no treatment or exercises are provided, only advice, then this visit is recorded as '0', which is why some clinicians have an average treatment to release less than 1.

There is a range of reopened care plans (1.52–23.89%) across clinicians. Overall, reopened care plans account for only 11.41% of care plans (Fig. 3). Five clinicians have over 20% of their care plans reopened, whilst 6 have them reopened less than 4% of the time, representing a significant range.

The mechanism of injury (Fig. 4) analysis found repetitive overuse the highest TTR (3.69), and the lowest for traumatic injuries (3.18). Clinician variability is wide for some variable options, such as repetitive overuse, whereas it is much narrower and tighter for the option of 'traumatic'. Repetitive overuse usage varies between 2.55% and 84.21% across clinicians. Traumatic injuries are associated with fewer body regions treated (1.72) and fewer joints (1.48) compared to other mechanisms as traumatic injuries tend to be more localized to a body region. Static postural issues demonstrated the highest number of joints treated on average (2.88).

Obstacles to recovery (Fig. 5) were documented in 30.14% of complaints, with substantial variation across clinicians, ranging from 1.86% to 85.39%. Clinicians who documented obstacles more did so across all subcategories of obstacles. Although some clinicians preferred categories for recording obstacles, one clinician documented medical history factors in 58.42% of cases, and another documented compliance and communication issues in 41.88% of cases. Among the most common compliance and communication issues were language barriers and patients' failure to follow home-strengthening programs. Where any obstacle was recorded, mean treatments to release was substantially higher (4.87) compared to the overall dataset mean of 3.43. Workplace and health obstacles were associated with the longest treatment episodes. Psychosocial obstacles were recorded in 7.26% of complaints, with physical and emotional dependence on treatment, high levels of stress, and high pain catastrophising the most identified factors. Many heavily researched psychosocial factors, such as poor coping mechanisms (documented in 0.21% care plans) and fear avoidance (documented in 0.20% of care plans), were documented much less frequently. Seven clinicians recorded that psychosocial factors may influence recovery in less than 2% of complaints.

Clinicians matched their expected prognosis to actual treatments to release in 16.89% of care plans, with a clinician range of 4.29–28.51% (Fig. 6). In 63.36% of care plans, patients recovered faster than the clinician predicted, indicating a consistent tendency to overestimate recovery length across the dataset. This pattern was unexpectedly stable across all lengths of service groups, suggesting that prognosis

accuracy does not improve with clinical experience. While overestimation was consistent across clinicians, the degree varied considerably, with 41.89–88.60% of individual clinician care plans resolving faster than predicted.

Discussion

This proof-of-concept study demonstrates a practical methodology for analyzing EHR data to identify clinician learning opportunities, addressing critical gaps in high-reliability systems and information infrastructure identified in patient safety research. The results demonstrate variability in how clinicians enter data into the EHR, which may offer opportunities for learning and for developing clinical quality and safety measures. The findings present starting points for dialogue and feedback with clinicians to address clinician skill, bias, EHR training or EHR design factors that may influence data capture to then further develop digital audit and feedback systems, on the way to developing a learning health system.

The analysis does not indicate that any clinician is better than any other at resolving patient complaints, nor that clinicians do not enter accurate data. These determinations would require further analysis outside of the scope of this paper. In assessing clinician data to develop a learning health system, uncertainty is to be embraced, and exploration in line with existing external evidence and local knowledge is encouraged [29]. We believe, based on clinical experience managing cases within this organization, that the results are due to a mix of factors, including clinician skill, bias, and documentation habits, EHR training and design, as well as organizational and individual contextual factors.

Interpreting clinician variability

Multiple contextual factors influence the metrics presented, which will vary across systems, settings, and organizations. Managers, clinical leads, and digital health champions should use established EHR quality analysis frameworks [12, 30–32] to analyze data quality and gain a deeper understanding of a dataset's strengths and weaknesses, then assess metrics appropriate to the clinic’s goals and mission.

Organizational governance, such as institutional policies, processes, and accountabilities, significantly influences clinician documentation behaviors and therefore data quality [33]. For example, this organization's goal of eliminating pain and restoring pre-injury work capacity differs from high-performance settings, which aim to optimize athletic performance, or from student clinics, where students may prioritize patient volume to meet graduation requirements. These varying goals may influence the number of treatments required to be released from care. In each setting, interdependencies between many contextual factors, such as supervisor relationships in student clinics, can influence individual data collection and metrics [34].

Comparisons enable identification of clinician-specific performance patterns relative to peers and personal benchmarks. For example, in our analysis, the average TTR for the elbow and shoulder regions is 3.89, higher than other body regions. Average TTR for hips/upper leg is 3.2, where clinicians range from 0.2 of 5.9 TTR. Individual training strategies may be appropriate for outlier clinicians with hip and

other body-region conditions, whereas a group training strategy may be more applicable for uncovering why elbow and shoulder conditions take longer to resolve [35]. A curious mind may find remarkable insights. Potentially, outlier clinicians are better at more fully resolving patient issues, and we could learn from them.

Recurrence rates demonstrate wide variability between clinicians. As we attempted to control for workplace environment and workload variability in our study, this variation warrants further investigation and may offer clinicians an important learning opportunity. Besides clinician skill and organizational governance, patient workplace-specific factors are likely to affect clinical outcomes. For our example, factors such as access to the program and employees' ability to leave their positions on the production line may influence the treatment numbers and recurrence rates. However, from a clinical training perspective, excessive recurrences may represent clinicians addressing areas of the patient's pain yet failing to address the root cause of the patient's presenting condition, such as biomechanical considerations across the whole body. There may be consequences for patients when clinicians fail to resolve their complaints, leading to reliance on care, or when patients believe they must live with a condition that could be resolved with a different approach, as in our patient with an injured shoulder, as described in the introduction. The quality indicator mapping revealed that no quality indicator directly measures recurrence rate as an outcome, which should be further explored as a potential quality indicator.

Our results support existing findings that body-stressing mechanisms of injury take longer to recover than those with traumatic injuries in the workplace [36]. Therefore, clinicians should understand the mechanism of injury to effectively guide recovery. For example, repetitive overuse injuries likely require deep analysis of all movements and biomechanics associated with the overuse, whereas traumatic injuries may not. The data suggest clinicians effectively capture traumatic mechanisms but inconsistently document repetitive overuse, potentially affecting patient outcomes.

Obstacles to recovery represent critical prognostic data that appear challenging to capture. The consistent capture across categories between clinicians indicates that the clinician variability found (1.9–85.4%) is likely a documentation habit [37]. It cannot be assumed that, just because the obstacles are not documented, they were not inquired about with the patient in the treatment room [38]; therefore, a deeper understanding by discussing the findings with clinicians would be valuable. For example, some clinicians may avoid documenting obstacles when unsure of appropriate interventions, such as addressing psychosocial issues beyond the clinician's scope of knowledge [39, 40]. This may be a potential reason for lower recording rates of fear-avoidance beliefs than of physical dependence on treatment in our dataset. A recent UK-wide survey found that psychosocial assessment in MSK physiotherapy remains inconsistent and largely informal, with clinician confidence more closely linked to exposure to psychosocial screening tools than to years of clinical experience [41]. However, undocumented obstacles cannot be monitored throughout a care episode or used to inform personalized treatment [16]. For patients experiencing fear avoidance or poor coping, the absence of

these factors in the clinical record may reflect a missed opportunity to address the full picture of recovery limitations.

Prognosis accuracy requires a clinician to identify patient-centered factors that influence an individual patient's recovery, enabling them to develop targeted plans and goals. Clinicians demonstrated consistent over-estimation of prognosis regardless of experience level. Notably, in this organization, clinicians may tend to overestimate to ensure production managers can appropriately plan for patients' time on modified duties. Clinical and quality dashboards can improve adherence to care processes and may help improve patient outcomes [42]. Visualization of this data to clinicians may improve future performance. Notably, while existing quality indicator frameworks require clinicians to document prognosis and align treatment length with it, no validated quality indicator currently measures the accuracy of that estimate. The observed variation, independent of clinical experience, suggests that the accuracy of prognosis measurement is a candidate metric for inclusion in future MSK quality indicator development.

Building a learning profession

Research demonstrates that clinicians are at risk of overestimating their clinical performance, and there is a gap between clinicians' self-assessment and objectively measured competence [43]. This can be viewed as a critical safety issue. In the general population, despite 95% of people believing they are self-aware, only 10–15% may actually be self-aware enough to recognize specific weaknesses [44]. The overconfidence hypothesis suggests that clinician overconfidence is a major contributor to diagnostic errors [45]. These findings from the broader literature underscore the value of objective comparative data. Without it, and without an understanding of potential bias, clinicians lack essential information to identify opportunities for improvement.

Visualization of performance data, such as we have presented, is increasingly being used and researched [46]. Clinician feedback may help improve patient safety [3] with systematic reviews demonstrating that clinical audit and feedback interventions result in modest but meaningful improvements in clinical practice, particularly when clinicians can see how their own performance compares to high-performing peers, where it helps them take action on significant clinical issues and where there is considerable room for improvement [47]. The effectiveness of audit and feedback depends, however, on the organizational culture in which it operates [11]. Within the chiropractic profession, only 23% of safety research has examined clinician beliefs, values, and attitudes in safety culture, suggesting the cultural foundations for clinicians to act on performance data require further establishment [10].

The World Federation of Chiropractic explicitly calls for collecting, analyzing, and publishing high-quality, transparent safety data (21), as a strategic initiative to build professional credibility as a learning profession. Efforts will support the Patient Safety Taskforce and contribute to data repositories for the WFC Global Observatory. Whilst medical professions are moving quickly towards learning health systems and providing decision-support tools to monitor and improve patient quality and safety,

musculoskeletal professions desperately need the foundational infrastructure, such as EHRs, that enable standardized, structured data collection to move forward.

Industry reports suggest patients increasingly expect clinicians to use data to inform their decisions [48], a trend supported by emerging evidence that patients respond positively to data-informed care [49]. A patient's choice of clinician should not be the only factor influencing their care outcome; a clinician with access to objective information to inform their care plans may help achieve a certain quality of care.

Practical Implementation

Clinicians should choose appropriate practice management software that supports clinical data analytics, as clinicians are more likely to capture high-quality data when they receive value from its collection, such as through analytic tools [12]. Education and professional development must target digital health competencies, with student clinic transformation to implement EHR analytical capabilities. For the profession, work must continue to develop standardized terminology appropriate for MSK clinicians [9, 50, 51] and integrate this into existing clinical terminologies. Professional associations and must 1) develop guidance for organizations to address change management strategies required for a cultural shift towards data-driven care, 2) develop guidance for organizations governance models that promote a quality culture, 3) work together to understand mechanisms to collate clinical data, with a focus even more broadly than reactionary measurement of adverse events, toward proactive analysis of everyday clinical practice in line with Safety II principles and MSK quality indicators. The analysis should enable the profession to learn from successful outcomes, understand practice variability, and identify the conditions that enable safe, effective care across diverse clinical contexts, thereby continuously improving our outcomes.

In the digital health age, healthcare is moving towards more transparent, accountable, and data-driven care. Clinical governance must include measurement and monitoring of digital clinical data to demonstrate compliance with quality and safety indicators. As health systems look to alternative funding models such as value-based care, professions and practices demonstrating measurable value, as evidenced by quality and safety metrics, may gain competitive, partnership [52] or reputational advantages. In medicine, payers tie reimbursement to quality metrics such as readmission rates, with financial penalties for poor performance [53]. While MSK is still developing equivalent, validated quality indicators [16], the metrics derived from the clinical EHR data used in our paper may be considered candidate indicators.

Strengths and limitations

The study demonstrates that learning opportunities can be identified with clinical EHR data analysis. The methodology was possible due to structured data collection [54], digital health workforce capacity, and a value-based care model that prioritizes outcome measurement. The ability to build visualizations and dashboards of clinical EHR data provides clinical leaders and clinicians with accessible and easy-to-read feedback on outcomes without requiring advanced technical knowledge. The present study focuses on the outcome and process domains of the Donabedian quality indicator framework [17], whereas the

structural domain, encompassing organizational governance, EHR infrastructure, and clinician engagement with data quality, are not addressed in this study, yet have been addressed in our prior studies [12, 13], which outline the EHR dataset quality analysis.

The study was not designed to definitively determine whether findings reflect clinician skill, knowledge gaps, or organizational governance factors. This would require further investigation through discussion with clinicians and longitudinal monitoring to determine whether patterns change following targeted interventions. As the proof-of-concept analysis intended to identify signals for discussion rather than draw conclusions about clinician performance, descriptive statistics with confidence intervals were considered the appropriate approach. Formal comparison through inferential testing between clinicians was not undertaken, as this would imply evaluative claims about individual performance that fall outside the scope of this analysis.

The analysis was limited to a single organization operating in the food manufacturing industry in Australia, limiting generalizability to other clinical settings. The selected outcome variable of treatments to release was well-suited to this organizational context, but may not translate directly to other practice models. Finally, as with all EHR-based analyses, findings reflect documented practice rather than actual clinical behavior, and variability in data entry habits may influence results independently of the clinical patterns being examined.

Future research would implement performance analytics dashboards with targeted interventions to monitor whether data patterns change over time and create continuous improvement cycles.

Conclusions

The study demonstrates that analyzing routine EHR data can reveal clinical patterns in practice that would remain invisible to individual clinicians without access to comparative, objective metrics. Findings included variability in clinicians' treatment requirements for release from care, the accuracy of prognoses, documentation of obstacles to recovery, and mechanism-of-injury coding. The findings reflect opportunities for discussion with clinicians and for developing infrastructure for proactive performance measurement and monitoring. The findings are not a reflection of individual clinicians quality and safety performance, but rather an argument for building systems that could support clinicians in further helping their clinical and patient outcomes.

Measurement and monitoring of clinical EHR data is a step toward modelling patient safety and quality of care outcomes. This study demonstrates that structured data collection, analytical curiosity, and organizational knowledge are sufficient to generate actionable insights. Building a functioning learning health system requires governance frameworks that treat clinical data as a learning asset, transparent performance monitoring, and digital health competency as a core clinical skill, as demonstrated in this study.

Healthcare systems globally are moving toward greater transparency, accountability, and data-driven quality improvement. Health professions that invest now in the infrastructure and culture of proactive performance monitoring will be better positioned to meet that standard, to demonstrate the value of what they do in clinical practice, and ultimately to improve patient outcomes.

Declarations

Ethics approval and consent to participate

This study was approved by the RMIT University Human Research Ethics Committee (Ethics Approval #26603). As the study involved analysis of de-identified retrospective data, individual participant consent was waived in accordance with the approval conditions.

Consent for publication

Not applicable

Availability of data and materials

The data that support the findings of this study are available from the author, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Study data are, however, available from the authors upon reasonable request and with permission of Work Healthy Australia.

Competing interests

The authors Melinda Wassell, Karin Verspoor, Henry Pollard and Kerryn Butler-Henderson have no relevant financial or non-financial interests to disclose.

MW was the former Chief Health Informatics Officer and Clinical Lead at the data-generating organization for 3 years during the EHR dataset generation.

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Authors' contributions

The analysis is an original idea of MW. MW developed the study design. MW conducted the statistical analysis. The first draft of the manuscript was written by MW, which was reviewed by HP, KV and KBH. All authors read and approved the final manuscript.

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References

1. Harden RM, Stevenson M, Downie WW, Wilson GM. Assessment of clinical competence using objective structured examination. Br Med J. 1975;1(5955):447–51.
2. Pamplin J, Nemeth CP, Serio-Melvin ML, Murray SJ, Rule GT, Veinott ES, et al. Improving Clinician Decisions and Communication in Critical Care Using Novel Information Technology. Mil Med. 2020;185(1–2):e254–61.
3. Meyer AND, Upadhyay DK, Collins CA, Fitzpatrick MH, Kobylinski M, Bansal AB, et al. A Program to Provide Clinicians with Feedback on Their Diagnostic Performance in a Learning Health System. Jt Comm J Qual Patient Saf. 2021;47(2):120–6.
4. van der Bij S, Khan N, ten Veen P, de Bakker DH, Verheij RA. Improving the quality of EHR recording in primary care: a data quality feedback tool. J Am Med Inf Association: JAMIA. 2017;24(1):81–7.
5. Wise S, Hall J, Haywood P, Khana N, Hossain L, van Gool K. Paying for value: options for value-based payment reform in Australia. Aust Health Rev. 2022;46(2):129–33.
6. Leao DLL, Cremers HP, van Veghel D, Pavlova M, Groot W. The Impact of Value-Based Payment Models for Networks of Care and Transmural Care: A Systematic Literature Review. Appl Health Econ Health Policy. 2023;21(3):441–66.
7. Global regional, national burden of other musculoskeletal disorders. 1990–2020, and projections to 2050: a systematic analysis of the Global Burden of Disease Study 2021. Lancet Rheumatol. 2023;5(11):e670–82.
8. Schofield D, Kelly S, Shrestha R, Callander E, Passey M, Percival R. The impact of back problems on retirement wealth. Pain. 2012;153(1):203–10.
9. Coleman BC, Rubinstein SM, Salsbury SA, Swain M, Brown R, Pohlman KA. The World Federation of Chiropractic Global Patient Safety Task Force: a call to action. Chiropr Man Ther. 2024;32(1):15.
10. Wright DS, Kleppe M, Coleman BC, Funabashi M, Ferguson AG, Brown R, et al. Patient safety culture research within the chiropractic profession: a scoping review. Chiropr Man Th. 2025;33(1):46.
11. Hollnagel E, Wears RL, Braithwaite J. From safety-I to safety-II: a white paper. Published simultaneously by the University of Southern Denmark, University of Florida, USA, and Macquarie University, Australia: The Resilient Health Care Net; 2015. 2017.
12. Wassell M, Butler-Henderson K, Verspoor K. From Clinic to Research: Strengthening EHR Data Quality for Musculoskeletal Injury Outcomes Research. J Sci Med Sport. 2025;28:S6–7.
13. Wassell M, Murray JL, Kumar C, Verspoor K, Butler-Henderson K. Understanding Clinician EHR Data Quality for Reuse in Predictive Modelling. Stud Health Technol Inf. 2024;310:169–73.

14. Wassell M, Vitiello A, Butler-Henderson K, Verspoor K, Pollard H. Generalizability of a Musculoskeletal Therapist Electronic Health Record for Modelling Outcomes to Work-Related Musculoskeletal Disorders. J Occup Rehabil. 2025;35(1):125–38.
15. Westby MD, Klemm A, Li LC, Jones CA. Emerging Role of Quality Indicators in Physical Therapist Practice and Health Service Delivery. Phys Ther. 2016;96(1):90–100.
16. Braybrooke A, Baraks K, Burgess R, Banerjee A, Hill JC. Quality Indicators for the Primary and Community Care of Musculoskeletal Conditions: A Systematic Review. Arch Phys Med Rehabil. 2025;106(3):459–72.
17. Donabedian A. The quality of care. How can it be assessed? Jama. 1988;260(12):1743–8.
18. Johansen I, Klokkerud M, Anke A, Børke JB, Glott T, Hauglie U, et al. A quality indicator set for use in rehabilitation team care of people with rheumatic and musculoskeletal diseases; development and pilot testing. BMC Health Serv Res. 2019;19(1):265.
19. Peter WF, van der Wees PJ, Hendriks EJ, de Bie RA, Verhoef J, de Jong Z, et al. Quality indicators for physiotherapy care in hip and knee osteoarthritis: development and clinimetric properties. Musculoskelet Care. 2013;11(4):193–202.
20. Oostendorp RAB, Rutten GM, Dommerholt J, Nijhuis-van der Sanden MW, Harting J. Guideline-based development and practice test of quality indicators for physiotherapy care in patients with neck pain. J Eval Clin Pract. 2013;19(6):1044–53.
21. Dorflinger LM, Gilliam WP, Lee AW, Kerns RD. Development and application of an electronic health record information extraction tool to assess quality of pain management in primary care. Transl Behav Med. 2014;4(2):184–9.
22. Chartered Society of P. Musculoskeletal Physiotherapy Service Standards. London, United Kingdom: Chartered Society of Physiotherapy; 2022.
23. Teo PL, Hinman RS, Egerton T, Dziedzic KS, Kasza J, Bennell KL. Patient-reported quality indicators to evaluate physiotherapy care for hip and/or knee osteoarthritis: development and evaluation of the QUIPA tool. BMC Musculoskelet Disord. 2020;21(1):202.
24. Kleppe M, McCarey J, Kedilaya S, Vining R. Assessing the importance and feasibility of quality measures for chiropractic care. a national survey of U.S. chiropractors. Chiropractic & Manual Therapies; 2026.
25. Wassell M, Vitiello A, Butler-Henderson K, Verspoor K, McCann P, Pollard H. Electronic Health Records for Predicting Outcomes to Work-Related Musculoskeletal Disorders: A Scoping Review. J Cccupational Rehabilitation. 2024.
26. Hayden JA, Wilson MN, Riley RD, Iles R, Pincus T, Ogilvie R. Individual recovery expectations and prognosis of outcomes in non-specific low back pain: prognostic factor review. Cochrane Database Syst Reviews. 2019;2019:11.
27. Razmjou H, Rahnama L, Diaz S. Work status following a cervical spine injury: role of gender and psychosocial flag signs. Eur J Physiotherapy. 2022;24(5):297–303.

28. Oostendorp RA, Rutten GM, Dommerholt J, Nijhuis-van der Sanden MW, Harting J. Guideline-based development and practice test of quality indicators for physiotherapy care in patients with neck pain. J Eval Clin Pract. 2013;19(6):1044–53.
29. Friedman CP. What is unique about learning health systems? Learn Health Syst. 2022;6(3):e10328.
30. Kahn MG, Callahan TJ, Barnard J, Bauck AE, Brown J, Davidson BN, et al. A Harmonized Data Quality Assessment Terminology and Framework for the Secondary Use of Electronic Health Record Data. EGEMS (Wash DC). 2016;4(1):1244.
31. Liaw ST, Guo JGN, Ansari S, Jonnagaddala J, Godinho MA, Borelli AJ, et al. Quality assessment of real-world data repositories across the data life cycle: A literature review. J Am Med Inf Assoc. 2021;28(7):1591–9.
32. Wassell MB-H, Verspoor K. K. A Framework for Transparent Reporting of Data Quality Analysis Across the Clinical Electronic Health Record Data Lifecycle. Preprint arXiv 260300921 (csDB) 2026.
33. Wassell M, Butler-Henderson K, Verspoor K. Clinician Engagement and Lifecycle Reporting to Advance Data Quality for EHR Data Reuse (Under Review). BMJ Health Care Inf. 2025.
34. Sebok-Syer SS, Small WR, Lingard L, Glober NK, George BC, Burk-Rafel J. Leveraging Electronic Health Record Data and Measuring Interdependence in the Era of Precision Education and Assessment. Acad Med. 2024;99(4S):S48–56.
35. Tomson CR, van der Veer SN. Learning from practice variation to improve the quality of care. Clin Med (Lond). 2013;13(1):19–23.
36. Xiang J, Mittinty M, Tong MX, Pisaniello D, Bi P. Characterising the Burden of Work-Related Injuries in South Australia: A 15-Year Data Analysis. Int J Environ Res Public Health. 2020;17(6):2015.
37. Cohen GR, Friedman CP, Ryan AM, Richardson CR, Adler-Milstein J. Variation in Physicians' Electronic Health Record Documentation and Potential Patient Harm from That Variation. J Gen Intern Med. 2019;34(11):2355–67.
38. Soto CM, Kleinman KP, Simon SR. Quality and correlates of medical record documentation in the ambulatory care setting. BMC Health Serv Res. 2002;2(1):22.
39. Henning M, Smith M. The ability of physiotherapists to identify psychosocial factors in patients with musculoskeletal pain: A scoping review. Musculoskelet Care. 2023;21(2):502–15.
40. Singla M, Jones M, Edwards I, Kumar S. Physiotherapists' assessment of patients' psychosocial status: are we standing on thin ice? A qualitative descriptive study. Man Ther. 2015;20(2):328–34.
41. Henning M, Palmer S, Walsh N. Psychosocial assessment in musculoskeletal care: A survey of UK physiotherapists. Musculoskelet Sci Pract. 2026;82:103485.
42. Dowding D, Randell R, Gardner P, Fitzpatrick G, Dykes P, Favela J, et al. Dashboards for improving patient care: review of the literature. Int J Med Inf. 2015;84(2):87–100.
43. Davis DA, Mazmanian PE, Fordis M, Van Harrison R, Thorpe KE, Perrier L. Accuracy of physician self-assessment compared with observed measures of competence: a systematic review. JAMA. 2006;296(9):1094–102.

44. Eurich T. What Self-Awareness Really Is (and How to Cultivate It). Harv Bus Rev Digit Articles. 2018:1–9.
45. Cassam Q. Diagnostic error, overconfidence and self-knowledge. Palgrave Commun. 2017;3(1):17025.
46. Yang Z, Alveyn E, Dey M, Arumalla N, Russell MD, Norton S, et al. Impact of visualising healthcare quality performance: a systematic review. BMJ Open. 2024;14(11):e083620.
47. Ivers N, Yogasingam S, Lacroix M, Brown KA, Antony J, Soobiah C, et al. Audit and feedback: effects on professional practice. Cochrane Database Syst Rev. 2025;3(3):Cd000259.
48. HIMSS. The Future of Healthcare Report. 2022.
49. Stern BZ, Pila S, Joseph LI, Rothrock NE, Franklin PD. Patients' perspectives on the benefits of feedback on patient-reported outcome measures in a web-based personalized decision report for hip and knee osteoarthritis. BMC Musculoskelet Disord. 2022;23(1):806.
50. Funabashi M, Gorrell LM, Pohlman KA, Bergna A, Heneghan NR. Defining and classifying adverse events following joint manipulation and mobilization: An international e-Delphi study and focus groups. PLoS ONE. 2025;20(11):e0334151.
51. Wassell M, Butler-Henderson K, McCann P, Pollard H, Arabi S, Wang W, et al. The state of standardized musculoskeletal terminology for healthcare reuse:A scoping review. Int J Med Informatics. 2026;211:106318.
52. Teisberg E, Wallace S, O'Hara S. Defining and Implementing Value-Based Health Care: A Strategic Framework. Acad Med. 2020;95(5):682–5.
53. Yu ZAGM. Pay-for-Performance and Value-Based Care. Treasure Island (FL): StatPearls Publishing[Updated 2024 May 2].
54. Vuokko R, Mäkelä-Bengs P, Hyppönen H, Lindqvist M, Doupi P. Impacts of structuring the electronic health record: Results of a systematic literature review from the perspective of secondary use of patient data. Int J Med Inf. 2017;97:293–303.

Figures

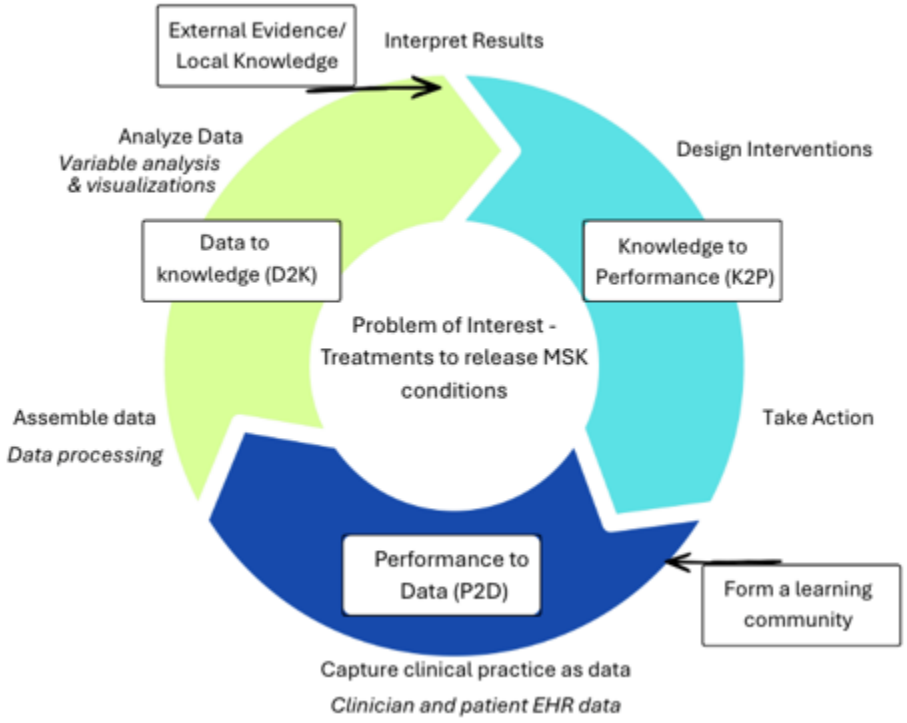
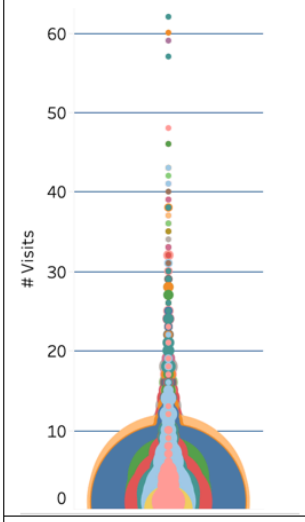


Figure 1

Methodology mapped to Friedman Learning Health System Cycle

Adapted from Friedman CP (2022). What is unique about learning health systems? Learn Health Syst. 6(3):e10328.

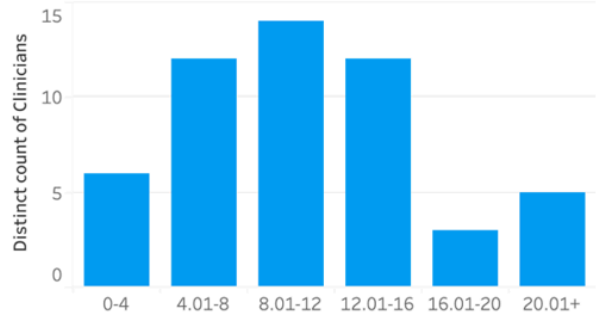
Italics represents stages of study methodology mapped to learning health system phases

Range of VTR	Body Region	N (%)	Clinician Range TTR (n)	Mean (95%CI)
	Head & neck	8,526 (18.32%)	0.70(33) – 5.42(127)	3.33 (3.26–3.39)
	Shoulder & upper arm	8,197 (17.61%)	0.36(11) – 6.37(51)	3.89 (3.80–3.97)
	Elbow & lower arm	10,771 (23.14%)	1.94(17) – 6.52(65)	3.89 (3.82–3.96)
	Upper back & chest	5,229 (11.24%)	1.14(22) – 5.38(40)	2.92 (2.85–2.99)
	Low back & pelvis	7,973 (17.13%)	0.85(20) – 4.37(130)	3.24 (3.17–3.31)
	Hips & upper leg	1,683 (3.62%)	2.15(102) – 5.93(14)	3.16 (3.02–3.30)
	Knee & lower leg	4,155 (8.93%)	0.24(17) – 5.03(32)	3.24 (3.15–3.34)
Colour is clinician, size is # records. #	All body regions	46534* (100%)	1.02 (132) – 5.16 (305)	3.43 (3.23-3.63)

One outlier removed from graph for anonymity
*5 records missing body region

Figure 2

Clinicians' treatments to release by body region



Reopened care plans	Total number of patient visits*	N care plans reopened (%)	Clinician Range	Av (95% CI)
Reopened care plans	166377	5312 (11.41%)	1.52-23.89%	10.53 (8.90-12.16)

Clinicians are grouped on x axis by % of reopened care plans to demonstrate range of reopen care plans between clinicians

Figure 3

Reopened care plans (% by clinician)

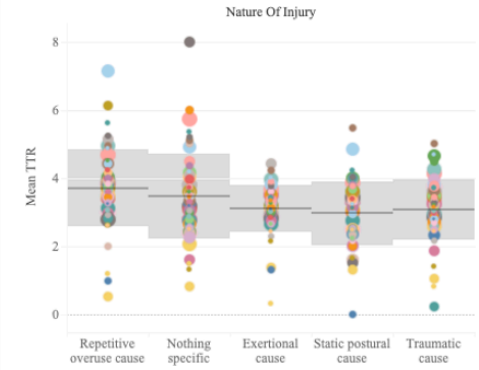
Mechanism of injury variation by clinician*	Subvariable	n	Mean Usage (95% CI)	Clinician Usage Range (n)	Mean TTR (95% CI)
	Repetitive overuse	18,889 (40.6%)	40.89% (34.81–46.97%)	2.55%(56) – 84.21%(96)	3.69(3.64–3.74)
	Exertional cause	10,596 (22.8%)	26.23% (21.80–30.65%)	8.63%(67) – 80.71%(113)	3.29(3.23–3.35)
	Nothing specific	8,627 (18.5%)	15.40% (11.32–19.49%)	1.66%(32) – 50.82%(155)	3.51(3.43–3.58)
	Static/ Postural	4,937 (10.6%)	9.98% (7.93–12.03%)	2.54%(74) – 29.12%(129)	3.26(3.18–3.34)
Clinician is colour and circle size is # records	Traumatic cause	3,490 (7.5%)	7.50% (6.76–8.24%)	4.34%(49) – 15.91%(21)	3.18(3.08–3.29)

Figure 4

Mechanism of Injury

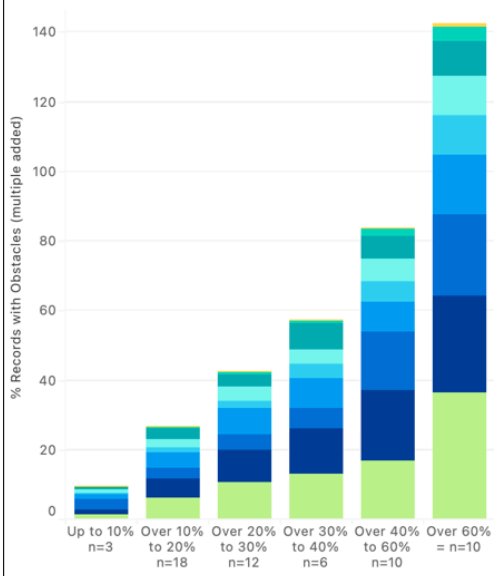
Obstacles recorded for complaints by clinician groups	Key	Obstacle category	n (%) care plans with obstacles	Clinician range % care plans	Mean TTR (95% CI)
		Medical History	5,683 (12.21%)	0.0%(364) – 58.42%(1294)	5.27 (5.14–5.40)
		Physical	5,385 (11.57%)	0.0%(364) – 49.86%(728)	5.32 (5.18–5.46)
		Compliance & Communication	3,628 (7.80%)	0.0%(114) – 41.88%(967)	5.44 (5.28–5.60)
		Psychosocial	3,384 (7.27%)	0.0%(269) – 20.40%(1294)	5.74 (5.56–5.92)
		Workplace	2,219 (4.77%)	0.0%(269) – 12.13%(1294)	6.07 (5.84–6.30)
		Injury	2,022 (4.34%)	0.0%(364) – 24.16%(149)	5.80 (5.54–6.06)
		Job	1,604 (3.45%)	0.0%(364) – 23.4%(1423)	5.43 (5.17–5.69)
		Health	564 (1.21%)	0.0%(189) – 8.81%(1,294)	5.90 (5.46–6.34)
		Outside Work Physical Activity	79 (0.17%)	0.0%(967) – 2.81%(1423)	3.70 (3.04–4.36)
		Any obstacle	14,029 (30.14%)	1.86%(269) – 85.39%(1294)	4.87 (4.80–4.94)

Figure 5

Obstacles to Recovery

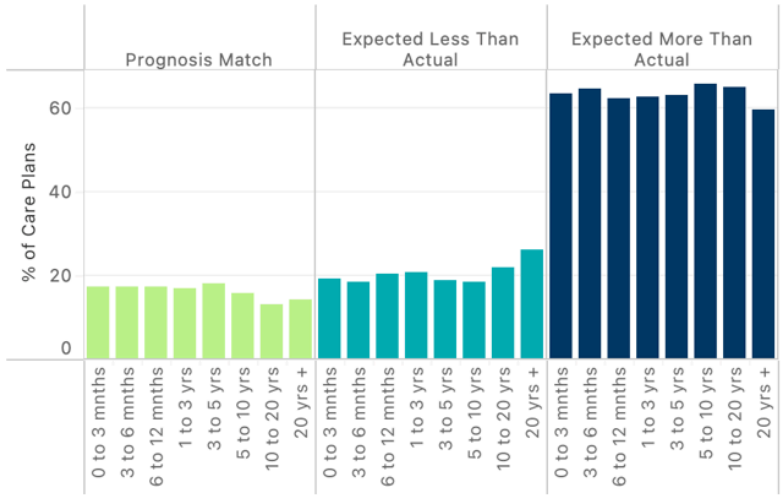
Prognosis accuracy by length of employment	Prognosis	Clinician Range %	Mean (95% CI)
	Match	4.29 - 28.51	16.89 (16.55-17.23)
	Expected less than actual	7.02-32.45	19.75 (19.39-20.11%)
	Expected more than actual	41.89-88.60	63.36(62.92-63.79)

Figure 6

Prognosis accuracy for clinicians' estimation of treatments required to release them from care.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterial1MapToQualityIndicatorsa.pdf
- STROBERECORDChecklistIdentifyingQSLearningOpportunities.docx
- ChiropracticManualTherapiesManuscriptChecklist.docx