Learning from the Adoption of a Readmissions Clinical Decision Support Tool: A Group Model Building Approach

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Abstract

Background: Computerized clinical decision support (CDS) can improve care, reduce unwanted variations, and lower overall healthcare costs. Prior work has identified factors that affect adoption, such as clinicians' expectations of usefulness. Because CDS function within a complex system of behaviors and workflows that change over time, there is a need to additionally understand how these dynamics lead to successful implementation; this information can be used to develop strategies to improve adoption and clinical outcomes.

Objective: To understand the dynamic factors that affect CDS adoption, we developed a study to explore a single use case, the implementation of "Unplanned readmission model version 1", developed by Epic Medical Records System, at Duke University Health System (DUHS) using system dynamics modeling.

Methods: We conducted group model building workshops with case managers, medical doctors, physical and occupational therapists, and staff who participate in decisions about discharging patients. Facilitators guided participants to identify and connect variables in causal loop diagrams. We coded workshop transcripts in DynamicVu software to identify themes, aggregated them into a single casual loop diagram, and reviewed with participants to converge on a common model. Simulation of the loops identified conditions leading to full, limited, or no adoption of a tool.

Results: We identified key balancing loops around responses to external pressure that drive initial adoption and reinforcing loops around internal perceived benefits that sustain the effort. The simulation model clarified conditions under which the balancing loops would only lead to limited long-term tool adoption, and situations in which the reinforcing loops will lead to more complete and sustained adoption.

Conclusions: External pressure to improve can be a strong motivator for initial adoption, but in the face of conflicting demands for attention, it can fall short of sustained long-term tool use. Tools are more likely to have extensive and sustained use when those using the tools are able to perceive internal benefits.

Keywords (3-10): Clinical Informatics, Implementation Science, Risk Prediction, Clinical Decision Support Tools

Introduction

Background:

Computerized clinical decision support (CDS) tools, health IT systems that deliver patient-specific recommendations during clinical workflows, have the potential to transform healthcare delivery. They provide clinicians with real-time, evidence-based guidance at the point of care, ultimately leading to better patient outcomes and can also predict future resource needs based on patient data and trends, allowing healthcare organizations to plan and allocate resources efficiently. [1–4] A targeted literature review published in the Interactive Journal of Medical Research found that clinical decision support systems positively impacted quality assurance in 69% of the studies analyzed and provided clinical benefits in 41% compared to usual care.[5] Quality assurance was supported through improved adherence to clinical guidelines, better diagnostic support, monitoring practices, and improved screening and treatments. Clinical benefits included improved diagnosis accuracy, clinical decision-making, and treatment selection. The effectiveness of CDS tools is closely linked to successful adoption at the bedside.

Understanding the factors that influence clinicians' adoption of CDS tools is essential for designing effective implementation strategies. The Unified Theory of Acceptance and Use of Technology (UTAUT), developed in 2003, has identified four key concepts theorized to influence new information technology adoption: performance expectancy (belief that using the system will help one improve job performance), effort expectancy (ease associated with the system including individual perceptions and design features), social influence (perceived social pressure to use the system), and facilitating conditions (perceived organizational and technical support for system use) [6]. Lui et al. (2021) found that effort expectancy and performance expectancy were significant predictors of CDS adoption, and that these beliefs depended on individuals having autonomy and agency [7]. A meta-analysis that examined predictors of healthcare practitioners' intention to use AI-enabled CDS through the lens of the UTAUT also found that the UTAUT concepts predicted intention to use AI-enabled CDS, and that facilitating conditions had an effect on performance and effort expectancy [8]. A recent study by Wang et al. (2025) demonstrated the importance of top management support, in which senior administrators recognize the importance of the information system and are actively engaged in its implementation, for adoption by positively shaping not only performance and effort expectancies but also social influence [13]. Other work has shown that clinicians will more likely adopt tools that they view as accurate and useful when they integrate with existing workflows and have resources available to act on the risk scores [9,10]. Conversely, tools perceived as irrelevant and interruptive to workflows have led to "alert fatigue" and low utilization rates [11,12]. Because CDS function within a complex system of behaviors and workflows that change over time, there is a need to understand how these dynamics lead to successful implementation are important for strategies to improve adoption and clinical outcomes.

To understand the complexity of factors that affect adoption, we developed a study to explore facilitators and barriers in the adoption of a single use case, the implementation of "Unplanned readmission model version 1", developed by Epic Medical Records System, at Duke University Health System (DUHS) using system dynamics modeling[14]. Readmissions have been identified as an essential quality indicator, and have been linked to institutional financial incentives through the Centers for Medicaid and Medicare (CMS) Hospital Readmission Reduction Program (HRRP).[15,16] Due to the significant impact on patients and institutional stakeholders, many readmission risk scores have been developed to target high-risk patients with an improved discharge process.[17,18] We engaged interest holders in developing a system dynamics model by conducting group-based modeling sessions with health system staff actively involved in the discharge process: case managers, physical and occupational therapists, and medical doctors. Through these sessions, we aimed to uncover factors that inhibit or promote use of the readmission risk score and identify potential solutions to enhance its adoption and effectiveness. After completing the workshops, we built a mathematical model to explore the logic captured in the causal loop diagram. The model provides a chance to see if the loops can create the behaviors reported in the workshops and under what conditions they may create other, not yet observed, behaviors.

Methods

Setting:

In 2017, Duke Health implemented Epic's "Unplanned readmission model version 1" (hereafter referred to as the Epic readmission risk score) in response to the need to reduce unplanned readmissions. CMS considers readmissions a key quality indicator and thus has implemented the Hospital Readmissions Reduction Program to provide financial incentives to institutions to reduce their readmission rate.[16] Duke University Hospital (DUH) is a full-service tertiary and quaternary care hospital located in Durham, North Carolina. As a tertiary hospital, it provides specialized medical care, including advanced diagnostic services, treatments, and surgical procedures across various specialties such as cardiology, neurology, oncology, and organ transplants. The hospital serves a diverse patient population from Durham County, Wake County, and surrounding areas in North Carolina.

At a hospital like DUH, with almost 1,200 beds and an average of more than 100 discharges a day, it would be impossible and unnecessary to apply all discharge resources to every patient. Hospitals like DUH need to stratify their time and resources based on patients who have the highest risk of being readmitted. The Epic readmission risk score was introduced at DUHS in November of 2017 to proactively identify patients at high risk of readmission and implement targeted interventions to reduce readmission rates.[14] This CDS tool analyzes Epic's electronic health record (EHR) data to generate a readmission risk score, ranging from 0 to 100, along with corresponding color codes: red for high risk, yellow for medium risk, and green for low risk. Predictors such as patient age, laboratory variables, clinical diagnosis variables, medication numbers and classes, order types, and utilization variables are used to populate the score. This score and color code are then displayed within the patient's electronic health record, allowing clinicians to make informed decisions about post-discharge care and follow-up. Figure 1 shows the proposed integration into clinical workflows with multidisciplinary review at discharge and the implementation of close follow up and additional services upon discharge.

Project Design:

To explore adoption in this setting, we used group model building. This process engages stakeholders in developing a system dynamics model, with different groups of clinicians involved in the discharge process. These clinicians included case managers, physical and occupational therapists, and medical doctors. The workshops aimed to understand the factors influencing the uptake and sustained use of these tools. In each session, the team facilitated the production of a causal loop diagram meant to represent the utilization of the Epic readmission risk score at the hospital, from the participants' perspectives.

A final review session was conducted with a few members of each group, along with the chief medical officer at DUH, who led the initial implementation of the tool in 2017. Before the sessions, a script was created detailing the intended agenda of the workshops. The team adopted a process for variable elicitation from Scriptapedia, a handbook of scripts for developing structured group model building sessions [19,20]. In this structure of group modeling, there are facilitators who lead the discussion, a "wall builder" who constructs the causal loop diagram and a recorder who takes notes and documents important themes. Facilitators first introduced themselves and the problem of declining use of the risk score, as well as set objectives and goals for the workshop. Participants were prompted by facilitators to discuss their experiences, or lack of experience, with the tool, as well as describe their role in the discharge process. During the workshop, the "wall builder" wrote down key variables and relationships and then worked with the group to organize them into a causal loop diagram. These workshops were transcribed, and then the transcriptions were coded for key variables and causal links. These key variables and causal links were then used to construct a causal loop diagram, which was subsequently converted into a mathematical simulation model to assess internal validity.

Results

As we explored one tool, we developed a set of dynamic hypotheses based on workshop participant insights. We performed three workshops with small groups of participants from three specialties: social work, physical and occupational therapy, and medicine and surgical resident physicians. A final review session was held with members from all groups, as well as the chief medical officer who initially led the implementation of the tool. The analysis revealed three key themes that explain dynamics observed in the organization's efforts to lower the readmission rate. The three themes included institutional level learning and reinforcement, individual level learning and reinforcement, and training and support of a champion (Figure 2).

Organizational Response to Lower Readmission Rates

The first feedback loop identified was the organization's response to the external desire to lower the readmission rate ("Institutional Incentives" loop). This initiative to implement the Epic unplanned readmission score, driven by the institution's general concern for reducing readmissions, began prior to these modeling workshops. The initial adoption of the readmission risk tool occurred when an individual champion encouraged staff via training programs to use the tool. The hope was that training in this tool would lead to more use and thus better discharge plans for patients with a high risk of 30-day readmission. The initial push for tool use led to more training and awareness.

Our workshops led us to believe that while some staff still use the tool, many are unaware of its presence or capabilities, with use generally falling off over time rather than becoming widespread. We explored with staff potential explanations for lack of widespread awareness and use of the tool, resulting in a balancing feedback loop, in which initial training that aimed to equip staff with the necessary skills to achieve the desired outcomes dropped off and other circumstances distracted attention away from continued training and use. We heard several reasons why training may have fallen. These included normal turnover and events such as the COVID-19 pandemic that placed other constraints on training. Additional changes, including arguably positive ones, changed the workflow by incorporating alternative practices and tools that may have been inspired by and substituted for the tool. The case managers described how the pilot program to introduce the score had changed their behavior, by providing a visual cue to collect more information for specific patients indicated as "high risk" for readmission with a red alert; however, once they understood the criteria associated with a red alert, those characteristics instead served as the cues. For example, one case manager said:

> "I think that the dots started out like great in the beginning because it was the startup of a new system. So, it was like, hey, this is your visual to know that we have to do something. And maybe now we lost part of that visual because now we know what we're looking for. Practice had changed since the introduction of the score to collect additional information for patients flagged as "high risk" for readmission. We just knew when we saw the [score] ...that was going to be extra support for them in the community and then we knew when we asked the questionnaire is that that was going to be like oh well, maybe we need to tell the provider like this patient doesn't have insurance so they can't get their medication. So now we know. Oh, the patient doesn't have insurance. They're going to have barriers to get in their beds. What can we do to put that into place? Right. And it just became part of our workflow of knowing in our assessment, like of room to assess more in depth, right, if that makes sense. It gave us the tools to then ask more in depth questions, but then that became part of our assessment process."

This organizational level balancing loop indicates that over time, as the readmission rate reaches a certain threshold, the institutional interest, driven by external pressure from the CMS penalty, will eventually drop.[16] The level of institutional interest, in turn, would affect individual staff's interest in using the score. For example, staff most directly involved in discharge, such as the general medicine doctors who treat hospitalized patients, may obtain financial incentives to reduce readmission because of an institutional push to use the score. As one medical doctor said, "… incentives reinforce the overarching goal of our institution to reduce readmission rate..."

Reinforcement through Perceived Benefits

Over the long term, however, as the initiative transitions from the initial training phase to broader institutionalization, the efforts of these champions may be partly or wholly replaced by individual or organizational learning processes that reinforce tool use. See “Individual Motivation” and “Team Use” loops that are reinforcing. These feedback loops emerged from the hope that staff would recognize the benefits of the training and the resulting improvements in readmission rates.

At both the individual and team levels, reinforcement can come from staff using the tools, observing the tool's appropriateness for their work, and becoming more committed to its use. Staff said that they would value the data generated from the score if it contained information that would affect their decisions in real time. One medical doctor said, "The only scores that we have time to spend on in medicine when we're running around 8000 times a day are the ones that directly affect our decision making in that exact moment." They would then incorporate the information into the discussion during multidisciplinary rounds, which aligns with institutional interests. One case manager described a push for bringing multi-disciplinary teams together at the same time as the introduction of the readmission risk tool: “There's been a push for pulling the multidisciplinary team together to improve communication. So, there's been lots of work all happening at the same time, and then we've got the hospital care hub... part of the interdisciplinary ... case reviews and rounds.”

These reinforcing loops were based on the expectation that visible positive outcomes would motivate continued engagement and institutionalization of the practices introduced during the training. A medical doctor said, “If the institution is saying we need to reduce readmissions at the end, I'm going to do everything I can to reduce readmissions if I'm incentivized to do so…If using this helps, then I will keep using. So then that gets into clinical utility.” A physical therapist suggested a similar sentiment, saying that their use would depend on evidence that the score had clinical utility for the kinds of factors that they assess to prevent discharge. For example, “I think it would be helpful if we knew a little bit more about … what's contributing to the score and if there's any… factors…that relate back to discharge...”

Risk for reinforcement

We additionally recognized areas of risk that could prevent this reinforcement from taking over. In our setting, the reinforcing loops could be weak and thus unable to sustain the program at a high level. The "Individual Motivation" loop may be weak because readmission is a rare event, so team members are unlikely to see the immediate impact of their action by seeing fewer readmissions. In addition, the clear causal connection between the recommended interventions and the intended outcome may be difficult to see in real time. Therefore, the natural reinforcing loops are weak and external reinforcement through training and awareness campaigns are required. However, the ongoing work of champions and reinforcement can be disrupted in various ways, leading to a decline in tool awareness and use over time. As people change roles and take on new tasks, the ongoing active support of champions is likely to diminish, leading to a drop in training and awareness, especially as other changes crowd out efforts to support the use of the tool. Reinforcement relies on individuals being able to observe the tool's value in their work or at higher administrative levels, recognizing the value of the tool and creating incentives. One medical doctor described how awareness of a tool would decline over time if perceived as inappropriate for their workflow and not easily integrated into the work of new team members: "... that institutional knowledge you have to maintain over those cycles. And that means that it has to be, like directly applicable, because I'm helping set up my interns who will then help set up someone for another four years, right. So, if like, if I don't know about it now, then no one... [will] four years from now."

Additionally, participants expressed difficulty observing the tool's value at an individual level for low-probability events (re-admission is a relatively low probability event, making it harder to see the tool's signal). Resistance to broader changes in the workflow for how decisions are made could also impede use of the tool. For example, participants observed barriers while the institution encouraged moving to a more consultative, multi-disciplinary group process. As one medical doctor said, "I think one thing is hierarchical decision making is a barrier in the sense that like if the case managers or the residents are the target utilizers for the tool, but we're not the primary stakeholders in decision making, then it's …

kind of futile like I, I guess to make it very concrete. It may be difficult for individuals or organizations to recognize the value of the tools, and it may be challenging to find ways to ensure continued use."

Internal validity test with simulation modeling

A mathematical simulation model was developed from the initial causal relationships (Figure 3; see Supplemental Figure for equations). The primary objective in building the mathematical model was to hold as close as possible to the causal-loop diagram. To that end, the equations leverage the simplest possible 'accounting' or probabilistic logic wherever possible. As an example of an 'accounting' logic, "Awareness" is modeled as the "Number of Trained Individuals" with that number increasing when people are trained and falling when trained staff depart. As an example of probabilistic logic, the "Likelihood of Red Alert Use" is modeled as the fraction of people involved in discharges who are trained (the Number of Trained Individuals divided by the Number of People Involved in Discharges) multiplied by the fraction of discharges trained individuals pay attention to the score. The product of these two variables should capture the fraction of people involved in each discharge who are both trained to use the score and are looking at the score.

The "Readmission Avoidance Rate" is central to the model, which captures the reduction in readmissions. This equation leverages probabilistic logic. The "Readmission Avoidance Rate" is the product of three things, the "Likelihood of Red Alert Use", the "Fraction of Discharges with Red Alerts", and the "Effectiveness of Score Use." In the best possible case, three things are true. First, every red alert is given full attention (the Likelihood of Red Alert Use equals 1). Second, everyone and only those who would later be readmitted is given a red alert (the Fraction of Discharges with Red Alerts equals the Normal Discharge Rate with no false positives). Third, attention to the score leads to interventions that are entirely effective in avoiding readmission (the Effectiveness of Score Use is equal to 1). If these things are true, the "Readmission Avoidance Rate" will equal the "Normal Readmission Rate" and readmissions will drop to zero.

Understanding this logic around avoiding readmissions takes us most of the way to understanding how the model captures two key balancing loops emerging from the workshops. The first loop is the Training loop and the second is the Institutional Attention loop. The Training and Institutional Attention loops are strong initially, when Readmissions are high enough to drive Institutional Interest in the Score, leading to training and individual attention to the score. The Training loop is a balancing loop because if training is successful, use of the tool will lead to readmissions and thus the penalty to fall, causing a drop in the institutional interest, and with it training. The Institutional Attention loop is balancing with a similar logic, except rather than the reduced readmission rate leading to a fall in training, it leads to a fall in individual interest in the score.

We grounded the connection between the readmission rate and institutional interest in the score using the CMS "Excess Readmission Rate Penalty." When institutional readmission rates exceed the CMS goal, the CMS payments to institutions fall, driving institutional interest in tools (in this case the score) that can lower the rate to be below the CMS Goal for the Readmission Rate. For simplicity, we've assumed that this penalty depends on the fractional amount by which the institution's readmission rate exceeds the CMS goal. (footnote: This is both a simplified calculation of the CMS penalty and a change in wording from the CMS original word 'score' to 'penalty' to avoid using the word 'score' for multiple different ideas in the model).

We can see the behavior of these two balancing loops in a run of the model (Figure 4) set so that these are strong loops, and the other (reinforcing) loops are weak. Here, training is quick (all untrained people are trained within one month), and turnover is low (only 1% per month), so the number of qualified individuals can rise quickly and, if so, stay high. Red alerts are set to match the regular readmission rate with no false positives, so attention to the score always leads to avoiding readmission. In addition, we have assumed the institution has little need to address conflicting priorities. With this favorable set of parameters, the high initial readmission rate relative to the CMS Goal leads to high institutional interest that drives training and individual interest in the score. With trained people using the score regularly, the readmission rate falls rapidly. The number of qualified individuals never quite rises to equal the number of individuals involved in discharges because of the delay in training as staff depart.

Additionally, institutional and individual interest in the score falls as the readmission rate gets closer to the CMS goal. While we see a highly successful introduction of the tools with widespread and effective use, external pressure can only drive the effort so far. As the institution gets better, we can expect balancing loops to stop short of complete success because the organization relies on some continued external pressure (provided by high readmission rates) to sustain interest.

As is likely apparent from the discussion above, many things could limit the effectiveness of these two balancing loops. A second run (Figure 5) shows one of these affecting both loops. Imagine a setting where the institution faces substantially higher conflicting priorities such as a pandemic or a stronger focus on reducing length of stay. As the readmission rate falls, institutional interest drops sooner due to conflicting priorities, leading to less training and less individual interest in the score. While still successful, the program results in fewer people trained and a more minor reduction in readmissions. The shortfall is even more significant because the organization relies on continued pressure (provided by even higher readmission rates) to sustain interest.

Having set the parameters (notably raised the attention to conflicting priorities) so that the balancing loops alone lead to limited success, we then explore conditions under which the reinforcing loops could take over and drive more significant use of the tool and improvement in the readmission rate (Figure 6). The main change in this run is to reduce the Required Evidence, which is how many discharged patients each month must avoid readmission for individuals and groups involved in discharges to perceive tool success. In this case, the readmission rate falls below the CMS goal, causing a drop in institutional interest. Despite the loss of external pressure from CMS, the program continues to be driven by the excitement generated internally from perceived tool success. Institutional interest is even lower than before, and thus so is training, though it is buoyed by internal pressure from use on rounds. Still, individual interest is far higher, which offsets the drop in training.

Discussion

The Causal Loop Diagram represents hypotheses that came from workshops about adoption of a readmission risk prediction tool. The analysis of these feedback loops provided insights into the organizational dynamics and the factors influencing the success and sustainability of the initiative to lower readmission rates. The findings motivated the development of a mathematical model to explore the logic of these loops in greater depth.

The balancing loops identified during the workshops highlighted challenges in maintaining the momentum of training and the need for ongoing reinforcement to achieve the desired reduction in readmission rates. Eagerness to reduce readmission rates to meet an external goal can only take adoption so far. While we would hope that loops based on an external goal would close the gap entirely, as the gap falls it will lead to less effort as well. Depending on how quickly the effort falls with the gap, as it might do rapidly in the face of strong external pressure for attention elsewhere, effort may fall too low before the gap is closed, and the tool may be used to far less than its potential.

For sustained success, we believe the implementation of the readmission risk score requires additional input. The workshops provided indications that these additional inputs, in the form of reinforcing loops, would likely come from individuals across a number of disciplines perceiving internal benefits from the tool. If these internal reinforcing loops are strong, the process is likely to sustain itself without additional training or input from the tool developer. There is a risk of relying too heavily on the education of clinical team members and getting them to incorporate it into their own workflow. If the reinforcing loops are not strong, input could also come from the use of a champion who would function as an integral control to monitor the goal-performance gap and remind staff to use the tool. The key lesson then is that widespread and sustained adoption is far more likely if those who use the tool are able to see a positive impact in daily practice on patient care decisions and outcomes.

While we looked at one specific outcome of CDS tool use, where there remains uncertainty about the widespread adoption of the tool into clinical workflow, the workshops and modeling point to the potential for a range of different outcomes in different settings. The drop in adoption of this specific score likely relates to the rare nature of the event, as there is limited real-world experience of the impact of the risk model on day-to-day experiences, combined with the decrease in active training and promotion due to competing priorities with a COVID-19 pandemic and an additional focus on length of stay. Understanding the implementation of these risk algorithms in a dynamic system will help developers iterate and improve implementation moving forward. Further research is planned to test the model predictions against a wider range of cases and settings, calibrate the model to test for external validity of the arguments, and refine the lessons.

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Figure 1: Workflow for integration of Epic Readmission Risk Score into clinical workflows used during training and the initial implementation.

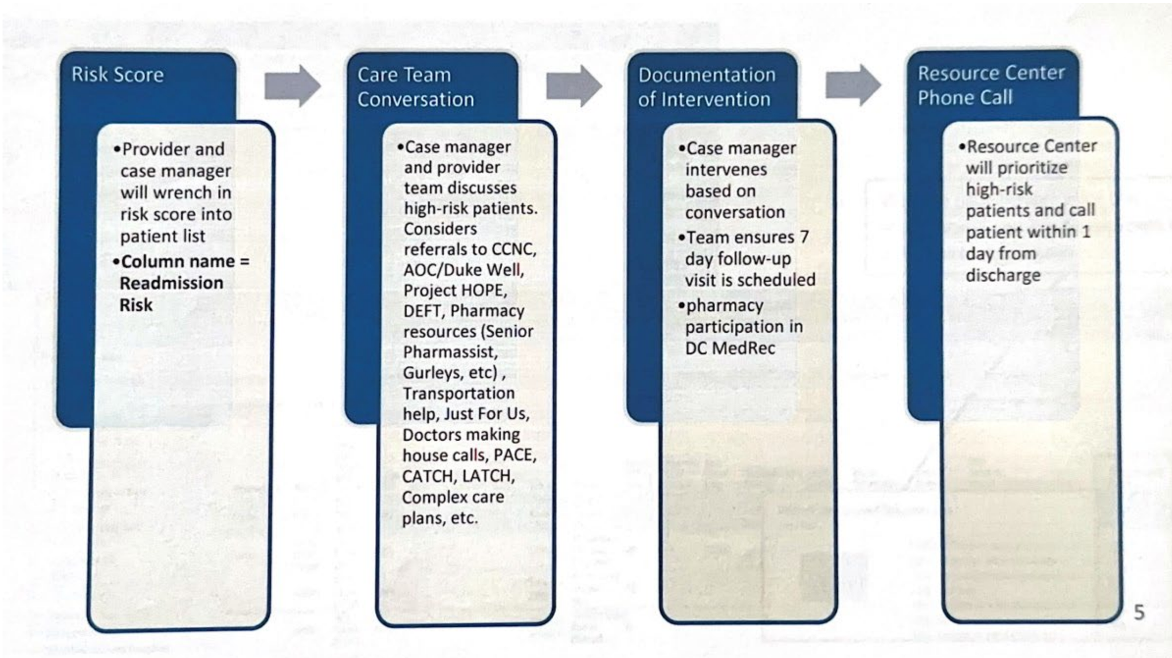


Figure 2. Simplified Causal Loop Diagram developed from the workshops directly.

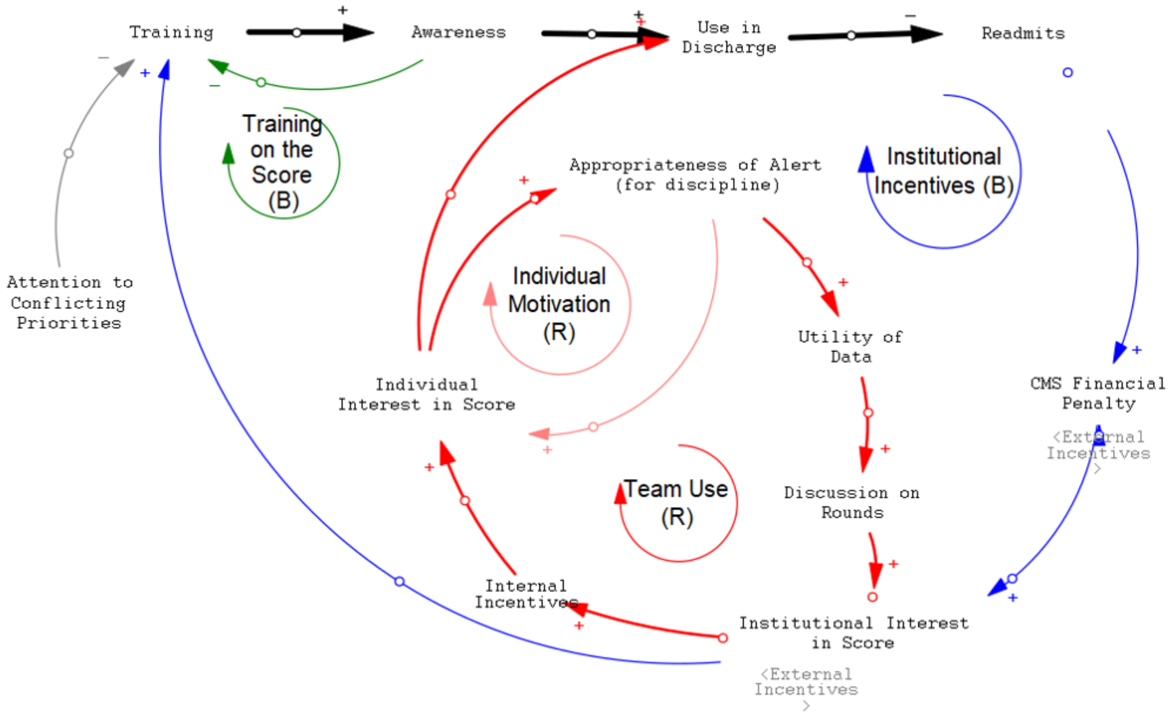


Figure 3: Simulation Model derived from the Causal Loop Diagram

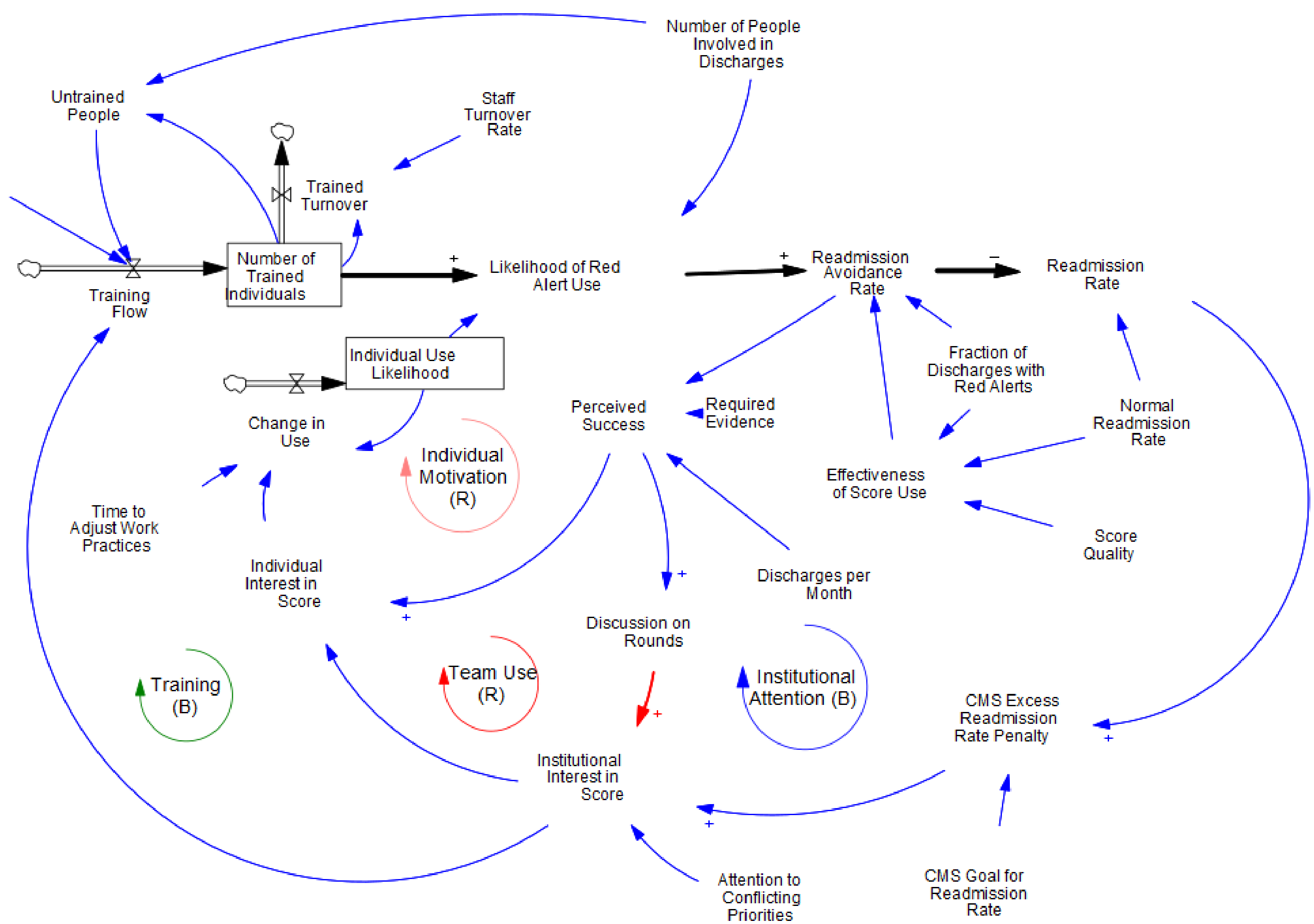


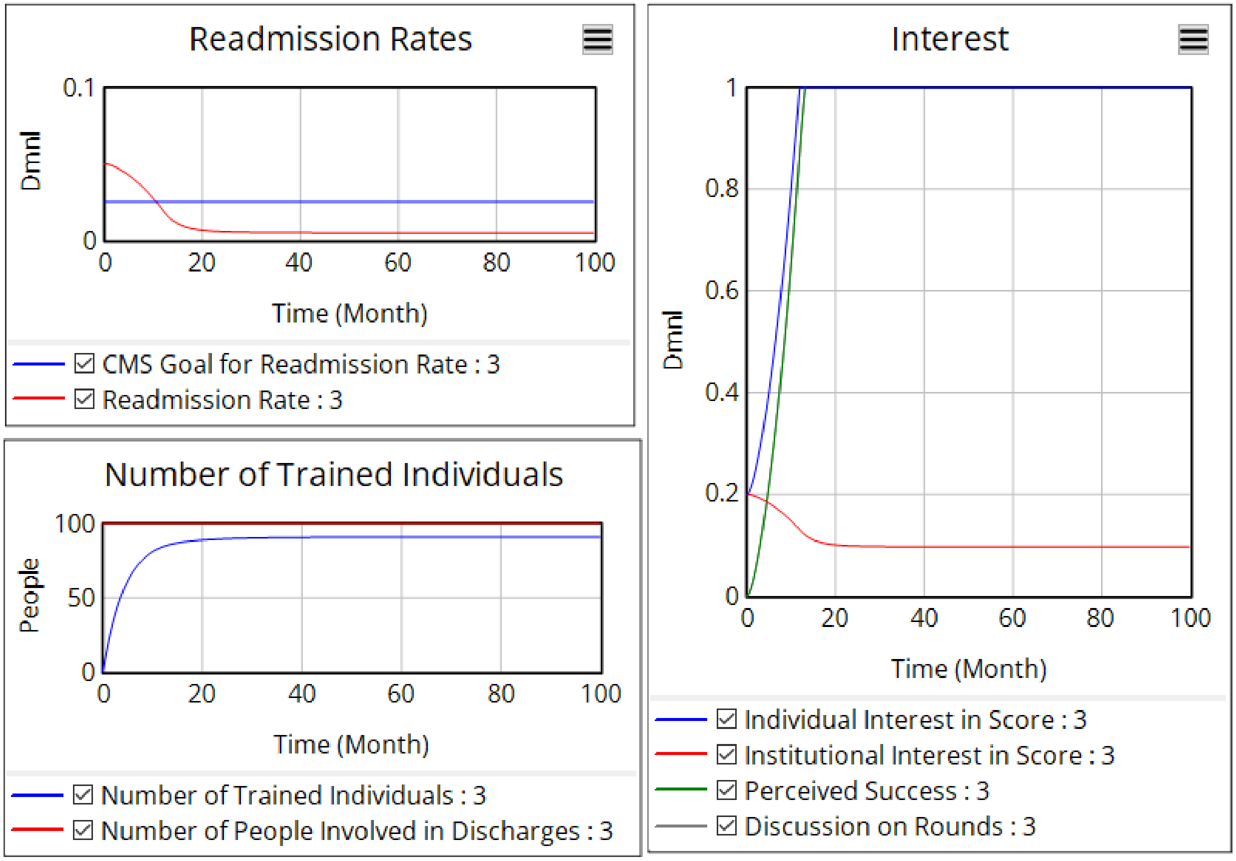
Figure 4: Simulation Run with Strong Balancing Loops

Note: The equations and parameters for this run are given at the end of the paper

Figure 5: Simulation Run with Greater Attention to Conflicting Priorities Weakening the Balancing Loops

Note: In this run, the Attention to Conflicting Priorities has been raised from 1 to 5 with no other changes to the model equations or parameters from the previous run

Figure 6: Run with Reduced Required Evidence Strengthening the Reinforcing Loops



Note: In this run, the Required Evidence has been reduced from 100 persons/month to 3.5 persons/month with no other changes to the model equations or parameters from the previous run

Model Equations

(01) Attention to Conflicting Priorities= 1
Units: Dmnl [1,10]

(02) Change in Use= (Individual Interest in Score - Individual Use Likelihood) / Time to Adjust Work Practices
Units: Dmnl/Month

(03) CMS Excess Readmission Rate Penalty= (Readmission Rate - CMS Goal for Readmission Rate) / CMS Goal for Readmission Rate
Units: Dmnl

(04) CMS Goal for Readmission Rate= 0.025
Units: Dmnl [0,0.2]

(05) Discharges per Month= 100
Units: People/Month [0,200]

(06) Discussion on Rounds = Perceived Success
Units: Dmnl

(07) Effectiveness of Score Use= Score Quality * MIN(1, (Normal Readmission Rate / Fraction of Discharges with Red Alerts))
Units: Dmnl [0,1]
This says how often a readmission will be avoided when the score is used for a red alerted patient. We assume no type I error (all red alert patients are patients will be readmitted if not prioritized for care) up to the point where red alerts become more common than readmission (above which additional red alerts represent type II error, alerts for patients who are not going to be readmitted) thus the effectiveness must fall to represent use on patients who would not normally be readmitted.

(08) FINAL TIME = 100
Units: Month
The final time for the simulation.

(09) Fraction of Discharges with Red Alerts= 0.05
Units: Dmnl [0.01,1]

(10) Individual Interest in Score= MIN(1, Institutional Interest in Score + Perceived Success)
Units: Dmnl
We're assuming people's interest can be driven by institutional interest and by direct evidence of success, with a maximum interest of 1 (meaning the person will always pay attention to the score)

(11) Individual Use Likelihood= INTEG (Change in Use, 0)
Units: Dmnl

(12) INITIAL TIME = 0
Units: Month
The initial time for the simulation.

(13) Institutional Interest in Score= MIN(1, (Discussion on Rounds + CMS Excess Readmission Rate Penalty) / Attention to Conflicting Priorities)
Units: Dmnl

(14) Likelihood of Red Alert Use= (Number of Trained Individuals / Number of People Involved in Discharges) * Individual Use Likelihood
Units: Dmnl

(15) Normal Readmission Rate= 0.05
Units: Dmnl [0,0.5]
Without use of the tool, this is the readmission rate we would expect

(16) Normal Time to Train= 1
Units: Month [1,10]

(17) Number of People Involved in Discharges= 100
Units: People [0,500]

(18) Number of Trained Individuals= INTEG (Training Flow-Trained Turnover, 0)
Units: People

(19) Perceived Success= Readmission Avoidance Rate * Discharges per Month / Required Evidence
Units: Dmnl

How many people are being helped relative to the number needed to be compelling to care team

(20) Readmission Avoidance Rate= Likelihood of Red Alert Use * Effectiveness of Score Use * Fraction of Discharges with Red Alerts
Units: Dmnl

(21) Readmission Rate= Normal Readmission Rate - Readmission Avoidance Rate
Units: Dmnl
Readmissions fall when patients are given red alert priority

(22) Required Evidence= 100
Units: People/Month [1,100]
How many people per month being prioritized effectively is needed to show clear success to someone using the score

(23) SAVEPER = TIME STEP
Units: Month [0,?]
The frequency with which output is stored.

(24) Score Quality= 1
Units: Dmnl [0,1]
This says what fraction of the patients given red alerts would avoid readmission. It is a baseline value under the conditions that (a) all red alerts are given attention, (b) the red alert fraction is equal to the normal readmission rate, The actual avoided readmissions (see the Readmission Rate and Perceived Success equations) will be lower if red alerts are not being attended to and if the number of red alerts starts to climb relative to actual likely readmissions.

(25) Staff Turnover Rate= 0.01
Units: Dmnl/Month [0,0.1]

(26) TIME STEP = 0.125
Units: Month [0,?]
The time step for the simulation.

(27) Time to Adjust Work Practices= 3
Units: Month [1,12]

(28) Trained Turnover= Staff Turnover Rate * Number of Trained Individuals
Units: People/Month

(29) Training Flow= Institutional Interest in Score * (Untrained People / Normal Time to Train)
Units: People/Month

(30) Untrained People= Number of People Involved in Discharges - Number of Trained Individuals
Units: People