

Supercharged CDI: NLP, intelligent workflow and CAC revolutionize CDI program at UPMC

In today's healthcare environment, information is the engine that drives activity and care delivery. But the data found within the electronic medical record (EMR)—especially the physician narrative—often exhibits deficiencies. These deficiencies, such as lack of specificity or clinical clarity, can adversely impact a caregiver's ability to make appropriate decisions, as well as an organization's quality rankings and reimbursement.

Natural language processing (NLP) technology has a proven track record of identifying and interpreting clinical information from various electronic sources. While NLP is the intelligence backbone of computer-assisted coding (CAC), NLP can also address the challenges of documentation deficiencies through the automation of traditional clinical documentation improvement (CDI) programs.

This paper will discuss why NLP will become essential for a cost-effective concurrent CDI program. Automating CDI using a sophisticated NLP engine will improve both the comprehensiveness and the workflow of clinical documentation review and bring with it other unexpected but meaningful benefits.

Limitations of manual CDI programs

According to the American Health Information Management Association (AHIMA), CDI programs "initiate concurrent and, as appropriate, retrospective reviews of inpatient health records for conflicting, incomplete, or nonspecific provider documentation."

In traditional, manual CDI programs, a team of documentation specialists reviews a sampling of medical records to determine if the documentation is complete. If a specialist identifies a deficiency in documentation, he or she requests additional clarification from the treating physician by initiating a physician query. The physician responds by either verifying or refuting the premise of the query. If a more specific diagnosis is verified, the response becomes part of the patient's medical record and justifies a more accurate DRG. If the diagnosis is verified after a claim has been submitted, it becomes the grounds for an amended claim.

CDI programs have a history of improving the specificity and clinical clarity of medical records. For example, UPMC—an integrated health system headquartered in Pittsburgh—utilizes a retrospective CDI program that identifies \$1 million a month system-wide in additional revenue. But traditional CDI programs have limitations.

CDI specialists are limited by the number of medical records they can review.

Documentation specialists face a challenge similar to that of coders—limited time to completely comprehend complex medical records. Time will be even more limited once the ICD-10 transition takes place. Timing is also critical in a concurrent CDI program. A physician may make a relevant change to the medical record after the CDI specialist has reviewed the record.

Many records subjected to CDI review don't need documentation improvement.

Cases for CDI review should be selected based on their potential fit with a clinical scenario by CDI specialists who understand complex medical encounters. Reviewing a case to find whether it fits a clinical scenario is a labor-intensive process, especially considering that most record reviews don't result in a query. A survey by the Association of Clinical Documentation Improvement Specialists (ACDIS) showed that seven out of eight CDI specialists found documentation deficiencies in less than 50 percent of the records they reviewed.

Some physician queries won't receive a response.

Even when deficiencies are found and a physician is queried, it does not necessarily lead to remediation. While the UPMC CDI program identifies \$12 million in unbilled revenue per year, it also suffers from wasted queries. The organization found that a third of its queries were either ignored or invalidated, representing a significant waste of time and resources.

Quality of response with retrospective queries is questionable.

The timeliness of queries is also a consideration. Querying physicians while a patient is still in the hospital is the best method for getting an accurate, timely response from a physician. Retrospective queries—those that happen after the patient is discharged—are less likely to result in a response. Retrospective queries initiated long after the patient was treated and monitored also may be less defensible in an external audit.

An ACDIS survey showed that seven out of eight CDI specialists found documentation deficiencies in less than 50 percent of the records they reviewed.

Automated CDI addresses the challenges of manual programs

As a pioneer in automating manual coding processes using NLP, UPMC determined to supercharge its CDI program with a concurrent program backed by an automated, NLP-based solution. Knowing firsthand the benefits of Optum's advanced compositional NLP system, UPMC chose Optum as its development partner. Optum and UPMC launched the industry's first inpatient computer-assisted coding solution in 2008. The resulting CAC system, now known as Optum CAC, was accurate, efficient, and effective, helping organizations dramatically increase case mix index and coder productivity.

Optum CAC was designed with an intuitive user interface and an optimized workflow, and relies on a high-powered, sophisticated NLP engine, LifeCode®. The CDI solution is a module of Optum CAC and follows the same successful template. It uses the robust LifeCode technology along with CDI-specific business rules, leveraging them for precise, automated CDI case-finding and physician querying, which are the most time-consuming aspects of CDI workflow.

The Optum CDI Module maximizes the efficiency and productivity of CDI specialists. By automating patient medical record review, the CDI Module can review hundreds of cases per day and identify those that have a high probability for documentation improvement. This allows CDI specialists to prioritize the cases on which they work, and minimizes the number of queries a physician needs to review to determine clinical relevance. The solution also addresses low query response rates by integrating queries directly into the physician's routine workflow.

Automating CDI with compositional NLP and CDI-specific business rules closes the clinical documentation loop. CAC improves the output of clinical documentation—coding and reimbursement—by reviewing and analyzing the entire patient record. The result is accurate coding that reflects what is present in the documentation. Automated CDI, on the other hand, improves clinical documentation input.

- **CDI specialists become more efficient and productive.** By automating the review of documentation contained in patient medical records and using the LifeCode NLP engine, hundreds of cases per day can now be reviewed. The CDI Module automatically identifies cases that have a high probability for documentation improvement, which helps CDI specialists focus their efforts.
- **Queries become more clinically relevant.** LifeCode uses compositional NLP technology to gather discrete data from the entirety of the medical record. This data is combined to create highly accurate clinical markers that indicate a need for documentation clarity and specificity.
- **Physicians become more likely to accept queries and augment documentation.** Physicians are alerted to queries within the patient's medical record while the patient is still in the hospital. This allows for timely documentation completion while the physician is still treating the patient and the case is top of mind.

Initial tests have shown that automated CDI can result in more accurate measurement of severity of illness and risk of mortality, measures that affect an organization's quality rankings. For example, in a UPMC case where the CDI Module found a major complication/comorbidity (MCC) for cerebral edema, the APR-DRG severity of illness score for that case increased from a 1 to a 2, while the APR-DRG risk of mortality score went from a 2 to a 3. In today's healthcare environment, correctly measuring for quality is critical. Quality scores are made public, and facilities are compared against each other, affecting where insurers steer their members as well as where patients decide to go for inpatient care.

From a revenue perspective, the cerebral edema MCC increased the reimbursement value of the case from \$12,900 to \$29,800, a difference of \$16,900. Overall, UPMC anticipates a significant increase in revenue accuracy from the CDI Module. The organization has run multiple audits comparing the findings of its CDI specialists with the findings of the automated CDI process. In each test, the automated process found more documentation deficiencies than identified by human review of the same cases. The average difference was an increase in estimated reimbursement of \$138 per inpatient case. When projected across all UPMC hospitals, this equates to nearly \$10 million in billable revenue per year, in addition to the \$12 million already identified for those same records by UPMC's retrospective CDI program.

One of the compelling reasons UPMC partnered with Optum to develop the CDI Module is the upcoming ICD-10 transition. The onset of ICD-10 not only brings with it the need for greater documentation specificity, but, under ICD-10, using manual CDI processes would require a small army of documentation specialists. UPMC anticipates that the CDI Module combined with the comprehensive coding of its Optum CAC solution will yield significant documentation improvement opportunities and will facilitate a smoother transition to ICD-10.

With a concurrent CDI program implemented through the CDI Module, UPMC expects a lower external audit risk. Documentation accuracy and completeness will increase, while the amount of retrospective queries will decrease. These factors will make UPMC's data more defensible should they be involved in external audits. The organization also expects the CDI Module to diminish the amount of rework and rebilling as a result of denials. All these factors can also contribute to labor cost savings.

The Optum CDI Clinical Information Model

The foundation of the UPMC/Optum CDI gap-finding technology is a three-tiered information model. This model, found in Figure 1, relies on a baseline of discrete data called clinical indicators, which combine to make up clinical scenarios. The scenarios, taken together, are the evidence for clinical markers. Clinical markers provide the basis for CDI specialists to query physicians about potential documentation deficiencies. The following is a deeper description of how this model works.

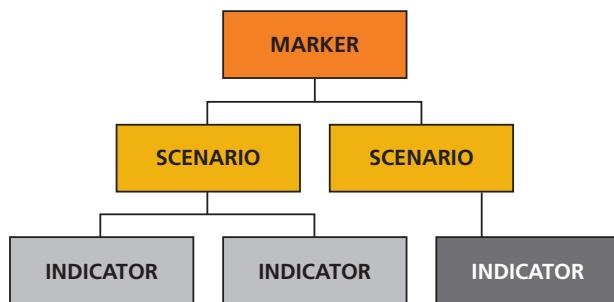
A clinical indicator is a specific fact or event recognized by the NLP engine. Clinical indicators are discrete data points pulled from either structured or unstructured data sources that are captured from the various medical record components. Examples of clinical indicators include pieces of information from an EMR, test results found in lab, radiology, and pharmacy systems, or the documentation of results or observations found in transcribed or typed notes.

A clinical scenario is a group of indicators that, when combined, are points of evidence for a diagnosis or a procedure. All of Optum's clinical scenarios are drawn from collaboration with clinical experts and with national references and standards for identifying CDI opportunities. A strength level of high, medium, or low is attached to each scenario, indicating how likely the scenarios are to yield a result.

A clinical marker represents one or more scenarios, each of which may fit the clinical profile of a specific condition. If the condition was not documented to the required specificity or with definitive clinical clarity, then a marker provides the evidence to support a physician query.

Optum's three-tiered information model makes the technology consistent in how it represents information, and it also makes the technology scalable. The software can incorporate new markers, and it can reuse indicators in different scenarios and even across different markers. Also, the software doesn't limit the number of clinical markers that can be associated with a case. LifeCode's compositional NLP technology makes the information model possible. The NLP engine can review data stored in various sections of the medical record and combine those indicators into cohesive scenarios.

Figure 1. The Optum CDI Clinical Information Model



How does the CDI Module build a clinical marker?

One example from UPMC's product testing illustrates the usefulness of this three-tiered approach. The UPMC/Optum team encountered a record of an acute patient that was receiving intensive therapies and tests: the administration of intravenous furosemide—a diuretic used to treat fluid retention—within a critical care unit; an echocardiogram that showed an ejection fraction of 30 percent; and a chest x-ray showing pulmonary vascular congestion. In the medical record, the physician indicated "fluid overload" about a dozen times. The loop diuretics, the cardiothoracic tests, the location of the patient within the facility, and the mention of "fluid overload" were all clinical indicators. Taken together, those indicators made up multiple clinical scenarios, all of which pointed to a clinical marker of acute systolic heart failure. Since the physician never wrote the term "heart failure," the case could not be coded to an appropriate specificity. However, the clinical indicators clearly demonstrated that the patient was being treated for congestive heart failure, and the case ended up being marked for CDI. The CDI specialist validated the findings in the clinical record and presented them to the physician in a non-leading query, with the references to clinical scenarios clearly marked within the medical record. The physician was then able to more clearly state the diagnosis as acute systolic heart failure in the patient's record.

Automated CDI makes UPMC's concurrent CDI program possible

A traditional CDI program addresses two types of documentation deficiencies: specificity and clinical clarity. When physicians use clinical terms, such as "CHF" or "kidney disease," and the documentation suggests a more specific diagnosis, CDI specialists request additional specificity. When physicians use vague terms, such as "fluid overload," CDI specialists need additional clinical clarity. They do so by presenting the treating physicians with a constellation of relevant data and requesting that they identify a diagnosis. Experienced CDI specialists can find conditions that aren't well documented—merely alluded to in vague terms. The Optum CDI Module excels in finding all such documentation deficiencies—the easier "specificity" deficiencies, as well as the more difficult "clinical clarity" deficiencies. Here's how UPMC is leveraging the Optum solution:

First of all, to take advantage of technology-enabled efficiency and to conform with industry best practices, UPMC is moving from a retrospective CDI program to a concurrent program. By running the CDI Module while patients are receiving inpatient care, the solution assigns a working DRG, identifies gaps in documentation as the record is built, and electronically queries physicians as they are updating the patient's medical record. All this makes for a faster, more accurate, and more compliant case conclusion.

The concurrent documentation review process begins when the patient is admitted and the first documents are added to the patient record. The NLP engine instantly analyzes the clinical documentation and suggests codes via the CAC solution. Based on this coding activity, the CDI Module assigns a working DRG. A working DRG can serve as the basis for moving a case into the CDI workflow if an organization determines the DRG to be high risk or problem prone.

The NLP engine continues to analyze the components of the patient record—physician documentation, lab work, diagnostic testing, nursing and other clinical documentation—as more data is added to the case. The CDI Module aggregates clinical indicators in the documentation and then applies specific rules that can also trigger CDI workflow when the indicators coalesce into scenarios that meet the requirements for a high-, medium-, or low-strength CDI marker.

Workflow routing rules configured by the provider organization determine which cases require review by the CDI specialist, and upon review, whether an individual case merits a query. When a query is necessary, the technology automatically generates the query based on the scenarios that make up the clinical markers. Because the scenarios are included in the query, along with appropriate references to the patient record, physicians see exactly what justified the query. This capability relieves the CDI specialists or coders of building a query that is clinically relevant. It also helps the facility remain compliant with the Centers for Medicare and Medicaid Services requirement for non-leading queries and for focusing queries on what the medical record contains rather than what it does not contain.

Once the specialist accepts the query, he or she can then add the query to the physician's EMR workflow with the click of mouse. In some specific cases, the system can automatically send a query directly to the physician without any review from a CDI specialist. For example, if a patient's serum sodium level is 125 with a glucose level of 120 and the physician didn't indicate hyponatremia as a diagnosis to support the medical necessity for serial electrolytes, the system would automatically mark the case for CDI and deliver a system-generated or "auto-query" to the physician.

Connecting the CDI Module with the Optum CAC solution streamlines the query process and improves downstream coding. While the CDI specialist is reviewing cases and managing queries, the NLP engine continues to suggest codes. Although the case's coding won't be final until after the patient is discharged, the CDI Module automatically validates its findings against Optum CAC's suggested codes as they are added. If, for example, the CDI Module identifies a clinical marker for sepsis, but the NLP has already suggested a code for sepsis that matches the severity of the clinical marker, the case requires no further clarity and the system resolves the marker without moving the case into the CDI workflow.

When a query is necessary and prompts the doctor to add specificity or clinical clarity to the medical record, the NLP technology resets the documentation analysis, resolves the clinical marker, and updates the code suggestions. When the patient is discharged and the case is ready for coding, the documentation and the codes associated with the documentation are more likely to be accurate and complete. Because coders can see a history of CDI activities and physician queries, they are less likely to need to request a retrospective query and more likely to choose the correct set of codes.

New frontiers for natural language processing

The LifeCode engine is remarkably scalable—it can look for a multitude of scenarios within medical records. Such scenarios could include hospital acquired conditions, core measure information, patient safety indicators and other quality standards. This scalability also bodes well for the ICD-9 to ICD-10 transition, where the complexity of coding and documentation will increase dramatically. LifeCode is designed to handle the more complex scenarios of ICD-10.

The future of health information technology is being able to do large-scale, longitudinal analytics on patient data, so that providers can affect outcomes through intelligent processing. To make such analysis happen, systems need complete, mineable information. If providers can change the quality of the data going into their information systems, they can improve the quality of the information output. This allows for deeper knowledge about individual patients and patient populations, which can then be used to improve the way providers care for patients.

UPMC has noticed a few cases where a query comes through to a physician and the clinical markers point to a potential diagnosis that isn't entirely obvious. Rather than simply influencing documentation, the system is also influencing care. At this point, such an occurrence is a side effect of the CAC/CDI system, but the potential is there for LifeCode to have a much more proactive influence on clinical quality improvement.

The combination of computer-assisted coding and automated clinical documentation improvement fills a huge need in the healthcare industry. Accurate, complete documentation and a thorough review of such documentation are critical for quality improvement and revenue integrity. Use of LifeCode's natural language processing technology for CAC and concurrent automated CDI is only beginning to scratch the surface of its usefulness.

Endnotes

- 1 AHIMA, "Clinical Documentation Improvement Toolkit" (2010): 3-4.
- 2 AHIMA. "Managing an Effective Query Process." Journal of AHIMA 79, no.10 (October 2008): 83-88.
- 3 Adele Towers, Nancy Soso, and Tamara Needham. "Implementation of Inpatient Computer Assisted Coding at the University of Pittsburgh Medical Center." 2009 AHIMA Convention proceedings, October 2009.
