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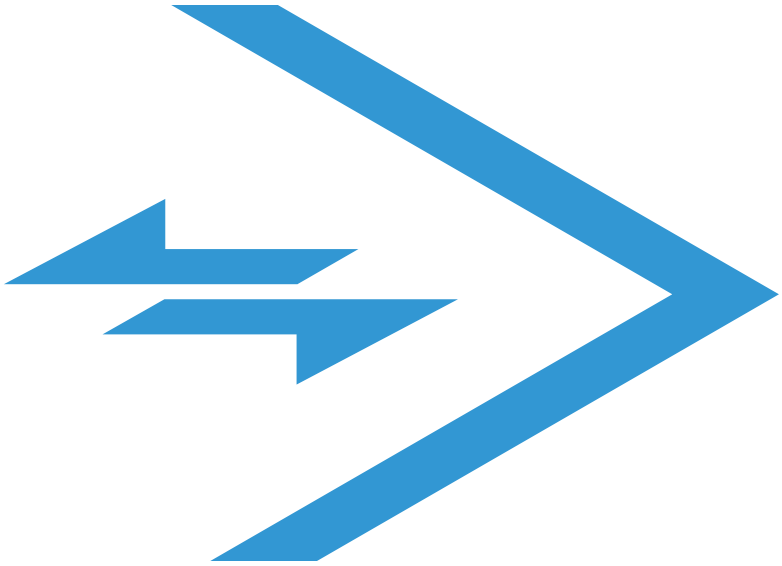

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The Impact of Computer-Assisted Coding

Focus: Coder Productivity and Roles

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1 Introduction

Clinical coding in the United States has undergone a dramatic shift in purpose, function and perspective since the introduction of the Prospective Payment System in the 1980s. Because of this shift, the healthcare industry has experienced significant challenges related to the coding process, including fraud and abuse, a shortage of qualified coding personnel and increasing operating expenses due to coder vacancies. To attack these problems, healthcare organizations and their clinical coding departments use computer technology – specifically encoders, remote coding and computer-assisted coding.

The focus of this white paper is to explore the newest of these technologies, computer-assisted coding (CAC). Specifically, this paper discusses the impact of CAC on coder productivity and coder roles. But before we focus on computer-assisted coding, let's look at two other technologies that have helped improve the coding process – encoders and remote coding.

2 Technology in Coding: Look How Far We've Come

Encoders and remote coding have already had a significant impact on the coding profession. ***Encoders,*** first introduced in the 1980s, have helped improve the productivity and accuracy of coders. In a survey conducted by Medical Record Automation and Management Report, one hospital reported a drop from 3.6 days to 2.5 days in accounts receivable.[1] The same study also reported a case of unbilled accounts dropping from $3.5 million to less than $50,000 in three years following the implementation of encoder technology. And a study in *Medical Records Briefing* reports increases in coding accuracy as high as 34 percent with encoders. Today's encoders incorporate logic, rules engines and instant access to a variety of information needed by coders, such as the American Hospital Association's *Coding Clinic* and the American Medical Association's *CPTAssistant.*

A more recent technology – ***remote coding*** – has helped reduce the coder vacancy rate. Remote coding provides technology that enables coders to work from any location, including home. Since the majority of coding professionals are women, the ability to work from home has become a strong recruitment and retention tool for employers.

In 1999, the vacancy rate for coders and billers was 18 percent nationwide, according to the American Hospital Association (AHA).[2] Remote coding was introduced in 2000. In 2004, the vacancy rate according to the same survey was 8.5 percent, nearly 10 percentage points lower. One can assume that remote coding played a role in reducing this rate.

Like encoders, remote coding technology is becoming more advanced. Second generation remote coding systems now combine advanced workflow, encoders and CAC. So what is CAC and how will it impact coding?

[1] Pavelchak, Barbara (1997). Use of Encoders Growing. The INK, 9 (5), [on-line resource], available at: http://www.hanys.org/prodser/hsipub/ink/fall97.htm

[2] American Hospital Association, Workforce Studies 1999 and 2004. Available at: www.aha.org

3 Computer-Assisted Coding Defined

CAC is defined by the American Health Information Management Association (AHIMA) as the: "… use of computer software that automatically generates a set of medical codes for review, validation and use, based upon clinical documentation provided by healthcare practitioners."[3]

Currently, there are two technology options for CAC. The first is natural language processing (NLP) and the second is structured input. Both options are computer-assisted coding models. The computer-assisted model relies on human intervention to review, validate and approve (or edit) codes generated by the computer system.

In contrast, automated coding systems send computer-generated codes directly to billing with little or any human intervention. While a completely automated coding process may be part of our future, the technology used today relies on the expertise of a qualified clinical coder.

3.1 Option 1: Natural Language Processing (NLP)

First introduced in the 1950s, natural language processing is a form of artificial intelligence that electronically reads transcribed or voice documents. Natural language processing software is often referred to as a NLP "engine." NLP engines use either semantic rules or computer-based reasoning to identify specific words within the transcription, analyze their context and then derive a logical meaning. For clinical coding, the NLP engine then converts the words to codes, such as ICD, CPT, etc.

For each record, the system places these codes into a review queue for the coder to review, edit, approve and finalize. Coders begin the coding process by viewing "suggested" codes instead of working from scratch. As this white paper will discuss, coders starting with a list of recommended codes greatly improves productivity and elevates the coder's role from researcher to quality data analyst.

In order for NLP engines to be most effective, electronic documents (transcription or voice files) should be based on some type of template or standard format. The physicians do not need to change how they speak, but rather, need to dictate in accordance with a standard format and section headers. For the most part, physicians already do this. For example, the report should include a section called "History", a section called "Exam" and so forth.

The two different types of NLP engines available today are rules-based or reasoning-based. With a rules-based NLP engine, each facility defines the coding rules it wants the engine to apply. For example, rules are used to assign the "place of occurrence" E-code in certain states for reporting requirements.

With a reasoning-based system, the engine builds its ability to read text as documents are coded. The engine uses reports that have already been coded to create a baseline. The software can then guess how to code new reports, based on similar reports that were previously coded. Therefore, the success of the engine depends on the quality of coders who are using the system initially. If the pool of previously coded reports is large and the reports have been coded well, the system has a greater chance of accurately assigning codes with little, if any, human intervention.

[3] AHIMA, Delving into Computer-assisted Coding (AHIMA Practice Brief), Journal of AHIMA, Nov-Dec 2004.

The advantages of rules-based NLP engines are that they provide flexibility, as well as coding consistency based on the specific coding guidelines of a specific organization. The disadvantage is that the rules must be modified and maintained as new guidelines are created. With a reasoning-based system, there is less rules creation and maintenance, but poor coder quality could result in faulty code assignment.

3.1.1 Where NLP Works Best

Just as the Internet started as a way to send messages and has grown to encompass virtually every aspect of our lives, natural language processing for use in CAC is starting in specific clinical care settings. Additionally, NLP engines work best for coding when an interface to the transcription system is available and the system can be accessed remotely.

The specific care setting where NLP works best is outpatient. This is because clinical documentation in these settings is often already electronic (dictated or template-based) and there are a limited number of medical terms. According to AHIMA's Practice Brief[4] and healthcare organizations who have implemented CAC, NLP engines work best in the following settings:

> Radiology
> Gastroenterology procedures
> Pathology
> Emergency medicine
> Interventional cardiology
> Orthopedics
> Podiatry
> Pulmonary medicine
> Urology procedures
> General medicine and primary care
> Other medicine subspecialties

NLP engines also work best when they receive the data and text files electronically from an electronic template, dictation or speech recognition system. While not absolutely necessary for CAC, it is recommended that a transcription interface be implemented for optimal workflow.

Lastly, the NLP engine (as part of the overall CAC system) should be accessible to coders working from remote locations, including home. CAC should be integrated with remote coding to deliver the maximum increase in coder productivity. In addition, easy access to abstracting and encoder applications helps codes navigate between and among systems and saves additional time during the coding process.

3.2 Option 2: Structured Input

The second option, structured input, is "… based on the use of menus that contain clinical terms."[5] Structured input for CAC is most commonly seen in the physician office setting. The clinician uses a hand-held computer system to document his or her visit. As the clinician points and clicks on words and phrases, sentences and paragraphs are created. Diagnoses and procedures that should be coded are automatically identified and mapped to the correct clinical code. Since each physician's workflow has a limited number of diagnoses and procedures, structured input works well in this environment.

Once the codes are assigned, they are then presented to the clinician for confirmation and may or may not be forwarded to a coder for manual code review.

[4] AHIMA, Delving into Computer-assisted Coding (AHIMA Practice Brief), Journal of AHIMA, Nov-Dec 2004.

[5] AHIMA, Workforce Study 2003, Available at: www.ahima.org

4 Current Issues Driving the Use of CAC

There are three key issues driving the adoption of CAC and other coding technologies. These are:

> National coder shortage and future demands for coding – the need to do more with fewer coders;
> Impact of coding on healthcare reimbursement – coding is directly related to payment; and
> Anti-fraud regulations and compliance – CAC can assist with anti-fraud activities.

Because there is a shortage of qualified coders and studies predict that 40 percent more HIM professionals will be needed within the next decade,[6] the main focus of CAC technology is to do more coding with less staff and in less time. CAC does this by giving the coder a list of suggested codes from which he or she can either approve or edit. This makes the coder more productive, makes coding more consistent and further automates the coding process.

Secondly, coding is directly related to reimbursement. When coding is backlogged, cash is left sitting in the HIM Department instead of in the organization's bank account. And if incorrect codes are submitted, coding must be done again, causing further delays and time constraints for the coding staff. Therefore, if coding is performed faster and more accurately, the healthcare provider receives the correct payment sooner. CAC can help achieve this goal.

To support the premise that CAC can improve coder productivity, two separate studies were performed in 2004. The results are detailed on page 8. They provide a good benchmark for health-care organizations to understand how CAC may impact their coding performance. In addition, one organization that currently uses CAC has also provided results which may be of interest to other hospitals considering this technology.

Finally, there are current and future anti-fraud initiatives that can be supported through the use of CAC. At the time of this paper, AHIMA's Foundation of Research and Education (FORE) is working together with the Office of the National Coordinator for Healthcare Information Technology (ONCHIT) to identify ways in which CAC software can address healthcare fraud issues. The final report is scheduled to be completed in September 2005.

[6] AHIMA, Workforce Study 2003, Available at: www.ahima.org

5 CAC Technology Study: The Proof is in the Productivity

In 2004, two coding productivity studies were performed using remote CAC technology from MedQuist Inc. The system, CodeRunner™, was used by MedQuist's own coding staff to assess the impact that CAC would have on coder productivity for Emergency Department (ED) records.

Study Parameters: Five coders participated in the studies. ED records from five different hospitals were used and each coder was paired with a facility and assigned 100 random ED records from that facility. Coding was performed by MedQuist's professional, outsourced coding team. All records had to comply with both MedQuist's internal 95 percent accuracy rate and the specific hospital's guidelines for coding and billing.

Research Process: All documents used were electronically transcribed or voice text files from the ED. They were entered into CodeRunner via a direct interface with the existing transcription systems.

Once in the CodeRunner system, the records for each coder were processed through CodeRunner's NLP engine and "suggested" codes were presented to the coder. Several weeks later, the same 100 records were viewed by the coder using CodeRunner, but not sent to the NLP engine for review.

Measurement Technique: Coder productivity was measured for each batch of records coded. Productivity was measured in two ways: number of records per hour and number of codes per hour. For the number of records per hour, the total time each individual coder spent completing his or her batch of records was divided by 50. The code per hour ratio was determined by dividing:

> the number of codes included in each batch of records by
> the total number of hours the coder used to complete the batch.

Results: The study found that every coder increased their productivity ratios (both charts per hour and codes per hour) when the NLP engine was used. Averaging the five coders, the study found that records per hour increased 96 percent with the use of the NLP engine. The average code per hour ratio increased by 85 percent. From a quality perspective, all records had to comply with both MedQuist's internal 95 percent accuracy rate and the specific hospital's guidelines for coding and billing.

	Records Per Hour		**Percent Improvement**	**Codes Per Hour**		**Percent Improvement**
	Without NLP	With NLP		Without NLP	With NLP	
CODER A	6.72	12.76	90%	92.01	178.22	94%
CODER B	10.78	22.92	113%	128.88	268.52	108%
CODER C	17.54	29.15	66%	109.65	173.18	58%
CODER D	12.33	30.37	146%	58.90	118.10	101%
CODER E	10.13	17.36	71%	123.10	209.20	70%
AVERAGE	**11.50**	**22.51**	**96%**	**102.51**	**189.44**	**85%**

6 CAC In Real Life: South Shore Hospital

South Shore Hospital is a 282-bed, acute care teaching hospital in South Weymouth, Massachusetts. With 77,000 ED visits annually, seven expansions within three years and only two full-time facility coders, ED coding was seriously backlogged. South Shore's per record coding costs had skyrocketed and many of the facility's ED visits remained un-coded for days, weeks and even months.

MedQuist's CodeRunner remote, CAC system helped South Shore avert a coding crisis with its three-tier approach. First, the system electronically captured transcribed and voice recognition ED reports. Coders no longer wasted time searching for charts or reconciling reports. Secondly, CodeRunner used computer-assisted coding technology to "read" the electronic files and present the coder with possible codes. Coders started with the recommended baseline codes instead of working from scratch. Finally, the system serves as a remote coding solution. Once proven in the hospital setting, South Shore ED coders began working from home where they realized additional productivity improvements.

Before using CAC, the ED coders averaged about 12 to 15 records an hour. Within a few months, they were coding anywhere from 18 to 21 records an hour in the office environment. The addition of CAC increased their productivity approximately ***40 percent***. While not accounted for in the productivity measurement, it is important to note that the coding of ED professional fees were also added to the coder's responsibility during this time period, thereby doubling their workload.

7 Coder Report: CAC and the Coding Profession

Once seen as a threat to coders, CAC is now viewed in a similar light as encoders were in the 1990s. CAC is a technology tool that helps the coder become more productive. By giving coders "suggested" codes, the system expedites the entire coding process and transitions coders from researchers to data quality analysts. According to AHIMA, "CAC technology should be viewed as a tool to assist coding staff rather than as a replacement for coding staff."[7] As more and more coders begin using CAC tools, the difference becomes apparent.

At first, the coders admit that they were skeptical about the capabilities of the NLP engine. However, once they became familiar with CAC's capabilities, they became confident with the system. Coders who use CAC tools every day report that they would never consider going back to a manual form of coding. "I enjoy using CodeRunner because I believe it is valuable to both the coder and the hospital," says Tina Branik, CCS. "The system is smart, it accurately finds codes that may have been missed otherwise and in turn, makes me very productive," she adds.

One of South Shore's ED coders encourages fellow coders to try CAC. In his role, the focus has shifted from pure coding to a higher level auditing of the suggested codes. Once coders view and make any edits, they click "Ready to Bill" and move on to the next chart.

Finally, Sandra Leonard, CCS, CCS-P, comments, "It was always my dream to work from home. CodeRunner made my dream come true. It is an extremely user-friendly system and an excellent coding tool – nothing better!"

With CAC, the coder's role changes in a positive way. Coders are now focused exclusively on doing just one piece – the coding. And isn't that what it's all about?

8 Conclusion

Computer-assisted coding is here to stay. Just as the Internet has changed and evolved, CAC will continue to improve and expand its capabilities beyond the outpatient setting. Within a few short years, CAC systems will be available for all clinical environments, including inpatient.

Savvy coders, managers and HIM directors are wise to understand CAC and its capabilities today. While the coder shortage may have diminished, it is not going away. And surveys tell us that greater volumes of coding workloads are just beyond the horizon.

[7] AHIMA, Delving into Computer-assisted Coding (AHIMA Practice Brief), Journal of AHIMA, Nov-Dec 2004.