

Delving into Computer-assisted Coding

This practice brief discusses computerized tools available to automate the assignment of certain medical or surgical codes (ICD-9-CM and CPT/HCPCS) from clinical documentation that are traditionally assigned by coding or HIM professionals as well as clinical providers. It also outlines the driving forces that are shaping the current and future applications of this technology, examines application of the technology, and provides guidance about the steps necessary to position coding professionals for the coming coding revolution. AHIMA chartered the computer-assisted coding e-HIM™ work group to help healthcare organizations navigate and understand how to prepare for and thrive in a profoundly changing work environment.

Background

The healthcare industry is creating powerful tools to transform clinical data input into useful clinical data output. Clinical coding is approaching a tipping point where an increasing amount of work is done by machine, saving precious time and human resources for more complex coding and much needed data analysis tasks.

Many factors directly influence this change, including advances in natural language processing and informatics, adoption of electronic health records (EHRs), compliance issues, and a mandate for reducing labor-intensive administrative reporting processes. In addition, as epidemiological classification systems such as ICD-9-CM have been utilized increasingly for reimbursement purposes, greater attention has been placed on productivity and compliance. The work process for coding has changed over the past 25 years, with data collection going from manual indices and logs to computerized databases. Use of ICD-9-CM alone for statistical data capture has been replaced by the use of both ICD-9-CM and CPT/HCPCS codes. Manual coding is now facilitated through the use of encoding systems that contain various edits and references.

Automation in the form of computer-assisted drafting and computer-assisted manufacturing, for example, has revolutionized many industrial processes and allowed humans to build structures and machines not previously possible (e.g., computerized axial tomography [or CAT] scan). The same process is on the horizon for clinical coding.

In the coding workflow, clinical documentation (paper or electronic) is analyzed by a person and translated into ICD-9-CM or CPT/HCPCS codes (using a book or a software program) and entered into a database. New automation tools for coding allow the translation process to be assisted by computer software instead of manual review and translation alone. These new tools are not dependent on a fully implemented EHR, but as EHRs proliferate, adoption of these tools is expected to accelerate. EHRs with an embedded clinical terminology, such as SNOMED CT, will be a catalyst for significant change. A granu-

lar clinical terminology used for data capture in an EHR greatly simplifies the task of generating automated codes in a classification system. As the US adopts ICD-10-CM and ICD-10-PCS and automated maps become available, these automated tools for coding will become even more practical and valuable.

Current State of the Technology

What Is Computer-assisted Coding?

There are many tools to assist coding professionals in the code assignment process, including bar codes, pick or look-up lists, automated super-bills, logic or rules-based encoders, groupers, imaged and remote coding applications, and hard coding via chargemaster tables.

Advances in computer technology have resulted in computer applications that go a step further and actually suggest potentially applicable medical codes. Various terms are used for such systems, including automated coding, automated documentation, autocoding, computer-generated coding, and computer-assisted coding, each of which has various implied meanings. For the purposes of this practice brief, we define computer-assisted coding (CAC) 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.

The technology that enables CAC tools, particularly natural language processing (NLP), started years ago, as early as the 1950s with formal language theory. In earlier years, progress was slow, but since the late 1990s, technology has progressed more rapidly and is currently advancing at a furious pace. Many factors within the healthcare industry are driving this technology, including the movement to adopt EHRs and create a national health information infrastructure. This document addresses the various industry forces more in-depth in a later section. A timeline depicting key advancements in the evolution of CAC technology accompanies the online version of this practice brief, available in the FORE Library: HIM Body of Knowledge at www.ahima.org.

How Does Computer-assisted Coding Work?

CAC can be accomplished using either NLP or structured input. In simple terms, NLP is a software technology that uses artificial intelligence to extract pertinent data and terms from a text-based document and convert them into a set of medical codes to be used or edited by a coding professional. NLP is also known as computational linguistics, in which the study of linguistics, semantics, and computer science is used to abstract information from free text. For example, a natural language processor would determine if the phrase “history of cancer” means the patient does or does not have a personal or family history of cancer by analyzing the context and semantics of the rest of the sentence. With this method of CAC phy-

sicians can document health record information using their preferred terms. See appendix A online for more information on how NLP uses artificial intelligence to emulate human understanding of natural language in free text. More detailed information on computer linguistic competence can also be found in appendix B in the online library.

Structured input, also known as codified input, is based upon the use of menus that contain clinical terms. As an individual menu item is chosen, a narrative text phrase is produced and becomes part of the health record documentation. Each menu item that affects coding is directly mapped to its relevant code. For example, the pre-op diagnosis menu item of “acute tear lateral anterior horn of the meniscus” is directly mapped to the applicable ICD-9-CM diagnosis code (836.1). The physician chooses the applicable clinical menu item, and the ICD-9-CM code is automatically produced to be used or edited by the coding professional. In contrast to NLP, this method records “history of cancer” as “family” history when it is entered in the specific data field for family history.

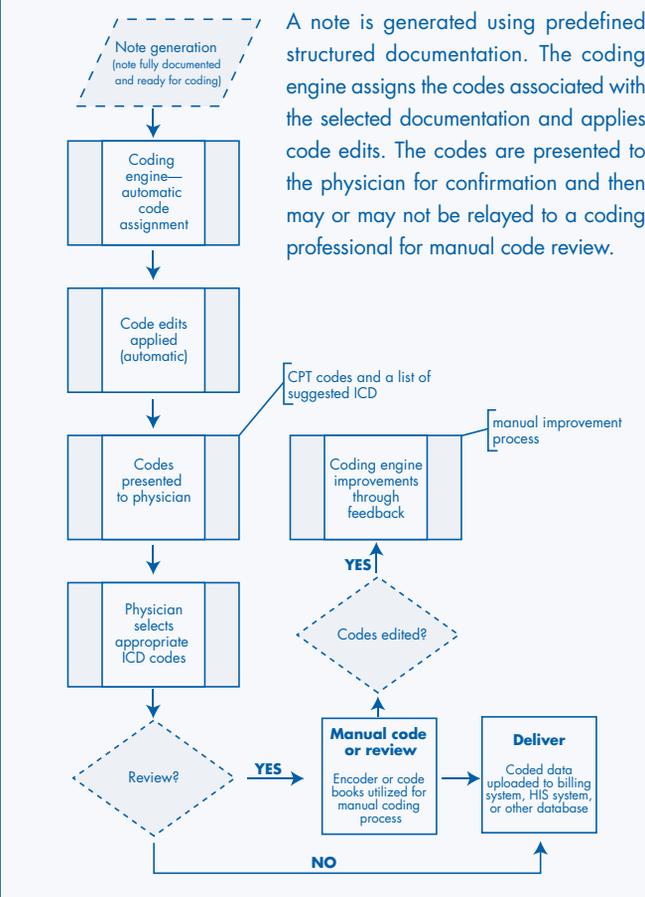
Structured input is differentiated from a pick list because it does not require human intervention to select the code. For example, a physician documenting a polypectomy would be prompted to select the specific technique used to remove the polyp. The applicable medical codes for each technique available in the menu are embedded within the system. Advantages of this method of CAC include reduction in the cost of medical transcription and improved documentation.

Industry Forces Affecting Development of CAC Why Does the Healthcare Industry Need CAC Tools?

Since the 1980s clinical coding has become increasingly complex. Prospective payment systems (PPSs) have expanded to multiple healthcare settings. As this occurred, each PPS brought specific reporting requirements that a coder must understand and recall. Other reporting requirements, such as the correct coding initiative and payer-specific coverage policies, have also expanded the various rules that a coder must apply correctly. At the same time, the compliance liability for erroneous or fraudulent claims has increased, leaving little tolerance for coding errors. In addition, healthcare financial pressure to send (drop) the bill or claim to the insurance company as efficiently as possible has increased dramatically, and the physical time to code a record has significant impact on an organization’s accounts receivables, so there is also an increased emphasis on productivity. Meanwhile, medical care continues to advance and increase in complexity, requiring coding professionals to increase their understanding of pathophysiology and even pharmacology. And this is occurring in an industry where there is already a shortage of skilled HIM-educated and certified coding professionals.

The current coding workflow is expensive and inefficient. The coding process requires that coders know more and code with greater accuracy and speed than ever before. This has created a demand to further improve the process. For example, much of the coding in the outpatient arena is repetitive and well suited to computerized tools that will reduce the

Coding Workflow with Use of a Structured Input CAC Tool



workload on the professional coder, freeing these individuals for more complex coding tasks. The industry needs automated solutions to allow the coding process to become more productive, efficient, accurate, and consistent.

In addition to these industry-wide forces, there are factors related to the technology itself that affect the development of CAC. There are many advantages to CAC, which drives technology advancement. However, there are currently disadvantages as well, which present barriers to implementing CAC technology. Below is a brief summary of the key advantages and barriers to use of CAC tools. Refer to appendix C online for a full discussion of the advantages and disadvantages.

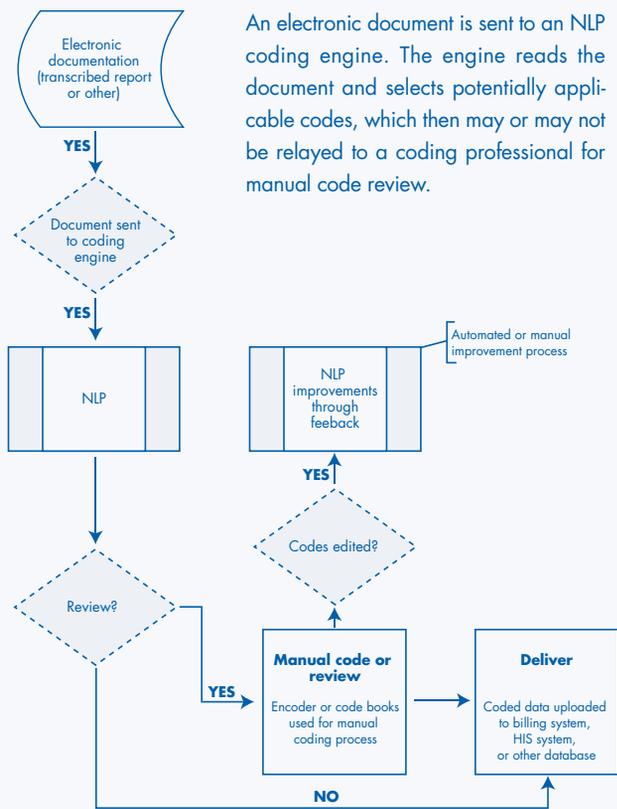
Advantages of CAC include:

- Increased coding productivity
- Increased efficiency; frees professional from mundane tasks
- Comprehensive code assignment
- Consistent application of rules
- Electronic coding audit trail

Barriers to CAC include:

- Cost of CAC hardware and software
- Complexity, quality, and format of health record documentation

Coding Workflow with Use of an NLP CAC Tool



- User resistance to change
- Technological limitations
- Potential increase in errors in the coding process
- Lack of industry standards

Application of CAC Technology CAC in Use Today

Computer-assisted coding, as defined for the purposes of this practice brief, is currently in use or under development for specific pockets of outpatient reporting including, but not limited to, the following “best scenario” applications:

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

The use of CAC depends on the availability of an electronic text-based document (whether that text is produced using structured input, free-style dictation and transcription, speech recognition, or canned template text). Electronic documentation is most typically found in the ambulatory environment at this time, such as physician office, radiology, pathology, emergency departments, and other hospital outpatient departments. In addition, CAC works best within medical domains that have a limited vocabulary. NLP-based tools in particular work best where there is a limited number of source documents that must be analyzed for code selection and less extensive coding guidelines. Development of a CAC tool for hospital inpatient use is much more complex because it involves multiple forms and formats created by multiple healthcare providers. At the time of this report, the work group identified only one CAC application to facilitate the code assignment process for inpatient acute care reporting for reimbursement purposes.

CAC is clearly making headway in both accuracy and consistency of code selection and productivity gains for clinical indexing and claims processing in the specific domains included in the bulleted list above. There are demonstrated cases in the physician coding and billing domain, as well as in the hospital outpatient environment, where CAC is improving both accuracy and speed of coding. There are many potential uses of coded data beyond administrative reporting. See appendix D online for a discussion of potential uses. A description of several CAC use cases can be found in appendix E, also online.

How Does CAC Affect the Coding Workflow?

Computer-assisted coding tools, whether utilizing NLP or clinician-friendly structured input, have great potential and have begun revolutionizing traditional workflow in certain domains (see the workflow diagrams above). As these diagrams illustrate, the traditional coding workflow is significantly altered with the use of either an NLP or structured input coding tool. In both workflows, the coding engine will improve based on feedback from the coding professional. This feedback loop may be automated (as with a statistics-based NLP tool) or manual (as with rules-based NLP or structured input-based tools).

Presently, CAC tools are typically implemented as a best practice via the code-assist model. This model utilizes software that does an initial screening against well-defined terms and produces a preliminary set of draft codes, which are reviewed, edited, and revised by a human coder to generate the final set of codes. The final assessment of codes remains the responsibility of coding professionals who can edit and correct these codes using their expert knowledge along with other tools and references. Currently, the best practice is to review 100 percent of the cases, but as CAC systems mature, this will be done more commonly via exception audits, with the system indicating which cases require review.

It must be noted that there will be situations where the complexity of care or newness of terminology or technique may result in inaccurate or missed code assignments. The reliability and validity of the CAC tool should be audited

routinely to maintain coding integrity. In addition, continuous assessment is helpful in determining efficiency gains and quality improvement results. Ongoing assessment can also identify workflow problems or bottlenecks in the coding process. An important consideration in the adoption of a CAC tool is continual evaluation of the point at which the time to edit becomes less than the original time to code. This is a prime indicator of return on investment.

Can a Computer Code as Well or Better Than a Human Coder?

The limited research available suggests that NLP-based CAC tools have improved since 2000. A summary of available NLP research in appendix F is available online. Studies assessing the accuracy rate of NLP-based CAC tools, within limited domains, have reported accuracy rates ranging from 57 percent to 98 percent.¹⁻⁹ However, when assessing the quality of the code output from NLP-based CAC tools, researchers struggle with defining coding accuracy. A major problem encountered is the variability of the codes assigned by human coders against which the NLP output is compared. Research on the accuracy and consistency of human coders shows inherent variability. One study performed to evaluate reported levels of agreement between code selection by physicians and coders showed variation as high as 20 percent.¹⁰

In general, the work group found that CAC tools, though much faster, are not necessarily more accurate and may be a bit less accurate, depending on the domain and technique, than human coders. However, CAC technologies are improving and evolving rapidly and must continue to be monitored for applicability in the coding process across different practice domains.

Will Computers Replace Human Coders?

As CAC technology becomes increasingly sophisticated there will be less demand for coders to perform manual coding tasks. Computers will not replace all of the people who are currently working as clinical coders, but computers will begin to reduce the number of hours spent manually assigning codes. Computers are not capable of taking on the new roles and responsibilities and performing the review, validation, and oversight tasks that will be created as a result of computerization of clinical coding.

Just as software applications have continued to slowly evolve over the past several decades to create tools that assist transcriptionists (versus replacing them), CAC technology should be viewed as a tool to assist coding staff rather than as a replacement for coding staff. Though it is anticipated that computers will take over some coding tasks, computers are not expected to replace human coders. Just as transcriptionists who work with the latest technology (e.g., speech recognition) have modified their role to become “expert editors,” automation tools for coding will likely result in a role change for coding professionals and will result in the better use of such staff for complex decision support tasks.

It should be noted that there may be some circumstances where CAC can be applied without human intervention today. Users reported to the work group limited instances

where confidence in the CAC code output was high and only random editing was performed. An example of this is code assignment for normal mammogram reports. As these systems advance, the range of which situations will be acceptable for direct computer-generated coding is expected to increase. Overall, however, CAC, without human review, is not to the point where large displacement of the coding work force can occur to any significant degree.

Preparation for CAC

CAC software is fast and efficient, but machines are not yet capable of all of the aspects of interpretation and analysis that human coding professionals provide. Coding professionals are still needed, but it is predicted that they will move from “production” coders to knowledge workers through expert use and adaptation of CAC tools. The competencies and skill sets of the knowledge-worker coder are different than those of the production coder. With the use of computer-assisted coding tools, coding professionals will no longer be tasked with the time-consuming, repetitive code assignment that can be accurately performed by a computer. Instead, knowledge workers will concentrate on tasks involving critical thinking skills, such as interpretation and analysis of documentation or aggregate data—in short, the tasks a computer cannot perform.

Computers can do many tasks faster or more efficiently than human coding professionals. However, computers cannot do everything that coding professionals can do. Coding professionals should concentrate on perfecting their skills related to the tasks that computers cannot do to ensure long-term success. “Migration of Coding Tasks” (opposite) includes tasks performed by clinical coders today and shows the migration of coding tasks to knowledge-worker tasks as well. This illustrates where the professional coder’s role may expand when the computer performs the routine task of manually assigning codes. “Suggested Activities for Developing Knowledge-Worker Skills” on page 48F, provides suggestions for developing the skills that will be necessary to fill these expanded roles.

With the use of computer-assisted coding tools, coding professionals will challenge themselves to further develop their skills and competencies in the clarification and scrutiny of data. In the future, a computer will do simple tasks that do not require critical thinking. Coding professionals should begin to evaluate the tasks they currently perform now. Identify the simple tasks, the repetitive, mundane things that you do by memory. Expect that, eventually, a computer will do these tasks faster and more efficiently. Also identify the tasks that require your judgment and intellect. These are your strengths, the skills that make you invaluable. Concentrate on building your skills and expertise in these areas. Build your unique expertise so that you are positioned to capitalize on the advantages offered by computer-assisted coding tools.

Practice Guidance

Building Blocks to Prepare an Organization for CAC

Evaluate existing clinical documentation. CAC tools require electronic clinical documentation. Determine what portions of

Migration of Coding Tasks		
Task	Could be performed by:	
	Human Coding Professional	Computer-assisted Coding Tool
Straightforward assignment of diagnosis codes, procedure codes, modifiers. Example: chronic otitis media with myringotomy including tube insertion is something the computer can assign accurate codes to and production coders assign accurate codes from memory.	X	X
Apply reporting guidelines (e.g., NCDs, NCCI edits, LMRPs)	X	X
Interpret documentation for correct code assignment; that is, extrapolate correct meaning from context on specific cases. Example: review and edit codes suggested by a CAC tool; determine if "postoperative anemia" indicates a condition occurring in a defined time period, after surgery, or if it is a postoperative complication.	X	
Request clarification in ambiguous documentation, whether nonspecific or inconsistent. Example: a structured input CAC system can prompt the physician for clarification at the point of input to avoid ambiguous documentation; a coder may need to review the entire record to identify the principal diagnosis or may need to initiate a physician query to clarify a diagnostic statement of "urosepsis" which could be a UTI or septicemia.	X	X
Participate on documentation improvement teams, serving as a resource on specific documentation elements needed to assign codes to the highest degree of specificity. Example: documentation to support time-based codes such as hospital discharge day management, CPT codes 99238-39; documentation of aspiration pneumonia; documentation delineating a comprehensive examination.	X	
Validate accuracy of codes assigned; recognize inappropriate application of rules. Example: application of rules, such as E codes cannot be listed first; inpatient coding guidelines applied to a rehab patient type; correct application of context-specific coding guidelines such as sequencing of respiratory failure or use of late-effect codes.	X	X
Interpret coded data to obtain information. Example: assist a physician in identifying individual cases of community-acquired pneumonia, not separately classified in ICD, by using other types of abstracted data such as core measures data or data for patient safety goals such as prophylactic antibiotics.	X	
Ensure data integrity within multiple internal systems and reporting integrity issues. Example: all systems fed in, no omissions; verify charges on accounts are accurate such as combining outpatient and inpatient charges to comply with 72-hour window rule.	X	
Educate others in the area of data retrieval, data analysis, internal data systems, and data integrity. Example: annual code changes and associated documentation requirements.	X	
Use multiple databases including, but not limited to, clinical, health plan, and national and state comparative systems for data retrieval using various report-writing tools. Example: assist in the interpretation of databases such as Leapfrog, HEDIS, OSHPD in California.	X	
Aggregate data and identify patterns. Example: respiratory cases with high-dollar charges and no ventilator management reported.	X	X
Interpret aggregate data on comparative or benchmarking data and create reports of the analysis. Example: investigate a statistically significant variation on the OIG report related to specific DRGs 14/15 or 79/89, verify that variation is valid; analyze physician practice patterns of complication rates and collaborate with physician to validate patterns.	X	
Assist in the development of complex integrated database design, development, or implementation. Example: data dictionary integration and crosswalks between disparate results reporting information systems.	X	
Provide input on coding guidelines, seek to obtain guidelines where there is no clarification. Example: send questions to AHA's <i>Coding Clinic</i> .	X	

the health record are used for code assignment and what portions of this are available in or could be converted to electronic form. Assess how current systems could be used to capture original data in a structured format using standards (such as Health Level Seven's clinical document architecture) to the extent possible. Consider what adjustments would be necessary to work with a CAC tool. Is existing clinical documentation, in whatever form, sufficient for accurate code assignment to the highest degree of specificity available in the coding system? If

not, where can improvements be made, and can CAC facilitate this process? Evaluation of clinical documentation must be performed for each unique treatment setting (e.g., outpatient, physician office, inpatient, ED) with input not only from HIM but also from a diverse provider and user work force.

Assess current coding workflow. Assess what is being done currently, step by step, and identify how use of a CAC tool would alter the current workflow. Also identify processes in the current workflow that may be improved by CAC, made superfluous by

Suggested Activities for Developing Knowledge-Worker Skills	
Skills to Perfect	Activities to Achieve Skills
Become a documentation expert	Participate in concurrent documentation improvement processes Obtain formal education in health information management Pursue professional development (e.g., enroll in Web-based training)
Strengthen skills beyond general, straightforward code assignments	Become intimately familiar with coding guidelines and how they are determined Focus on more difficult, specialty coding and applying guidelines that vary based on context Take a proactive attitude toward learning and understanding payer-specific coding interpretation
Develop effective audit techniques	Look for opportunities to cross-train with individuals who perform audits within the HIM department or other departments such as billing, compliance, or risk management or other areas where auditing is performed
Be comfortable with technology, information systems, and statistical applications such as spreadsheets and databases	Team up with IT/IS staff; take an active role in development and testing of new applications, software upgrades, coding updates, computer input screens, or other health record documentation tools Obtain training in statistical applications (e.g., Microsoft Excel and Access) View demonstrations and visit with CAC vendors at state and national conventions
Develop interpersonal skills (e.g., effective communication skills, consulting skills, and critical decision making)	Get involved on multidisciplinary committees; work with medical and administrative staff on health record documentation standards Offer in-service educational programs related to clinical coding, documentation, coding, and abstracting software for interdepartmental staff

CAC, or may hinder the utility or acceptance of a CAC tool.

Define expectations for balancing productivity and accuracy. Identify your “gold standard” for translating clinical data into medical codes. Define current productivity and accuracy rates for code assignment and the organization’s tolerance level for coding variances. Will the organization expect the same accuracy rate from a CAC tool? What level is acceptable? What level of productivity does the organization expect from the CAC tool? Define the expectations for balancing productivity and accuracy to achieve a return on investment.

Define organizational goals and objectives. Determine what the organization wants to accomplish and evaluate whether or not a CAC tool can help achieve this. For example, a CAC tool may be helpful for a radiology practice that currently employs no professional coding staff and wants to improve compliance. A CAC tool may be helpful for an organization that is chronically short staffed in the coding division and desires improved productivity for existing staff. However, while an NLP-based tool can facilitate improved documentation through feedback, it will not necessarily generate better documentation.

Broaden coder skill sets. Equip staff with the required skills to capitalize on advantages offered by CAC tools. Support and encourage all coding professionals to pursue personal professional development to move up the coding and clinical data management career ladder.

Plan carefully to successfully manage the change. Clarify exactly what change needs to occur. Outline the steps to implementation. Is it a major transformation of work processes or an adaptation of existing practices? Does it affect a sole unit, or will it cut across multiple functions? Who is and is not involved? Will customers be affected, and in what way? The clearer you are about the change and expected behavior, the more likely people will be to respond. Communication is key to preparing for successful change. People need time to prepare. Communicate early and often.

Guidance in Evaluating CAC Tools

Understand the available technology. Become familiar with structured input and NLP technologies relating to CAC,

how they work, and the advantages and disadvantages of each. Attend vendor presentations and evaluate the tools available for your clinical domain. Remain informed on advances in this technology, especially in your practice area, so you can help your organization make an informed decision.

Determine the best form of data input. How patient clinical documentation is captured and stored is a primary consideration for determining which main type of CAC tool to evaluate (structured input versus NLP). If physicians are already using a template for documenting patient care, they may be able to convert to a structured input tool fairly easily. If physicians insist on free text (i.e., unstructured documentation) or a combination of structured input and free text, investigate NLP tools. In addition, a system already in place may determine which CAC software application is best based on compatibility.

Consider the desired output. If the code-assist model is adopted, what information (clinical and nonclinical) will be presented to the coder and in what format? Are suggested codes linked to the documentation that supports the code assignment? Is an interface with an encoder, abstract database, or billing system desirable? Will the coding output be shared with other clinical users? Can reports be generated off the CAC data? To what extent does a tool accommodate data represented in standard format, such as Health Level Seven’s clinical document architecture?

Identify specific criteria for evaluating code assignment functionality. Define minimum coding accuracy and productivity levels and consider how this may be validated. Address expectations for version control, including what version of the code system, NCCI file, or E&M documentation guidelines is used; the mechanism and timeliness of implementing updated versions; and what mechanism exists for creating a history of code assignment for compliance (e.g., are individual cases stamped with the software version?). Are mapping techniques or decision pathways appropriately driving code assignment? What ongoing quality controls are in place to assess this? Does the CAC tool suggest modifiers on CPT codes? Are specific payer requirements considered? Request that the vendor provide evidence of reliability.

Web-based Training to Prepare the Upcoming Knowledge Worker

Building skills in the following areas can help position professionals to capitalize on the advantages of CAC tools:

- Clinical data management
- Healthcare data analytics
- Clinical documentation improvement methods
- Conversational information technology (IT)
- Project management for IT
- SNOMED CT basics

AHIMA offers online courses in these and other topics. Go to <http://campus.ahima.org> for more information on Web-based training or to <http://imis.ahima.org/orders> for other professional development opportunities.

Suggestions for Coding Professionals Working with CAC Tools

Develop a testing and audit plan to validate the results of the software application. Consider development of a “golden document set” (fully coded and validated) that can be used to test and compare initial software integrity, subsequent updates, and machine logic. Document the findings and, as necessary, create a project management plan to facilitate rapid reconciliation of issues, revisions, necessary upgrades, or refinements. Define acceptable confidence thresholds for various coding systems (e.g., ICD-9-CM, CPT, E&M, HCPCS) to optimize the advantages of using the tool and to provide a baseline for applicable specialty use. For example, is it acceptable if the CAC tool correctly extrapolates procedure codes for a mammogram 98 percent of the time?

Use the software for its intended purpose. Once you have tested the system and validated it, use the software as intended. Coding staff should function as editors and validators and should resist the temptation to recode the entire record on every case. Use your knowledge of the system’s strengths and weaknesses to maximize your efficiency. In time it is likely that you will learn to trust the system’s logic and will focus your attention on the areas and cases you know are weak or have been selected for more detailed review.

CAC is currently available in the outpatient or physician practice domains and will continue to evolve and be adapted. As the transition to EHRs and the adoption of ICD-10-CM and ICD-10-PCS occur in the US, the detailed and logical structure of these systems will increase the use of CAC tools across many different domains. In addition, as CAC technology becomes increasingly sophisticated, there will be less demand for coding professionals to perform traditional clinical coding tasks. CAC software applications that assist coding professionals in their workflow by allowing them to review and edit a draft set of codes will require coding professionals to further develop skills and competencies in the clarification and scrutiny of data. Computer-assisted coding is a budding technology whose time has come, and it heralds a new era for coding professionals.

Appendices

The following appendices are available in the online version of this practice brief, available in the FORE Library: HIM Body of Knowledge at www.ahima.org.

- Appendix A: Primer on NLP for Medical Coding
- Appendix B: Continuum of Linguistic Competence
- Appendix C: Advantages and Disadvantages of CAC Technology
- Appendix D: Potential Uses of Structured Code Output
- Appendix E: Summary of Use Cases
- Appendix F: Resources:
 - Annotated Bibliography
 - Available Research Testing NLP-based CAC Tools
 - CAC Web Resources
- Appendix G: Glossary of Terms
- Appendix H: Timeline of CAC Evolution

Prepared by

AHIMA computer-assisted coding e-HIM work group:

Sean Benson
 Jim Bowman, MD, MSM, FACS
 Glorianne Bryant, BS, RHIT, CCS
 Win Carus, PhD
 Ray Chien, MS
 Colleen Deighan, RHIT, CCS
 Christy DeLellis, RHIT
 Melissa Ferron, RHIA, CCS
 James Flanagan, MD
 Margaret M. Foley, MBA, RHIA, CCS
 Gail Garrett, RHIT
 Darice M. Grzybowski, MA, RHIA, FAHIMA
 Robert A. Jenders, MD, MS, FACP
 Kathy M. Johnson, RHIA
 Karen Karban, RHIT, CCS
 Diana McWaid-Harrah, MS, RHIA, CCS, CPC
 Janice Redden, CCS, CPC-H
 Gregory L. Schnitzer, RN, CCS, CCS-P, CPC, CPC-H, RCC, CHC
 Vickie Schraudner, RHIA
 Rita Scichilone, MHSA, RHIA, CCS, CCS-P
 Mary H. Stanfill, RHIA, CCS, CCS-P
 Robin K. Stults, RHIA
 David Sweet, MLS
 Adriana Van Der Graaf, RHIA, CHP, CCS
 Joe Weber, MS, MBA
 Martha Weiner, RHIA

Acknowledgments

Assistance from the following individuals is gratefully acknowledged:

- Peter L. Elkin, MD
- Kenneth Macklem
- Senthil Nachimuthu, MD
- Aldo Tinoco, MD
- Pat S. Wilson, RT(R), CPC

The computer-assisted coding e-HIM work group was supported by a grant to the Foundation of Research and Education from MedQuist.

Notes

1. Hripcsak, George, Carol Friedman, Philip O. Alderson, William DuMouchel, Stephen B. Johnson, and Paul D. Clayton. "Unlocking Clinical Data from Narrative Reports: A Study of Natural Language Processing." *Annals of Internal Medicine* 122, no. 9 (1995): 681–88.
2. Elkins, Jacob S., Carol Friedman, Bernadette Boden-Albala, Ralph L. Sacco, and George Hripcsak. "Coding Neuroradiology Reports for the Northern Manhattan Stroke Study: A Comparison of Natural Language Processing and Manual Review." *Computers and Biomedical Research* 33, no. 1 (2000): 1–10.
3. Warner, Homer, Jr. "Will Natural Language Processing Help Coders Any Time Soon?" AHIMA National Convention proceedings, October 2001. Available online at www.ahima.org.
4. Warner, Homer, Jr. "Good Isn't Enough." *Health Management Technology* 22, no. 6 (2001): 30–31.
5. Warner, Homer, Jr. "Can Natural Language Processing Aid Outpatient Coders?" *Journal of AHIMA* 71, no. 8 (2000): 78–81.
6. Warner, Homer, Jr., John Holbrook, David Evans, and Douglas Stetson. "Has Natural Language Processing Finally Arrived? Autocoding and Data Mining Examined." HIMSS panel presentation, session 49, February 2001.
7. Mamlin, Burke W., Daniel T. Heinze, and Clement J. McDonald. "Automated Extraction and Normalization of Findings from Cancer-Related Free-Text Radiology Reports." *Proceedings of the 2003 American Medical Informatics Association (AMIA) Annual Symposium*, 420–24.
8. Schadow, Gunther, and Clement J. McDonald. "Extracting Structured Information from Free Text Pathology Reports." *Proceedings of the 2003 AMIA Annual Symposium*, 584–88.
9. Friedman, Carol, Lyudmila Shagina, Yves Lussier, and George Hripcsak. "Automated Encoding of Clinical Documents Based on Natural Language Processing." *Journal of the American Medical Informatics Association* 11, no. 5 (2004): 392–402.
10. Lorence, Daniel P., and Awad Ibrahim. "Disparity in Coding Concordance: Do Physicians and Coders Agree?" *Journal of Health Care Finance* 29, no. 4 (2003): 43.

References

"Clinical Data Specialist." In *Evolving HIM Careers: Seven Roles for the Future*. Chicago: AHIMA, 1999.

AHIMA. "Natural Language Processing as a Means to Increase Productivity." Audio seminar, May 13, 2004. Available online at <http://campus.ahima.org/audio/2004seminars.html>.

Beinborn, Julie. "Automated Coding: the Next Step." *Journal of AHIMA* 70, no. 7 (1999): 38–43.

Boelle, Pierre-Yves, Antoine Flahault, Laurent Letrilliant, and Cecile Viboud. "Automatic Coding of Reasons for Hospital Referral from General Medicine Free-text Reports." *Proceedings of the 2000 AMIA Annual Symposium*, 487–91.

Bowman, Jim, and Mary Stanfill. "Physicians Cast Wary Eye at Computer-assisted Coding." *Journal of AHIMA* 75, no. 8 (2004): 76–77.

Chuang, Jen-Hsiang, Carol Friedman, and George Hripcsak. "A Comparison of the Charlson Comorbidities Derived from Medical Language Processing and Administrative Data." *Proceedings of the 2002 AMIA Annual Symposium*, 160–64.

Evans, David, John Holbrook, Douglas Stetson, and Homer Warner Jr. "Has Natural Language Processing Finally Arrived? Autocoding and Data Mining Examined." HIMSS panel presentation, February 2001.

Franz, Pius, Udo Hahn, Rudiger Klar, Stefan Schulz, and Albrecht Zaiss. "Automated Coding of Diagnoses—Three Methods Compared." *Proceedings of the 2000 AMIA Annual Symposium*, 250–54.

Friedman, Carol, George Hripcsak, and Irina Shablinsky. "An Evaluation of Natural Language Processing Methodologies." *Proceedings of the 1998 AMIA Annual Symposium*, 855–59.

Garvin, Jennifer, and Valerie Watzlaf. "Current Coding Competency Compared to Projected Competency." *Perspectives in Health Information Management* 1, no. 2 (2004). Available online at www.ahima.org.

Hagland, Mark. "Revolution in Progress: How Technology Is Reshaping the Coding World." *Journal of AHIMA* 73, no. 7 (2002): 32–35.

Hieb, Barry. "NLP Basics for Healthcare." Gartner Research, August 16, 2002.

Hripcsak, George, John H. M. Austin, Philip O. Alderson, and Carol Friedman. "Use of Natural Language Processing to Translate Clinical Information from a Database of 889,921 Chest Radiographic Reports." *Radiology* 224, no. 1 (2002): 157–63.

Johns, Merida. "A Crystal Ball for Coding." *Journal of AHIMA* 71, no. 1 (2000): 26–33.

Lussier, Yves A., Lyudmila Shagina, and Carol Friedman. "Automating SNOMED Coding Using Medical Language Understanding: A Feasibility Study." *Proceedings of the 2001 AMIA Annual Symposium*, 418–22.

Morris, William C., Daniel T. Heinze, Homer R. Warner Jr., Aron Primack, Amy E. W. Morsch, Ronald E. Sheffer, et al. "Assessing the Accuracy of an Automated Coding System in Emergency Medicine." *Proceedings of the 2000 AMIA Annual Symposium*, 595–99.

Schnitzer, Gregory L. "Natural Language Processing: A Coding Professional's Perspective." *Journal of AHIMA* 71, no. 9 (2000): 95–98.

Schnitzer, Gregory L., and Mary H. Stanfill. "Outwit, Outlast, Outcode: Surviving in the Autocoding Era." *Journal of AHIMA* 72, no. 9 (2001): 102–4.

Stollman, Neil, and Matthews, Kathleen. "Positive Productivity, Better Billing." *Health Management Technology*, August 2002: 22–26.

Zender, Anne. "From Coder to Knowledge Engineer." *Journal of AHIMA* 74, no. 7 (2003): 104.