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Review

Evaluation Study of Computer assisted coding in Revenue Cycle Management

Sahanasharma Ventakesh Sharma[1*],

[1*] *Scholar, Griffith College Dublin, Carrigaline , Cork ,Ireland*

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*Author for Correspondence: Sahana Sharma V
Email: Sahanasharma90711@gmail.com

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Abstract

Computer Aided Coding (CAC) has been around since the 1950s and is projected to reach $4.75 Billion by 2022. Be that as it may, it has not been on the emergency clinics' need list until 2014. Computer-assisted coding is an innovation programming that reduces out the coding work process, lessen overabundances by expanding efficiency, and assists coders with exploring broadened, more intricate diagrams all the more rapidly. Innovation is a kind of man-made brainpower. The possibility of Computer-assisted coding turned out to be more forefront with the execution of electronic health records (EHRs) and the requests of a more prohibitive repayment from payers. Precision, consistency, and, undoubtedly, efficiency has been critical to all associations. Because of the expansion in trend setting innovations, Computer-assisted coding has progressed in its exhibition. Nonetheless, the inquiry stays as to in the event that it has satisfied the new promotion before the execution of CA to expand efficiency, precision, consistency, improve clinical documentation, and so on This examination was directed utilizing a survey to overview the viability of Computer-assisted coding in revenue cycle management. The consequences of the overview show that there are associations that are as yet not utilizing CAC. The general view of the respondents feel CAC isn't a must-have innovation to code proficiently in any case, with the CAC, the general coding measure is agreeable yet at the same time needs improvement.

Keywords: Computer Assisted Coding (CAC), Revenue Cycle Management (RCM), Medical Coding, Electronic Health Records (EHRs), Clinical Documentation, Accuracy and Efficiency, Healthcare Industry, Artificial Intelligence (AI).

1. INTRODUCTION

Introduction being the first chapter of the research provides the reader with a basic understanding of the study. This chapter consists of an overview of medical coding and Computer Assisted Coding (CAC), followed by the purpose and objectives that drive the research, and finally explains the significance of the study. The structure of the research is also presented to give the reader a clear layout of the work (Fang, 2018).

1.1 Overview

In today's world of ongoing research and rapidly evolving technology, innovations are continuously transforming healthcare practices. This research is aimed at studying and evaluating Computer Assisted Coding (CAC), which is emerging as a significant development in the field of medical coding, along with its role in revenue cycle management (RCM). The research journey begins by understanding the origin of medical coding, its benefits, and the challenges faced by traditional methods. It then explores the reasons for adopting new technology, which led to the development of CAC (Versova, 2010). The study proceeds with an examination of existing data on CAC, including its capabilities, global implementation, major players in the industry, and the financial aspects of its adoption. It also reviews the existing framework of revenue cycle management and its evolution with CAC. Finally, a survey in the form of a questionnaire was conducted to collect feedback from medical coders regarding the impact of CAC on their professional lives, the financial aspects of organizations, and the overall coding industry. Using this data, the research evaluates revenue cycle management in relation to CAC (Versova, 2010).

Research Purpose and Objectives

- The purpose of this research is linked to the objectives that inspired the study. The key objectives are:
- To identify the importance of computer assisted coding in the healthcare industry.
- To determine the role of computer assisted coding in revenue cycle management.
- To examine developments in the healthcare industry due to computer assisted coding.
- To evaluate changes in revenue cycle management within the coding industry after the implementation of CAC.

Significance of the Study

As CAC technology is still in its emerging phase in many countries and relatively new to many medical coders, this study contributes significantly to the literature on medical coding (Jin, 2010). It also provides insights into the coding industry and serves as a base for future researchers. The major significance of this work lies in the analysis of data collected from medical coders, which provides insights and conclusions on the role of CAC in revenue cycle management.

Structure of the Study

The research is structured to guide the reader through the journey of medical coding. It begins with the origin of medical coding, followed by an explanation of traditional coding methods, including their benefits, challenges, and shortcomings. It then highlights the need for new technology to address these challenges and discusses existing literature on medical coding and the healthcare industry. CAC implementation and its role in revenue cycle management are examined, and data for evaluation is collected through a survey questionnaire, which provides qualitative insights. The collected data is analyzed to draw conclusions that address the research objectives. This chapter therefore introduces the topic by presenting the research purpose and objectives, outlining the significance of the study, and describing the overall structure of the research.

2. METHODOLOGY AND RESEARCH DESIGN

According to Polit and Beck (2004), methodology refers to the ways of obtaining, systematizing, and analyzing data. Creswell (2003) describes methodology as a logical group of methods that complement one another and are capable of delivering data and findings that reflect the research question and suit the researcher's purpose. Similarly, Bowling (2002) explains methodology as the overall structure of the research study, including the sample size and methods, the practices and techniques used to collect data, and the process of analysis. This third chapter of the research describes the type of research undertaken, along with the methods, strategy, approach, philosophy, and design. It also explains the different techniques used to obtain data, how the data are analyzed, and the ways in which they are connected to the literature in order to derive results.

2.1. Research Method

Research approach is defined as a plan and process that outlines the significant stages of data collection, analysis, and interpretation. Research experts have classified approaches into three main categories: inductive, deductive, and abductive.

- In the inductive approach, researchers use observed data to generate untested generalizations and build theories from specific findings (Choy, 2014).
- The deductive approach begins with established premises; if they are valid, the conclusions must also be valid (Elkin et al., 2016).
- In the abductive approach, investigators use known premises to create testable conclusions (Elkin et al., 2016).

For this study, the inductive approach was the most suitable, as it does not require hypothesis formulation. The research began with specific aims, objectives, and research questions and then proceeded to collect relevant data to address them. The process followed the typical inductive sequence: observations → patterns → theory. In this study, observations were made, patterns identified, and theories developed to arrive at conclusions (Yan et al., 2010).

2.2. Research Strategy

A research strategy serves as an action plan that guides the researcher through a systematic process to ensure quality results (Beckman, 2014). This study adopted a qualitative strategy within the interpretive paradigm, supplemented by quantitative elements where appropriate. Quantitative research explains phenomena through numerical data analyzed using statistical methods (Kukafka et al., 2016), whereas qualitative research explores the reasons and motivations behind human behavior, providing in-depth insights (Kukafka et al., 2016). In this study, both approaches were valuable. For example, the survey strategy allowed data to be obtained from multiple respondents, thereby helping to understand perceptions of CAC technology and its benefits in the healthcare industry (Beckman, 2014).

2.3 Research approach

As noted earlier, inductive, deductive, and abductive approaches each serve different purposes. The inductive approach was chosen for this research, as it allows exploration without predetermined hypotheses (Clawson et al., 2017). This study began with the aim of exploring Computer Assisted Coding (CAC) and Revenue Cycle Management (RCM). Data were collected using a questionnaire, analyzed thematically, and then used to identify patterns and formulate theories. Based on these theories, conclusions were drawn that aligned with the research objectives (Beckman, 2014; Cope, 2015).theory is formulated. based on the theory a conclusion is drawn which meets the objective (Beckman, 2014).

2.4. Research philosophy

Research philosophy concerns the beliefs underpinning how knowledge is gathered, assessed, and developed. Common philosophies include pragmatism, positivism, realism, and interpretivism (Friedman et al., 2016).

- Pragmatism focuses on practical solutions, retaining ideas that work and discarding those that do not (Friedman et al., 2016).
- Positivism emphasizes acquiring knowledge from natural phenomena and observable facts (Holden and Lynch, 2004).
- Realism assumes that knowledge exists independently of perception (McNicholas, 2016).
- Interpretivism incorporates human interests, acknowledging that reality is socially constructed through shared meanings and language (Myers, 2008).

This research is based on interpretivism, as it involved interpreting the perceptions of medical coders through surveys. The philosophy supported qualitative data collection and analysis by focusing on participants' views and experiences (Walker, 1997).

2.5. RESEARCH DESIGN

Research design provides a blueprint for data collection and analysis (Sloane-Seale, 2009). The three main strategies are qualitative, quantitative, and mixed-methods (Perera et al., 2014). This study is primarily qualitative, involving an in-depth examination of medical coding, its evolution, challenges, and the role of CAC. Data were collected through surveys of coding professionals and supplemented by secondary literature. While quantitative aspects were incorporated, the focus remained on qualitative analysis to evaluate CAC in RCM (Basias and Pollalis, 2018; Perera et al., 2014). A case study approach was also relevant, as it enabled detailed analysis of CAC in the context of healthcare RCM. Case studies are particularly useful for exploring "how" and "why" questions in complex environments (Kaur and Rani, 2015; Hsu et al., 2014). This approach was more appropriate than action-oriented or grounded theory, given the study's focus on feedback and evaluation rather than hypothesis generation (Cuervo-Cazurra et al., 2017).

2.6. Data collection techniques

Two types of data collection were employed: **primary** and **secondary**.

Primary data:

Collected through questionnaires administered to medical coders, capturing their perspectives on CAC and RCM (Panas et al., 2010; Stanfill et al., 2010). This method was chosen as it allowed participation from many coders in a short time, especially during the COVID-19 pandemic when interviews were impractical.

Secondary data:

Obtained from literature, online platforms, research papers, blogs, and articles (Kielmann et al., 2012). This complemented the primary data and provided context.

2.7. Role of Researcher

The researcher, being a medical coder by profession, was able to use professional networks to distribute questionnaires and encourage participation. Access to a coding team meeting, supported by a previous manager, further facilitated data collection. This dual role as both professional and researcher added depth to the study and provided valuable insights (Walraven and Demers, 2011).

2.8. Sampling and access

The study employed purposive sampling to target medical coders, ensuring participants had relevant expertise (Kiely, 2012; Veresov, 2010). Snowball sampling was also used, where participants referred others, helping expand the sample. Data collected were later represented using graphs and charts to aid analysis (TenHouten, 2017; Sadler et al., 2010).

2.9. Data analysis

Data analysis involved applying both logical and statistical tools to derive meaningful insights (Chung and Park, 2018). Thematic analysis was chosen, as it identifies patterns within qualitative data, enabling a deeper understanding of participants' perspectives (Swart, 2018). Survey responses were categorized and analyzed, combining both open-ended (qualitative) and close-ended (quantitative) data (Check and Schutt, 2012; Ponto, 2015).

2.10. Research ethics

Ethical guidelines ensured the integrity and confidentiality of data collection (Fang, 2018; Buchanan and Hvizdak, 2009). The ethical principles followed included:

- Respecting the dignity of respondents.
- Safeguarding confidentiality of data.
- Preventing misuse or fraudulent use of collected information.
- Adhering to institutional guidelines to avoid misrepresentation.

The ethics application form from Griffith College was successfully filed and approved by the thesis supervisor, confirming compliance with all ethical requirements. This research adopted an inductive, interpretivist, qualitative approach, supported by surveys and secondary sources. Data were collected using purposive and snowball sampling, analyzed thematically, and interpreted within the framework of CAC and RCM. The methodology ensured that both professional perspectives and academic literature informed the findings.

3. DISCUSSIONS

The fourth chapter of this research presents and discusses the findings derived from data collection. The results are analyzed using suitable techniques and then discussed in relation to the research objectives. This analysis provides the foundation for drawing conclusions about the research problem and serves as the pathway to final insights.

3.1 Overview

The primary data in this study consists of responses from the survey questionnaire, while secondary data includes information obtained from literature and digital platforms. The survey responses were downloaded into an Excel file, where each question was categorized and analyzed. These findings are then compared and discussed to arrive at meaningful conclusions.

3.2 Findings and Discussion

Two main sources of data were analyzed:

1. Secondary data – from existing literature and digital sources.
2. Primary data – collected from survey responses.

From the literature review, the following points about CAC were highlighted:

- CAC can generate financial benefits for the coding industry.
- Documentation procedures can be improved through CAC.
- CAC eases the work of coders and enhances accuracy.
- Some research suggests CAC may replace traditional coding methods.
- Implementation of CAC can reduce denials and decrease payment time.

Based on these insights, a set of questions was designed to gather coders' perceptions. The questionnaire included items on participants' years of experience, training and knowledge of coding tools, hands-on experience with CAC software, and their opinions about CAC's impact on the industry.

Findings and Analysis

1. Introduction

Five categories of questions were included in the survey. These covered years of experience, training in coding tools, expertise with these tools, use of CAC software, and perceptions of CAC's future in the industry. This structure allowed the research objectives to be linked with the data collected, providing insights into how CAC influences coders' work, company finances, and the coding industry overall.

2. Overview of participants

There was a total of 92 respondents in which 100% (n=92), that is 92 people, participated voluntarily and agreed that their responses could be used in the research. Among the participants when asked for years of experience, it was found that the least experienced participant was 6 months job experience and the highest experienced participant has 9 years' experience.

- 13 people were having less than 2 years of experience.
- 39 people had between 2 and 5 years of experience.
- 40 people were having more than 5 years of experience.

The above data indicates the feedback from the survey comes from people having a mix of different years of experience, but the significant majority, approximately 86%, have over 2 years of experience. In which 43% around 40 people have more than 5 years of experience. This data adds a good weightage to the findings of the thesis as it comes from the people with very good knowledge, insight, and experience in this field.

3. Training and Experience with coding tools:

The six most common coding tools mentioned in the survey were: *Find a Code, My Coding, Encoder Pro, Flash Code, Super Coder,* and *ICD10.com*. Participants rated their training on these tools from "none" to "a lot of training."

Analysis revealed that:

- *ICD10.com* had the highest number of trained users, followed by *Super Coder* and *Encoder Pro*.
- Participants with more years of experience generally reported higher levels of training across all tools.
- Experience was therefore directly proportional to training levels, with percentages varying slightly between tools.

Table 1: A table showing the number of people trained in each coding tool.

		The multiple-choice options to choose from				
		none	A little	somewhat	A good amount	A lot of training
Coding tools mentioned in the question	Find a code	8	16	23	29	16
	My Coding	14	15	23	28	12
	Encoder pro	15	4	18	30	25
	Flash code	15	6	22	22	27
	Super coder	12	4	19	27	30
	icd10.com	7	8	16	34	27

Find a code:

There were 29 people who had a "good amount" of training in find a code tool, in which around 72% (21 out of 29) were having more than 3 years of experience in medical coding. When considering people who had "a lot of training" 14 out of 92 had it and 13 out of 14 which is around 93% were having more than 3 years of experience.

My coding:

There were 28 people who had a "good amount" of training in my coding tool, in which around 71% (20 out of 28) were having more than 3 years of experience in medical coding. When considering people with "a lot of training" 12 out of 92 had it who were having more than 3 years of experience. 9 out of 12 which is around 75% were having more than 5 years of experience.

Encoder pro:

There were 30 people who had a “good amount” of training in encoder pro tools, in which around 83%(25 out of 30) were having more than 3 years of experience in medical coding. When considering people with “a lot of training” 25 out of 92 had it and 17 out of 25 which is around 68% were having more than 5 years of experience.

Flashcode:

There were 22 people who had a “good amount” of training in flash code tools, in which around 72%(216 out of 22) were having more than 3 years of experience in medical coding. When considering people with “a lot of training” 27 out of 92 had it and 14 out of 27 which is around 52% were having more than 5 years of experience.

Super coder:

There were 27 people who had a “good amount” of training in super coder tools, in which around 74%(20 out of 27) were having more than 3 years of experience in medical coding. When considering people with “a lot of training” 30 out of 92 had it and 20 out of 30 which is around 67% were having more than 5 years of experience.

icd10.com:

There were 34 people who had a “good amount” of training in the icd10.com tool, in which around 80%(27 out of 34) were having more than 3 years of experience in medical coding. When considering people with “a lot of training” 27 out of 92 had it. 12 out of 27 which is around 45% were having more than 5 years of experience. From the above data of the findings, we see that the number of people trained in icd10.com is the highest and then comes supercoder and encoder pro. When we look closer and compare the years of experience against the training in each tool, the higher the experience, the more well trained the participants are. This indicates years of experience is directly proportional to the training received. And this is true across all the training tools with the percentages slightly varied.

The third type of question asked in the survey was about the expertise in using the coding tools. The same 6 coding tools were included in the question and the participants had to choose their expertise in each tool from the multiple choice given like no knowledge - in case of zero expertise in using the tool, a little knowledge - signifying very little surface level knowledge, working knowledge - a good amount of knowledge in which one can manage to work on, a lot of knowledge - a very good amount of knowledge by which one can work with ease and expert - signifying a great amount of knowledge by which participant is considered as a top user of the tool. This question was included in the survey in order to know the working knowledge and hold on the particular tool by the participant which can be used to know the nature of the participants in their working environment. The below table represents the data on the expertise of each tool, all the 6 coding tools are mentioned in the columns and results from the questionnaire that is the number of people with expertise in each tool and people with 3 plus years of experience are mentioned in rows.

Table 2: A table showing the number of people who have expertise in each coding tool.

		Different tool on which the questions about expertise were asked					
		Find a code	**My coding**	**Encoder pro**	**Flash code**	**Super coder**	**icd10 .com**
Results from the questionnaire	No. of people with high expertise in that tool	18 (19.5%)	13 (14%)	28 (30%)	28 (30%)	30 (32%)	25[Jean Anne5] (27%)
	People with 3 plus years of experience	13 (72%)	11 (85%)	26 (93%)	24 (86%)	22 (73%)	18 (72%)

The above table shows the findings from the responses of the question, which are number of people with high expertise in that tool: this number includes participants with a lot of knowledge and the participants who are expert in using that tool. The table also shows the people with more than 3 years of experience.

Find a code:

There were a total of 18 participants which is around 19.5% who had “a lot of knowledge” and “expert” in using that tool. Out of those 18 participants 13 of them had more than 3 years of experience. That accounts to 14% of the total participants.

My coding:

There were a total of 13 participants which is around 14% who had “a lot of knowledge” and “expert” in using that tool. Out of those 13 participants 11 of them had more than 3 years of experience. That accounts to 11% of the total participants.

Encoder pro:

There were a total of 28 participants which is around 30% who had “a lot of knowledge” and “expert” in using that tool. Out of those 28 participants 26 of them had more than 3 years of experience. That accounts to 28% of the total participants.

Flash code:

There were a total of 28 participants which is around 30% who had “a lot of knowledge” and “expert” in using that tool. Out of those 28 participants 24 of them had more than 3 years of experience. That accounts to 26% of the total participants.

Super coder:

There were a total of 30 participants which is around 32% who had “a lot of knowledge” and “expert” in using that tool. Out of those 30 participants 22 of them had more than 3 years of experience. That accounts to 23% of the total participants.

icd10.com:

There were a total of 25 participants which is around 27% who had “a lot of knowledge” and “expert” in using that tool. Out of those 25 participants 18 of them had more than 3 years of experience. That accounts to 19.5% of the total participants. From the above findings we can see that Super coder coding tools has the highest number of expertise followed by flash code, encoder pro and icd10.com. We also see that participants with more than 3 years of experience have more expertise in using these tools than the freshers, this signifies that the well trained and the expertise group of people lie in the experienced section of the participants. By the data, one can state that experience is directly proportional to the expertise in that tool.

4. Use of CAC software

The survey included two questions on CAC. First, 34 of 92 participants (37%) reported using CAC in their career, with 85% (29 of 34) having over five years of experience. This indicates that CAC use is concentrated among senior professionals, highlighting the value of experience in adopting the technology. Second, 25 participants (27%) had received CAC training, of which 80% (20 of 25) also had more than five years of experience. Training is therefore primarily directed at experienced coders, who already possess strong expertise in traditional tools. The remaining five trained participants had less than five years of experience, representing fast-learning “CAC enthusiasts.” Coders with three or more years of experience were identified as the core group for future training, as they combine sufficient tool expertise with adaptability. In summary, CAC usage and training are largely reserved for experienced coders, while mid-level professionals represent the next generation of CAC adopters.

5. The Future of CAC

The Fifth type of question asked in the questionnaire survey was about CAC. Participants were asked to rate their opinion and by this, participants' perception about CAC could be known. They were then also given an opportunity to give comments about the future of CAC. The first one being, will CAC make industry more efficient. The responses were like this: 70% (64 participants out of 92) feel that CAC software would make the industry more efficient. 14% totally disagreed with this and 15 participants, that is 16% were neutral, this signifies one third of the people does not believe about the CAT's ability to make industry more efficient. But seeing table 1 and 2 there are many knowledgeable and trained professional who will get into CAC and their skill will add up in making the industry efficient along with CAC’s capability in making industry more efficient. The eight and the final question was, CAC improves clinical documentation. The responses were like this: 70% (64 participants out of 92) agreed that it improves clinical documentation and 19 participants ,21% disagree. The documentation part in the coding industry has always been the main point on which the whole result depends, so this new technology will therefore improve the documentation as the computer will accept the structured and clear data. Hence making the documentational improvements in the process. To summarize the above findings, there were a total of 92 participants in the survey questionnaire, who were highly knowledgeable and a significant majority were highly trained. The coding tool in which the highest number of participants trained was icd10.com and the coding tool in which the highest number of people's expertise lies is super coder. The above finding tells us that years of experience is directly proportional to the knowledge and expertise on the coding tools.

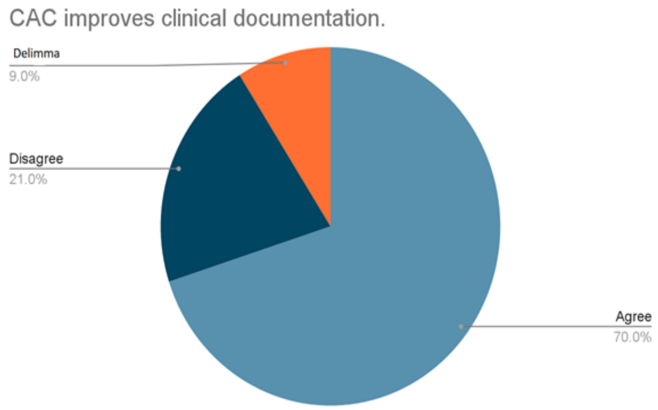

Fig 1: Pie Chart showing percentages of responses "CAC improves clinical documentation"

Currently the CAC is being used by people having more than 5 years of experience. The people who tried their hands on CAC were mostly experienced people in the coding industry and the trained people were also having 5 plus years of experience. This means that it is seen that participants with 3 or more years have tried their hands on CAC software, but are not trained. These people are the future of the coding industry, they have the right amount of experience to understand CAC, they are enthusiastic and they have knowledge and ability in all other coding tools which makes them fast learners to CAC. These should be trained. Finally, after listing down all the findings and analysing them, it could be concluded that CAC is useful for the medical coding industry and is the future. The survey justifies that CAC will make the coders job easy, decreasing errors, increasing accuracy and increasing the profit in the industry. This would also replace traditional coding frameworks and make documentation easy. Thus, CAC would be the next very big thing in the coding industry and has a great future. This fourth chapter was all about listing out the findings and discussing it, as we see there were two kinds of data: primary and secondary of which secondary was from the literature, which were the conclusions of experiments of other researchers. The second one being the survey questionnaire, is the actual data collected by the efforts of the researcher in order to arrive at the conclusion on the research aim and meet the research objective. So this chapter lists out the findings, discusses it and provides a base to conclude.

5. Concluding Thoughts

As we arrive at the final and the fifth chapter of the research, "Concluding thoughts" the implications of the findings for the research question are mentioned, contributions and the limitation of the research are given out. The recommended practices after implementation of CAC and recommendations for the future researchers are listed. Finally, the final conclusions and reflection are written on the ending note of research.

5.1 Implications of findings for the research question

The research question which was the source motivation to do this research is "Evaluating the Computer Assisted Coding in Revenue cycle management". So the research aims in studying the CAC, its implementation, collecting the data which could be used to evaluate the CAC in revenue cycle management. It is implied from the findings that the percentage of opinions from the secondary data in support of the primary data are high. The below implications can be formulated about the research question.

- Evaluation of CAC can be done using the existing and collected data.
- CAC reduces the denials and decreases payment time.
- Data from the findings imply that the documentation in the CAC would be of less ease and gets the job done in less time.

- The outcome of CAC will have more accurate results and this would increase profits.

So, from the above implications it is clear that CAC will contribute in the revenue cycle management by decreasing the processing time and payment time, decreasing the denials as it is more accurate, making the documentation easy which in turn reduces errors and that will fetch profits as it can deliver accurate data. The mentioned points have already been a part of literature of this research, the conclusion from the findings justifies all the mentioned points in the literature.

5.2 Contributions and Limitations of the research

This study makes a significant contribution to the limited literature on Computer Assisted Coding (CAC). Few researchers have combined this type of data collection and analysis to evaluate CAC, making the findings particularly valuable. The results not only highlight CAC's capabilities but also provide a foundation for future studies, encouraging researchers to explore its impact in greater depth.

CONTRIBUTIONS

Clinical coding consistency is vital for hospitals employing coders with varying levels of expertise. Research shows that greater coding accuracy reduces case denials and missed reimbursements, while CAC can also help control costs by lowering overtime and review expenses. CAC's ability to run reports and generate analytics on cloud platforms allows coded data to be linked with enterprise data warehouses, benefiting business intelligence teams in monitoring efficiency. It also improves transparency and consistency, as audit trails and accuracy checks provide managers with valuable insights into workflows and coding decisions. Survey findings indicate that most trained CAC users have over five years of experience, making them key drivers of current implementation. Meanwhile, coders with three or more years of experience represent the next generation of CAC adopters, as they are well positioned to be trained and contribute to future growth.

LIMITATIONS

Like most emerging technologies, CAC has limitations. It is not a quick solution and requires continuous Clinical Documentation Improvement (CDI) and coder training to remain effective. Maintaining high data integrity is critical, as overuse of copy-paste, abbreviations, or symbols in documentation can reduce CAC accuracy. Hospitals may need risk-mitigation strategies to address this. Language barriers also pose challenges. Natural Language Processing (NLP) engines sometimes struggle with sentence structures such as negation or uncertainty, which may hinder accurate code suggestions. This can be addressed by supplementing CAC with contextual patient information and domain-specific databases. Additionally, CAC cannot interpret handwritten notes, as it depends on structured text or documents readable by Optical Character Recognition (OCR). Vendors should therefore ensure compatible electronic formats before implementation. Finally, adoption is limited by the lack of industry standards and the knowledge levels of HIM professionals implementing the systems, making strong oversight essential to preserve data reliability.

5.3 Recommendations for practice

At this point of the research, much literature on medical coding and CAC, contemplations before moving to a CAC have been mentioned. Here are the few recommendations for practice mentioned in order to implement before practicing CAC.

- The documentation by the doctors or the scribers should follow new guidelines in order to write a document readable by the software.
- The workflow of CAC's environment should be explained to all the professionals in the coding industry as their work environment will change after implementation of CAC.
- The recommendations to the billing section are that they should increase their speed of work as CAC would make the coding faster.
- As seen in the survey, CAC is mostly used by coders having more than 5 years of experience who are trained, but the coders with more than 3 years of experience are very capable hence, they should be trained. They are the ones on whom CAC's future depends.
- Recommendations for the doctors is that they are the main source of documentation, so they should revise their system of documenting the patient's status. This will help in smooth implementation of CAC.

- Recommendations of the insurance industry is that they should be well versed with the new coding norms after CAC implementation in order to be in sync with the coding output.
- So, the evolution of CAC gives the present business in medical coding a new opportunity by which they should change their standards to the new market standards of CAC. Hence giving them a place for growth.

5.4 Recommendations for future researchers

This study is one of the few to evaluate CAC in relation to revenue cycle management, providing a foundation for future research. Subsequent studies could focus on specific indicators such as accuracy, errors, time, or denials to assess CAC's impact more precisely. Future researchers may also adopt alternative data collection methods, including personal or group interviews, to gather richer, region-specific insights. In addition, targeted studies could examine narrower topics such as changes in documentation quality or accuracy after CAC implementation. Overall, this research offers multiple pathways for further investigation, encouraging deeper exploration of CAC's role in healthcare.

CONCLUSION

Computer Assisted Coding (CAC) represents a major technological shift in the coding industry, integrating computer intelligence into the coding process. This research aimed to evaluate CAC within revenue cycle management (RCM). It began with a review of existing literature on CAC and RCM, followed by a survey that captured coders' perceptions and experiences. The findings confirmed that CAC improves accuracy, efficiency, and documentation, aligning with prior studies. It also highlighted its financial impact and the role of coder experience in successful adoption. Importantly, the study provides both a literature-based and coder-based perspective, making it one of the few evaluations of CAC in RCM. By combining existing knowledge with practical insights, this research adds value to the limited body of work on CAC and serves as a foundation for future studies in the field.

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