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Current Applications of Artificial Intelligence in Billing Practices and Clinical Plastic Surgery

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Summary: Integration of artificial intelligence (AI), specifically with natural language processing and machine learning, holds tremendous potential to enhance both clinical practices and administrative workflows within plastic surgery. AI has been applied to various aspects of patient care in plastic surgery, including postoperative free flap monitoring, evaluating preoperative risk assessments, and analyzing clinical documentation. Previous studies have demonstrated the ability to interpret current procedural terminology codes from clinical documentation using natural language processing. Various automated medical billing companies have used AI to improve the revenue management cycle at hospitals nationwide. Additionally, AI has been piloted by insurance companies to streamline the prior authorization process. AI implementation holds potential to enhance billing practices and maximize healthcare revenue for practicing physicians. *(Plast Reconstr Surg Glob Open 2024; 12:e5939; doi: 10.1097/GOX.0000000000005939; Published online 1 July 2024.)*

INTRODUCTION

Artificial intelligence (AI) is revolutionizing healthcare, advancing functionality and applicability with a projected cost savings of more than $300–$450 billion annually by McKinsey & Company in 2013.[1] In plastic surgery, AI has been used for various tasks such as generating a diagnosis, surgical simulation, predicting patient outcomes, and creating individualized treatment plans.[2] Although beneficial in clinical applications, AI also streamlines the medical revenue cycle and improves billing practices.

Many subdisciplines of AI exist, including machine learning, natural language processing (NLP), deep learning, and facial recognition. Plastic surgeons can utilize these to improve their surgical practice and optimize patient care.[2,3] Machine learning, a subdiscipline of AI, analyzes large datasets using algorithms to identify patterns and make predictions.[3,4] This is further subdivided into supervised learning, in which pre-existing datasets train algorithms to predict outcomes in new data, and unsupervised learning, which does not use a training dataset but is helpful to identify patterns within data.[3–5] NLP is a type of AI that uses machine learning software to understand, interpret, and manipulate human language.[3,6] Deep learning, a subset of machine learning, uses neural networks with continued training datasets to improve automated predictions.[3,7] This article describes the utilization of AI in plastic surgery to enhance patient care and outcomes, the current state of billing, and the application of AI to optimize billing practices.

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Current Applications in Plastic Surgery

AI has broad applications in plastic surgery. Within microsurgery, supervised machine learning has recently been implemented in postoperative free flap monitoring.[8,9] Current techniques, including handheld Doppler ultrasonography, implantable Doppler, or laser Doppler flowmetry, require continuous monitoring, invasiveness, cost, user complexity, and expertise.[8,10] Supervised machine learning models can effectively monitor vascular compromise by learning from postoperative free flap photographs and clinical determination of arterial or venous insufficiency, followed by subsequent validation of the model. Huang et al[8] created a random forest prediction model of postoperative flap circulation with an accuracy of 98.4% by assessing temperature and color differences between the flap and surrounding skin to determine sufficient circulation, arterial insufficiency, and venous insufficiency. Machine learning for free flap monitoring may help reduce the subjectivity of clinical evaluations and allow early detection of vascular compromise with prompt intervention.[8]

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For implant-based breast reconstruction after mastectomy, supervised machine learning can improve predictive ability of the risks of postoperative complications, such as periprosthetic infection and explantation.[11] Hassan et al[11] developed an algorithm to predict periprosthetic infection and explantation with an accuracy, defined by area under the receiver operating curve (AUROC), of 0.73 and 0.78, identifying nine and twelve important predictive factors, respectively.

In orthognathic surgery, supervised machine learning has also been used to diagnose, stratify risk, and facilitate clinical decision-making.[2] Knoops et al[2] trained a three-dimensional morphable model using databases of healthy volunteers and patients needing orthognathic surgery (for maxillary hypoplasia or mandibular hyperplasia), and the model was able to diagnose the orthognathic patients with a sensitivity and specificity of 95%. The model was additionally able to predict individualized postoperative patient face shape based on preoperative photographs, allowing for a more personalized preoperative surgical consultation, improving patient education, and enhancing surgical planning.[2]

In aesthetic surgery, AI can simulate postoperative images during preoperative consultation. Patients desiring cosmetic breast augmentation are highly interested in what their breasts will look like following surgery.[12] Current methods rely on manipulating 3D imaging with high cost and user complexity.[7,12] Chartier et al[7] recently developed a portable AI-based neural network, trained using real preoperative and postoperative patient images, that can generate artificial postoperative breast augmentation images to simulate realistic surgical outcomes based on patient preoperative photographs. These AI-generated postoperative images were comparable to the real surgical postoperative results.

AI can additionally be an educational resource for patients seeking aesthetic plastic surgery. ChatGPT (Open AI), an AI chatbot using NLP, can provide easily understandable and accurate answers to common consultation questions despite limited personalized advice.[13]

Takeaways

Question: How has artificial intelligence (AI) impacted billing practices and current clinical practices?

Findings: AI has been studied and implemented at various hospitals and clinic groups nationwide. AI implementation holds potential to enhance billing practices and maximize healthcare revenue for practicing physicians.

Meaning: This article describes the utilization of AI in plastic surgery to enhance patient care and outcomes, the current state of billing, and the application of AI to optimize billing practices.

Billing Practices in Surgery

Of the many uses of AI to aid in clinical diagnoses and outcomes, NLP and machine learning have garnered high interest due to their ability to generate current procedural terminology (CPT) codes from clinical documentation notes made of unstructured text in the electronic medical records (EMRs).[6,14,15] Billing and insurance-related expenses constitute a majority of the administration-related healthcare costs in the Unites States, with a minimum of 62% from previous studies.[14,16] In 2012 alone, billing and insurance-related activities accounted for an estimated $471 billion, based on data from the US National Health Expenditures, including $70 billion in physician practices and $74 billion in hospitals.[16] For one academic institution with EMR, Tseng et al[14] calculated that total professional billing costs in surgery account for an estimated 13.4% of generated revenue for each ambulatory surgical procedure and 3.1% for each inpatient surgical operations. They used a time-driven activity-based cost approach to estimate billing costs. Based on interviews with billing personnel and physicians, they found that estimated time spent on billing is 75 and 100 minutes for one ambulatory and one inpatient surgical procedure, respectively.[14] Physicians on average spent 15 minutes on billing, which equates to an estimated $51.20, for inpatient or ambulatory procedures.[14] Even minor improvements in billing efficiency can result in considerable gains in revenue. Reich et al[17] developed an automated point-of-care electronic charge voucher system to extract data from EMR and transmit it to a billing vendor for one academic anesthesiology practice and found a one-time 3% total annual gain with a 10-day decrease in accounts receivable.

The widespread use of CPT codes for translating medical care into a fixed set of codes to streamline documentation and billing necessitates that the accuracy of CPT codes is paramount.[6,18] Medical coding error rates as high as 38% for standard CPT coding in anesthesia have been noted.[19] The 2023 Centers for Medicare and Medicaid Services Comprehensive Error Rate, or improper payment rate, was 7.38%. This overall Medicare fee-for-service error rate equates to $31.23 billion of total overpayments and underpayments.[20] The improper payment rate ranges from 0.6% and 34.9% depending on subspecialty.[20] Although plastic surgery was not a provider type reported, surgical specialties overall had lower error rates, including 4.0% in general surgery, 7.2% in otolaryngology, and 10.7% in orthopedic surgery.[20] Of these error rates, incorrect coding accounted for 79.3% of errors in otolaryngology, 46.3% of errors in general surgery, and 41.8% of errors in orthopedic surgery.[20] There is a great need to understand and streamline both operative and clinic billing practices to prevent loss of revenue and maximize gains. AI with machine learning and NLP offers opportunities to develop accurate, efficient billing codes and optimize revenue for medical fields, and particularly within plastic surgery.

Potential Applications in Billing Practices

Healthcare billing is a very complex process. In the United States, billing is based on note documentation in the hospitals and clinics with codes to differentiate complexity. Broadly, the clinical encounter with performed services are assigned codes. Then, billing staff use the procedure codes to submit insurance claims or bill the patient. A simplified life cycle of revenue, created by Tseng et al[14] using data from 27 health system administrators and

34 physicians in 2016 and 2017, describes the start of a bill to when the operative note or clinic note is submitted for payment. The extraction of data to editing and auditing to the final payment received is generally labor-intensive and requires coding personnel. Physician notes are first assigned a monetary cost to the service provided, a process called charge entry, and then undergo coding into CPT codes.[14] From there, they undergo rounds of claim editing (verifying if codes are correct), then claim scrubbing (auditing claims to remove errors in billing), submission to insurance, and ultimately, to final payment received.[14] Furthermore, reimbursement rates have progressively reduced during the last 20 years, narrowing the gap between fiscal gains and overhead costs for physicians.[6,21]

Current literature has shown progress in using AI (both machine learning and NLP) to optimize billing practices by interpreting operative notes to generate and classify CPT codes and accelerating the billing process. NLP is currently used to analyze free-text clinical documentation in EMRs to generate codes for diagnoses and comorbidities, which subsequently improves billing workflow. Examples include Columbia University's Medical Language Extraction and Encoding, Brigham and Women's Hospital's open-source Health Information Text Extraction, and Mayo Clinic's open-source Text Analysis and Extraction System.[15,22,23] NLP has also been able to extract CPT codes from operative notes. Kim et al[6] performed a recent retrospective analysis of elective spine surgery operative notes from 2015 to 2020 to compare CPT codes generated by the billing department to those generated by a pilot model using a deep learning NLP algorithm and a random forest algorithm. The random forest machine learning model had an AUROC of 0.94 and an area under the precision-recall curve of 0.85 with a weighted average accuracy of 87% compared with the senior billing coder.[6] The deep learning NLP model had an AUROC of 0.72 and an area under the precision-recall curve of 0.44 with a weighted average of 59% compared with the senior billing coder.[6] This shows the potential for implementation of these models, with the random forest machine learning model outperforming the deep learning NLP model, for more efficient billing through automated generation of CPT billing codes from operative notes.[6]

Automated medical coding companies such as Nym Health (New York, N.Y.), CodaMetrix (Boston, Mass.), and Fathom (San Francisco, Calif.) have developed NLP-based systems to improve revenue cycle management. With an accuracy of 96%, Nym Health can decode provider notes within EMRs and generate International Classification of Diseases, Tenth Revision (ICD-10) and CPT billing codes within seconds along with traceable audit documentation.[24] This automated medical coding reduces workload for physicians and supports medical coders' ability to prioritize the more complex billing cases. Nym is currently automating the medical coding for more than 250 healthcare facilities around the nation, and has recently announced their expansion into ambulatory surgery and other outpatient visits.[25] CodaMetrix, originally developed for inhouse use at Mass General Brigham, uses a combination of machine learning, deep learning, and NLP to process notes and assign procedure and diagnostic codes for more than 111 hospitals nationwide.[26] CodaMetrix's uniqueness derives from configurability of the system, allowing the provider to determine which parts can be automated or coded manually.[26] Similarly, Fathom uses deep learning and NLP to analyze notes in EMRs to create ICD-10 and CPT codes and has recently partnered with Google Cloud Marketplace to streamline revenue cycle management.[27] Automated medical coding can improve revenue capture and reduce labor costs associated with manual coding. Burns et al[19] from the University of Michigan created supervised machine learning models with NLP to assess the accuracy of AI-classified anesthesiology CPT codes. These models had an overall accuracy, defined as AI-generated CPT code matching the institution-assigned anesthesia CPT code, of 87.9% and 84.2%.[19] The accuracy percentage of the two best models increased to 96.8% and 94% if the correct CPT code was among the top three chosen. These models have already been incorporated into the billing process at the University of Michigan to improve auditing and resubmission.[19]

AI can improve the billing workflow's accuracy, speed, and identification of prior underbilling and incorrect coding instances. Ye[28] created a neural network model to predict CPT codes from pathology report texts with an accuracy of 97.5%, and identification of incorrect CPT codes with an accuracy of 73.6%. Furthermore, AI models can process more than one million cases in less than ten minutes, whereas billing departments spend much longer processing the same information with more potential for coding errors.[19] Greenburg et al[29] demonstrated the ability of AI to recognize instances of incorrect coding. They engineered an open-source machine learning algorithm to interpret CPT codes from pathology reports and identify discrepancies compared with the original coder, which then alerts the original coder to re-evaluate the codes and assess if CPT codes are being underbilled.[29] Future directions of this AI tool will be used to evaluate the effect of underbilling on departmental revenue.[29]

Importantly, given the current state of healthcare, AI has additionally been used to streamline prior authorizations. A survey conducted by the American Medical Association found that 88% of physicians found that the burden of prior authorizations was high or extremely high, with 93% of physicians stating that prior authorizations have resulted in care delays and 82% stating that they resulted in patients abandoning their treatment.[30] A 2022 McKinsey & Company analysis has demonstrated that AI can automate between 50% and 75% of the manual work involved in prior authorizations.[30] Insurance companies have already applied AI to optimize the prior authorization process. Blue Cross Blue Shield of Massachusetts has implemented a pilot automated prior authorization process using the AI company Olive at New England Baptist Hospital.[31] This AI-based prior authorization process eliminates the need for phone calls, faxes, and other manual processes for payers and providers to reduce time from submission to decision, subsequently alleviating administrative burden and increasing physician satisfaction. The pilot included hip and knee procedures for 32 orthopedic

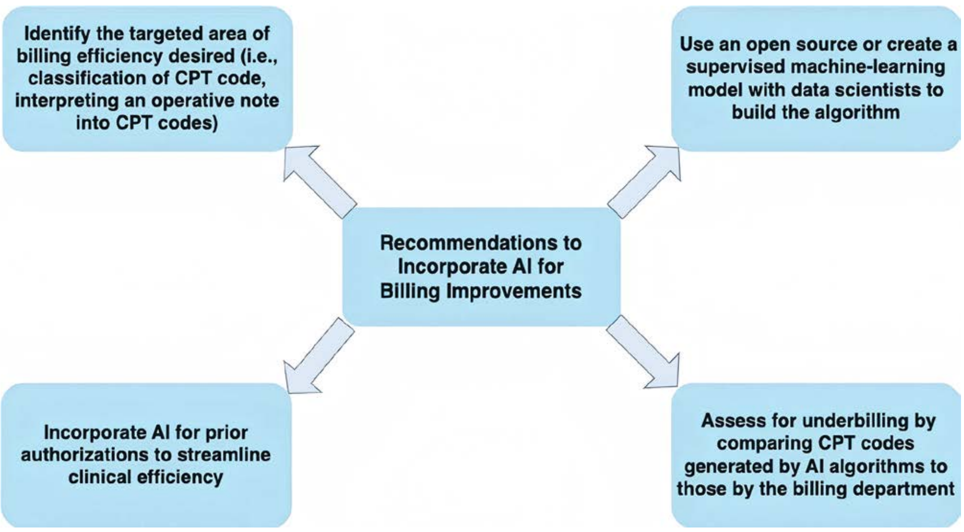

Fig. 1. Recommendations to incorporate AI for billing improvements. The AI-driven workflow involves identifying areas of billing inefficiency and utilizing or developing AI models, with comparison of results to those obtained by the billing department.

surgeons during a 4-month period, with 88% of prior authorization submissions processed automatically.[31] The AI performed cross-checking of Blue Cross prior authorization requirements in real time to determine if prior authorization was necessary, with instant notification to the provider to proceed with scheduling if it did not. For procedures that required prior authorizations, the AI cross-checked the clinical history in the EMR compared with the Blue Cross medical necessity criteria to automatically produce a recommendation in real time. The overall impact significantly reduced administrative burden and cost on Blue Cross Blue Shield of Massachusetts by reducing prior authorization approval time from an average of 9 days to an average of less than 1 day.[31] Furthermore, a multidisciplinary physician group in France, De Barros et al[32] created a machine learning model to assess the eligibility of spinal surgical candidates for lumbar spinal stenosis compared with the standard prior authorization process, which must be approved by medical directors. Based on 66 variables, including patient demographics, medical history, clinical symptoms and physical examination findings, and imaging, they created 500 medical vignettes to encompass a wide range of probabilities for surgical recommendations to train and test the model. De Barros et al discovered that the machine learning model had superior predictive accuracy, assessed by root mean square error, relative to recommendations made by individual medical directors, with root mean square error values of 0.1123 and 0.2661, respectively.[32] The AUROC and Cohen's kappa for the machine learning model were 0.959 and 0.801, respectively, compared with the individual medical directors' recommendations of 0.844 and 0.564, respectively. These results suggest that AI can be effectively applied to prior authorization approvals for lumbar spinal stenosis surgery.[32]

Broadly, AI can be extremely valuable for billing procedures in a plastic surgery practice by way of streamlining CPT codes in billing, reducing coding errors, and assisting with prior authorization approvals. However, the incorporation of AI into billing practices can lead to competing goals for providers and payers. Providers stand to gain from the ability of AI to enhance coding accuracy and maximize coding, while increasing administrative efficiency and shortening the duration from billing submission to final payment received. Conversely, payers, such as insurance companies may use AI to down-code procedures with the motivation to minimize payouts.

Recommendations to Incorporate AI for Billing Improvements

- Identify the targeted area of billing efficiency desired (ie, classification of CPT code, interpreting an operative note into CPT codes) (Fig. 1).
- Use an open source or create a supervised machine learning model with data scientists to build the algorithm.
- Assess for underbilling by comparing CPT codes generated by AI algorithms to those by the billing department.
- Incorporate AI for prior authorizations to streamline clinical efficiency.

CONCLUSIONS

AI disciplines of NLP and machine learning offer substantial opportunities to dramatically improve the clinical and administrative landscape in plastic surgery. Clinically, AI has been demonstrated to monitor free flaps postoperatively, diagnose and stratify risks for surgery, identify likelihood of postoperative risks, and generate aesthetic surgery postoperative images. Administratively, AI has been utilized successfully within the complex process of healthcare billing to analyze clinical documentation and generate CPT codes from operative notes with an accuracy like billing departments. Additionally, AI holds tremendous potential to reduce administrative burden with prior authorizations. AI can increase efficiency, by processing codes at a greater speed; help reduce human error in billing; and ultimately, maximize revenue.

However, there are ethical considerations and limitations with the use of AI. In the clinical setting, AI should serve as an adjunct to the shared decision-making process rather than solely drive decision-making. It is important that the datasets, particularly for facial recognition or postoperative imaging, used to train AI algorithms are representative of diverse patient populations. This prevents biases and enhances applicability of AI algorithms across various ethnicities and demographics.[3] In the billing process, automated medical coding can allow physicians and medical coders to prioritize the complex billing cases but not completely replace human input. Limitations of AI in previous studies assumed that CPT codes used to train the AI models are confirmed correct, when the original codes were likely assigned by one individual and prone to human biases.[29] The future of AI within plastic surgery may entail a synergistic integration into medical billing and coding processes, in addition to its potential to complement clinical decision-making.

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DISCLOSURE

The authors have no financial interest to declare in relation to the content of this article.

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