Quantitative Analysis of Uncertainty in Medical Reporting: Part 3: Customizable Education, Decision Support, and Automated Alerts

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Abstract

In order to better elucidate and understand the causative factors and clinical implications of uncertainty in medical reporting, one must first create a referenceable database which records a number of standardized metrics related to uncertainty language, clinical context, technology, and provider and patient data. The resulting analytics can in turn be used to create context and user-specific reporting guidelines, real-time decision support, educational resources, and quality assurance measures. If this technology can be directly integrated into reporting technology and workflow, the goal is to proactively improve clinical outcomes at the point of care.

Keywords Uncertainty · Reporting · Decision support

Introduction

In conventional medical practice, a healthcare provider responsible for diagnosis and treatment is tasked with translating textual report data into clinical action, which is often obfuscated by language of uncertainty and equivocation. One strategy for addressing the negative impact report uncertainty plays in clinical outcomes is to create a standardized methodology in which text-based report language can be objectively analyzed and quantified, thereby providing the clinician with a reproducible means in which the myriad of terms associated with uncertainty can be placed into clinical context and acted upon in a consistent and reproducible fashion [1]. The resulting uncertainty analytics can in turn be used to create referenceable uncertainty databases which analyze the language of medical reporting relative to the healthcare provider, clinical context, patient, and technology in use. The ultimate goal of such an analysis is to better understand the causative factors associated with uncertainty [2] and when applicable develop real-time interventional strategies at the point of care to improve clinical outcomes.

Uncertainty Database

Table 1 lists a number of individual data elements which could be recorded in the proposed uncertainty database in accordance with automated report analysis. Using the example of a radiology report, data could be automatically extracted from the radiology report, radiology information system (RIS), and DICOM header relative to the individual radiologic finding and/or disease, organ system, technical factors, provider identities, patient profile, and uncertainty language. These combined data could be subsequently used in the uncertainty analysis to identify trends (e.g., language used, clinical context) and creation of predictive analytics. When outcomes data is available (e.g., follow-up imaging study), this can provide valuable correlative data to understand the relationship between report uncertainty and clinical outcomes.

As large data samples are collected and subjected to analysis, trends may begin to emerge illustrating how uncertainty is communicated (i.e., specific language used), the clinical context it is associated with, provider and patient-specific statistics, relationship to technology and/or technical factors, and expected outcomes. These analyses may in turn be used for creation of data-driven community-wide report standards, provider (and patient) specific analytics, automated alerts and prompts, customizable education resources, and creation of decision support tools. Rather than attempt to define and characterize uncertainty on an individual basis, the database provides an objective means in which large numbers of reports can be pooled and analyzed with the goal of identifying

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Table 1 Database components

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1. Uncertainty language
 - a. Specific terminology
 - b. Quantitative score
 - c. Recommendations
 2. Clinical context
 - a. Finding
 - b. Disease
 - c. Anatomy/organ system
 3. Provider
 - a. Radiologist
 - b. Technologist
 - c. Referring clinician
 4. Patient
 - a. Demographics
 - b. Clinical profile
 - c. Compliance
 5. Technology
 - a. Image acquisition
 - b. Decision support
 - c. Information technology
 6. Clinical outcomes
 - a. Clinical/imaging tests
 - b. Procedures
 - c. Patient management
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reproducible trends and tendencies which can be prospectively acted upon.

While the principle data contained in the uncertainty database is textual in nature, other medical data can potentially be recorded in the database and incorporated into the analysis. Examples may include numerical data (e.g., laboratory report), graphical data (e.g., EKG report), imaging data (e.g., radiology report), and photographic data (e.g., dermatology report).

Real-time Education and Decision Support

At the most fundamental level real-time analysis of report uncertainty can provide valuable information to the authoring healthcare provider as to the presence of uncertainty and associated variables. By creating a real-time education and feedback tool (which can be easily turned on and off by the individual end user), all language related to uncertainty can be automatically highlighted and presented to the report author before completion of the report. This provides the report author with the ability to place uncertainty into clinical context before finalizing the report, with the goals of improved report clarity, confidence, and understanding. These highlighted regions of report uncertainty can in turn be reviewed by the

report reader, who in turn can initiate feedback and consultation with the report author in an attempt to clarify report questions and improve clinical understanding.

The uncertainty database can also serve as an educational and decision support resource during report creation. When uncertainty in the report is identified through computerized analysis, the database can be automatically queried to determine whether the language, context, and severity of report uncertainty are consistent with comparable reporting uncertainty. As an example, if a radiologist is describing an enhancing liver mass on CT, they may introduce uncertainty language related either to the diagnosis or need for follow-up testing (e.g., biopsy). Comparable CT reports (and corresponding images) from peers can in turn be retrieved from the uncertainty database to analyze how similar findings were described and characterized; with uncertainty qualifiers, differential diagnosis, and follow-up recommendations. The data from the uncertainty database analysis can in turn be presented to the current report author for review, in an effort to assist in current report optimization. If, for example, the data reveals that similar findings were described with lesser degrees of uncertainty severity and a more narrow differential diagnosis, this information may assist the radiologist in editing the current report by minimizing the degree of uncertainty along with changes in report language. At the same time, computerized image analysis of the pertinent liver images obtained for the patient in question may also provide assistance in diagnosis and additional testing requirements; which may further reduce the report uncertainty.

Since end-user feedback requirements may change over time, the technology should provide customization features which can be dynamically modified in general or specific manners. As an example, suppose an inexperienced end user (e.g., resident in training) has received feedback from his/her attending staff that uncertainty usage is somewhat excessive. As a result, the resident has requested that their reports be analyzed in real time to highlight all examples of uncertainty language. By doing so, he/she can better understand the frequency of uncertainty as well as the report context in which it is being used. As the resident becomes more experienced, they may find that the frequency in which they introduce uncertainty changes, and as a result they no longer require proactive identification of all report uncertainty. Instead, they elect to modify the automated report analysis to reflect only those situations where the severity of report uncertainty exceeds a predefined threshold. Alternatively, the resident begins to learn that his/her perception of uncertainty severity frequently differs from the perceptions of his/her clinical colleagues. When the report readers provide their perceived uncertainty severity scores, there is frequently a difference in uncertainty perception between the two parties. The resident then requests that all uncertainty severity perceptual differences be highlighted and saved for future review. By doing so, the

resident is able to glean important insights on uncertainty perceptual differences specific to different clinician groups, exam types, and report findings.

Since the resident is practicing in an academic medical institution, all reports they generate are secondarily read by an attending physician. The resident can activate the uncertainty report analysis function which allows one to identify changes in report content between the preliminary and final reports. This tool functions to identify, highlight, and analyze all differences in report uncertainty between the preliminary and final versions (which would also be applicable in teleradiology). By requesting automated feedback, the uncertainty report analysis tool can automatically record and highlight these report differences and send them to the end user for review at a time of their choosing. This serves an important educational function by providing insight as to how report content changes over time and between different end users.

Another automated notification option is to provide real-time feedback to the report author whenever predefined criteria in the report are identified. As an example, suppose the physician has requested that whenever an uncertainty severity score of ≥ 4 is identified (i.e., high levels of uncertainty), the report language in question is highlighted in real time and an automated prompt is sent to the end user which must be acknowledged before the report can be finalized. If desired, the report author can query the uncertainty database for alternative language options which may convey a lower level of uncertainty. This automated feedback feature provides report authors with greater insight as to the presence and severity of report uncertainty during the report creation process, with the goal of minimizing, reducing, and/or clarifying unnecessary or exaggerated uncertainty language.

Another important decision support application is the ability to identify when report language does not contain uncertainty language which would be expected, based upon comparable historical report analysis. As an example, in a MRI report of the brain, a radiologist describes a “poorly defined area of enhancement in the right frontal lobe indicative of a vascular malformation” (uncertainty score 0, corresponding to no uncertainty).

When analyzing large numbers of comparable brain MRI reports (from the same and other radiologists) containing similar report language, it is determined that the finding of “poorly defined enhancement in the brain” is routinely associated with varying degrees of uncertainty, with a mean uncertainty score of 3.1 (i.e., intermediate level of uncertainty). The absence of uncertainty in the current report is unexpected given analysis of comparable reports, so the specific report content of question is highlighted and presented to the authoring radiologist along with derived report statistical analysis. The radiologist would then have the option of editing the report or leaving it “as is.” This example of a report finding with disparate uncertainty scores (i.e., statistically significant

difference between observed and expected uncertainty scores), would be classified as an *uncertainty outlier*. Identification of these uncertainty outliers is particularly important when identifying individual report findings which exceed user-specific norms. If, for example, a radiologist who routinely uses low-level uncertainty language with a specific finding (e.g., lung nodule) was to uncharacteristically use high-severity uncertainty language, this outlier takes on heightened importance and likely requires further scrutiny.

In another application of the invention, report content can be analyzed to identify uncertainty *associated factors*, which are variables or data elements contained within the report with a high positive correlation with report uncertainty. Examples for a medical imaging report may include (but are not limited to) variables such as image quality deficiencies (e.g., improper positioning, noise, poor contrast resolution), artifacts (e.g., motion, respiratory, beam hardening), patient attributes (e.g., obesity, morbidity, non-compliance), and anatomy (e.g., not visualized, anatomic variation, congenital abnormality). When uncertainty “associated factors” are identified within a report (i.e., through computerized analysis) and expected uncertainty language is not present, the highlighted report content in question is presented to the authoring provider with comparable data from report analysis to provide them with the opportunity to modify the report. As was the case with the other applications, statistical data and representative report examples can be provided for supplemental information and all resulting actions are recorded in the uncertainty database.

Automated Notifications and Alerts

An important feature of the proposed technology is the ability to automate uncertainty alerts and notifications in keeping with defined rules (i.e., standardized alerts) and individual end-user preferences (i.e., customizable alerts). These notifications can be predicated on a number of different uncertainty-related variables including uncertainty frequency, specific language used, uncertainty severity, follow-up recommendations, and associated factors.

A standardized alert would be triggered when a predefined uncertainty threshold was achieved and would be defined by rule-based algorithms. These algorithms could be created by legislative, professional societal, and/or institutional guidelines. As an example, if an uncertainty severity score exceeding 3 (in either positive or negative form) is reported for a specific diagnosis (e.g. breast cancer) or finding (e.g. breast mass), predefined guidelines may mandate an automated alert to both the report authoring and recipient healthcare providers. Once received, the corresponding provider would be required to confirm receipt of the alert, acknowledge understanding of the clinical implications, and provide feedback of future

actions (e.g., order follow-up imaging exam, schedule biopsy, order surgical consultation).

These automated alerts can be initiated both before and after report completion. Alerts transmitted before report completion are intended to provide feedback to the report author while the report is being created (i.e., report in progress), with the goal of notifying the report author of ensuing actions required based upon report uncertainty in its present form. This would allow the healthcare provider authoring the report with a real-time and prospective opportunity to modify the report uncertainty language, engage and utilize decision support tools before report completion, seek peer consultation, and/or query the uncertainty database for relevant context-specific statistical analysis. The goal is to provide the report author with uncertainty knowledge and understanding before finalizing the report.

Alerts provided after report completion are intended to notify appropriate parties to the presence of uncertainty and its clinical importance and can be based upon predefined rules established by the institution, professional society, and/or legal entities.

In addition to isolated (i.e., single) automated report alerts, automated alerts or prompts can also be triggered by largescale (i.e., collective) report analysis. This in effect consists of statistical analysis of large numbers of reports which can evaluate a number of report uncertainty variables (e.g., frequency, severity, context) for a given end user. In the event that the resulting analysis identifies an uncertainty variable exceeding a predefined threshold, an automated alert or prompt is sent notifying the responsible party of the statistical outlier. If, for example, a physician was identified as utilizing excessive uncertainty language (in frequency and/or severity) over a prolonged time course, an automated alert may be triggered notifying both the physician of record and designated quality assurance personnel (e.g., department chief, hospital administrator, quality assurance coordinator). The goal of this application is to identify collective trends in report uncertainty and the need for intervention based upon comparative peer analysis.

In addition to automated alerts based upon standardized guidelines, automated uncertainty prompts and alerts can also be triggered in accordance with individual end-user preferences. In this case, an individual end user will define the specific uncertainty parameters which he/she would like to receive automated notification, as well as the time and method of automated notification.

To illustrate how these automated alerts can be integrated into everyday workflow and reporting, we will take the example of a patient undergoing screening mammography for breast cancer screening. As the radiologist is creating the corresponding mammography report, he/she issues the following statement:

“A poorly defined 2.6 cm density is visualized at the 9 o’clock position of the left breast, which may or may not represent cancer.”

Based upon the report analysis, an uncertainty score of 5 is assigned to the finding (i.e., 2.6 cm breast density) and diagnosis (breast cancer). Based upon institutional guidelines, an automated alert is immediately transmitted to the authoring radiologist during report creation through a pop-up box which identifies the report language of concern and the triggering event. The radiologist acknowledges receipt of the alert by right clicking on the alert and selecting from a menu of ensuing options (e.g. edit report language, request for decision support, data mining of Uncertainty database, consultation with referring clinician, maintain language in present form).

If the radiologist elects to select the option for Decision Support a number of decision support options are presented (e.g. imaging database of comparable findings [i.e. poorly defined 2.6 cm breast density on mammography), computerized differential diagnosis, BI-RADS classification system, on-line educational resources).

If the radiologist selects the option for data mining, the uncertainty database will automatically be queried to provide statistical and text-based analysis of comparable mammography reports using the finding “poorly defined (2.6 cm) breast density.” In this analysis, the radiologist will be presented with representative examples of comparable report language, the frequency of terms used, an analysis of accompanying uncertainty, and analysis of follow-up recommendations.

If the radiologist selects the option to edit report language, the radiologist would input the modified language, which would in turn trigger a new report uncertainty analysis. In the example provided, the modified language could include the following:

Original report language:

“A poorly defined 2.6 cm density is visualized at the 9 o’clock position of the left breast, which may or may not represent cancer.”

Uncertainty Terminology: may or may not represent cancer

Uncertainty Severity Score: 5

Modified report language:

“A poorly defined 2.6 cm density is visualized at the 9 o’clock position of the left breast, which is suspicious for cancer.”

Uncertainty Terminology: suspicious for cancer

Uncertainty Severity Score: 3

The radiologist may elect to use the modified language in the final report or input other report language options. As new report language options are introduced, a corresponding computer-derived analysis is presented for review. This provides the report author with the input and analyzes different forms of uncertainty language in real time, with the goal of optimizing report language commensurate with his/her intended degree of uncertainty and follow-up recommendations.

Once this exercise has been completed, the report is finalized and the final report uncertainty analysis is performed, with corresponding data recorded in the uncertainty database. In the event that this final report language exceeds a predefined threshold for automated notification, automated alerts would be sent to the authoring and healthcare providers of record. While the intended purpose of the proposed technology is to provide for intervention options before report completion (i.e. while the report is “in progress”), the same options for report modification can be performed after report completion. In the event that any of these report modification options are performed after the final report has been generated, a time-stamped report addendum will be generated and recorded in the uncertainty database.

Uncertainty Outcomes Analysis

When uncertainty is introduced into medical reporting, it is frequently accompanied by an adverse effect on patient outcomes, which may be economic, clinical, or time related (Table 2). While decisive and unequivocal report language is certainly no guarantee as to diagnostic accuracy, uncertainty often results in the recommendation for additional tests/procedures, time delays, consultations, and hesitation on the part of clinical care providers. These time delays may delay diagnosis and/or treatment planning, prolong hospital length of stay, and allow underlying disease to progress. Follow-up recommendations may consist of additional medical imaging exams, clinical tests, provider consultations, and interventional procedures/surgeries. These follow-up tests and procedures can in turn be associated with a variety of adverse clinical actions including increased radiation exposure, allergic reactions, and iatrogenic injury (associated with increased morbidity/mortality).

If these uncertainty outcomes metrics are recorded in the uncertainty database and subjected to longitudinal analysis, one could in effect quantify the time, financial, and clinical costs associated with uncertainty in medical reporting. This uncertainty outcomes analysis can take into account the clinical context in which uncertainty is applied, the individual healthcare provider, technology in use, and the individual patient, in order to better define confounding variables.

In some circumstances, the uncertainty is repetitive in nature and falls into a predictable pattern. As an example, suppose a radiologist interpreting a pelvic radiograph on an elderly patient for trauma routinely qualifies the report by stating the following:

“While no pelvic fracture is identified, CT correlation is recommended if occult fracture remains of clinical concern.”

Table 2 Uncertainty outcomes analysis metrics

1. Follow-up recommendations
2. Delays in diagnosis or treatment
3. Disease progression
4. Iatrogenic complications
5. Increased cost
6. Length of hospital stay
7. Additional medical visits
8. Healthcare provider consultations

Since this uncertainty transfers clinical responsibility and uncertain diagnosis to the ordering physician, the overwhelming majority of these reports (e.g., 90%) do result in a follow-up CT exam, of which only 3% are found to be positive for fracture. The net effect is that a large number of patients receiving pelvic x-rays are unnecessarily undergoing follow-up CT which adds significant cost, radiation exposure, and anxiety to the corresponding patients.

If one was to compare uncertainty data from this radiologist with that of his/her peer group for the same clinical context (i.e., trauma), exam type (i.e., pelvic radiograph), and patient population (> 65 years old); one could determine the relative frequency for recommendations for CT follow-up. While the uncertainty language and severity may vary in the reporting language, the initial outcomes analysis will be limited to the follow-up recommendation alone. In this analysis, the mean frequency of CT follow-up recommendation for the clinical context, exam type, and patient population is 24%, which suggests that the radiologist of primary concern is introducing excessive uncertainty in approximately 66% (i.e., 2/3) of cases. Furthermore, the positivity of these recommended follow-up CT exams (i.e., those which do contain a fracture) is 40% of cases for the larger group of radiologists compared with the radiologist of primary concern whose positive rate for follow-up CT exams is only 3%. Since the cost, radiation dose, and time delays associated with these “unnecessary” CT exams is easily determined, the corresponding data can be quantified and used for outcomes analysis.

As this data is accumulated and subjected to analysis, the outcomes data contained within the uncertainty database can be presented to the healthcare provider at the point of care, in order to provide them with correlating data to assist them in their reporting (i.e., another form of decision support). In this example, each time the radiologist of record recommends a follow-up CT for an elderly patient pelvic radiograph in the setting of trauma he/she will have this comparative data presented for review. The resulting actions taken by the radiologist will then be subsequently recorded so as to determine whether this outcomes data affected current report uncertainty. In addition to contemporaneous feedback at the time of report creation, periodic (e.g., quarterly) uncertainty outcomes

analysis data can be presented to the healthcare provider for review, in an effort to improve their individual uncertainty outcomes analysis, specific to the clinical context.

Using population health data of large sample size data, these follow-up recommendations can be further scrutinized to determine what specific variables are associated with higher positive predictive values. In the previous example, collective data of a large number of radiologists and patients demonstrated a positive rate of pelvic fracture in 24% of all cases. Now, if one was to further analyze attributes of those 24% of cases compared with the negative group of 76% patients without fractures, they may identify specific variables with a high association of positive fractures. Examples of positive predictors may include the method of trauma (e.g., motor vehicle accident), bone mineralization (e.g., osteoporosis), patient gender and age (e.g., female, greater than 78 years old), and radiographic finding (e.g., cortical irregularity). These “high-risk” variables may be presented to interpreting radiologists at the time of interpretation to assist them in uncertainty assessment and the recommendation for CT follow-up. In the opposite case, suppose a radiologist interpreting a trauma pelvic radiograph fails to recommend a follow-up CT when several of these high-risk variables are present. In that scenario, the outcomes analysis can be automatically presented as a form of

decision support to alert them to the higher-than-expected statistical likelihood of fracture.

Conclusion

The goal of the proposed technology is to objectively analyze uncertainty in medical reporting in real time, when the maximum impact on patient outcomes can be achieved. Through the creation of a referenceable uncertainty database a number of analytics can be derived, with the goal of improved clinical and economic outcomes through the longitudinal analysis of uncertainty data and its relationship to healthcare providers, patients, technology, and clinical context.

References

1. Reiner B. Quantitative analysis of uncertainty in medical reporting. Part 1: Creating a standardized and objective methodology. *J Digit Imaging* (accepted for publication)
2. Reiner B. Contextualizing causation of uncertainty in medical reporting. *J Am Coll Radiol* 2017 (in press)