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Summarization of Clinical Information: A Conceptual Model

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Abstract

Background: To provide high quality and safe care, clinicians must be able to optimally collect, distill, and interpret patient information. Despite advances in text summarization, only limited research exists on clinical summarization, the complex and heterogeneous process of gathering, organizing and presenting patient data in various forms.
Objective: To develop a conceptual model for describing and understanding clinical summarization in both computer-independent and computer-supported clinical tasks.
Design: Based on extensive literature review and clinical input, we developed a conceptual model of clinical summarization to lay the foundation for future research on clinician workflow and automated summarization using electronic health records (EHRs).
Results: Our model identifies five distinct stages of clinical summarization: 1) **A**ggregation, 2) **O**rganization, 3) **R**eduction and/or **T**ransformation, 4) **I**nterpretation and 5) **S**ynthesis (AORTIS). The AORTIS model describes the creation of complex, task-specific clinical summaries and provides a framework for clinical workflow analysis and directed research on test results review, clinical documentation and medical decision-making. We describe a hypothetical case study to illustrate the application of this model in the primary care setting.
Conclusion: Both practicing physicians and clinical informaticians need a structured method of developing, studying and evaluating clinical summaries in support of a wide range of clinical tasks. Our proposed model of clinical summarization provides a potential pathway to advance knowledge in this area and highlights directions for further research.

1. Introduction

The ability of clinicians to appropriately collect, distill, and interpret patient information is critical to the practice of medicine. Clinicians are often presented with an excess of data from a variety of sources and must work to separate important clues from background noise.(1) Likewise, they must constantly condense and refine information to better communicate with colleagues and provide continuous and coordinated care.(2, 3) The way this information is structured and presented to clinicians can profoundly influence their decision-making(4-7) and thus, an accurate, well-designed and context-specific summary can potentially save time, improve clinical accuracy and mitigate potential errors. However, medical information is often fragmented, existing in a wide range of locations and formats, which puts patients at an increased risk of errors, adverse events and inefficient care.(8) This fragmentation makes the creation of an optimal clinical summary more challenging.

Clinical summarization can be defined as the act of collecting, distilling, and synthesizing patient information for the purpose of facilitating any of a wide range of clinical tasks. Examples of high-level summarization, such as the discharge summary, daily progress notes, patient handoff at change of shift, and oral case presentation, are commonplace in medicine. For the purposes of this paper, we refer to *clinical summarization* as any act, carried out by a healthcare provider and potentially assisted by a computer system, which presents a subset of available patient-specific clinical data in a format that assists in communication and clinical decision-making. This differs significantly from the established concept of *text summarization* which refers broadly to the creation of a text summary from one or more source documents (e.g. scientific articles, literature abstracts, and multimedia).

While certain aspects of clinical summarization have become easier through the use of electronic health records (EHRs), others are now more complex. Today, clinicians may collect and process enormous amounts of clinical information rapidly, thus creating a hazard for information overload and error.(9-11) Information overload can lead to frustration, inefficiency and communication failures(12) as well as to important clinical data being overlooked.(13, 14) These problems are likely to increase with the use of health information exchanges (HIEs) which allow sharing of patient data more broadly. Moreover, suboptimal presentations of clinical information can also impair medical decision making, contribute to medical errors and reduce care quality.(15-17)

In the interest of advancing the study of clinical summarization, we have developed a comprehensive conceptual model based on existing theories of summarization and real-world use of clinical summaries. Our goal in creating this model was to characterize the tasks inherent in clinical summarization as well as the structure and function of clinical summaries. We also apply this model to a hypothetical example of automated clinical summarization in order to further illustrate each distinct step.

2. Material and Methods

2.1 Literature Review

Much of the current research on summarization in the biomedical domain has focused on *text summarization*, in which one or more texts is reduced to a single condensed reference text.(18) Text summarization strategies have been developed for automated summarization of scientific literature(19, 20), generation of literature abstracts(21, 22), monitoring of disease

outbreaks from multiple sources(23), and summarization and translation(24), among others. However, the vast majority of this research focuses exclusively on the analysis of a narrative or expository text (or texts) with the goal of producing a text-based summary. This differs substantially from the issue discussed here: the summarization of mixed-source patient and clinical information with the goal of creating a structured data summary which in turn supports clinical tasks.

Numerous examples of text-based and non-text-based *clinical summarization* exist, ranging from verbal exchanges (e.g. patient handoffs), written documents that might be structured or free-text (e.g. discharge summary), or structured data displays (e.g. graph of patient data over time). Some summaries are automatically generated by a computer, while others are created by a clinician with or without assistance from a computer program. Given the complexity of healthcare, a wide variety of summaries are essential for efficient, longitudinal and continuous patient care. These include (among others):

- discharge summaries,(25) which support patient discharge from the hospital
- patient handoff summaries,(26) which facilitate provider shift change
- oral case presentations,(27) which are used for transfer of information from overnight admission to the care team and attending
- progress notes,(28) which provide daily status of inpatient, to do list, outstanding issues, and care plan
- patient summaries for use during rounds,(29) which promote transfer of information to a multidisciplinary team of clinicians
- patient "overview" screens or "dashboards",(30) which provide an efficient view of information in emergency or for population level surveillance, or administrative tasks
- data-specific displays,(31) which can help providers identify trends and notable findings in large amounts of patient data
- referrals to sub-specialists,(32) which facilitate transfer of information from generalist to specialist

If summaries are overly informal, unstructured or of poor quality (2, 12, 33-37), they pose vulnerabilities that lead to errors and communication failures.(3, 34, 38-40) Clinician instruction on how to formulate clinical summaries is frequently ad hoc and occurs informally.(41, 42)

Standardization of patient handoffs can improve continuity of care and sign-out quality, shorten rounding time, and reduce resident workload.(33, 43) Likewise, standardized discharge summaries are preferred by physicians (44, 45) and considered to be of higher quality.(46, 47) Even for oral case presentations, efforts have been made to develop more consistent presentation skills and better means of teaching these skills.(27, 41, 48, 49) Computerized tools can improve the quality of information available in patient hand-offs(43, 50) and support the production of discharge summaries.(12, 36, 47, 51) Despite apparent benefits of greater standardization and computerization, there exists a paucity of research on clinical summarization.(3, 35)

2.2 Types of clinical summarization

Broadly, clinical summaries can be divided into three interrelated categories: *source-oriented*, *time-oriented* and *concept-oriented views* (52, 53). The source-oriented view derives from the traditional paper chart in which information is filed in separate categories to facilitate document retrieval (54). This view persists in most EHRs, in which information is organized according to where it comes from, allowing it to be grouped into categories such as laboratory

results, imaging studies and medications. *Time-oriented* views organize information based on when it was collected and present data chronologically (i.e., either in normal time order or in reverse time order – most recent first). They may delineate a sequence of events or details of a care plan and are also common within sections of paper and electronic records. Finally, in a *concept-oriented* view, data is organized around specific clinical concepts such as medical problems or organ systems and requires the application of a significant clinical knowledge base (physician expertise or a computerized knowledge database). This view can speed information retrieval and improve medical decision making.(55-57) Each view, alone or in combination, can provide a valuable means of analyzing patient data across a wide range of clinical tasks, depending on specific provider goals.

All summaries, including text-based and non-text-based clinical summaries, can also be characterized as *extracts* (condensing information without altering it) or *abstracts* (application of additional contextual knowledge to create a more sophisticated, synthesized summary).(18) *Extracts* are considered "knowledge-poor" modes of summarization while *abstracts* are "knowledge-rich" (58) but the goal of both forms is to determine what information is of value and appropriately condense this content. "Knowledge poor" methods of summarization require less context-specific knowledge to create the summary while "knowledge rich" methods necessitate larger and more advanced knowledge bases.

Some of the simplest forms of clinical summarization, such as graphical displays of vital signs over time, are knowledge-poor *extracts*. They reduce and organize clinical data without altering it and without necessitating knowledge-based interpretation of patient state. In contrast, other modes of summarization, such as patient handoff summaries, require knowledge-rich *abstraction*. For handoff summaries, clinicians, possibly assisted by automated programs, must aggregate data collected over the course of the day and distill the information into a form relevant to oncoming clinicians; this requires a nuanced understanding of a patient's clinical status. In the clinical domain, knowledge-poor summaries can be considered to be those that do not require any knowledge-based interpretation of a patient's state (patient-state independent) or advanced clinical expertise, while knowledge-rich abstracts require such knowledge (patient-state dependent).

In some cases, identical modes of summarization (e.g. graphing) can be used to create both *extracts* and *abstracts*. An *extract* of a patient's cholesterol levels might graph these data points over time. In contrast, an *abstract* might flag clinically important values and trends on the graph and correlate them with other aspects of patient history (e.g. initiation of a statin for treatment of hyperlipidemia). Not surprisingly, state-dependent *abstraction* is more difficult to accomplish (both for humans and computers) than *extraction* because it requires an understanding of patient-specific data and the application of advanced clinical knowledge.

We now build on this existing knowledge of categorizing clinical summaries, and describe a conceptual model of clinical summarization that can be used to understand how summaries are created and what areas are in need for further scientific development.

2.3 Model Formulation

Based on our review of the literature on clinical summarization and available automated summarization tools, we identified the following important themes and concepts:

1) *Current summarization formats are heterogeneous*: There is a wide variability in the methods of generating a specific clinical summary across different institutions. For example, patient handoffs can occur in a number of different formats including: 1) verbal

exchanges, 2) handwritten notes, 3) Microsoft Word documents, and/or 4) computer-generated summaries.(34, 35, 43, 59) This variability is due, at least in part, to the diverse nature of clinical tasks these summaries support.

2) *Formal instruction on creating clinical summaries is lacking*: Clinical summarization may be taught in an ad-hoc, informal manner "on the wards," with trainees mirroring the skills of their teachers. For instance, there is no consistent tool or standard used to improve oral presentation skills.(27) In part, this may also be a byproduct of the variable, context-specific uses of clinical summaries.
3) *There is a trend toward standardization of summaries*: We identified a series of efforts to standardize the format, content and presentation of many types of clinical presentation. For example, some hospitals reported moving towards templated handoffs, often with written or computer-generated text to ensure that salient information is not omitted (33). This mirrors a broader trend towards more standardized care delivery and the application of evidence-based guidelines (60, 61).
4) *The effect of standardization and computerization is often but not universally positive*: A standardized or automated approach to producing summaries might result in increased summary quality. For instance, for discharge summaries, this approach led to more complete summaries that were ready sooner while in the case of patient handoffs, omission of pertinent medical information was reduced using an automated system.(36, 43)
5) *There has been limited formal study of clinical summarization*: For example, a recent comprehensive review of discharge summary literature cites a lack of high-quality investigations, with few randomized controlled trials to evaluate methods of improving summary quality over a 28 year period (1977-2005).(3) In general, the vast majority of research on summarization focuses on the production of text summaries from one or more text documents.(18)

Based on these trends, we identified the need for a conceptual model of summarization that would achieve four goals:

1) Provide a common framework applicable to clinical summaries of different types (narrative vs. structured) and uses (e.g. discharge summary, patient hand-off);
2) Describe a method of analyzing both human- and computer-generated summaries;
3) Facilitate standardization or automation of clinical summaries;
4) Encourage future research on clinical summarization using this unified framework.

3. Model of Clinical Summarization

Building upon the concepts above and existing literature, as well as the goals we identified, we developed a framework for summarization of clinical data: the "AORTIS" model. The creation of clinical summaries can be modeled in the following five steps: **A**ggregation, **O**rganization, **R**eduction and **T**ransformation, **I**nterpretation and **S**ynthesis. Any or all of these steps could potentially be performed by either a clinician or an automated system in order to produce a concise and accurate summary.

The model is designed to be sequential (**Figure 1**), with the output from one step flowing to the input of the next, and task-dependent, with the content of each step varying based on the clinical task the summary is designed to support. Not all steps are necessarily of equal importance or apply to every summarization scenario. For example, if only one data type is aggregated (e.g., weight), there may be little need to organize the data (e.g., sort by time/date)

before reducing (e.g., finding the most recent or current value or the maximum, minimum or mean) or transforming (e.g., graphing) it, and this phase may be bypassed, with data from the aggregation step flowing directly to reduction and transformation. The model can also terminate early – for example, aggregating and organizing lab results may be useful, even without reducing, transforming, interpreting or synthesizing.

As one progresses through the stages of AORTIS, the risks and benefits change. After aggregation, all data is present, so there is a maximal risk of information overload (shown in the continuum at the left of **Figure 1**). However, as the model progresses and raw data is eliminated or modified to be more interpretable, the risk of information overload dissipates, but the risk of information loss, erroneous interpretation or communication failure increases.

The summarization process is also governed by a second continuum of clinical knowledge (**Figure 1**). The initial steps of aggregation and organization do not require clinical knowledge. Interpretation and synthesis, in contrast, require such knowledge and, in some cases, particularly synthesis, necessitate advanced knowledge bases and a clinical understanding of patient state. Intermediate steps (reduction and transformation) may require a limited general knowledge base, but one much smaller and simpler that is not dependent on patient state (including elements such as a unified vocabulary and statistical operations but comparatively less clinical knowledge).

We now describe each step of the AORTIS model in detail using the summarization of a patient's low-density lipoprotein (LDL) cholesterol levels as a running example.

3.1 Aggregation

Aggregation is the collection of clinical data from various available sources. For example, data may exist in both paper and electronic formats, or in multiple databases and multiple care sites in organizations with EHRs. Types of data include: numerical (e.g. laboratory results), structured and/or coded text, (e.g. problem list), and unstructured free text (e.g. progress notes). Data *aggregation* may be accomplished by the clinician and facilitated by electronic tools when available (e.g. a lab results review module).

An example of *aggregation* is the collection of a patient's LDL cholesterol results over the past ten years. Accomplishing this basic task of *aggregation* is relatively straightforward if the patient received care primarily at one location with an integrated EHR (e.g. a VA healthcare facility) but may be exponentially more difficult if the patient moved or changed providers and data exists in multiple places and/or under multiple naming conventions. After aggregation, clinical data is often available in excess and difficult to interpret. This difficulty increases dramatically as the amount of stored information increases.

3.2 Organization

Organization is the structuring of data according to some principle without condensing, altering, or interpreting it. Two common organization operations are grouping (e.g. putting all HbA_{1c} values together) and sorting (ordering lab results by date or value). When using paper charts, organization typically occurs following aggregation but in EHRs organization can occur near-simultaneously with aggregation. Realistically, most patient information must progress at least to the organization stage in order to be of significant clinical value. Despite this relationship, aggregation, the process of collecting the information, and organization, the process of arranging this information, are distinct stages, each with their own unique challenges.

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For LDL cholesterol tests, results could be sorted chronologically, by value, or grouped based on laboratory of origin (hospital, PCP, previous PCP, VA, etc.). Both source and time-based organization of LDL values aids the clinician in understanding aggregated data. In paper records, these views must be created manually by clinicians or administrative staff. Physical properties of the record may also be designed to accomplish organization (e.g. an hourly flowsheet or space for daily progress notes, if used appropriately, automatically create time-oriented organization). Electronic systems, by contrast, can be programmed to carry out and present data in any of these ways near-instantaneously.

3.3 Reduction & Transformation

Without further processing following organization, the clinician remains vulnerable to information overload. Further condensation of data to facilitate comprehension and communication can occur through either of two distinct pathways: *reduction* or *transformation*. *Reduction* is the process of culling salient information from the database without altering it to decrease the amount of data presented. For numerical information, this might include selection of most recent values, maximum values (i.e., medication peak levels), minimum values (i.e., medication trough levels), or statistical reductions such as medians. For text-based information, this might include selecting results or notes over a certain range of time or of a certain category (e.g., endocrinology consult notes, radiology reports, all notes that mention the term "back pain" or the "assessment" section of all progress notes).

In contrast, *transformation* is the process of altering the data view or data density in order to facilitate understanding. One simple form of transformation is trending: the qualitative description of a basic pattern in data (e.g. transforming an array of HbA_{1c} values to the statement "the patient's HbA_{1c} level decreased 29% (from 8.6 to 6.2) over one year"). Another example is the graphical display of laboratory results (e.g. HbA_{1c} levels) over time. In this transformation, values are translated from numeric representation to spatially-oriented displays. Transformation can also be accomplished using other visual tools such as a metaphor graphics, overlaid on schematic diagrams of the human body or timelines.(62, 63)

Reduction and transformation require the application of comparatively less contextual clinical or general scientific knowledge (e.g. such as relatively simple concepts like the fact that HbA_{1c} is a numeric value and one can find the mean by summing all values and dividing by the number of values summed, or that qualitative urine human chorionic gonadotropin is a discrete text value). In the absence of high-level summarization, reduction and transformation are tools for producing extracts because these steps do not depend on patient-specific information.

Continuing the LDL example, reduction might be used to create an extract of a patient's LDL by reporting the most recent or the maximum and minimum results for a given time-period. Transformation might yield a line graph of available values over time or a description of the data's trend (also considered an extract).

3.4 Interpretation

Interpretation is the context-based analysis of a single type of clinical data through the application of general (versus patient-specific) medical knowledge. For example, selecting abnormal lab results to include in a patient handoff summary requires interpretation because a clinician or computer program must be able to identify which results are abnormal. Many lab result reports include an indication of abnormally high or low results where the computer uses a knowledge base of abnormal and critical ranges for lab tests to determine which flags to apply.

This is an example of simple interpretation because it applies general medical knowledge to a single data type for a specific patient.

Interpretation requires access to a clinical knowledge base and is a necessary step towards producing *abstracts* of clinical information. Despite progress in machine learning, artificial intelligence, expert systems, natural language processing and clinical decision support, much interpretation (beyond basics like abnormal flags and reference ranges) still remains largely in the domain of the clinician. However, for the purpose of accomplishing a highly specific clinical task, automated high-level systems can be created, such as computer-assisted acid-base interpretation (64) and EKG interpretation (65).

Interpretative elements can also be added to transformed data. For example, one could add a text alert indicating recent changes such as "LDL level has increased over the past year and now exceeds goal level." A graphical interpretative element could be the addition of horizontal lines showing the limits of the normal range, thus facilitating visualization of the fact that a patient's results are outside normal limits. Both of these tools require general medical knowledge in order to define "goal levels."

3.5 Synthesis

The final phase of the AORTIS model, *synthesis*, is the combination of two or more data elements along with knowledge-based interpretation of patient state to yield meaning or suggest action. Synthesis is the most sophisticated and valuable form of clinical summarization because at this stage *concept-oriented views* become possible. Following knowledge-based interpretation, clinical information can be understood in relation to other parts of the medical record and can be viewed with respect to the patient's unique clinical status. Synthesis depends heavily upon the previous steps to create a reliable and complete summary of clinical information.

When one interpreted piece of information, such as an abnormal lab result, is synthesized with other types of patient information, such as medications used to treat the condition causing the abnormal results or medications which can affect these results, more sophisticated meaning is generated. For example, a simple synthesis of LDL results might yield the statement "In response to elevated LDL levels on 12/01/09, a statin was initiated and LDL levels decreased to normal on 2/1/10." This synthetic statement brings together the identification of an abnormal value with pertinent medical history (initiation of a statin) and provides a rich array of patient information succinctly. The statement thus captures 1) a previous abnormal LDL on December 1, 2) the now normal LDL on February 1, 3) the initiation of a lipid-controlling medication, 4) the downward trend in LDL, 5) the implication that medication helped lower LDL, and 6) the impression that the patient's hyperlipidemia is well-controlled with medication.

Robust synthesis brings multiple data elements together to allow clinicians to rapidly process clinical information. In addition, it provides a meaningful roadmap that guides clinicians more efficiently to detailed information contained in the patient record. Clinicians, in general, are well suited to completing these final high-level steps in summarization. However, it's possible that with further study of clinical cognition and workflow that automated tools could also support these high-level summarization steps across a broader range of clinical tasks.

4. Example of Clinical Summarization

In order to fully illustrate our conceptual model, we now present a hypothetical case study of clinical summarization and then apply the AORTIS model. There exists a diverse array

of clinical tasks for which a well-designed summary could potentially be of value. Our example describes an instance of clinical summarization in an outpatient primary care setting, and represents just one scenario of many that can be supported by a clinical summary. The content and design of a clinical summary would differ substantially in other clinical situations. For example, in the ICU setting, a patient's distant medical history and minor chronic issues are far less relevant than in the primary care setting; a provider may instead need to focus with a great deal of specificity on data gathered during the patient's ICU stay, or even over the least few hours. Likewise, in the emergency department setting, urgent issues are of the highest priority but may also be informed by relevant medical history. The requisite clinical summary would thus also differ substantially between different providers and clinical environments, as would the content of each stage of the AORTIS model.

We will use the following example to illustrate each of the distinct stages of the AORTIS model: *Patient J.S. is a 67-year-old diabetic man with a history of hypertension and hyperlipidemia who presents to his PCP for a routine physical on 10/1/10. His blood pressure is 135/90, his total cholesterol is 250 mg/dL and HbA_{1c} is 7%. He takes low-dose simvastatin (25 mg QD) for his cholesterol, hydrochlorothiazide (25 mg QD) for his hypertension, and metformin (1000 mg BID) for his diabetes. His first documented visit in the clinic EHR was his previous annual physical on 10/1/09. He saw his PCP for follow-up on 2/1/10 after initiation of a statin and anti-hypertensive. He was briefly admitted to the hospital on 6/1/10 for a rule-out MI and followed-up with his PCP 2 weeks later on 6/15/10.*

In order to illustrate the potential for automation of clinical summarization, we also describe a hypothetical task-specific electronic summarization tool used to assist J.S.'s PCP in the three main facets of this patient's diabetes risk management: glycemic control, lipid control and blood pressure control. In this example, the electronic summarization tool would be triggered by the presence of the coded problem "diabetes" on J.S.'s problem list. **Table 1** describes the actions which occur at each stage of the AORTIS model as applied to J.S. and **Table 2** shows the results of the process, and how J.S.'s data is represented at each stage.

4.1 Aggregation

The electronic summarizer first aggregates all available patient data pertaining to glycemic control (HbA_{1c}'s, clinically-monitored blood glucose levels, anti-diabetic medications), lipid control (lipid panels, lipid medications) and blood pressure control (blood pressure levels from the clinic and hospital, anti-hypertensive medications). For patient J.S., this includes four HbA_{1c}'s, two fasting blood glucose levels, four lipid panels, nine blood pressure readings and three medications as shown in **Table 2**.

In this idealized scenario, all this information can be automatically aggregated from a single system in real time. In reality, however, some of this data may exist in paper-charts or non-integrated systems (e.g. a hospital with different clinical information systems or a home blood glucose monitor). Upon aggregation, a significant amount of irrelevant, duplicative or old data may be available. For most real patients, the amount of data aggregated would be several times larger than that which is present in J.S.'s electronic record.

4.2 Organization

The electronic summarizer can then automatically organize aggregated data by time (e.g. chronological, reverse chronological), by source (e.g. clinic, hospital), and/or by data type (e.g. medication, laboratory test, vital sign) and can switch instantaneously between different modes

of organization depending on the clinician's preference. Simple time-oriented and grouped organizations of available data are shown in **Table 2**. Available data for each facet of diabetes risk management, including available lab data (HbA_{1c}'s, lipid panels, and blood pressure readings) and medication changes, are sorted using a variety of methods.

4.3 Reduction and Transformation

Once aggregated and organized, the number of discrete data elements available may be very large. Even for one type of information, such as J.S.'s blood pressure readings, the amount of data available exceeds what is clinically relevant or desirable to review. As a result, the summarizer might reduce this available data and only report values such as the most recent value, highest, lowest and average. For example, the last HbA_{1c} value is the most interesting, so the summarizer removes the prior values in the reduction phase. The summarizer might also only show representative values such as median, maximum and minimum blood pressure measurements.

The summarizer can also transform available blood pressure data to graphical form, plotting J.S.'s results over time (such as in **Figure 2a**) or describe a data trend such as "HbA_{1c} has decreased by 30% (from 10% to 7%) over the last 12 months" (**Table 2**). The operations performed to create the reductions and transformations described do not require awareness of patient-state or advanced clinical knowledge.

4.4 Interpretation

Interpretation introduces general medical knowledge to facilitate understanding of clinical information. In the case of J.S., interpretation might involve delineating "normal" versus "abnormal" results in different ways. For example, the summarizer might provide a text prompt indicating "Current LDL exceeds recommended levels." The summarizer might also present a list of flagged lab values in order to call attention to abnormal results. (Here, past HbA_{1c}'s are automatically flagged as "HIGH.") Interpretive elements can be added to graphical displays such as in **Figure 2b,** which shows a normal systolic blood pressure alongside the patient's blood pressure readings and labels the date when an anti-hypertensive was initiated. These examples differ from simpler forms of summarization because they require non-patient-specific clinical information (in this case, a knowledge base that includes normal and abnormal lipid, HbA_{1c} and blood pressure ranges) to define normal and abnormal results.

4.5 Synthesis

Synthesis is the act of juxtaposing multiple types of patient-specific information with pertinent medical knowledge or guidelines. For example, the synthesis statement on lipid control (**Table 2**) indicates that control is "suboptimal" and "ATP III guidelines recommend adjusting the dosage of the medication." This synthetic step combines several data elements specific to patient state (diagnosis of diabetes, lipid panels, and a low-dose lipid-controlling medication) with non-patient-specific clinical knowledge (normal and abnormal lipid panel values and ATP III treatment guidelines). Synthetic combination of data elements provides a more complete picture of J.S.'s health status as well as an actionable care recommendation. A synthetic summary provides the foundation on which the clinician can base care decisions such as to provide J.S. with diet and exercise counseling, add a medication or adjust medication dosage.

Through several iterations of the AORTIS model, a clinical summary can be automatically produced (See **Figure 3a** for a hypothetical computer summary of J.S.'s data). An

electronic summarizer could theoretically perform all summarization steps near-instantaneously to produce a complete task-specific summary as shown. This summary could also be customized based on the preferences of the clinician viewing the record and integrated with an EHR to provide shortcuts to valuable clinical information and actionable recommendations (**Figure 3b**).

The final completed summary is task-specific and tailored to the needs and aims of outpatient primary care provider. In this example, the electronic summarizer tool highlights patient data relevant to chronic disease management, specifically the patient's diabetes care. The summary is a finely-focused but information-dense snapshot of information relevant to the task at hand. However, the value of this summary is limited to chronic diabetes management. Another clinical scenario would require a differently constructed summary and a different tool to accomplish this task, which makes the automated creation of clinical summaries potentially very challenging.

5. Discussion

As Marsden Blois wrote in "Clinical Judgment and Computers," "the most important question appears not to be 'Where can we use computers?' but 'Where must we use human beings?'". As Blois describes in his1980 paper, there exists a wide spectrum of cognitive demands on clinicians during the process of assessment, diagnosis and treatment (66). At one end of this spectrum is the initiation of care, where a great deal of potentially relevant clinical information exists. At the other is a final, specific diagnosis culled from a carefully-constructed differential and subsequent care decisions based on evidence and expertise. Blois posited that the former situation is well-suited to the thinking human clinician, who can make rapid decisions based on relevance (a concept that is exceptionally difficult to automate), while in the latter scenario narrowly-focused clinical objectives might be more accurately and consistently facilitated through the use of electronic tools.

Along Blois' spectrum, there exists many opportunities to create high-quality clinical summaries, tailored to specific tasks, that can aid in the diverse clinical reasoning process. By bringing together multifaceted clinical information, the ideal summary efficiently draws attention to relevant clinical information based on the specific task at hand. Effective summarization facilitates communication between clinicians, speeds information retrieval and aids in effective, evidence-based clinical decision-making. Building upon existing theories of summarization, the AORTIS model provides a comprehensive and nuanced theoretical framework for understanding and analyzing clinical summarization, which may be of value to both healthcare providers and clinical informaticians and to the development of new summarization resources in the future. By rigorously describing the complete process of clinical summarization, our model supplies a well-defined nomenclature for the various steps in summary creation and provides a new means of asking Blois' original question: where must we use human beings in the spectrum of cognitive tasks required of the clinician?

Prior to the advent of the EHR, the entire process of summarization was human-mediated. Clinicians were responsible for aggregating and organizing clinical information in paper charts. Likewise, reduction and transformation could only be accomplished through manual calculations and reviews of narrative information. Interpretation occurred on the basis of memorized clinical knowledge and paper-based references such as textbooks and journal articles. Finally, synthesis took the form of labor intensive dictations or manually typed narrative summaries.

Today, electronic information systems are beginning to take on significant roles in this process. They aid substantially in the aggregation and organization of clinical data, replacing the manual filing system of a paper chart. Electronic systems allow for near-instantaneous switching between different modes of organization. They can also effectively reduce and transform structured clinical data and automatically extract designated clinical information to make summary creation more efficient. In general, much simple summarization can potentially be accomplished through use of automated computer systems, although it is often still performed manually.

Some basic electronic summarization tools (like that described in the example) do exist. One such example is the Diabetes Monograph tool in Partners HealthCare's Longitudinal Medical Record (LMR) system, which collects and displays information related to diabetes management including graphs of recent BP, LDL and HbA_{1c}, relevant patient information such as weight, smoking status and last foot or eye exam, and major co-morbidities. Likewise, while the example above describes summarization for a single patient, the same concepts also apply to a group of patients. For example, at Kaiser Permanente, Northwest researchers have developed a Panel Support Tool that aggregates data from all patients on a clinicians' panel, calculates a gap between expected and current physiologic parameters for each patient, sorts the list in descending order based on this care gap, and allows users to identify patients in need of care (67). Similarly, at Partners Healthcare, researchers developed the ARI Quality Dashboard, which compares individual provider's antibiotic prescribing behaviors to that of their peers and national quality benchmarks (68). The goal of both these tools is to improve quality of care for a wide range of patients, rather than just the individual.

In spite of limited advances in natural language processing, advanced clinical decision support and other techniques, more advanced summarization remains primarily in the domain of the clinician and those automated tools available (such as the Diabetes Monograph and ARI Quality Dashboard) are often relevant only to a narrow range of tasks. There remain substantial challenges at all stages of the model to developing an improved understanding of clinical summarization and creating more robust tools for supporting clinical tasks. Indeed, even the earliest steps of aggregation and organization can be very challenging in some circumstances and the creation of even a narrowly-focused electronic tool, such as that described in the previous section, would be challenging. Furthermore, the need to determine the relevance of given clinical information (through both common sense and general medical knowledge) remains one of the largest barriers to incorporating automation into many of these processes (66). In **Table 3**, we detail a number of these issues and potential means of addressing them. At each stage of clinical summarization described in the AORTIS model, the difficulty in attaining accuracy and completeness increases dramatically; errors or omissions early on in the summarization process can easily propagate and multiply as information is distilled into a summary. Overall, there is a great deal of additional research needed in order to lay the foundation for optimizing clinical summarization.

Robust electronic summarization may eventually offer dramatically new applications of clinical decision support that will aid clinicians at certain points in Blois' cognitive spectrum. With advancement in the field of clinical summarization, automated tools could significantly reduce the burden of basic extraction from clinician workflow, decreasing the amount of "scut" or "gopher" work required of the clinician (69). However, it is also important to understand that automated summaries do not serve as a substitute for medical decision-making; instead, they inform treatment decisions and facilitate care by reducing the burden of specific, narrowly-

focused clinical tasks in the clinician's workflow and by bringing the most relevant knowledge to the forefront. Eventually, automated concept-oriented and task-specific summaries may help physicians recognize new problems, implement preventive care and formulate care plans. However, the process of automatically identifying relevant problem-specific clinical information and creating a synthetic task-specific clinical summary remains one of the most significant challenges in implementing robust electronic summaries.

5.1 Limitations

We formulated a conceptual model based on existing research on summarization and modes of clinical summarization. This model is designed to provide a theoretical framework for the purpose of understanding clinical summarization and assisting in the development of new summarization tools. However, robust research is needed in the future to identify information relevant to particular summary types and to standardize and optimize clinical summaries. Although we present a hypothetical case study for illustration purposes, the model will need to be validated in the real-world setting. The next steps in developing this framework will be to further characterize existing applications of summarization and their variability in current practice and to develop and implement healthcare IT tools that aid in one or more parts of the summarization process. In our current work, we are developing an electronic summarization tool similar to that described in the case study that may be useful to assist in chronic disease management in the primary care setting.

6. Conclusion

Models and strategies for creating accurate, well-designed and task-specific clinical summaries are valuable in the fields of both medicine and clinical informatics. The AORTIS model integrates existing concepts of clinical summarization into a five-stage model that may provide a useful theoretical framework for future research on how clinical information can be best summarized for use by clinicians.

7. Acknowledgements

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Table 1: Summarization stages for diabetes risk factor management summary

	Glycemic control	**Lipid Control**	**Blood Pressure Control**
A	Aggregate all HbA_{1c}, clinic blood glucose levels. Aggregate all medications related to diabetes.	Aggregate all lipid panels. Aggregate all lipid controlling medications.	Aggregate all blood pressure measurements from hospital and clinic. Aggregate all anti-hypertensives.
O	Group laboratory results and medication changes by type and sort by date.	Sort all laboratory results and medication changes by date.	Sort all laboratory results and medication changes by date.
R	Reduce to most recent HbA_{1c}.	Reduce to most recent LDL levels.	Reduce to average, min and max blood pressure.
T	Describe downward trend of HbA_{1c}.	Describe recent upward trend of LDL.	Graph available blood pressure values.
I	Flag past HbA_{1c} values as high.	Flag current LDL as high.	Graph available blood pressures with indication of normal range and treatment initiation.
S	Glycemic control is acceptable according to ADA guidelines.	Lipid control is suboptimal and ATP III guidelines recommend adjusting dosage.	Blood pressure control is suboptimal and JNC VII guidelines recommend adding a medication.

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Table 2: Summarization of sample patient data

	Diabetic Risk Management		
	Glycemic control	**Lipid Control**	**Blood Pressure Control**
A	Aggregate: HbA_{1c}, blood glucose levels, anti-diabetic medications • Clinic - HbA1c : 10/1/09: 10% • Clinic - HbA1c: 10/1/09: 140 • Clinic - HbA1c: 2/1/10: 9.5% • Clinic - HbA1c: 6/15/10: 8% • Clinic - HbA1c: 10/1/10: 7% • Clinic - HbA1c: 10/1/10: 145 • Medication: metformin 500 mg BID started 10/1/09 • Medication: metformin increased to 1000 mg BID 2/1/09	Aggregate: lipid panels, lipid medications • Clinic: 10/1/09: total = 260, HDL = 35, LDL = 170 • Clinic: 2/1/10: total = 180, HDL = 60, LDL = 125 • Hospital: 6/1/10: total = 180, HDL = 60, LDL = 125 • Clinic: 10/1/10: total = 250, HDL = 40, LDL = 175 • Med: simvastatin, 20 mg, QD, started 10/1/09	Aggregate: blood pressure values, anti-hypertensive medications • Clinic - BP: 10/1/09: 150/105 • Clinic - BP: 2/1/09: 135/95 • Clinic - BP: 6/15/10: 140/95 • Clinic - BP: 10/1/10: 135/90 • Hospital - BP: 6/1/10: 150/100 • Hospital - BP: 6/1/10: 145/95 • Hospital - BP: 6/1/10: 140/95 • Hospital - BP: 6/2/10: 145/95 • Hospital - BP: 6/2/10: 130/85 • Med: hydrochlorothiazide, 25 mg, QD, started on 10/1/09
O	HbA_{1c}: • 10/1/09: 10% • 2/1/10: 9.5% • 6/15/09: 8% • 10/1/10: 7% Glucose • 10/1/09: 140 • 10/1/10: 145 Medication Changes • Medication: metformin 500 mg BID started 10/1/09 • 2/1/10: metformin increased to 1000 mg BID 2/1/09	All lipid panels and medication changes: • 10/1/09: 260/35/170 • 10/1/09: start simvastatin, 20 mg, QD • 2/1/10: 180/60/125 • 6/1/10: 180/60/125 • 10/1/10: 250/40/175	Clinic blood pressure readings • 10/1/09: 150/105 • 2/1/09: 135/95 • 6/15/10: 140/95 • 10/1/10: 135/90 Hospital blood pressure readings • 6/1/10: 150/100 • 6/1/10: 145/95 • 6/1/10: 140/95 • 6/2/10: 145/95 • 6/2/10: 130/85 Medication Changes • 10/1/09: start hydrochlorothiazide, 25 mg, QD
R	HbA_{1c} • Most recent: 7%	LDL levels • Most recent: 175	Blood pressure • Average: 141/95 • Max: 150/105 (on 10/1/09) • Min: 130/85 (on 6/2/10)
T	Text prompt: "*A1c has decreased by 30% (from 10 to 7) over the last 12 months."*	Text prompt: *"LDL has increased significantly since last available test."*	Graph available blood pressures • See figure 2a
I	Flagged lab values: • 10/1/09: 10% - HIGH • 2/1/10; 9.5% - HIGH • 6/15/10: 8% - HIGH	Text prompt: "*Current LDL exceeds recommended level."*	Graph available blood pressures • See figure 2b • Includes normal BP and indication of when treatment was initiated
S	Glycemic control is acceptable according to ADA guidelines.	Lipid control is suboptimal and ATP III guidelines recommend adjusting dosage of simvastatin.	Blood pressure control is suboptimal and JNC VII guidelines recommend adding a medication.

Table 3: Challenges and Future Research Directions

	Challenges & Problems	Potential Solutions & Future Research Directions
Aggregation	Incomplete electronic data	Increase data capture (improve user & system interfaces, device connectivity, voice recognition, data entry)
	Records distributed across multiple healthcare and information systems	Health Information Exchanges (HIEs)
	No unique patient identifier or central patient index	Community-wide Master patient index (MPI), statistical matching algorithms
	Health Information Portability & Accountability Act (HIPAA)	Business-associate agreements
Organization	Lack of controlled, structured, and coded data	Template data entry, natural language processing, development and use of standard terminologies
	Many jobs require task-specific organization techniques	Expanded clinical knowledge bases
	Dealing with temporal data and logic	Increased research in temporal systems in computer science and informatics (e.g. TSQL) (70, 71)
Reduction	Reduce data while preserving meaning	New statistical methods
	No methods for prioritizing data	Approaches for prioritizing data elements to display (REF: paper: half-life of notes?)
	Task-specificity of identifying relevant information	Improved understanding of relationships between different clinical data elements (relevance) (66)
	Inaccurate or irrelevant data	Robust method of distinguishing between clinically-significant outliers and noise/bad data
	Mismatch between clinical and statistical significance	New statistical methods (communication)
Transformation	Limited understanding of optimal data transformation for clinical reasoning	Additional research on workflow and clinical reasoning
	Limited EHR functionality to display data in various forms	Increased capabilities of EHR systems
	Task-specific understanding of trend	Investigation of task-specific needs and development of knowledge bases
	Superimposition of secular trends (confuses understanding of clinical trend)	More robust knowledge and better methods for separate trends (e.g. time-series analysis and Kolman filters)
Interpretation	Task- and condition- specificity for interpretations	Create a taxonomy of clinical tasks, conduct additional research on cognitive and workflow needs of different clinical tasks, develop new condition-specific knowledge bases to help interpretation
	Lack of understanding of clinician cognition	Additional research needed (72, 73)
	Heterogeneity of mental models of clinical processes	Study of cognition, standardization of treatment guidelines
Synthesis	High dependency on prior steps of the model and propagation of errors or missing data	New research and more advanced clinical tools to support aggregation, organization, reduction, transformation and interpretation
	Limited understanding of human pathophysiology	Research on mechanisms of diseases
	Lack of adequate computable clinical knowledge bases	Research to design, develop, implement and test new standardized clinical knowledge structures

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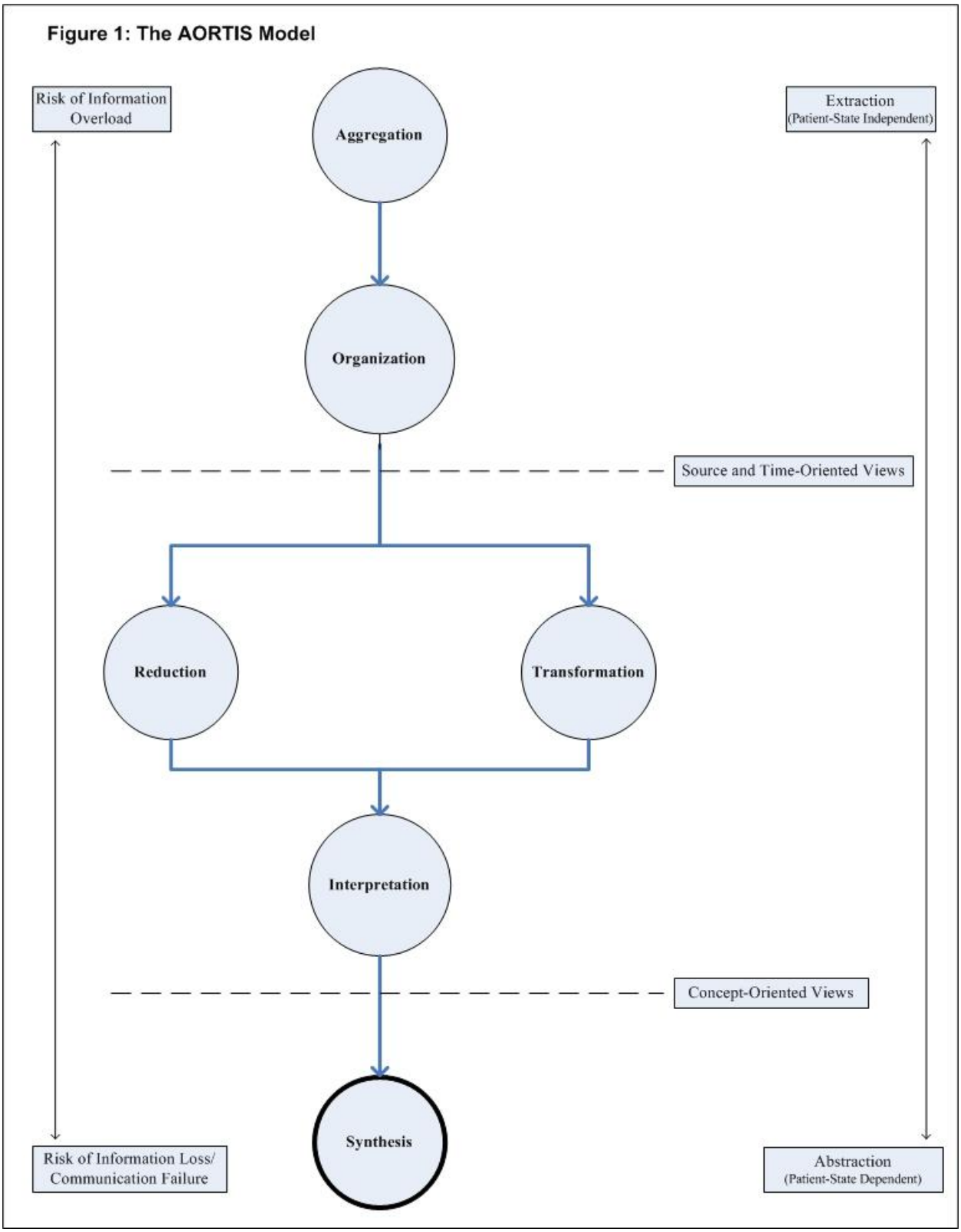

Figure 2a: Transformation of blood pressure readings

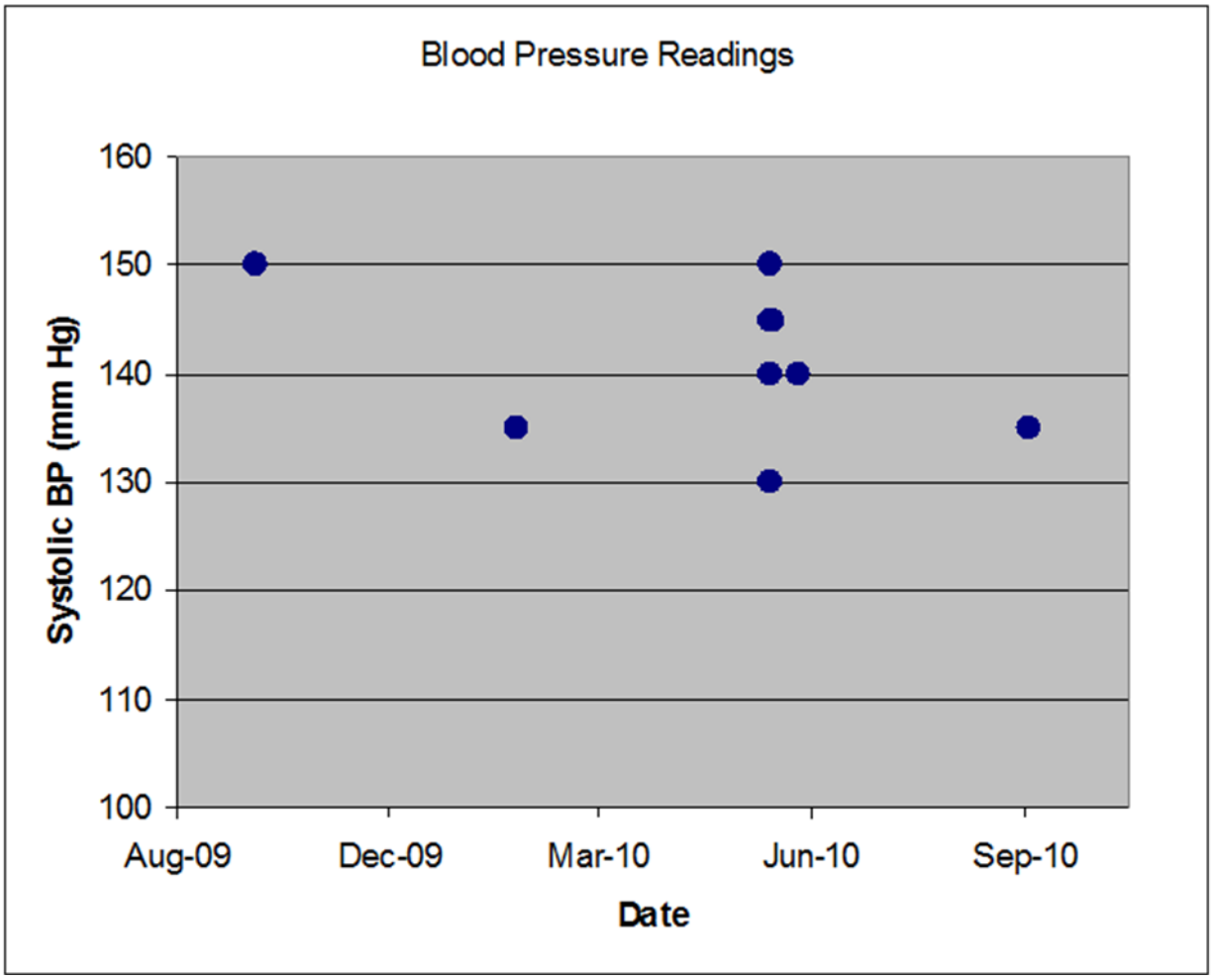

Figure 2b: Interpretation of blood pressure readings

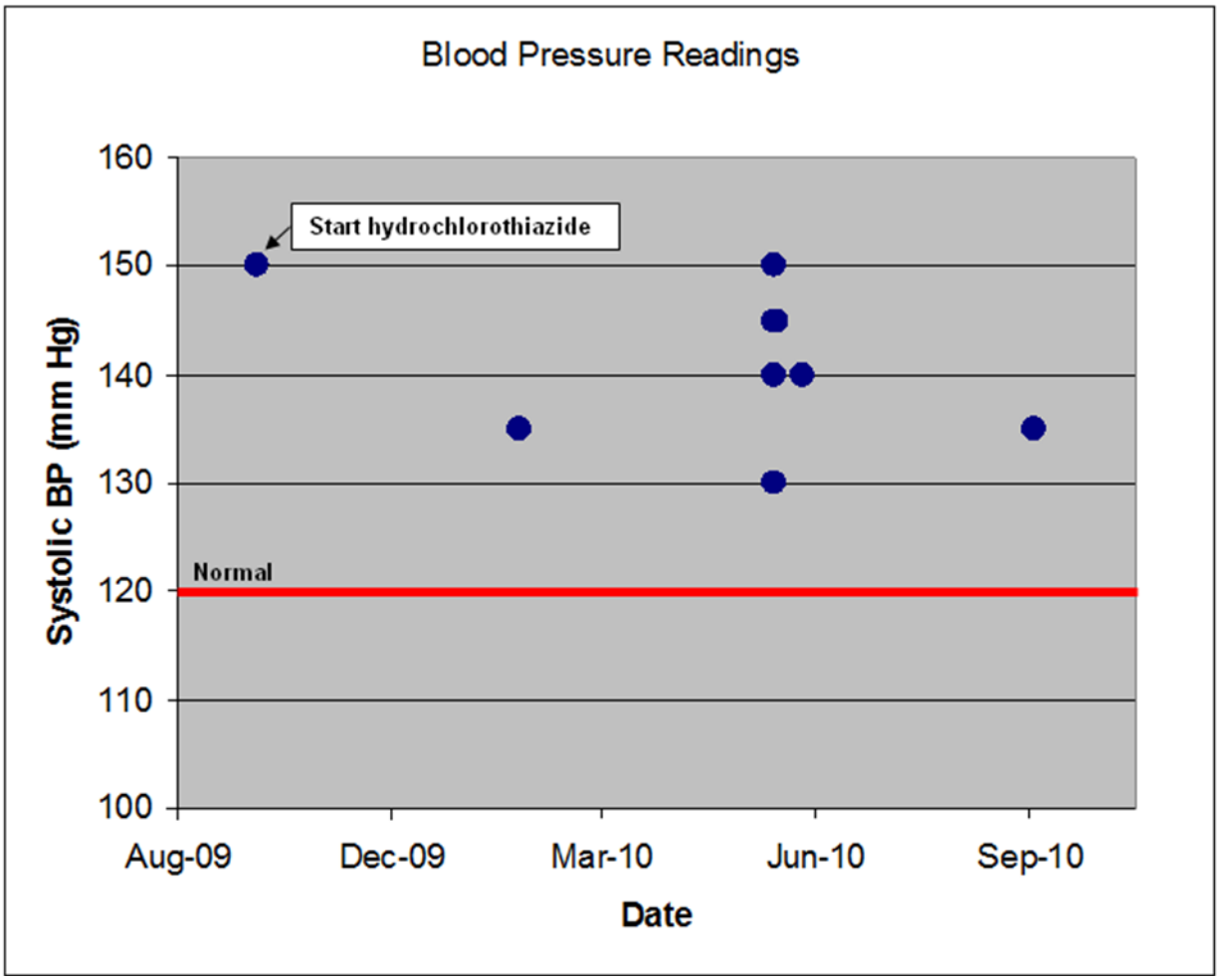

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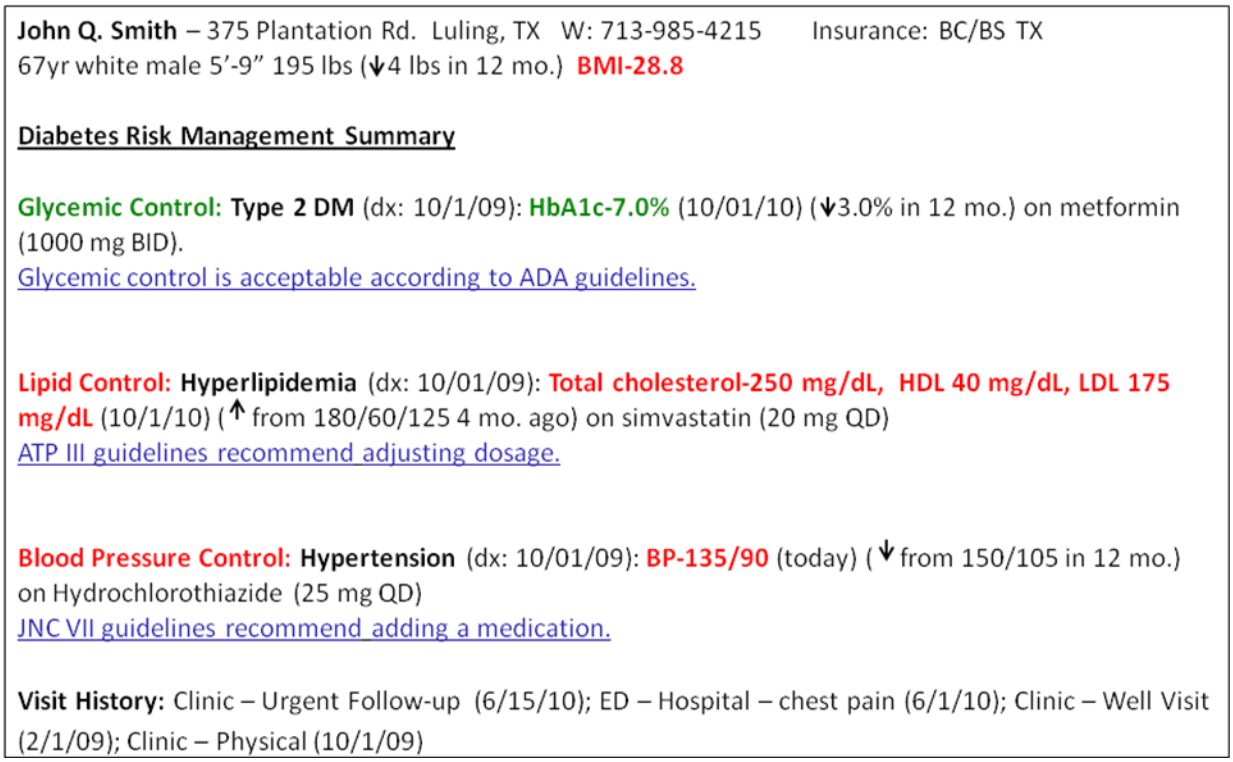
Figure 3a: Example of automatic clinical summarization (problem-oriented view)



John Q. Smith – 375 Plantation Rd. Luling, TX W: 713-985-4215 Insurance: BC/BS TX
67yr white male 5'-9" 195 lbs (↓4 lbs in 12 mo.) **BMI-28.8**

Diabetes Risk Management Summary

Glycemic Control: **Type 2 DM** (dx: 10/1/09): **HbA1c-7.0%** (10/01/10) (↓3.0% in 12 mo.) on metformin (1000 mg BID).
Glycemic control is acceptable according to ADA guidelines.

Lipid Control: **Hyperlipidemia** (dx: 10/01/09): **Total cholesterol-250 mg/dL, HDL 40 mg/dL, LDL 175 mg/dL** (10/1/10) (↑ from 180/60/125 4 mo. ago) on simvastatin (20 mg QD)
ATP III guidelines recommend adjusting dosage.

Blood Pressure Control: **Hypertension** (dx: 10/01/09): **BP-135/90** (today) (↓ from 150/105 in 12 mo.) on Hydrochlorothiazide (25 mg QD)
JNC VII guidelines recommend adding a medication.

Visit History: Clinic – Urgent Follow-up (6/15/10); ED – Hospital – chest pain (6/1/10); Clinic – Well Visit (2/1/09); Clinic – Physical (10/1/09)

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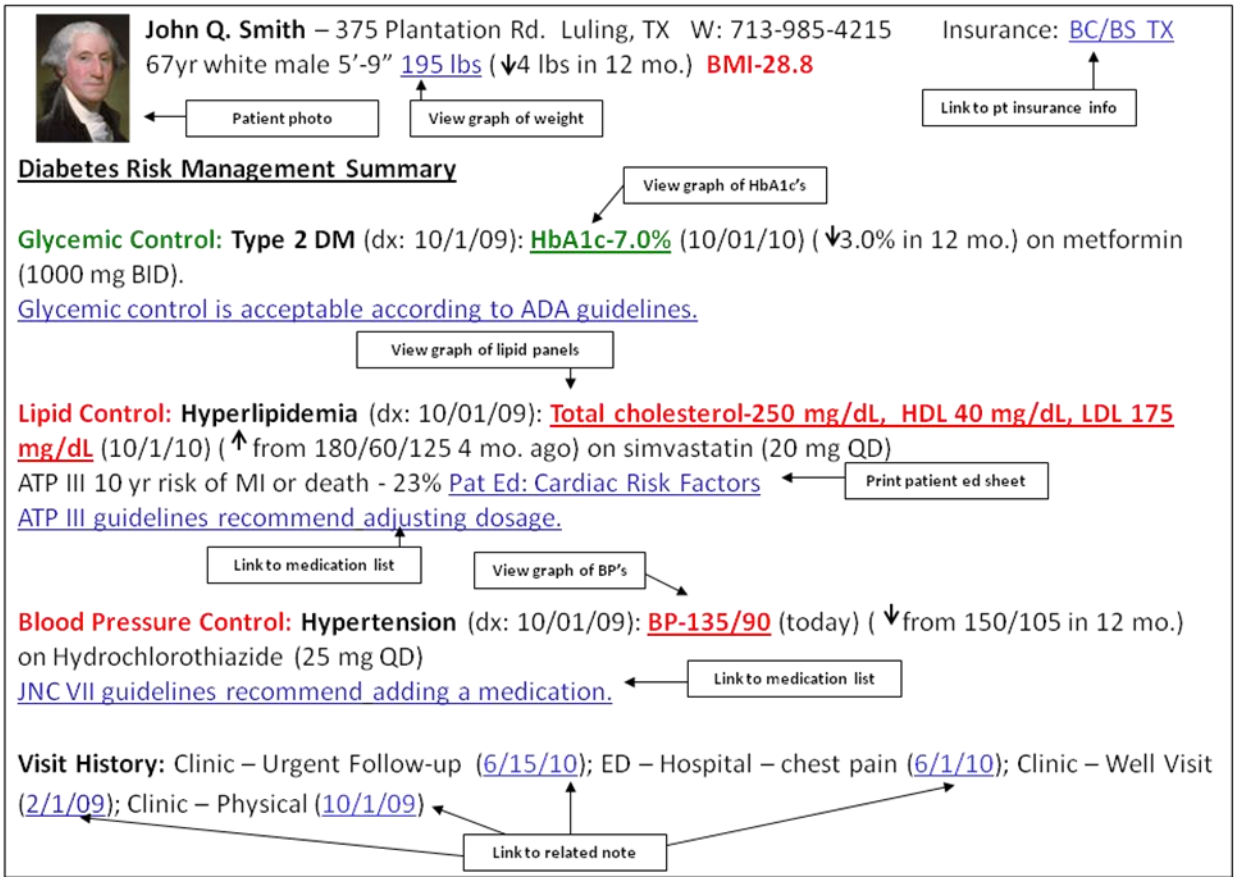
Figure 3b: Annotated example of automatic clinical summarization



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