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Cloud-Based Intelligent Accounting Applications: Accounting Task Automation Using IBM Watson Cognitive Computing

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ABSTRACT: This paper presents a cognitive computing model, based on artificial intelligence (AI) technologies, supporting task automation in the accounting industry. Drivers and consequences of task automation, globally and in accounting, are reviewed. A framework supporting cognitive task automation is discussed. The paper recognizes essential differences between cognitive computing and data analytics. Cognitive computing technologies that support task automation are incorporated into a model delivering federated knowledge. The impact of task automation on accounting job roles and the resulting creation of new accounting job roles supporting innovation are presented. The paper develops a hypothetical use case of building a cloud-based intelligent accounting application design, defined as cognitive services, using machine learning based on AI. The paper concludes by recognizing the significance of future research into task automation in accounting and suggests the federated knowledge model as a framework for future research into the process of digital transformation based on cognitive computing.

Keywords: cognitive computing; artificial intelligence; augmented intelligence; task automation; workforce.

INTRODUCTION

Task automation is a current phenomenon that is attracting and gaining significant attention within business and beyond. The phenomenon of task automation is not new, having origins traceable to the 1960s with the introduction of robotic manufacturing based on artificial intelligence (AI). What is new, after 30 years of developmental effort, is the expansion of task automation, based on AI, into more complex and less structured decision-making processes within society. Task automation based on AI increasingly impacts the workforce, and all indications suggest this trend is accelerating into the future. Some visionaries suggest the rate of acceleration of AI capabilities will soon overwhelm our society, while others are more optimistic regarding the value of a more benevolent virtual intellect (Kurzweil 2005; Brynjolfsson and McAfee 2011; Schwab 2016; Loi 2015). The most recent Executive Office of the President of the United States (2016) report, "Artificial Intelligence, Automation, and the Economy," recognizes not only the possible negative consequences but also the potential benefits of AI task automation, suggesting that within the accounting industry, improvements in strategy, innovation, and operations lead to increased sales, higher-quality services, and lower operating costs.

AI technologies are recognized as a disruptive innovation in our society (Tschakert, Kokina, Kozlowski, and Vasarhelyi 2016; Kokina and Davenport 2017). The challenge for organizations is to accept and adopt such a disruptive innovation and, in this case, transform the disruption into an advantage (Executive Office of the President of the United States 2016; Tschakert et al. 2016) Task automation, that is computerization, is exponentially advancing and impacting virtually all segments of society. Google announced autonomous-AI, where machine learning (ML) can ingest a set of formalized rules and, in record time,

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Supplemental materials can be accessed by clicking the link in Appendix B.

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develop levels of performance far exceeding referent human experts (Cellan-Jones 2017). Additionally, the AI system based entirely on unsupervised ML took only 72 hours to develop performance capabilities that were superior to those developed by the same AI system during months of human-supervised learning. Another example of the turbulence being created by AI is that the U.S. Congress is considering legislative oversight of the logic and decisions made by cognitive computing (CC) systems in healthcare, with technology firms lobbying for autonomy through self-regulation (Ross and Swetlitz 2017). The recent advancements of these new emerging intelligent systems suggest firms will increasingly consider and adopt task automation for a competitive advantage (Executive Office of the President of the United States 2016; Davenport and Kirby 2016).

The impact of task automation on the workforce is increasingly dramatic, with certain jobs being eliminated, many jobs being redefined, and new jobs being created (Autor and Dorn 2013; Brynjolfsson and McAfee 2011; Goos and Manning 2007; KPMG 2017; Frey and Osborne 2017; Schwab 2016; Davenport and Kirby 2016). Simultaneously, as the general workforce is being transformed by automation, Tschakert et al. (2016) specifically identify the human element within the accounting industry as an impediment to growth. Given these contributory factors, accounting as an industry will experience dramatic changes as a result of task automation and should prepare accordingly (Frey and Osborne 2017; Tschakert et al. 2016; Kokina and Davenport 2017; Vasarhelyi, Kogan, and Tuttle 2015; No and Vasarhelyi 2017).

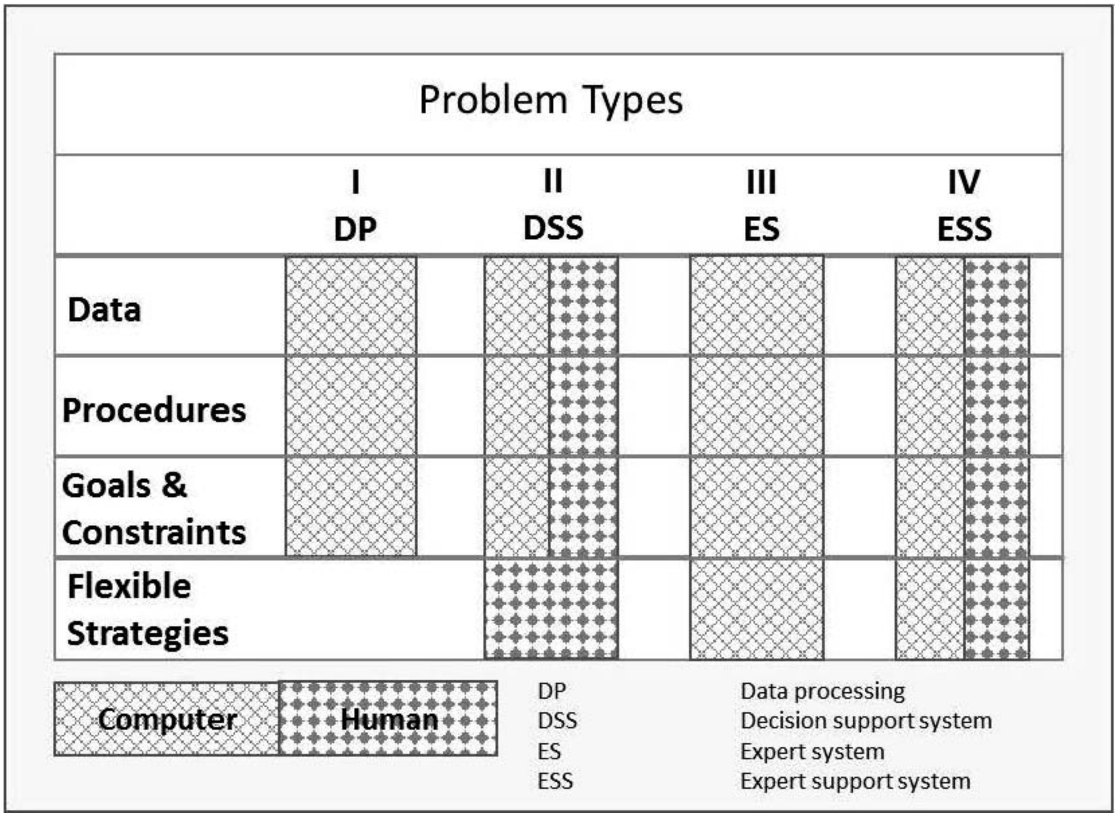
Frey and Osborne (2017) examined job classes, based on standard occupational classification (SOC) codes, and identified 70 occupations that will be significantly transformed by redesign. They also ranked jobs by SOC with a probability for computerization. Based on their analysis, Frey and Osborne (2017) believe the routine aspects of accounting and auditing as a job code (SOC 13-2011) will be substantially automated. On the more optimistic side, Frey and Osborne (2017) identify other related jobs less susceptible to automation, such as financial manager (SOC 11-3031), management analyst (SOC 13-1111), and compliance officer (SOC 13-1041). Their analysis supports the role of compliance officer (SOC 13-1041) as a job type that cannot be entirely automated, as compared to the many routine tasks of accounting and auditing (SOC 13-2011), which they perceive can be entirely automated. From an organizational perspective, "What these technologies make clear is that human and digital labor will increasingly coexist in organizations, raising a key challenge for leaders and human resources (HR) professionals alike: create a productive integration as opposed to a destructive disconnection between both aspects of labor" (KPMG 2017). Productive integration for competitive advantage in the accounting industry necessitates organizational and HR support in task redesign for automation (Tschakert et al. 2016). Creating a coupling of automation, as digital labor, and human labor is essential in delivering a work environment that supports reassignment to higher-value activities for sustaining increased competitiveness and a greater sense of job satisfaction for the individuals affected.

Task Automation

Many recent task automation advancements can be associated with eCommerce technologies, including Big Data, ML, natural language processing, AI, and other developing algorithmic approaches to analytics, such as recommenders, classifiers, and predictors. The foundation of these technologies is the capability of collecting, storing, and processing Big Data with massive parallel processing at an economic cost point. These AI technologies are making it possible to overcome engineering bottlenecks and transmit volumes of data that would have been impossible in the recent past (Frey and Osborne 2017). Luconi, Malone, and Scott-Morton (1986) propose a forward-thinking framework (Figure 1) for information systems that includes AI support for unstructured tasks. In general, structured tasks are routine, requiring less judgement, while unstructured tasks are less routine requiring greater levels of judgement. Before recent advancements in AI, unstructured tasks have been challenging to computerize. AI is changing the way we address many unstructured accounting tasks (Kokina and Davenport 2017). The Luconi et al. (1986) framework identifies unstructured decision types that benefit from computer support through expert systems (ES) and expert support systems (ESS), both based on AI (Figure 1). Implicit in this framework is that AI does not necessarily replace humans, but can also synergistically support human problem solving, especially in less structured tasks. In addition to matching task structure to IS type, the framework includes Alan Newell's (1980) problem-solving components of data, procedures, goals and constraints, and flexible strategies (Newell and Simon 1972). The framework helps explain implementing task automation for decision support based on AI, especially when the decision making is less structured and provides a context for evaluating tasks and processes that might be suitable for automation using AI.

As task automation progresses beyond the structured tasks associated with data processing, the framework assigns control for problem-solving components between the computer and humans. As Figure 1 shows, task automation began with a focus on data, procedures, and goals and constraints in more structured problems (Types I and II) and now, with advancements in AI, is progressing to support flexible strategies associated with less-structured problems (Types III and IV). The future ability of machines to evaluate and select optimal flexible strategies in a decision scenario may prove to be the most significant impact of AI in supporting human behavior and task performance (High 2012; Kokina and Davenport 2017).

FIGURE 1
The Luconi, Malone, and Scott-Morton IS Framework



Source: Adapted from Luconi et al. (1986).
The full-color version of Figure 1 is available for download, see Appendix B.

In summary, prior research has documented task automation for structured decision making, but recent research has expanded task automation to encompass unstructured decision making, with AI assuming a greater role in the collaborative decision-making effort. New capabilities and computational architectures associated with ML, especially deep ML, are allowing AI to participate more in the flexible strategy component of the decision-making process. AI's capability to support less-structured decision making provides the accounting profession with the opportunity to transform a disruptive technological innovation into a competitive advantage.

Accounting Task Automation

Kokina and Davenport (2017) and Tschakert et al. (2016) present compelling arguments for significant and fundamental changes in the automation of accounting and auditing resulting from recent advancements in data analytics and AI. Acknowledging that the topic is not new, Kokina and Davenport (2017) use an economic model of supply and demand forecasting the rapidly approaching convergence of information and technology as transformation catalysts in the accounting industry. The authors delineate audit phases by aggregate task structure (structured, semi-structured, and unstructured) to identify tasks suitable for automation (Kokina and Davenport 2017). While many are recognizing the impending structural changes in accounting, as previously mentioned, accountants are often viewed as an impediment to moving accounting practices forward in the acceptance and adoption of advanced technologies (Tschakert et al. 2016).

Managerial beliefs impose a bounded rationality that affects an individual's responsiveness to disruptive changes impacting their industry (Vecchiato 2017; Tripsas and Gavetti 2000; Smith, Tayler, and Prawitt 2016; Simon 1955). Being conservative by nature and, in general, more subject to bounded rationality may exacerbate the accounting industry's deliberate response to task automation (Bailey, Daily, and Phillips 2011; Lamberton, Fedorowicz, and Roohani 2005; Smith et al. 2016). Given the trend of AI and automation to significantly impact tasks associated within accounting and auditing job classes (Issa, Sun, and Vasarhelyi 2016; No and Vasarhelyi 2017; Kokina and Davenport 2017; Tschakert et al. 2016), the challenge facing the accounting profession is how to redefine itself to enhance marketplace relevancy and continue economic prosperity (Tschakert et al. 2016; Kokina and Davenport 2017).

Drivers of task automation within accounting are similar to those found across many industries (Issa et al. 2016; Kokina and Davenport 2017). Cost reductions, increased speed, greater agility, and increased profitability are common automation drivers (Protiviti 2016; Kokina and Davenport 2017). Other drivers of task automation include better utilization of resources and improved service capabilities of out-sourced or under-serviced capabilities. While automation began with routine tasks, non-routine unstructured tasks are now within the scope of automation (Figure 1, Task Types III and IV). Task automation is present and successful in the healthcare, financial, banking, and insurance industries (Executive Office of the President of the United States 2016). Accounting, as an industry, has the opportunity to automate tasks to increase effectiveness, efficiency, agility, quality, and profitability (Tschakert et al. 2016; Kokina and Davenport 2017; Davenport and Kirby 2016).

Big Data has served as a catalyst accelerating advancements in CC and data analytics. While related, CC and data analytics support human decision making from different perspectives. CC is designed to provide augmented intelligence and to "think like a human" by understanding the complexities of unstructured data, applying reasoning to generate and test hypotheses, and learning from each process iteration (High 2012; Kokina and Davenport 2017). Cognitive computing has been described as focusing on "doing the right things" while data analytics emphasizes "doing things right" (KPMG 2016a). Cognitive computing is logically driven by "what to know," while data analytics is most often programmed by focusing on "what to do." Integrated together, CC and data analytics form a synergistic discovery and analytic platform with the capability of providing deeper insights and explanations to augment human decision making.

Data analytic technologies, driven by the data explosion, have created new algorithms to support descriptive, predictive, and prescriptive analytics. Data analytics provide support by answering questions related to measuring, monitoring, comparing, predicting, preventing, and optimizing based on logic (KPMG 2016a; Tschakert et al. 2016). Cognitive computing provides decision-maker support by understanding, applying reasoning to generate and test hypotheses, and learning from previous experiences. Cognitive computing relies on inference-based processing and probabilistic models to provide augmented intelligence to enhance human decision-making performance. "[D]eep learning, modeled on the human brain, is infinitely more complex. Unlike machine learning, deep learning can teach machines to ignore all but the important characteristics" KPMG (2017). Using deep learning on an inference-based system, such as reverse inferencing or inference chaining, provides additional benefits by allowing decision makers to identify new questions and concepts that may not be apparent without CC (High 2012). Deep learning associated with CC, when compared to more conventional data analytics, can provide decision makers with fresh insights (Kokina and Davenport 2017) and provide augmented intelligence in a natural manner to enhance human task performance. Therefore, the use of CC to provide augmented intelligence for accountants is a natural progression of the industry accepting and adopting developing technologies associated with data analytics based on Big Data (Vasarhelyi et al. 2015; Issa et al. 2016; Kokina and Davenport 2017).

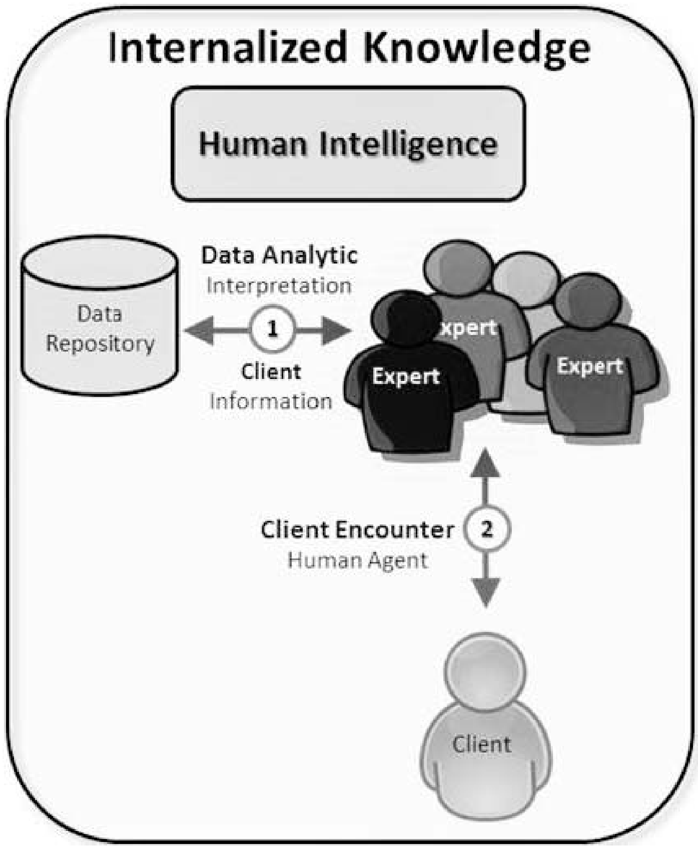
By developing task automation capabilities based on CC technology, accountants can better deal with the increasing complexities of practice (Mock, Srivastava, and Wright 2017). CC has the ability to intelligently manage the volumes of structured and unstructured data being created. In many cases, through extended ML, CC recognizes patterns and relationships in data more effectively than humans. Cognitive computing for augmented intelligence is based on ML and often starts by working with humans from the humans' perspective using supervised training. CC then uses ML to leverage its knowledge by recognizing concepts or signals in the information that contribute to its interpretation and valuation. With reinforced ML, the CC system then takes the initial understanding and, by inference of unsupervised learning, expands that power across the data available. Inference-based logic allows the knowledge base to adapt, expand, and improve, while human-directed reinforced training supports behavior monitoring and continuous improvement.

There are many suppliers of AI technology for CC, including IBM, Google LLC, Microsoft Corporation, Amazon.com, Inc., Facebook, Yahoo!, and Intel corporation. Evans (2017) and Kokina and Davenport (2017) note that KPMG is working with IBM Watson to develop their accounting AI, while several other accounting firms are using multiple AI vendors. In this paper, we use Watson to illustrate our conceptual AI framework for accounting because Watson is available as an AI platform as a service (PAAS), and because KPMG is using Watson for accounting automation.

Augmented Intelligence

Augmented intelligence, based on IBM's Watson CC, is designed for AI not to replace humans but to augment human performance through collaboration (Figure 1, Problem Type IV). Using the Watson CC technology platform, organizations capture knowledge in computational form that can be replicated and democratized as an investment in intellectual capability. Additionally, the Watson CC platform uses ML, supervised and unsupervised, to leverage its knowledge base providing for adaptability, evolution, and continuous improvement of system capabilities. With Watson, knowledge engineers create and

FIGURE 2
Traditional Computing Model



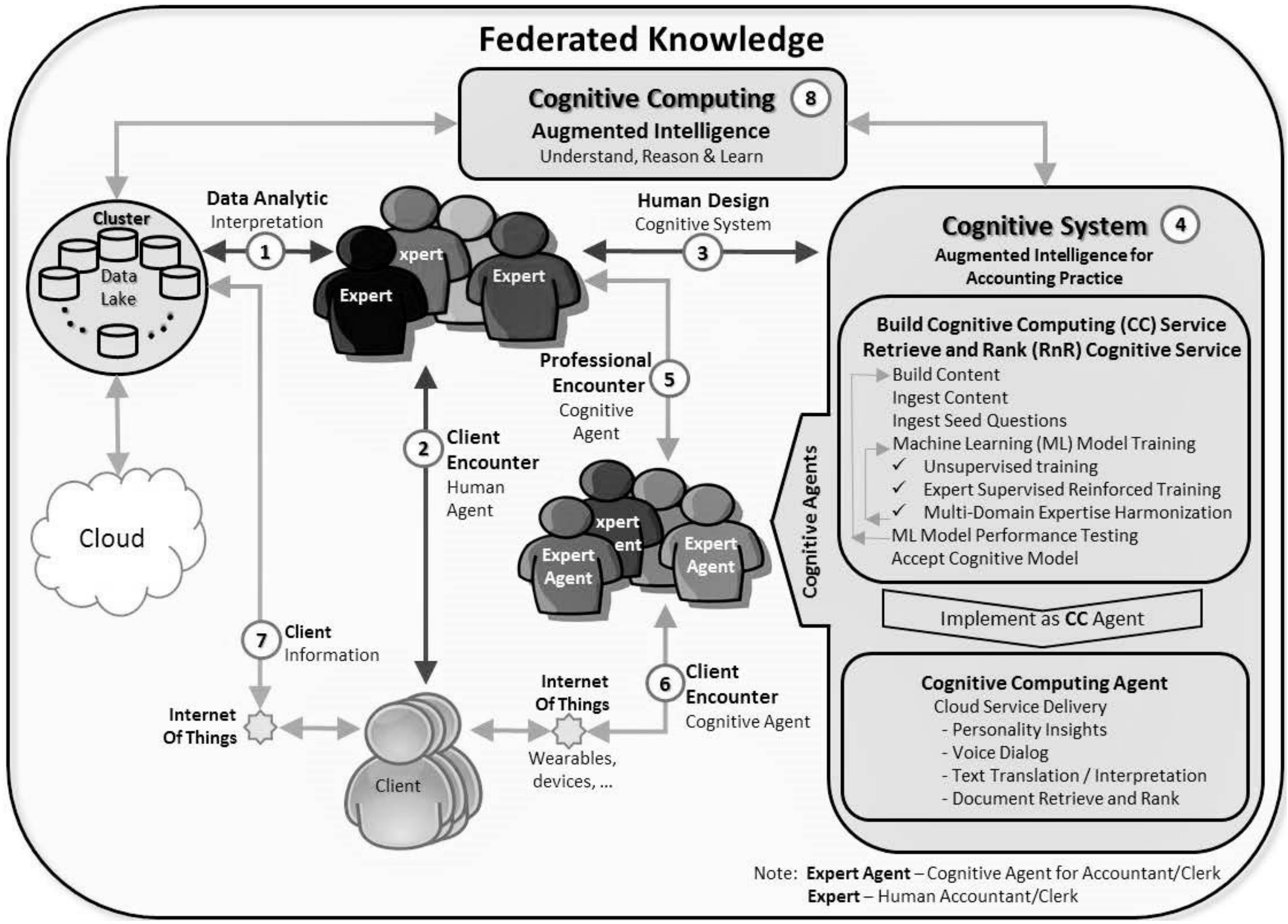
Source: Adapted from Marshall et al. (2017).
The full-color version of Figure 2 is available for download, see Appendix B.

manage a dynamic, real-time, and robust knowledge base supporting flexible strategy recommendations in less-structured tasks (Figure 1, Problem Types III and IV).

In the accounting industry, CC presents a new capability to manage, in a timely and agile manner, issues such as the complexities, volatility, and voluminous nature of so many of the industry governance and policy boards that dictate practice and compliance (Kokina and Davenport 2017; Tschakert et al. 2016). In the auditing industry, recognizing that every client is distinctive requires that an individualized audit plan be developed for each engagement. Cognitive computing systems support individualized audit plans by including a broad set of data such as client business type and industry, applicable laws and regulations, and information systems and controls. Additionally, CC has the capacity to provide tremendous benefits to the accounting practice by democratizing and federating the intellectual processing power of individuals in the firm to enhance individual job roles and improve quality standards. By democratizing and federating knowledge, CC can make audit and subject matter expertise available to less experienced and knowledgeable auditors, thereby raising the overall expertise, effectiveness, quality, and efficiency of all auditors within in a firm, a company, or a government entity.

The Luconi et al. (1986) framework delineates human problem solving as consisting of data, procedures, goals and constraints, and flexible strategies (Figure 1). The traditional computing model generally provides support to human task performance by presenting the computer as a tool focusing on data, procedures, and goals and constraints. Under this traditional model, users access the computer for information that they internally process to form a value (Figure 2, Reference 1). As an example, accountants might look at a financial report and form an opinion regarding a potential business-strategic decision. The accountant would then directly engage the client in providing a service (Figure 2, Reference 2). The traditional model based on internalized knowledge supports computerized control for data analytics: data, procedures, and goals and constraints (Figure 1).

FIGURE 3
Federated Knowledge Cognitive Computing



Source: Adapted from Marshall et al. (2017).
The full-color version of Figure 3 is available for download, see Appendix B.

Flexible strategies under the traditional computing model are generally controlled by the human as represented in Figure 1, Problem Type II.

Viewing the computer as a source of cognition, federated knowledge is a different model, as represented in Figure 3. Federated knowledge for augmented intelligence includes traditional system use for data analytics (Figure 3, Reference 1) and best practices in client engagement (Figure 3, Reference 2). CC captures cognitive processes from humans (Figure 3, Reference 3), democratizes those processes in a knowledge base in the CC system (Figure 3, Reference 4), and then exposes that knowledge through cognitive agents (Figure 3, References 4 and 5) that exhibit seemingly intelligent behavior within a domain. In this manner, CC provides augmented intelligence to support human-computer task performance.

Augmented intelligence might include scenarios of cognitive agents recommending:

- a decision based on a multi-criteria multi-option decision model such as evaluating an audit engagement for risk, expense, and profit;
- procedures for protecting personally identifiable information (PII) transported across international borders based on mining open text documentation to satisfy international data protection requirements;
- a market/customer perspective based on integrating social and corporate data for a closely held organization;
- a classification of a significant and extraordinary financial transaction based on mining open text documentation from court adjudications;

- the client provides additional documentation supporting a qualified series of transactions, for example associated business travel expenses; and
- context-appropriate procedures for assessing internal controls of an IT implementation using a knowledge base to support generally accepted auditing standards.

The preceding models demonstrate differing views of computer support: the traditional computing model programmed to execute procedural code—"what to do"—and CC systems designed to understand, reason, and learn—"what to know." Also in the federated knowledge model is the use of the cognitive agent by experts to augment their knowledge and performance (Figure 3, Reference 5). With this CC architecture, cognitive agent use by experts promotes enhanced cognitive-based jobs for humans impacted by automation (Figure 3, Reference 5). In addition, a significant difference between the models is that the CC system evolves by using unsupervised and supervised ML to continuously refine and extend itself, that is CC is designed to understand, reason, and learn.

Cognitive Task Automation Management

Until recently, cognitive tasks most susceptible to automation have been associated with jobs in the middle of the workforce skills spectrum (Frey and Osborne 2017; Autor and Dorn 2013; Brynjolfsson and McAfee 2011; Goos and Manning 2007). Because of technological pressure on jobs in the workforce that fall between low-skill, low-cognition jobs and high-skill, high-cognition jobs, there have been increases in low-skill and high-skill jobs with a decrease of jobs in the middle (Frey and Osborne 2017). This middle-skill area may be a zone of replacement where automation can replace human resources. Goos and Manning (2007) described this job trend as "hollowing out of the middle" as they present their case of workforce polarization between low-skill manual work and high-skill cognitive work. Placing tasks on a spectrum of requisite skills to perform suggests that routine tasks with little cognitive judgement are highly automatable with AI (Figure 1, Problem Type III). Tasks requiring a greater degree of human judgement will be more prone to using AI to provide augmented intelligence that enhances human task performance (Figure 1, Problem Type IV). As CC systems evolve and technology advances, it is reasonable to expect that computers will develop the capability to determine, suggest, and implement optimal flexible strategies in both Problem Types III and IV of the Luconi et al. (1986) framework (High 2012; Brynjolfsson 2016; Kokina and Davenport 2017; Davenport and Kirby 2016; Marshall, Champagne-Langabeer, Castelli, and Hoelscher 2017).

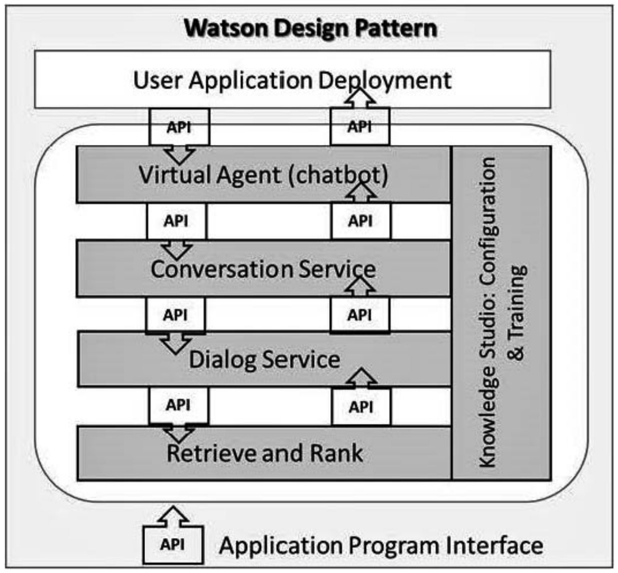
Task automation in accounting, based on CC, must be effectively managed to accomplish the objective of transforming the disruptive innovation of AI into a competitive advantage (Tschakert et al. 2016). Risk management and governance programs are critical for a successful implementation of cognitive task automation (KPMG 2016b). Prioritizing accounting tasks for automation can be systematically managed by evaluating a task for its logical nature for automation, task/process maturity, task data availability, and the derived value of task automation (Protiviti 2016; Davenport and Kirby 2016). When evaluated on cognition, tasks identified that are routine, resource intensive, and critical in nature might qualify as a high priority for task automation (Kokina and Davenport 2017). Tasks considered for potential automation should be appropriately structured, mature, and include the returned value to justify the effort. Job tasks requiring judgement within a rules base are potential candidates for cognitive task automation (KPMG 2017). Potential tasks for automation should be systematically evaluated, scored, and considered as a portfolio of cognitive projects for executive management consideration.

The federated knowledge model supports redeployment of impacted humans to more value-added activities within the organization, including roles of system use for augmented intelligence and CC quality assurance. The model begins by having experts establish best practices through system use (Figure 3, References 1 and 2), and codify those practices by designing the CC system (Figure 3, Reference 3). After building the cognitive model, the CC system generates cognitive agents that exhibit behaviors based on the codified knowledge base. Based on human expertise in supervised training sessions, the CC supports monitoring and improving agent behavior. The CC platform uses reinforced learning to monitor and improve cognitive agent (expert agent) behavior through professional encounters with experts (accountants) and clients (Figure 3, References 5 and 6). Cognitive computing systems are designed to be collaborative and provide augmented intelligence to enhance human task performance. Organizationally, implementation can facilitate human redeployment to higher-value activities. The cloud architecture provides a stable CC platform to support automating complex cognitive-based accounting tasks as cognitive agents.

COGNITIVE COMPUTING DESIGN

Cognitive computing provides augmented intelligence as a platform designed to support problem solving by enhancing and scaling human expertise. The underlying principles of operation in CC are for the computer to understand, reason, and learn (High 2012; Kokina and Davenport 2017). Watson's logic is driven by an evolving probabilistic system based on

FIGURE 4
CC Design Pattern for Intelligent Content and Document Management



The full-color version of Figure 4 is available for download, see Appendix B.

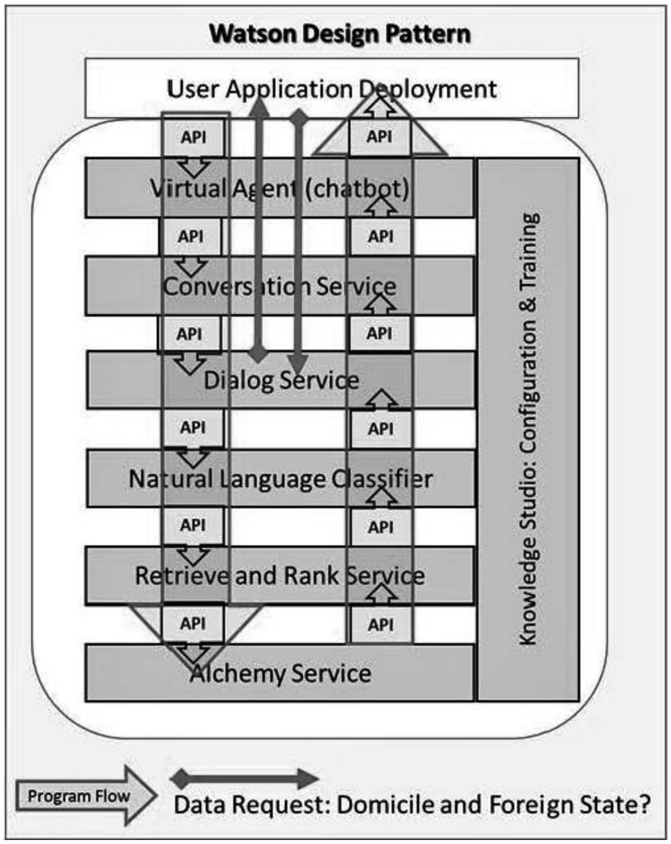
understanding facts and learning, as compared to the traditional approach of using a pre-determined decision-tree-driven model of programmed control (High 2012). In this new architecture, cognitive agents present services, based on cognitive processes, that interact with users in an intelligent and natural manner. In CC, cognitive services are used in design patterns to create applications. Technologies such as natural language processing (NLP), ML, and deep learning are foundational to CC. Design patterns are built around understanding a user's context and intent before reasoning to provide a dialog that creates behaviors from cognitive agents that would be expected from a knowledgeable human. Dealing in the abstract of problem solving, CC uses conceptual meanings within the context of the user's perspective for NLP and deeper problem solving. IBM uses NLP, in context, to deliver natural language understanding (NLU), which supports the principle of understanding, reasoning, and learning. Designing CC using IBM Watson technology involves creating a design pattern by assembling cognitive service agents through application programmer interfaces (API) to automate the task. The assembly of services defines the depth of complexity of the cognitive agent offered in that particular design (see Appendix A for a selection of Watson services).

Cognitive Computing Design Pattern

Developing a CC design might begin by using a virtual agent as a cognitive service to support conversations between the users and the AI. The exposed virtual agent is connected to a series of cognitive services that together create a user dialog session. The AI uses these dialog sessions to define user context (intent), entities, and appropriate dialogs. An important note is that the specific dialog executed by the system is determined by the CC meta-system based on user context and intent. Given the foundational CC system, machine learning on "contextually rich" ingested data is used to establish, confirm, and refine the knowledge base and cognitive agent behaviors. Watson includes a knowledge studio component for knowledge management that addresses harmonization within and between domains, employing annotators for fine tuning agent behaviors and knowledge-base representations.

Figure 4 presents a CC design pattern for intelligent content and document management with an interface using a virtual agent referred to as a "Chatbot." The conversation services in the design pattern are codified by using a graphical user interface (GUI) to establish user intentions, entities, and dialog. A service for content and document retrieval named "Retrieve and Rank" is instantiated. The CC develops what is referred to as "ground truth" based on data from real users ingested into the system, and cognitive agents are trained as required. The "contextually rich" data used for training should be natural and contain human-oriented noise for the best learning effect. The system initially performs an unsupervised training session to be followed by supervised training for confirmation and refinement. Users and design engineers are provided with opportunities to refine the knowledge base using reinforced learning capabilities. Figure 4 presents one

FIGURE 5
More Complex Query Program Flow
"What are the schedules and enforcement/collection policies for out-of-state sales tax collected and not paid?"



The full-color version of Figure 5 is available for download, see Appendix B.

general design pattern, among a variety of potentially valid designs, for an intelligent application supporting content and document management.

An essential component to CC is program flow, which can be compared to the human concept of "line of reasoning." In AI-based systems such as Watson, the developer does not explicitly create the program flow, but the system, using inference-based processing, establishes what is believed to be the best flow or, in human terms, line of reasoning, given the problem-solving scenario. When possible, the CC responds directly to the user; otherwise, the system determines the best available program flow to satisfy the user's requirement. Using inference-based processing, the CC can consider many decision scenarios without requiring each scenario to have been preprogrammed. The CC can annotate the program flow to better suit the specific knowledge representation requirements.

Watson initially attempts to formulate a direct response within the conversation service by first seeking a direct answer and only performing deeper searches when it is unable to satisfy a query directly. More complex queries typically engage more cognitive services as the system creates program flows to represent the more complex reasoning. When Watson determines that more context data are required, it prompts the user to provide the additional data. Aspects of Watson's logic include temporal and spatial dimensions, allowing it to reason over time and locale. In accounting, these capabilities would support reasoning over reporting periods and legal jurisdictions. Watson's capabilities include measures of sentiment based on analytics requiring a deeper line of reasoning that necessitates the inclusion of additional cognitive service providers. For example, sources of sentiment data might include official departmental promulgations or court case adjudications. For this more complex query, representing a deeper line of reasoning, Watson uses cognitive services for qualitative factors of sentiment and emotion. As shown in Figure 5, this design includes sentiments and emotions by adding Alchemy, a cognitive service. In this manner, the same CC design pattern creates different logic flows—lines of reasoning—based on the complexity of the query at hand. Therefore, within the CC architecture, the

TABLE 1

Accounting Occupational Role Fusion

Accountant—Professional Work Activities Ranked	Occupational Role Fusion	Accountant—Clerk Work Activities (Ranked)
Interacting with Computers (1)		Interacting with Computers (2)
Processing Information (2)		Processing Information (3)
Getting Information (3)		Getting Information (1)
Evaluating Information to Determine Compliance with Standards (4)	CC	Augmented Intelligence
Augmented Intelligence	CC	*Documenting/Recording Information* (4)
Organizing, Planning, and Prioritizing Work (5)		Organizing, Planning, and Prioritizing Work (5)
Analyzing Data or Information (6)	CC	Augmented Intelligence
Communicating with Supervisors, Peers, or Subordinates (7)		Communicating with Supervisors, Peers, or Subordinates (7)
Updating and Using Relevant Knowledge (8)		Updating and Using Relevant Knowledge (6)
Augmented Intelligence	CC	*Identifying Objects, Actions, and Events* (8)
Making Decisions and Solving Problems (9)	CC	Augmented Intelligence

Adapted from Occupational Information Network, North Carolina Department of Commerce (https://www.onetcenter.org/overview.html).
Distinctive tasks between job roles are in italic; CC = cognitive computing; rank of activities within roles is in parentheses.

services within the application are only called if they provide value in goal resolution as determined by Watson's metalogic.

The previous models demonstrate that CC applications are design patterns based on associated or linked cognitive services, where program flow is controlled by understanding and solving the problem at hand. The next section discusses the application of cognitive task automation providing augmented intelligence in accounting. With cognitive task automation as a catalyst for job redesign, the discussion addresses occupational classifications related to accounting that might be morphed into a new job design based on shared knowledge. The section concludes by identifying organizational impacts of job redesign based on CC within the accounting domain.

AUGMENTED INTELLIGENCE AND ACCOUNTING JOB FUSION

Frey and Osborne (2017) identified two particular standard occupational classifications (SOC), the accounting professional and the accounting clerk, as highly susceptible to computerization. The Occupational Information Network (O*NET 2017)[1] specifies SOC based on features such as knowledge, skills, abilities, activities, and tasks. Table 1 presents a comparison of top-ranked work activities for accounting occupational job roles of "Professional" (SOC Accountant 13-2011.01, see https://www.onetcodeconnector.org/ccreport/13-2011.01) and "Clerk" (SOC Accounting Clerk 43-3031.00, see https://www.onetonline.org/link/summary/43-3031.00). Using top-ranked work activities from O*NET (2017), Table 1 highlights opportunities for cognitive task automation. Applying CC between the occupational roles creates a fusion of the work activities resulting in a new job design of the future (Brynjolfsson and McAfee 2011; *The Economist* 2016).

Activities such as evaluating compliance, analyzing information, and making decisions and solving problems, which are distinctive to the accountant-professional role, might be considered higher-priority cognitive processes suitable for task automation with CC. These higher-priority cognitive processing activities provide opportunities to generate organizational value by creating augmented intelligence based on CC. For the accountant-clerk, Table 1 shows that augmented intelligence through CC is expected to enhance job task performance. For the accountant-clerk, augmented intelligence also creates organizational value by accelerating and enhancing on-the-job experiential learning. Augmented intelligence provides greater opportunities for accountant-professionals to leverage their knowledge through federation, thereby freeing them to pursue activities that provide greater value to the organization. Empowering employees through augmented intelligence creates value through enhanced task performance, and increases job satisfaction by creating opportunities for employees to engage in higher value-added activities for the organization.

[1] The Occupational Information Network (O*NET) is a government service developed by the North Carolina Department of Commerce under the sponsorship of the U.S. Department of Labor/Employment and Training Administration.

By supporting two previously separate job roles through cognition, CC creates a new job role based on a fusion of knowledge bases (Table 1). These new job designs have the potential to leverage knowledge through cognitive automation (Rometty 2016). Job role fusion based on shared CC knowledge bases provides an environment of greater commonality for thought and ideas, which can lead to innovation (Sawyer 2007; Johnson 2010; Leonardi 2014; O'Leary 2016). This architecture of shared cognition creates a new job design, resembling a "federated innovation network" that, as an experiential learning environment, is conducive to innovation (Lyytinen, Yoo, and Boland 2016). Managed properly from an organizational perspective, CC systems that support innovation have the potential to make a significant return on investment to the enterprise.

Cognitive Computing's Potential Impact on the Auditing Profession

Public Company Accounting Oversight Board's (PCAOB 2013) Alert No. 11 indicates that, when auditing a given internal control that depends upon underlying computerized accounting information system controls, auditors should test not only the given control but also the underlying system controls upon which the given control relies. For example, suppose that an auditor tests the existence and completeness of accounts receivables summarized in a client's balance sheet by obtaining, from the client's computerized business system, a report listing detailed accounts receivables amounts by customer. The auditor selects a sample of these customers and requests each selected customer to confirm the accuracy of his or her accounts receivables balance shown on the report. In this case, the auditor should also test the internal controls over the client's information system that produced the accounts receivables report. This example hints at the daunting challenge of performing external audits of clients' financial statements in today's world where virtually all public corporations and government entities place significant reliance on their computerized business system that is also their accounting information system. An audit client's business systems may be in-house developed or one of the off-the-shelf (OTS) Enterprise Resource Planning (ERP) systems purchased from a software company such as SAP SE and Oracle Corporation. ERP systems vary by software vendor, by the size of the entity that an OTS ERP supports, by the industry supported, and by version. Also, each audited entity configures and customizes its OTS ERP to suit its unique business requirements. An AI system supporting a given external audit might store knowledge about each of the OTS ERP systems used by an auditing firm's audit clients and tailor each external financial statement audit specific to each audit client's ERP system. Each AI-designed audit plan would guide auditors in evaluating risks and controls specific to the ERP system that is the audit client's accounting information system. Auditors would have expert guidance in testing the financial controls and underlying system controls upon which the financial controls depend. For example, the audit AI might guide the auditor in testing the logical segregation of duties and access controls over the report of accounts receivables that the auditor uses for confirmations. The AI might also support the auditor in the accounts receivables confirmation test by selecting the sample of accounts receivables to confirm and performing the statistical analysis.

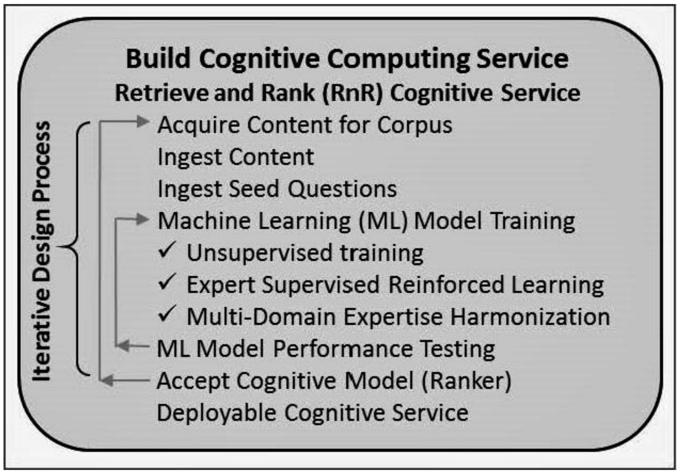
In addition, the audit AI could store knowledge about the information system (IS) infrastructure and its internal controls within which the audit client's ERP system resides and operates, such as the audit client's networks' systems controls, operating system (OS) controls, and database management system (DBMS) controls. For example, AI might analyze the client's demilitarized zone (DMZ)[2] including the setup of the routers and their access control lists (ACL), switches, and firewalls. The AI might contain knowledge about all firewalls and customize the network audit to be specific to the client's firewall. For example, the AI might run reports specific to the client's firewall, listing denied as well as allowed and logged internet protocol (IP) addresses that the auditor might then analyze with guidance from the AI. In addition, the AI might store knowledge specific to the client's DBMS. For example, if the vendor of the client's DBMS supplies default user accounts and passwords for installation of the DBMS, the AI might have an audit step that checks whether the client has deleted these default accounts and passwords. Also, the AI could contain specific information about each OS and provide expert audit guidance on running and evaluating reports available on the client's OS regarding the client's OS setup and security. For example, the AI might verify that the OS logs all users' OS activities and that each OS user always logs on with his or her unique user ID and password when accessing the OS. Hence, the AI would support advanced integrated auditing by containing expert knowledge that guides financial and IS auditors in performing annual financial audits. The AI would provide expert guidance for auditing the client's preparation of its financial statements in accordance with generally accepted accounting principles and the client's internal controls over its financial reporting system in accordance with the Sarbanes-Oxley Act of 2002. The audit AI system would help auditors to identify the client's external reporting requirements and the client's applicable laws and regulations.

The audit AI system could also consider the potential for fraud by identifying fraud risks and recommending audit tests beyond the normal scope of operations (Mock et al. 2017). Furthermore, the audit AI system might assist in the design,

[2] In computer security, DMZ, sometimes referred to as a perimeter network, is a physical or logical computer subnetwork separating a local area network (LAN) that is trusted from other untrusted networks, such as the internet.

American Accounting Association

FIGURE 6
Build Cognitive Computing Service



The full-color version of Figure 6 is available for download, see Appendix B.

development, and implementation of continuous monitoring routines by combining knowledge of the client's business system with an assessment of the client's fraud risks.

The audit AI system could also consider recognized internal control and audit standards and frameworks (Kokina and Davenport 2017), such as the information contained in the Committee of Sponsoring Organizations of the Treadway Commission's (COSO) *Internal Control—Integrated Framework,* updated in 2013, and the COSO *Enterprise Risk Management (ERM) Framework* updated in 2016 (see, https://www.coso.org). For example, the audit AI system might store and use COSO's (2013) five components and 17 principles of internal control to verify that it had considered all of the risks and internal controls specific to an audit client. The CC might also store the Information System Audit and Control Association's (ISACA) COBIT framework for the governance and management of enterprise IT (see, http://www.isaca.org/cobit/pages/default.aspx) and use the detailed information in COBIT in considering clients' risks and controls. The AI system might additionally quantify the inherent risks and monetary exposures of risks specific to the audit client and assess what internal controls would be appropriate to reduce the exposure for each risk to a level acceptable to the client and the auditor. Cognitive computing's inference-based processing and probabilistic models may provide automated evaluation of an entity's risks. Combined with Big Data regarding exposure costs should a given risk become a reality, the AI audit system may enhance auditor decision making regarding the COSO risk-based approach to auditing and implementing internal controls.

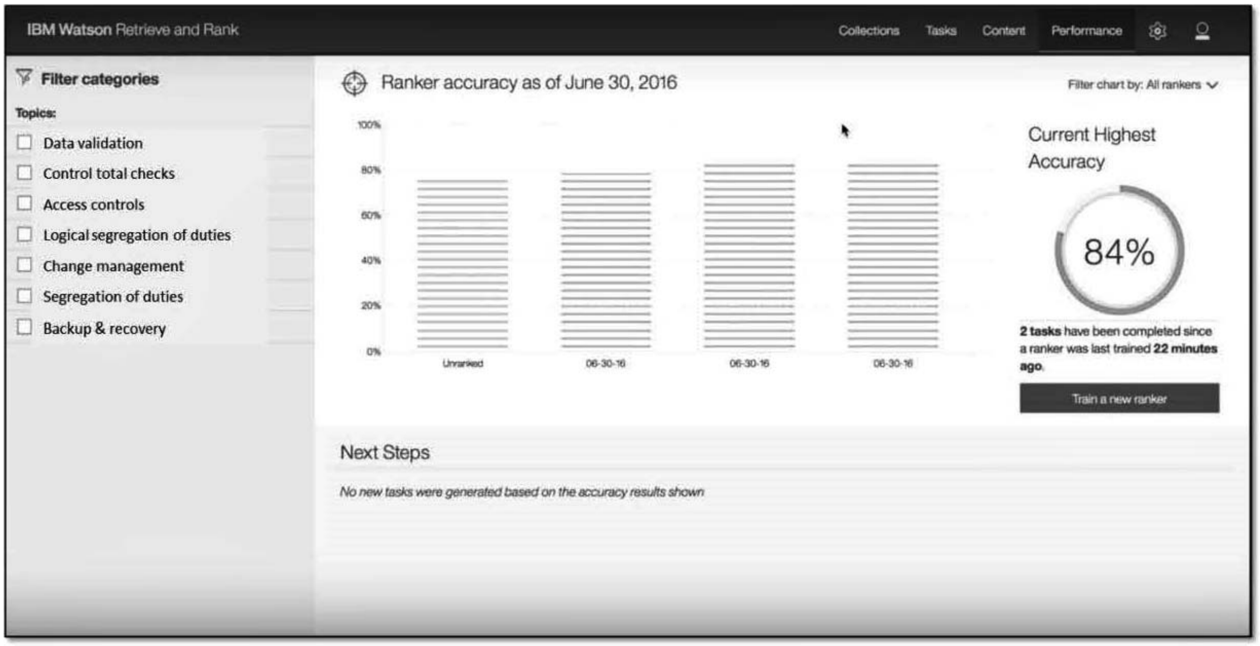
Watson CC Model—Retrieve and Rank (RnR)

Building a retrieve and rank (RnR) cognitive service is an iterative design process of data ingestion and model refinement, as shown in Figure 6. Given these references as a multi-domain corpus, IBM recommends initially structuring training sessions into a series of smaller sessions for each subdomain. Within each subdomain, given a series of documents and questions as a corpus, the CC develops an initial knowledge model by applying unsupervised ML. The unsupervised learning is followed by supervised ML sessions where experts rank question-response quality. As training develops with each subdomain, the CC system harmonizes the knowledge to resolve ranking conflicts as needed, directing human attention to priority training issues addressing relevancy and ambiguity.

Watson CC Design-Development Interface

The design process tasks begin by uploading a user's corpus data as text into the CC system. In this process, the user copies files into the graphical user interface (GUI). Recognizing new corpus data, the CC system then creates an associated task of entering questions that would be appropriate for the given corpus. These questions, referred to as "ground truth," are used in the initial unsupervised ML effort. After uploading the questions, the system creates a set of training questions, called training priority, to accelerate overall system learning. The system also classifies questions into pools for specific training. As the knowledge in the CC develops, the system identifies conflicts and creates a human task to review the issues through supervised ML. In a process called "question ranking," users rank an answer by indicating the value (4 best, 1 poor) of the response for the

FIGURE 7
Improving Ranker Performance



Source: IBM Watson, Knowledge Studio, Retrieve and Rank, 2017. Author's screenshot.
The full-color version of Figure 7 is available for download, see Appendix B.

question. Accepting a cognitive model is supported by evaluating a ranker's performance, as shown in Figure 7, and selecting the ranker to deploy.

Retrieve and Rank Summary

Building the retrieve-and-rank (RnR) cognitive service in Watson is an interactive design process of collaboration between the human and the CC system, creating a semantic layer to support question and answer scenarios. The process begins by ingesting documents into the CC to form the corpus. Providing a series of questions, as "ground truth," allows the CC to apply unsupervised ML to build the initial knowledge model. The CC then identifies a series of questions for supervised ML that will most quickly create value within the knowledge model. These processes accelerate the cooperative training of the system, leading to a faster realization of a more valuable and capable CC. If the system detects conflicts in the knowledge model, that is, a need to harmonize the knowledge, the CC creates a human task to review and resolve these conflicts. With a solid knowledge model, derived from supervised and unsupervised ML, the CC system builds a ranker that implements the knowledge model. The CC system provides a visualization of performance of this ranking (high relevancy and low ambiguity) as an alternative to search algorithms in identifying document content to return. Harmonizing the knowledge model through supervised and unsupervised ML, new rankers can be generated that improve performance. The ranker with the highest performance is then deployed as a cloud service. As a knowledge engineer, the CC system architecture supports the iterative nature of knowledge management and continuous improvement. The RnR service, a collaborative effort of human cognition and ML, demonstrates CC supporting a federated knowledge model with augmented intelligence.

CONCLUSION

This paper develops an organizationally oriented CC model, based on AI technologies, supporting cognitive task automation in the accounting industry. Economic trends and analysis suggesting structural changes in the global economy, and specifically in accounting and auditing, as a consequence of task automation are presented (Executive Office of the President of the United States 2016; Davenport and Kirby 2016; Kokina and Davenport 2017). These anticipated structural changes in the accounting industry provide an opportunity to create competitive advantage through disruptive-innovation adoption (Tschakert et al. 2016). To that purpose, a framework is offered for better understanding the components of human problem solving that have been automated and those components, including flexible strategies, that will be automated in the near future.

The model of federated knowledge, based on CC technologies, is proposed as a means to maximize the benefits of cognitive task automation from an organizational perspective. Insights into business drivers that are influencing accounting practice toward increased task automation, task prioritization for automation, and critical success factors for task automation are provided. We use e-commerce with current technologies as a business model to support task automation, with recommendations for application within the accounting industry. The paper includes a demonstration of the iterative design-process orientation of IBM Watson ML in building an intelligent accounting application supporting retrieval and ranking of documentation related to internal auditing.

Task automation based on AI is inevitable across all facets of our society, including the accounting industry (Davenport and Kirby 2016; Kokina and Davenport 2017). As with other disruptions, there are potential opportunities and losses. Opportunities are often reserved for those who move judiciously in time and manner. Given the advancing trend of AI and task automation to redefine accounting and auditing job classes, the challenge specifically facing the accounting industry at this critical moment is how to redefine itself in such a manner as to enhance marketplace relevancy and continue economic prosperity (Tschakert et al. 2016; Kokina and Davenport 2017). Failure of the accounting industry to respond to economic pressures and disruptive innovations such as AI is forecasted to result in a decoupled relationship in the marketplace between technology and humans. The most recent exponential trends comparing AI with human cognitive performance suggest an approaching inflection point where ML is rapidly advancing (Davenport and Kirby 2016; Kokina and Davenport 2017). Failure to respond to the disruptive innovation of AI places accounting and auditing in the zone of replacement for industry obsolescence (Kokina and Davenport 2017).

This paper argues for adopting a disruptive innovation for competitive advantage (Tschakert et al. 2016; Davenport and Kirby 2016) and presents technologies that are currently available for developing and managing CC applications in the cloud. The moment of opportunity for accounting to embrace cognitive task automation and structure a synergistic transformation to AI using augmented intelligence is perceived to be approaching (Tschakert et al. 2016; Kokina and Davenport 2017). Future research should investigate AI and cognitive task automation, including potential impacts extending to the future of the accounting industry and our knowledge-based economy.

Future Research

Given the potential impact of CC on accounting, future research investigating augmented intelligence in accounting based on CC may recognize the specialized roles of human and computer collaboration (Figure 1). Research investigating issues associated with human participation in developing and using CC systems for augmented intelligence may become critical (Figure 3, References 2, 3, 5, and 6). Research might investigate organizational-change management programs for augmented intelligence that leverage human accounting knowledge and skills, heighten task performance, and support effective accountant reassignment to tasks of greater organizational value, resulting in increased job satisfaction. In addition, future research may address issues associated with assurance of accounting CC system compliance with normative standards.

Beyond this paper, other scholars have enumerated the importance of future research in accounting data analytics (Vasarhelyi et al. 2015), including a focus on AI and "how today's world of audit will be transformed into the assurance of the future" (Issa et al. 2016; Tschakert et al. 2016; Kokina and Davenport 2017; Davenport and Kirby 2016). The Federated Knowledge Model (Figure 3) provides a framework for future research investigating artificial intelligence supporting cognitive task automation in accounting. This timely and developing stream of digital transformational research is critical in redesigning the accounting industry for a viable future.

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APPENDIX A

Selected Watson e-Commerce Applications

Social Customer Care → Better Customer Knowledge, Relations, Retention	
Personality Insights Uncover a deeper understanding of people's personality characteristics, needs, and values to drive personalization. *Natural Language Classifier* Interpret and classify natural language. *Tone Analyzer* Discover, understand, and revise the language tones in text.	Accountants can leverage the value of a customer by better understanding their customers, including personality traits, and offer more personalized services and products. Through a mass-customization model, accountants can use this type of design pattern to provide a more personalized relationship at a more economical cost.
Answer Retrieval → Better Document and Content Management	
Retrieve and Rank Enhance information retrieval with machine learning	Accountants can identify and retrieve data that are more meaningful from structured and unstructured data. Using machine learning, the system can improve the content delivered.
News Intelligence → Better Environmental Scanning and External View	
Alchemy Language A collection of natural language-processing APIs for text analysis.	Accountants can identify and retrieve data that are more meaningful from structured and unstructured data. Using machine learning, the system can adapt to improve the content delivered.
Alchemy Data News Provides news and blog content with natural language processing to allow for highly targeted search and trend analysis. *Tone Analyzer* Discover, understand, and revise the language tones in text.	Targeted news sources can assess client public relations. Social and public opinion data can be used to augment more structured forms of data.
Text Message "Chatbot" → Better Communications	
Conversation Add a natural language interface to your application to automate interactions with your end users. Common applications include virtual agents and Chatbot services that can integrate and communicate on any channel or device. *Alchemy Language* A collection of natural language-processing APIs for text analysis.	Accounting firms can configure chatbot services on top of a retrieve and rank document service, providing clients with customized information exchanges regarding their financial statements and reports. Clients can submit documents received or relevant for interpretation and response, including routing the documents to the appropriate internal agent(s) when appropriate.

APPENDIX B

jeta-52095_Figures 1-7: http://dx.doi.org/10.2308/jeta-52095.s01