ARTICLE IN PRESS
ACCINF-00370; No of Pages 14
International Journal of Accounting Information Systems xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

International Journal of Accounting Information Systems

journal homepage: www.elsevier.com/locate/accinf

"The reports of my death are greatly exaggerated"—Artificial intelligence research in accounting

Steve G. Sutton *, Matthew Holt, Vicky Arnold

Kenneth G. Dixon School of Accounting, University of Central Florida, United States

A R T I C L E I N F O

Article history:
Received 6 June 2015
Received in revised form 14 September 2015
Accepted 14 July 2016
Available online xxxx

Keywords:
Artificial intelligence
Expert systems
Knowledge based systems
Machine learning
Audit
Accounting

A B S T R A C T

Gray et al. (2014) examined the productivity of expert systems/artificial intelligence research in accounting and came to the conclusion that both research on and practice use of expert systems/ artificial intelligence had waned since the late 1990s. In our study, we reconsider these findings based on a broader view that is 'artificial intelligence' centric versus 'expert systems' centric. The results show that while there was a bit of a lull in the late 1990s, artificial intelligence research in accounting has continued to steadily increase over the past 30 years. Further consideration of artificial intelligence techniques as embedded modules in integrated audit support systems also suggest that use by practice continues to be robust. Based on these findings, we make a call for much more research on the usability, and use, of artificial intelligence techniques in accounting domains. Contrary to earlier perceptions, the research domain remains vibrant and holds great potential for AIS researchers to take a leadership role in advancing the field.

1. Introduction

Gray et al. (2014) analyze expert systems/artificial intelligence research in accounting through the lens of the life cycle of technology and paints a fairly bleak picture of the state of AIS research during a time of explosion in artificial intelligence applications outside of accounting (Brynjolfsson and McAfee, 2014). The findings of Gray et al. (2014) suggest that AIS research on expert systems/artificial intelligence has waned over the last decade plus, and suggest this may have been fueled by the abandonment of expert systems by the major accounting firms. However, this perceived abandonment of expert systems/artificial intelligence by the accounting firms appears in stark contrast with recent studies reporting extensive use of artificial intelligence in integrated audit support systems (Dowling and Leech, 2007, 2014), the targeting of management accounting practice by business intelligence vendors (Elbashir et al., 2011), and the calls for greater understanding of machine learning principles by accounting graduates (PwC, 2015, AACSB International Committee on Accreditation Policy, 2014).

The purpose of this study is to revisit the foundations underlying Gray et al. (2014) with an emphasis on the artificial intelligence side of the expert systems/artificial intelligence nexus in an effort to reconcile these differences in the literature and to better understand the role accounting academics should play in the future of artificial intelligence in accounting. The rationale behind this focus on artificial intelligence is that expert systems are a subclass of artificial intelligence applications, and the use of the more general classification of artificial intelligence seems the more relevant concern.[1] It is potentially less concerning if expert systems have simply waned and are

* Corresponding author.
E-mail addresses: SGSutton@ucf.edu (S.G. Sutton), Matthew.Holt@ucf.edu (M. Holt), Vicky.Arnold@ucf.edu (V. Arnold).

[1] For simplicity purposes, the Webopedia definition for expert system provides a fairly succinct explanation: "A computer application that performs a task that would otherwise be performed by a human expert… Some expert systems are designed to take the place of human experts, while others are designed to aid them. Expert systems are part of a general category of computer applications known as *artificial intelligence* (emphasis added)."

http://dx.doi.org/10.1016/j.accinf.2016.07.005
1467-0895/

being supplemented by other forms of intelligent systems that are possibly more advanced and are actually moving the research and practice disciplines forward, as opposed to the declining nature of being late in the life cycle or the so-called maturing and degrading phase of the Gartner Hype Cycle (Fenn and Linden, 2005; O'Leary, 2008; Gray et al., 2014).

To achieve this objective, this study first addresses the literature analysis as presented in Gray et al. (2014). Their study focused on the use of two search terms: *expert systems* and *artificial intelligence*. However, as noted in Gregor and Benbasat's (1999, 498) seminal paper on explanation facilities,

> “[K]nowledge-based (expert) systems (KBS) and intelligent systems in general, are important components of an organization's information systems portfolio… what we will label generically “intelligent systems” to indicate a broader focus than that of traditional KBS. The distinguishing feature of intelligent systems is that they commonly contain a knowledge component—a computerized version of human tacit and explicit knowledge. Such systems are based on the basic elements of artificial intelligence: knowledge representation, inference and control.”

This dance across terminology presented in the opening paragraphs of their paper highlights the complexity of defining the research area in narrow terms. As such, an effort is made in this study to use a broad set of search terms including artificial intelligence, expert systems, knowledge-based systems, intelligent systems, and so forth. The result is a very different conclusion on where AIS lies in the life cycle as the past decade reflects growth rather than decline in related research.

These findings lead to a further examination of the state of artificial intelligence use by accounting professionals in practice. Again, our research shows that the use of artificial intelligence in supporting knowledge-based systems is alive and well among accounting professionals; with a new emphasis on data analytics and the associated use of machine learning techniques, increased use of artificial intelligence in the future seems inevitable.

Based on these combined findings, our focus shifts to a discussion of the extant literature on artificial intelligence in accounting with an eye towards how academics can once again take a leadership role in the application of artificial intelligence techniques to support accounting decision making. This discussion also highlights the necessity for academics to assume the role of a conscience to the profession in highlighting the ethical and epistemological concerns that come with the likely increased use of artificial intelligence techniques.

This research contributes to the literature in several ways. First, the results provide a clearer picture of the role artificial intelligence has played in the extant accounting research and the sustained vibrancy of the research domain. Second, a bridge is established between early standalone expert systems applying artificial intelligence techniques and the more contemporary approach in practice of using integrated systems with expertise embedded into an array of intelligent systems. Third, the groundwork laid with the previous two contributions leads to the presentation of an agenda for research that can place AIS researchers in a leadership position in the advancement of artificial intelligence in accounting practice and establishes the vital role that researchers have in the overall ecosystem of artificial intelligence application in accounting domains.

The remainder of this paper is presented in four sections. The second section presents a reanalysis of the AIS publication history in the area of artificial intelligence. Section three follows with a reanalysis of the use of artificial intelligence in accounting practice. The fourth section focuses on future research directions while the final section provides a brief summary and conclusions.

2. Artificial intelligence life cycle in AIS research

At the heart of the Gray et al. (2014) study is a search for publications since 1980 that are at the intersection of artificial intelligence/expert systems and accounting. This set of identified publications become their basis for assessing (1) whether AIS research in the domain is in decline indicating a maturity and loss of interest, (2) who the major contributors to the research domain are, and (3) what universities have been the greatest producers of dissertations in the domain. The key is that everything in the Gray et al. (2014) study revolves around the initial search for publications.

There is no reason to question the accuracy of the study's data and results based on the authors' defined criteria. Gray et al. (2014, 433–434) conducted an extensive search for articles from the major databases including EbscoHost, Science Direct, Wiley, and Scopus. The initial searches were based on three pairs of key words: “expert systems & accounting”, “expert systems & auditing”, and “expert systems & tax”. After finding in their initial search that some authors preferred to use the term artificial intelligence, they replaced “expert systems” with “artificial intelligence” and reconducted the search to capture both dimensions. The result was the identification of 315 unique articles for the time period 1980–2011.

The first question raised in our study is whether “expert systems” is the fundamental concept of interest or whether the broader domain of “intelligent systems” should be considered. As noted earlier, Gregor and Benbasat (1999) highlight the closeness and almost interchangeable use of *expert systems* and *knowledge-based systems* that are indicative of a broader set of applications referred to simply as *intelligent systems*. Indeed, one of the ironies from the Gray et al. (2014) study is that they note the de facto journal for the Artificial Intelligence/Expert Systems Section of the AAA in its early years was the journal edited by Dan O′Leary entitled *International Journal of Intelligent Systems in Accounting, Finance & Management*. Yet, *intelligent system* was not a term used in their search criteria.

Please cite this article as: Sutton, S.G., et al., *“The reports of my death are greatly exaggerated”*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005

The terminology issue was exacerbated by the move from design science studies into more behavioral science studies. On the behavioral science side, there was heavy debate on what really constituted an expert system versus a decision support system versus a transaction processing system (Messier and Hansen, 1987). This became a critical review point among both reviewers and editors (one of the authors of this study is one of those editors) as to the terminology used in behavioral studies to discuss experimental software. This led to variants that hedged on distinct lines and attempted to ground systems in the middle territory, terming such systems as *intelligent decision aids* (Arnold and Sutton, 1998) or *intelligent decision support systems* (Arnold and Sutton 1996/97). As noted by Gregor and Benbasat (1999), knowledge components began to be embedded in many systems which led to their overall category use of *intelligent systems*, but these knowledge components were also often referred to as *intelligent agents* (O'Leary and Watkins, 1992; Masselli et al., 2002). It seems appropriate to note that this shifting terminology, as behavioral researchers worked on the preciseness of their descriptions, may be the reason that Gray et al. (2014) did not detect much behavioral work in the domain and viewed this as a missed opportunity.

Another way of looking at this is to consider one leading researcher in the artificial intelligence domain of AIS research (the co-editor of the *International Journal of Accounting Information Systems*, Stewart Leech) and his shifting use of terminology over time. Leech's earliest work on the design of the INSOLVE system used the term *expert system* (Leech et al., 1998; Collier et al., 1999) as well as the term *intelligent decision aid* (Leech et al., 1999). Subsequent work in behavioral science (Arnold et al., 2004b) and design science (Arnold et al., 2004a) using the same software system used the term *intelligent decision aid*. This was followed by additional behavioral science research that used the term *knowledge-based system* (Arnold et al., 2005, 2006). Most recently, Leech's work focuses on a subset of intelligent systems used in audit practice and adopts the more descriptive terminology of *audit support systems* (Dowling and Leech, 2007, 2014; Dowling et al., 2008). To further illustrate this problem, Fig. 1 provides an "Artificial Intelligence Tree" that diagrammatically shows the interrelationships among these terms and other contemporary technologies in the artificial intelligence realm.

In considering this examination, one concern regarding the Gray et al. (2014) study that should become apparent is that the use of *expert systems* appears in the 1990s, but subsequent work uses different emerging terminology relating to alternative classifications of knowledge-based systems. This raises a question as to whether the findings of decreased artificial intelligence/expert systems research in the post-2000 era is an actual maturity and downgrade period or whether it may be as simple as a search terminology phenomenon.

To further explore the phenomena reported in Gray et al. (2014) through a more comprehensive artificial intelligence lens, we reconducted their database search using a broader set of search terms. The three basic accounting search terms remained the same other than using a wildcard to capture various forms of audit and auditing. The parameter added to each artificial intelligence term was the extension "*AND (tax OR audit* OR accounting)*". An extended set of artificial intelligence terms were paired with the AND Boolean logic for the accounting terms. These terms (with the number of occurrences in our search provided in parentheses) consisted of:

- *expert system (532)*
- *artificial intelligence (299)*
- *intelligent system (265)*
- *knowledge based system (234)*
- *intelligent decision aid (10)*
- *intelligent decision support system (10)*

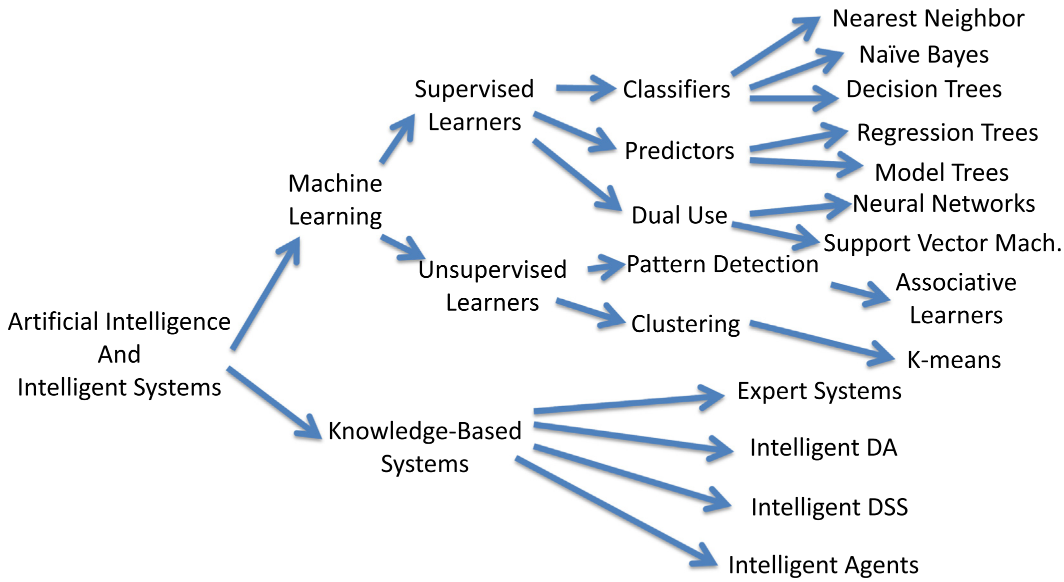


Fig. 1. The Artificial Intelligence Tree: The Many Branches of AI Application.

- *intelligent agent (36)*
- *audit support system (14)*

Based on advice from university librarians that were consulted, the databases from the Gray et al. (2014) study were limited to EBSCO and Science Direct. The librarians indicated that Wiley and SCOPUS would be redundant with these two broader databases.

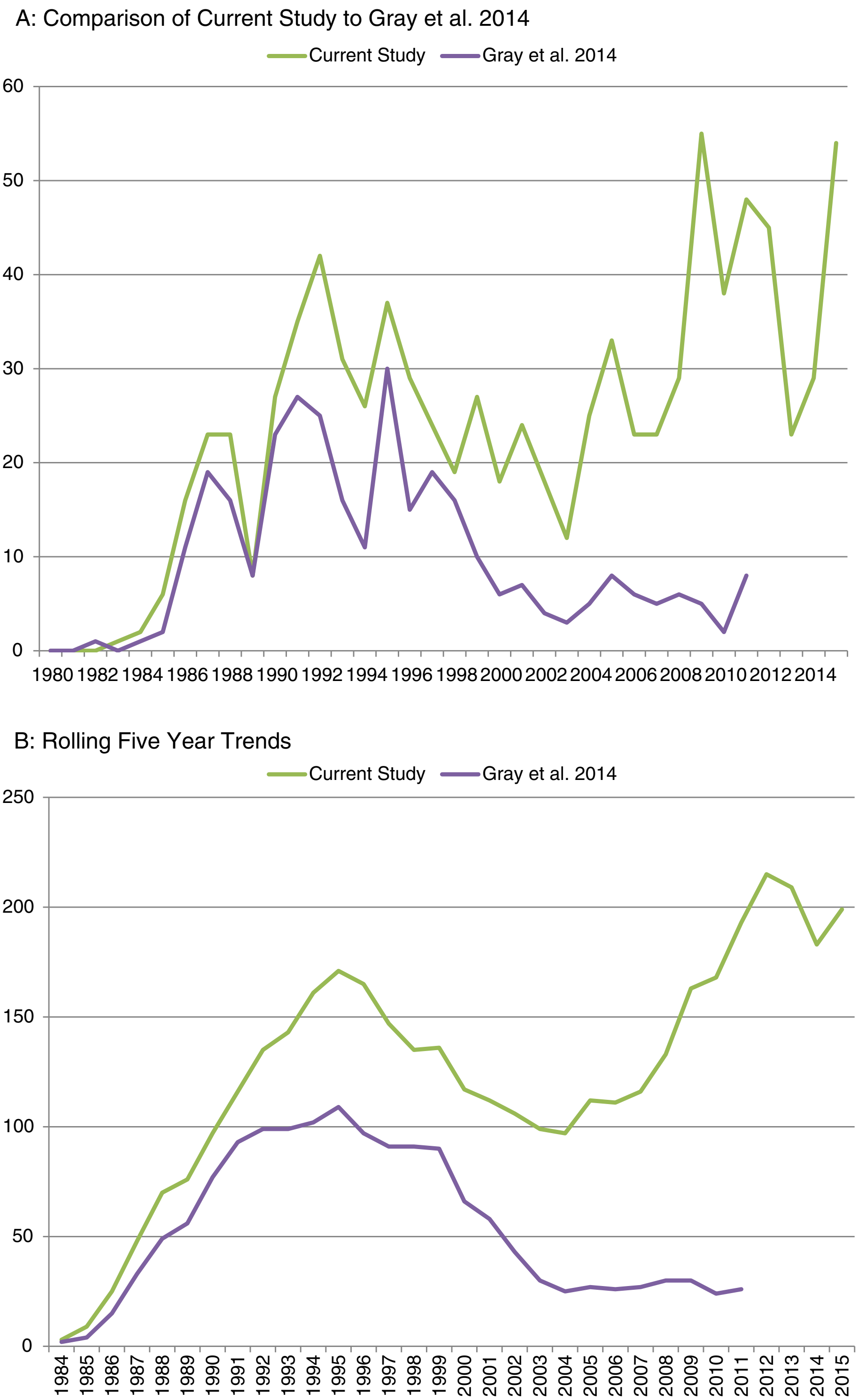


Fig. 2. Research Productivity Trends. Panel A: Comparison of Current Study to Gray et al., 2014 Panel B: Rolling Five Year Trends.

We were also aware that some early researchers in the domain had published their work in IEEE journals where particularly *IEEE Transactions on Systems, Man, and Cybernetics* was a not uncommon target for related work. The IEEE database was added to the search. Finally, changes in the American Accounting Association's (AAA) licensing of its journals created some differences in coverage of their various association-wide and section journals. Particularly *Journal of Information Systems* and *Accounting Horizons* appeared to have limited coverage in the other databases and were known to be common outlets for related research. So the AAA digital library was added to the search sources and each of the artificial intelligence terms from the other searches were conducted through the AAA digital library. Thus, the search libraries included:

- *EBSCO*
- *Science Direct*
- *IEEE database*
- *AAA digital library*

As expected, the searches flagged a large number of articles that included an extensive set of duplicates. Similar to Gray et al. (2014), we carefully reviewed the 2604 articles that were identified to eliminate all of the duplicates and to screen out the false positives (i.e. "studies under other disciplines that are outside the scope of this research" (Gray et al., 2014)). This resulted in a final set of 872 unique relevant artificial intelligence articles (an increase of 177% in the number of articles identified by Gray et al. (2014) with their narrower search term focus). It should be noted, however, that this difference could be partially due to difference in defining papers as to whether they are accounting or not which is a judgment call that had to be made by both research teams and it is not certain both teams would interpret the domain the same.

Our results of the analysis of research article productivity over time follows the Gray et al. (2014) results quite closely through the 1980s and 1990s when the focus of artificial intelligence researchers in AIS primarily focused on *expert systems*. While our searches identified a few more articles than Gray et al., the patterns are essentially the same through about 1999 (see Fig. 2 Panel A). At this point, we see a divergence. While both studies show a dip in the late 1990s to early 2000s, the dip is not as severe in our data. The biggest differences come after about 2003 when we see a steady rise in interest in artificial intelligence studies that actually exceed the productivity in the late 1980s and 1990s. The results of our analysis indicate that interest continues to build, and we may not have reached the peak in the life cycle. From the Gartner Hype Cycle perspective, the hype seems to be continuing.

Fig. 2 Panel B provides perhaps a clearer look at these trends. Panel B shows the trend over a rolling five year period that smooths out the inevitable variation created by peaks with special issues and valleys that occur on an unusual year where articles cluster before and after. The idea is to create a smoother picture of productivity similar to what most academic researchers encounter on their faculty annual reports where usually a three-year or five-year window of publications is used for assessment. Panel B provides a fairly smooth trend line that shows a peak in the research in the early to mid-1990s before a slight decline in the following decade (where interest is still relatively high based on historical productivity) before the research peaks even higher in the following period. Panel B shows a very distinct difference in the findings of Gray et al. (2014) and our analysis.

The changes between the Gray et al. (2014) study and our results, along with the disappearance of the major ebb in artificial intelligence related research in accounting, appears driven by the change in terminology (see Fig. 3). Just as "Expert Systems" tagged studies begin to drop off sharply in the early 2000s, there is sudden peaking of the use of "Intelligent Systems" that takes off beginning in 1991 (which probably is not coincidental that it coincides with the first issues of the *International Journal of Intelligent Systems in Accounting Finance & Management* being published in 1992). On the other hand, as can be seen in Fig. 3

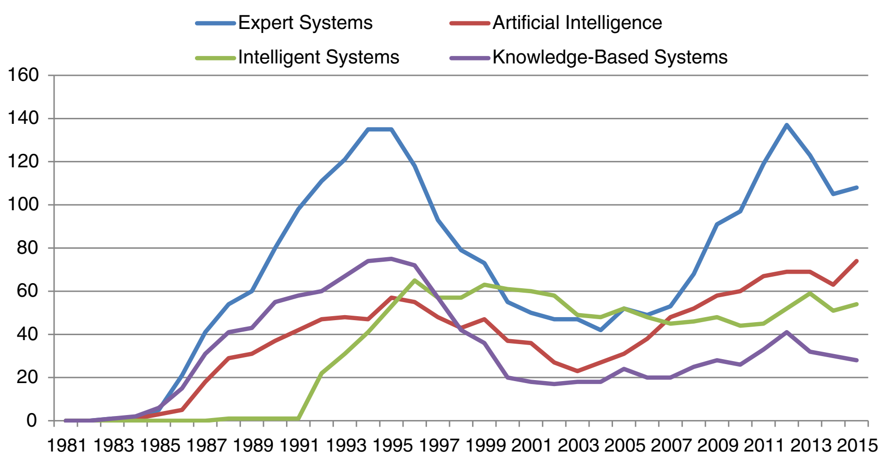


Fig. 3. Publication Trends by Search Term (Rolling Five Year Trends).

"Knowledge-Based Systems" follows a similar pattern to "Expert Systems" while "Artificial Intelligence" exhibits a more minor dip while overall it maintains a fairly steady increase over time. As noted earlier, the other four search terms (Intelligent Agent, Audit Support System, Intelligent Decision Aid, Intelligent Decision Support System) yield relatively minor numbers of papers (although 70 or a little over 8% in total) as compared to the four major search terms. Of these 70 papers, only 28 were not also identified by one of the other four major search terms (14 by Intelligent Agent only, 10 by Audit Support System only, and 2 each by only Intelligent Decision Aid or Intelligent Decision Support System).

The source of the research does make a difference, however, and the sub-categories do not necessarily reflect the same trends as the overall output. If we condense Gray et al.'s (2014) source types (see their Table 3, page 439) into three general categories—Academic (e.g., academic, conference proceedings (academic), discussions, and reply), Professional (e.g. professional journal articles and academic/professional journal articles), and Education (e.g. education oriented journal articles and conference proceedings (educational))—we see similar trends, as shown in Fig. 4, for both Professional and Education productivity to the effect described in Gray et al. (2014). This pattern does appear to be consistent with the Gartner Hype Cycle. It is only in the academic group where the dip in the late 1990s and early 2000s becomes more of a plateau before growth continues to escalate. The academic output curve is pretty well in a constant rise reflecting continuing and growing interest is artificial intelligence research.

Interpretation of this data should be done with caution, however. While the practice articles have dropped off substantially, we are also in an era where the major public accounting firms are sharing less and legal liability dictates largely what is shared. The trend also fits a decrease by the firms in support of academic research where availability of participants has become strictly limited and the firms funnel most of their research support through the Center for Audit Quality where more control can be exhibited over what research gets done. The tight bond between the firms and academic researchers has substantially eroded. Similar effects may also distort the educational interest in intelligent systems and artificial intelligence. Education research has fallen out of favor with the major research universities and in efforts to further develop international reputation the *Journal of Information Systems* has abandoned the publication of education research which has instead been picked up by the American Accounting Association special interest group via C3, an electronic resource for sharing educational materials and ideas (which also would not be picked up in any of the databases used for searches). The main accounting education journals prefer new, novel ideas so it is not surprising that they published a limited number of intelligent systems papers in the early years before becoming disinterested. This will likely change with the new accreditation efforts that mandate data analytics and machine learning coverage.

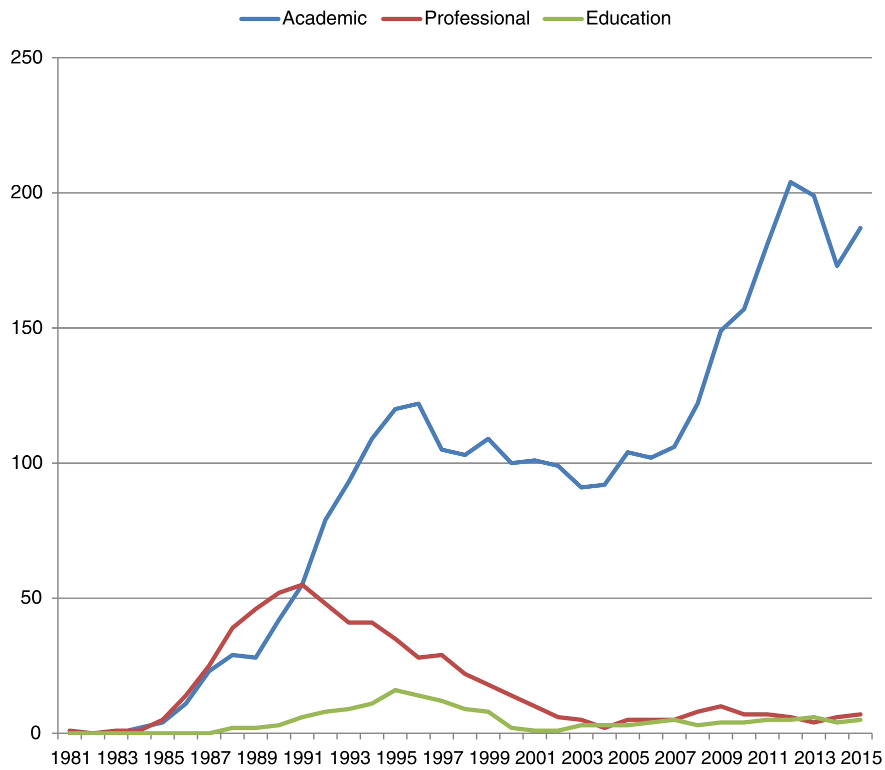
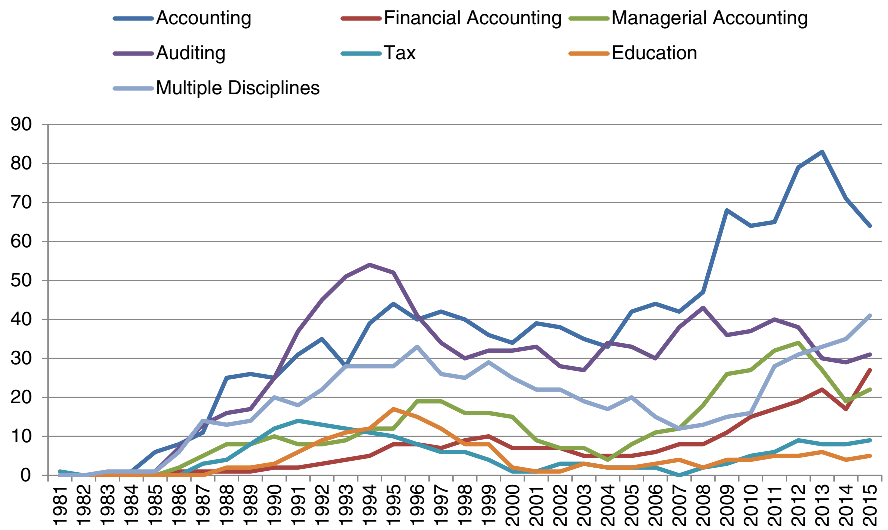


Fig. 4. Productivity Trends by Type of Publication (Rolling Five Year Trends).

Please cite this article as: Sutton, S.G., et al., *"The reports of my death are greatly exaggerated"*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005



(Note: The seven categories of accounting research area are used to maintain comparability with the Gray et al. (2014) study that used this same seven category breakdown.)

Fig. 5. Productivity Trends by Area of Accounting Research (Rolling Five Year Trends) (Note: The seven categories of accounting research area are used to maintain comparability with the Gray et al. (2014) study that used this same seven category breakdown.)

The results of our analysis suggest that research interest in artificial intelligence on an overall basis has not waned among accounting researchers. The research has changed as Gray et al. (2014) note. In the early years there was far more interest in design science approaches to the use of artificial intelligence techniques. In the early 2000s, this appears to balance out with a strong focus on behavioral science studies. Over the past several years, the new momentum appears to come from the use and comparison of machine language capabilities for explaining past occurrences and/or predicting future occurrences. This has also meant a change from audit related systems being of most interest to more interest in financial research such as bankruptcy prediction (Fig. 5). This recent focus of the research does risk having limited relevance to practice much the same way that more traditional archival financial accounting research is often questioned. This recent focus is also reflected in the trend that Gray et al. (2014) highlight related to specialty journals in AIS and expert systems/artificial intelligence. Specialty journals have tended to take these more mundane predictive studies away from the mainstream accounting and information systems journals. As shown in Fig. 6, the AIS journals have also not been major players in this movement. (Additional detail on the journals publishing intelligent systems and artificial intelligence based accounting research, and the authors producing this research, is provided in the Appendix) This does leave lingering questions as to whether the interest in practice has waned or whether there continues to be a pursuit of artificial intelligence based applications among accounting professionals.

3. Has accounting practice abandoned artificial intelligence?

Gray et al. (2014) make the parallel connection that the perceived waning interest in artificial intelligence/expert systems among AIS researchers was perhaps reflective of a dying interest within the practice community. However, Gray et al. (2014) do note that the practitioners whom they interviewed indicated that the standalone systems were gone but that decision aiding capability was still being provided to support activities. This is actually consistent with our argument that expert systems are no longer the leading viable use of artificial intelligence; rather, the array of other intelligent systems that include embedded knowledge components are where the advances are being made.

A close look at Dowling and Leech's (2014) case study on one Big Four firm's use of their audit support system makes it fairly clear that knowledge components are present; they are just embedded within the more useful integrated audit support systems in use by all of the major firms today (Dowling and Leech, 2007). The system documented in Dowling and Leech (2014) demonstrates how the audit support system manages the audit process—both from the auditor completing audit tasks and the reviewer of that audit work. When the auditor connects to the system on an engagement, they are immediately greeted by a dashboard that highlights the tasks they have remaining that are incomplete and new tasks that have been added to their workload. The system seamlessly connects the planning and risk identification activities with the strategy and risk assessment processes that follow, which then flow through to the audit execution and associated substantive tests. The system automatically generates a set of required audit procedures based on the client information available and the auditor must justify any procedure they wish not to complete.

Please cite this article as: Sutton, S.G., et al., *"The reports of my death are greatly exaggerated"*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005

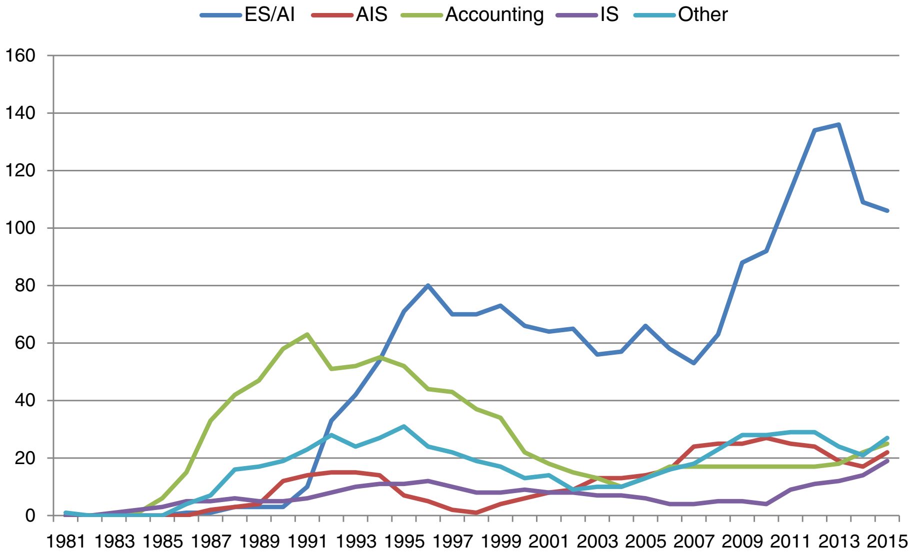


Fig. 6. Productivity Trends by Type of Journal Outlet (Rolling Five Year Trends).

Gray et al. (2014) point to Brown's (1991) paper as representing sort of the golden years of expert systems where she documents 43 expert systems being used by the then Big Six accounting firms. When you look at the capabilities of the system documented in the Dowling and Leech (2014) case study, most of the audit systems highlighted by Brown (1991) have an equivalent presence in the firm's integrated audit support system. The difference is that they are incorporated into audit support systems as opposed to operating as standalone systems.

An easier parallel can be drawn by comparing the Brown (1991) survey of expert systems in the then Big Six firms with the Dowling and Leech (2007) study of five major international firms' audit support systems components. While the Brown (1991) study identifies expert systems across all areas of the firms' practices, the subset of audit expert systems provide a useful comparison with what we know today about firms' integrated audit support systems. Table 1 provides a brief outline of the various audit expert systems identified by Brown (1991) along with the capabilities of the integrated audit support systems of the firms in Dowling and Leech (2007). Only a few of the systems in Brown (1991) do not have parallels in the knowledge-based components identified by Dowling and Leech (2007). Some of these may be due to cross-country differences as the Brown study was conducted in the U.S. and the Dowling and Leech study was conducted in Australia. Loan loss reserves and bank failure prediction may be very different between the two countries with the

Table 1
Comparison of early expert systems capability with contemporary audit support systems capability.

Brown (1991)	Dowling and Leech (2007)
Work Program Development	Program Development and Test Planning
Internal Control Evaluation	Internal Control Assessment
	IT Control Assessment
Risk Analysis and Assessment	Risk Identification & Assessment
Inherent Risk Analysis	
Tax Accrual and Deferral	(Unclear of differences potentially from Australian firm implementations of audit support systems).
Disclosure Compliance	Disclosure Compliance
	Need for Second Partner Review
Loan Analysis	
Bank Failure Prediction	
SEC AID	Compliance with GAAP
Sample Size	Sample Size Calculator
Automated Analytics	Automated Analytics
	Client Acceptance and Retention
	Materiality Calculator
	Need for Specialists to be Involved
	Need for IT Specialist for Control Risk Assessment
	Incomplete Work Identifier
	Review Risk Analysis to Assist Reviewer of Auditor's Work

Please cite this article as: Sutton, S.G., et al., *"The reports of my death are greatly exaggerated"*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005

much higher bank regulation in Australia, and the estimation of tax accruals and reserves could similarly differ quite significantly with differences in tax systems. At the same time, there are a number of additional modules highlighted by Dowling and Leech (2007) that were not present during Brown's (1991) survey. Many of these systems appear to have greater potential within the context of an integrated audit support system as opposed to operating as an independent expert system which is consistent with the perceived advances in artificial intelligence to provide embedded knowledge components.

Additionally, Gray et al. (2014) state that one reason the use of expert systems has not survived in firms is that personnel were not required to use these systems. It is noteworthy in the Dowling and Leech (2014) study that use is mandatory when put in the context of an integrated audit support system. Dowling and Leech (2007) suggest that this mandatory use differs by firm, but they also note that the move is towards more restrictive systems with mandatory use in order to improve the consistency of audit processes across engagements. This is largely due to regulatory pressures—an issue raised in the practitioner interviews conducted by Gray et al. (2014) as a potential factor that could make expert systems more viable in the long-term. Given the state of the art, mandatory use appears more likely to occur in the context of integrated systems with embedded knowledge components.

Given the apparent widespread use of artificial intelligence applications within the integrated audit support systems that are increasingly mandated for use in practice along with other reports indicating efforts by the major business intelligence vendors to use artificial intelligence based modules to increase the automation of management control systems (Elbashir et al., 2011), we argue that the question should be what role can AIS researchers play in providing guidance for the future rather than whether the research domain has lost its importance. This is consistent with arguments long made by leading artificial intelligence researchers in accounting (e.g., O'Leary, 1997). Accordingly, our remaining concerns focus on where AIS researchers have opportunities to provide leadership to the profession through their research.

4. The need for more AI research in accounting

One lesson we have learned over the past decades is that building complete systems are not necessarily AIS researchers' competitive advantage (Alles et al., 2008). In the initial editorial for the predecessor of this journal, *Advances in Accounting Information Systems*, the case was made that building expert systems was not the best use of AIS researchers' energies but rather the focus should be on pieces of the process—"better knowledge representation capabilities, better knowledge acquisition capabilities, better validation techniques, and methodologies for selecting among alternative techniques for a given domain based on attributes of the domain" (Sutton 1992, 9). That advice interpreted broadly is still applicable today.

If the primary advances in knowledge-based systems that have been made since 2000 are considered, many of the studies have focused on component parts of systems such as the links between knowledge elicitation and representation (O'Leary, 2007); development of explanation facilities (e.g. Arnold et al., 2004a; Smedley and Sutton, 2004), and the maintenance of current best practices knowledge in systems (O'Leary, 2009). Similarly, the behavioral research has worked collaboratively with the design science research to examine the potential effects of these design science advances as seen in the examination of knowledge differences and knowledge transferability (Thibodeau, 2003), selective use and effects of explanations by novices and expert users (Arnold et al., 2006; Smedley and Sutton, 2007), and effects from use of repositories of best practices knowledge (McCall et al., 2008). There has also been fairly extensive work into understanding how and why users rely on knowledge-based systems (Triki and Weisner, 2014).

While there have been many advances made in artificial intelligence research in accounting (that go beyond the aforementioned examples), the real concern that is raised by Gray et al. (2014) is whether AIS researchers have or should abandon artificial intelligence research. Given what is going on in the arena of artificial intelligence and the recent positions taken by the accounting profession, the thought of abandoning artificial intelligence research in accounting at this point in time is quite disconcerting. AIS researchers would miss a great opportunity to provide leadership in new technologies that the profession is still rather ill-equipped to address and utilize.

As baseline examples in support of the positions taken here as to the importance of recent artificial intelligence advances to the accounting profession, we draw upon two recent position papers. The first is the AACSB International Committee on Accreditation Policy (2014) whitepaper on the interpretation of the new accounting accreditation standard related to information technology and the focus on data analytics. Subsequent to the release of the standard and the interpretation came the PwC (2015) whitepaper on the data driven nature of business and accounting. This whitepaper notes that students need training in statistics, data analytics, use of R programming, and basic machine learning skills that apply to both structured and unstructured data. This also suggests a push for more wide spread use of different artificial intelligence skills. At the heart of this movement is machine learning which is a key stream within the artificial intelligence domain and, from all appearances, is becoming a target goal for widespread use in audit, tax, and consulting (and presumably management accounting practice in corporate and nonprofit entities). While the focus of discussion currently seems to be more around data visualization, this appears to be merely a current stage on an evolution towards more extensive machine learning applications.

To date there has been limited AIS research investigating this aspect of artificial intelligence use in accounting, although that has begun to change. In part, it is driven by the continuous audit and continuous monitoring stream (Kuhn and Sutton, 2010; Brown-Liburd et al., 2015; Vasarhelyi et al., 2015). But the use of complex data analytics is much broader across accounting domains and research needs to expand accordingly (Schneider et al., 2015). The issues are broad and the opportunities are great. From an artificial intelligence perspective, much of this revolves around how accounting decision makers can adapt to effectively use machine learning techniques and how they will incorporate such analytics into their decision making. Some machine learning techniques lead to identifiable and understandable patterns in the data. Will this lead to broader acceptance and reliance? For machine learning techniques that yield distinct patterns in data that have strong predictability, but for which the patterns cannot be explained to the user, will this result in more or less acceptance and reliance? Can accounting decision makers effectively discern the differences in explanatory versus predictive machine learning techniques in deciding how to use and rely on alternative machine learning techniques? Data analytics and their inevitable use across accounting domains raise many issues, particularly when more advanced machine learning techniques are adopted to execute richer analytics. The aforementioned research issues all lend themselves to behavioral science research in accounting where academics have competitive advantage in understanding both the technical issues as well as the cognitive issues that come into play. It is here where it is easiest for academics to seize competitive advantage.

Substantial advances are also being made in the area of natural language processing as evidenced in our everyday life by our mobile technologies and the use of things like Apple's Siri or Microsoft's Cortana (Brynjolfsson and McAfee, 2014). These systems are able to take users' voice commands and/or queries and translate them into answerable searches. Natural language processing has always been considered one of the most advanced forms of artificial intelligence and most difficult, but these recent everyday systems point to how this threshold is also being overcome and making applications more feasible. Language processing research is emerging as can be seen in early fraud detection studies such as that by Humpherys et al. (2011) who use software analysis to examine written financial disclosures to identify deceptive language. The potential with natural language processing is much greater though. For instance, the University of Arizona has been helping the Department of Homeland Security with an avatar system called ASK that interviews individuals entering the U.S. to screen out risky versus non-risky entrants through an interview by the system. The system uses facial recognition and tone detection to determine people who should be further interviewed by a human (Higginbotham, 2013). Such systems may have potential use in auditing to interview client personnel electronically before the auditor arrives at the client as a means of supplementing risk assessments. Again, the rapid changes in artificial intelligence are opening new avenues for the creative researcher who can see opportunity and is willing to commit during the incubator stage of these technologies' use. It is during this incubator period that design science researchers have their greatest opportunity to provide leadership.

Promoting the use of artificial intelligence technologies and their application in accounting is only one side of the research on which AIS researchers should be focused. The other side that AIS researchers should feel an obligation to consider is that such technologies could have detrimental effects and/or be misused. This line of research is more in line with what New Zealand law specifies as the responsibility of a Professor—to be the conscience of society and the profession.

There has been a body of research evolving primarily around the Theory of Technology Dominance (Arnold and Sutton, 1998) that should raise some alarm as to the unabated adoption of such technologies. This research to date has focused on the traditional artificial intelligence applications—expert systems, intelligent systems, knowledge-based systems, and audit support systems. The Theory of Technology Dominance posits (Proposition 5) that novices may actually make worse decisions when using a system that is more knowledgeable than the user. Research has shown experimentally that such effects can occur with the use of intelligent tax compliance aids (Masselli et al., 2002), knowledge-based system designed to help insolvency professionals (Arnold et al., 2004b), and in auditing (O'Leary, 2003).

The Theory of Technology Dominance also posits (Proposition 6) that intelligent systems should be used to collaboratively work with expert decision makers to help improve decision making—essentially by not having either the user or the technology subrogated to the other, but rather making them partners in the process. In the same study that showed novices making worse decisions (i.e. more bias in judgment) when using a knowledge-based system, Arnold et al. (2004b) demonstrated that experts using the same system improved their decision making through a de-biasing effect. However, little research has explored this collaborative effect. As the use of other artificial intelligence techniques becomes more prevalent in accounting, this may be a particularly fruitful area. Brynjolfsson and McAfee (2011, 2014) note an example from chess that holds promise in this area, showing that neither the best human experts nor the best expert system chess playing machine could outperform a couple of average chess players using a lower level chess playing program to help guide them in their playing decisions. The lower expertise players working collaboratively with lower expertise software programs were still superior performers. This collaborative approach will be critical as advanced artificial intelligence techniques are increasingly applied in accounting domains.

Proposition 7 of the Theory of Technology Dominance (Arnold and Sutton, 1998) discusses the risk technologies hold for the continued development of experts in a domain; these risks may also affect the viability of collaborative human/computer relationships in the future. Proposition 7 posits that the use of intelligent systems will have a deskilling effect on experts and those attempting to become experts as they become increasingly reliant on the intelligent systems during work task completion. This area has received quite a bit of study in short-term experiments attempting to overcome the effect through alternative system designs (e.g. Odom and Dorr, 1995; Mascha, 2001; Mascha and Smedley, 2007; Smedley and Sutton, 2007, McCall et al., 2008). But perhaps the most concerning is the study by Dowling et al. (2008) that examined the performance of experienced auditors on an audit task and found that those auditors from firms with highly restrictive systems that controlled the decision process were significantly weaker at conducting the task than equivalently experienced auditors with more flexible systems allowing auditor judgments. This same effect was seen in a similar follow-up study by Stuart and Prawitt (2012). These latter two studies show the deskilling effects occurring from technology dominated decisions and raise serious questions as the profession delves deeper into advanced artificial intelligence based systems.

Finally, Proposition 8 of the Theory of Technology Dominance (Arnold and Sutton, 1998) raises concerns that the epistemology of the accounting profession could stagnate if the development of new experts is limited through the myopia of their experiences. Epistemology grows from differences in thought and approaches that lead to debate and development of new processes and new knowledge that emerges from this diversity of thought. If every professional uses the same system, then they learn the same way and there no longer is a diversity of thought that breeds new epistemology. While this proposition appears to remain untested (and may potentially be untestable), academics and professionals should be cognizant of this concern as new applications are developed and implemented.

Brynjolfsson and McAfee (2011, 2014) take this one step forward as they question whether with the advanced state of artificial intelligence, and particularly the ability for machines to replace knowledge workers, what will we do when nobody needs to work anymore? These effects seem real when you consider the Committee for Economic Development of Australia's 2015 report on Australia's future workforce which notes the risk that 40% of existing Australian jobs could be displaced by technology within the next one or two decades (CEDA, 2015). This is reinforced in the Oxford Study that suggests that 94% of accounting professionals could be displaced by technology within the next 10 years (Frey and Osborne, 2013). From an accounting perspective, do we have a profession anymore if we do not need the human professionals? We are not at that state yet, but as technologies and their application evolve rapidly and as we see the new artificial intelligence based applications being pursued by the profession, academia has a responsibility to society to ponder and increase the discourse over what these technological advances mean to the future of the profession and of society.

5. Summary and conclusions

Our study evolves from the Gray et al. (2014) study which suggests that expert systems/artificial intelligence research has waned over the past fifteen years and that AIS researchers have lost interest in the domain. Our study takes a much broader look at artificial intelligence to consider the broader spectrum of research under this generalized domain of study. Similar to Gray et al. (2014), our findings, which cast a more expansive net over the search of artificial intelligence research, shows that there was a bit of a lull around the turn of the century. On the other hand, our results differ from Gray et al. (2014) by showing that artificial intelligence research in accounting has maintained a strong upward trend to date.

Our findings also led us to reexamine the position taken by Gray et al. (2014) that the use of artificial intelligence had also waned within the accounting profession, and in particular the major accounting firms. Reflecting on recent research examining the firms' utilization of integrated audit support systems (Dowling and Leech, 2007, 2014), we conclude that Gray et al. (2014) is accurate in terms of the waning of standalone expert systems, but may be misleading in regards to the application of artificial intelligence based technologies within the context of these larger integrated audit support systems. Most of the standalone expert systems identified by Brown (1991) have a corollary intelligence-based component in the contemporary audit support systems used by firms today (Dowling and Leech, 2007).

Based on our findings, consideration is then given to the role AIS researchers should consider in the future. The focus shifts to the changes in application of artificial intelligence techniques to other areas than expert systems, knowledge-based systems, etc. In particular, consideration should be given to the applications of machine learning, which appear to be the new reality of the future, as well as the potential of another area of artificial intelligence—that related to natural language processing. A word of caution is provided in this analysis however. While AIS researchers have a role to play in advancing these technologies and exploring the frontiers for their application, we argue that researchers also have a responsibility to step back and consider the ramifications for the future of accounting professionals, the accounting profession, and society as a whole. Questions must be asked as to the potentially detrimental side effects that could come from these technologies.

The overall conclusion, nonetheless, is that the death of artificial intelligence/expert systems in accounting research and practice has been overstated. Artificial intelligence applications continue to gain traction in both accounting research and accounting practice. AIS researchers continue to face the challenge of remaining on the bleeding edge of technology advancement in order to provide the leadership to the profession, and society, as artificial intelligence capability continues to rapidly expand; but, it is a duty that we cannot shirk. We have a responsibility to society to question and study the many issues surrounding the emergence of technology. If we wait too long, there may cease to be an accounting profession (see Frey and Osborne, 2013). Accounting academics should at least exercise their voice regarding this potential demise.

Acknowledgements

The authors would like to thank Dan O'Leary, Malik Datardina, and participants at the 2015 UWCISA Symposium on Information Integrity and Information Systems Assurance for their helpful feedback on earlier versions of this manuscript.

Appendix A. Supplementary Information on Researchers and Journals Publishing AI Research

Our data search suggests a vibrant research community with 1,410 total authors participating on at least one identified study. Not surprisingly for the technical nature of the research and the diverse knowledge and skills that must be drawn upon to conduct research in an advanced technology field, there are an average of 2.3 authors per paper. So while a subset of authors appear to publish a large percentage of the papers, when you consider there are 1,964 'author opportunities" (the total number of authors on all the papers when each author on each paper is counted separately) the authorship is diverse. As shown in Table A1, there is a subset of authors that have been particularly heavily involved in the research area.

Table A1
Authors Publishing Artificial Intelligence Articles in Accounting.

Author	Articles Published
O'Leary, Daniel	23
Brown, Carol	18
Hansen, James V.	17
Sutton, Steve G.	17
Zandieh, Mostafa	12
Vasarhelyi, Miklos	10
Leech, Stewart A.	9
Arnold, Vicky	8
Baldwin, Amelia	8
McCarthy, William	8
McDuffie, R. Steve.	8
Messier Jr, William F.	8
Michaelsen, Robert H.	8
Phillips, Mary	8
McKee, Thomas	7
Tsai, Chih-Fong	7
Wang, Wei-Kai	7
Abdolmohammadi, Mohamed	6
Bailey Jr, Andrew D.	6
Collier, Philip A.	6
Meservy, Rayman	6
Murphy, David	6
Murthy, Uday	6
Smith, L. Murphy	6
Back, Barbro	5
Boritz, J. Efrim	5
Changchit, Chuleeporn	5
Denna, Eric	5
Dowling, Carlin	5
Geerts, Guido	5
Gray, Glen L.	5
Holsapple, Clyde W.	5
Kogan, Alexander	5
Lenard, Mary Jane	5
Odom, Marcus	5
Sangster, Alan	5
Steinbart, John Paul	5
Yen, David C.	5
22 Authors	4
51 Authors	3
129 Authors	2
1170 Authors	1

Similarly, the research has been published in a diverse set of publications. There are 201 publications that have published at least one intelligent systems/artificial intelligence paper in accounting, auditing and/or taxation. However, as Fig. 6 showed, specialty journals quickly became the dominant players in the publication of this research. Table A2 shows the leading journals in terms of numbers of intelligent systems/artificial intelligence papers in accounting that they published. Most notable is that two specialty journals (*Intelligent Systems in Accounting Finance & Management* and *Expert Systems with Applications*) account for 42% of the published papers identified in our study.

Please cite this article as: Sutton, S.G., et al., *"The reports of my death are greatly exaggerated"*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005

Table A2
Journals Publishing at Least Five Artificial Intelligence Articles in Accounting.

Journal	Articles Published
Intelligent Systems In Accounting Finance & Management	228
Expert Systems With Applications	139
Journal Of Information Systems	53
Journal Of Emerging Technologies In Accounting	23
Decision Support Systems	19
Auditing: A Journal Of Practice & Theory	18
Knowledge-Based Systems	16
Accountancy	13
CPA Journal	13
Journal Of Accountancy	13
Accounting Horizons	11
International Journal Of Accounting Information Systems	10
Management Accounting: Official Magazine Of Institute Of Management Accountants	10
Accounting Education	9
The Accounting Review	9
Behavioral Research In Accounting	8
Issues In Accounting Education	8
Decision Sciences	7
Accountancy	6
European Journal Of Operational Research	6
Internal Auditor	6
Journal Of Management Information Systems	6
Accounting, Organizations & Society	5
Expert Systems	5

References

AACSB International Committee on Accreditation Policy, 2014. AACSB International Accounting Accreditation Standard A7: Information Technology Skills and Knowledge for Accounting Graduates: An Interpretation. AACSB International.
Alles, M., Kogan, A., Vasarhelyi, M., 2008. Exploiting comparative advantage: a paradigm for value added research in accounting information systems. Int. J. Account. Inf. Syst. 9, 202–215.
Arnold, V., Sutton, S.G., 1996/97. Order and recency effects in complex decision making: Iimplications for the design of audit-oriented IDSS. Account. Forum. Winter/Spring 21 (3-4), 225–250.
Arnold, V., Sutton, S.G., 1998. The theory of technology dominance: understanding the impact of intelligent decision aids on decision makers' judgments. Adv. Account. Behav. Res. 1, 175–194.
Arnold, V., Clark, N., Collier, P.A., Leech, S.A., Sutton, S.G., 2004a. Explanation provision and use in an intelligent decision aid. Int. J. Intell. Syst. Account. Financ. Manag. 12 (1), 5–27.
Arnold, V., Clark, N., Collier, P.A., Leech, S.A., Sutton, S.G., 2005. Using knowledge based systems to promote judgment consistency in multi-cultural firm environments. J. Emerg. Technol. Account. 2, 33–59.
Arnold, V., Clark, N., Collier, P.A., Leech, S.A., Sutton, S.G., 2006. The differential use and effect of knowledge-based system explanations in novice and expert judgment decisions. MIS Q. 30 (1), 79–97.
Arnold, V., Collier, P.A., Leech, S.A., Sutton, S.G., 2004b. The impact of intelligent decision aids on experienced and novice decision makers' judgments. Account. Finance 44, 1–26.
Brown, C., 1991. Expert systems in public accounting: current practice and future directions. Expert Syst. Appl. 3 (1), 3–18.
Brown-Liburd, H., Issa, H., Lombardi, D., 2015. Behavioral implications of big data's impact on audit judgment and decision making and future research directions. Account. Horiz. 29 (2), 451–468.
Brynjolfsson, E., McAfee, A., 2011. Race Against the Machine. Digital Frontier Press, Lexington, MA.
Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company, Inc., New York.
CEDA, 2015. Australia's Future Workforce? Committee for Economic Development in Australia, Melbourne
Collier, P.A., Leech, S.A., Clark, N., 1999. A validated expert system for decision making in corporate recovery. Int. J. Intell. Syst. Account. Financ. Manag. 8 (2), 75–88.
Dowling, C., Leech, S., 2007. Audit support systems and decision aids: current practice and opportunities for future research. Int. J. Account. Inf. Syst. 8 (2), 92–116.
Dowling, C., Leech, S., 2014. A Big 4 firm's use of information technology to control the audit process: how an audit support system is changing auditor behavior. Contemp. Account. Res. 31 (1), 230–252.
Dowling, C., Leech, S., Moroney, R., 2008. Audit support system design and the declarative knowledge of long-term users. J. Emerg. Technol. Account. 5 (1), 99–108.
Elbashir, M., Collier, P.A., Sutton, S.G., 2011. The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. Account. Rev. 86 (1), 155–184.
Fenn, J., Linden, A., 2005. Gartner's hype cycle special report for 2005. August 5. Available at http://www.gartner.com/DisplayDocument?doc_cd=130115.
Frey, C.B., Osborne, M.A., 2013. The Future of Employment: How Susceptible Are Jobs to Computerisation? Oxford University, UKhttp://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf
Gray, G., Chiu, V., Liu, Q., Li, P., 2014. The expert systems life cycle in AIS research: what does it mean for future AIS research? Int. J. Account. Inf. Syst. 15, 423–451.
Gregor, S., Benbasat, I., 1999. Explanations from intelligent systems: theoretical foundations and implications for practice. MIS Q. 23 (4), 497–530.
Higginbotham, A., 2013. Deception is futile when big brother's lie detector turns its eyes on you. Wired January 17. Available at http://www.wired.com/2013/01/ff-lie-detector/.
Humpherys, S., Moffitt, K., Burns, M., Burgoon, J., Felix, W., 2011. Identification of fraudulent financial statements using linguistic credibility analysis. Decis. Support. Syst. 50, 585–594.
Kuhn, J., Sutton, S.G., 2010. Continuous auditing in ERP system environments: the current state and future directions. J. Inf. Syst. 24 (1), 91–112.
Leech, S.A., Collier, P.A., Clark, N., 1998. Modeling expertise: a case study using multiple insolvency experts. Adv. Account. Inf. Syst. 6, 85–105.
Leech, S.A., Collier, P.A., Clark, N., 1999. A generalized model of decision-making processes for companies in financial distress. Account. Forum 23 (2), 155–174.

Mascha, M., 2001. The effect of task complexity and expert system type on the acquisition of procedural knowledge: some new evidence. Int. J. Account. Inf. Syst. 2 (2), 103–124.
Mascha, M., Smedley, G., 2007. Can computerized decision aids do "damage"? A case for tailoring feedback and task complexity based on task experience. Int. J. Account. Inf. Syst. 8 (2), 73–91.
Masselli, J., Ricketts, R., Arnold, V., Sutton, S.G., 2002. The impact of embedded intelligent agents on tax compliance decisions. J. Am. Tax. Assoc. 1, 60–78.
McCall, H., Arnold, V., Sutton, S.G., 2008. Use of knowledge management systems and the impact on declarative knowledge acquisition. J. Inf. Syst. 22 (1), 77–101.
Messier Jr., W., Hansen, J., 1987. Expert systems in auditing: the state of the art. Audit. J. Pract. Theory (Fall) 7 (1), 94–105.
Odom, M., Dorr, P., 1995. The impact of elaboration-based expert system interfaces on de-skilling: an epistemological issue. J. Inf. Syst. 9 (Spring), 1–18.
O'Leary, D., 2007. Knowledge representation of rules: a note. Intell. Syst. Account. Financ. Manag. 15 (1/2), 73–84.
O'Leary, D., 2008. Gartner's hype cycle and information system research issues. Int. J. Account. Inf. Syst. 9 (4), 245–252.
O'Leary, D., 2009. A comparative analysis of the evolution of a taxonomy for best practices: a case for 'knowledge efficiency'. Intell. Syst. Account. Financ. Manag. 16 (4), 293–309.
O'Leary, D.E., 1997. The internet, intranets, and the AI renaissance. IEEE Comput. 30 (1), 71–78.
O'Leary, D.E., 2003. Auditor environmental assessments. Int. J. Account. Inf. Syst. 4 (4), 275–294.
O'Leary, D.E., Watkins, P.R., 1992. Integration of intelligent systems and conventional systems: requirements for co-ordinating multiple agents for diagnostic decisions. Int. J. Intell. Syst. Account. Financ. Manag. 1 (2), 135–145.
PwC, 2015. Data driven: what students need to succeed in a rapidly changing business world. Available at http://www.pwc.com/us/en/faculty-resource/assets/PwC-Data-driven-paper-Feb2015.pdf.
Schneider, G., Dai, J., Janvrin, D., Ajayi, K., Raschke, R., 2015. Infer, predict, and assure: accounting opportunities in data analytics. Account. Horiz. 29 (3), 719–742.
Smedley, G., Sutton, S.G., 2004. Explanation provision in knowledge-based systems: a theory driven approach for knowledge transfer designs. J. Emerg. Technol. Account. 1, 41–61.
Smedley, G., Sutton, S.G., 2007. The effect of alternative procedural explanation types on procedural knowledge acquisition during knowledge-based systems use. J. Inf. Syst. 21 (1), 27–52.
Stuart, I., Prawitt, D., 2012. Firm-level formalization and auditor performance on complex tasks. Behav. Res. Account. 24 (2), 193–210.
Sutton, S.G., 1992. Can we research a field we cannot define? Towards an understanding of the AIS discipline. Adv. Account. Inf. Syst. 1, 1–13.
Thibodeau, J., 2003. The development and transferability of task knowledge. Audit. J. Pract. Theory 22, 47–67.
Triki, A., Weisner, M., 2014. Lessons learned from the literature on the theory of technology dominance: possibilities for an extended research framework. J. Emerg. Technol. Account. 11 (1), 41–69.
Vasarhelyi, M., Kogan, A., Tuttle, B., 2015. Big data in accounting: an overview. Account. Horiz. 29 (2), 381–396.

Please cite this article as: Sutton, S.G., et al., *"The reports of my death are greatly exaggerated"*—Artificial intelligence research in accounting, Int J Account Inf Syst (2016), http://dx.doi.org/10.1016/j.accinf.2016.07.005