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Understanding usage and value of audit analytics for internal auditors: An organizational approach[☆]

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A R T I C L E I N F O

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TOE

A B S T R A C T

Although internal auditors are increasingly aware of the importance and value of audit analytics, prior research indicates that the use of audit analytics is below expectation. This paper uses the Technology-Organization-Environment (TOE) framework to identify and examine factors at the organizational level that influence post adoption usage of audit analytics, as well as whether using audit analytics improves the performance of the internal audit process. Data were collected from clients of a major audit software vendor. Results indicate that application-level usage is influenced by management support, technological competence, and standards, while professional help, technological competence, and application-level usage drive feature-level usage. Finally, both application-level and feature-level audit analytics usages improve the performance of the internal audit process.

1. Introduction

The use of analytics in the auditing domain has been emphasized by both practitioners and academia (Audimation, 2011; PWC, 2012; Wang and Cuthbertson, 2014; Cao et al., 2015). Audit analytics is defined as a science of "discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modeling, and visualization for the purpose of planning or performing the audit" (AICPA, 2015). Audit software vendors[1] have developed many analytics tools to improve audit quality and enhance assurance. Some general data analytics software packages[2] are also being employed in the audit process. The usage of audit analytics not only increases operational efficiency by reducing costs (KPMG, 2012), but also helps quickly identify potential fraud and anomalies, thereby providing a higher level of assurance (EY, 2014).

Audit analytics provides benefits to both external and internal auditors. However, it creates unique opportunities for internal auditors to assess potential risks, identify operational inefficiency, and provide insights (PWC, 2012; Schneider et al., 2015). First, internal auditors conduct much broader tasks than external auditors, such as investigation on financial and operational matters, fraud

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[1] Examples of those audit software vendors include CaseWare International, Inc. and ACL Services, Ltd.
[2] Examples of those general data analytics software packages include R, WEKA, and SAS.

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risk evaluation, etc. (Araj, 2015; Carcello et al., 2017). Therefore, internal auditors should have more demands on the use of audit analytics in order to accomplish those tasks in an efficient and effective manner. Second, internal auditors usually have more frequent access to business accounting data, to which audit analytics can be employed to quickly detect anomalies and fraud. Finally, although current regulations for external auditors neither encourage nor prohibit the use of analytics, external auditors are likely to focus on the procedures that are explicitly required to satisfy regulatory requirements. By contrast, regulations for internal auditors are less strict than those for external auditors, allowing more flexibility in exploring various audit analytics tools. Not surprisingly, analytics are expected to become a core capability of internal auditors (Deloitte, 2016), and many researchers have devoted much effort into incorporating analytics to internal audit. For example, Thiprungsri and Vasarhelyi (2011) developed an analytical model to detect outliers from group life insurance claims. Kim and Vasarhelyi (2012) used analytics to identify potential fraud in the wire transfer payment process. Jans et al. (2014) demonstrated how internal auditors could use process mining of event logs as a new type of analytical procedure to detect deficient controls.

Although internal auditors are increasingly aware of the importance and value of audit analytics (Teammate, 2012; KPMG, 2015), surveys show that audit analytics is not being fully utilized by the majority of companies (AuditNet, 2012; EY, 2014; KPMG, 2015). Many auditors are not able to effectively incorporate audit analytics in their work and therefore only use it on an ad-hoc basis. While some articles (EY, 2014; KPMG, 2015) attempted to explore the barriers to the adoption of audit analytics, limited academic research has examined the actual usage level and the factors that result in the differences in its use.

The objective of this paper is to examine organizational factors that have an impact on audit analytics post-adoption usage at both the application-level and the feature-level, and whether using audit analytics improves the performance of internal audit. Prior studies have investigated use of technology in the audit process, such as general Computer Assisted Auditing Tools and Techniques (CAATTs) (Braun and Davis, 2003; Bierstaker et al., 2014; Mahzan and Lymer, 2014) and continuous auditing (Gonzalez et al., 2012; Vasarhelyi et al., 2012). However, compared to general CAATTs,[3] audit analytics requires special auditor knowledge and skills, which leads to new challenges. For example, audit analytics usually involves more advanced statistical techniques or data analytics tools (e.g. data mining) than general CAATTs (Brown-Liburd et al., 2015), of which most auditors have limited knowledge; therefore understanding those techniques could be a challenge. Failure to fully understand audit analytics could result in misuse of the methodology, as well as misinterpretation of its results. In addition, audit analytics is usually employed with large amounts of data, which could increase information load, and thereby affect decision-making processes of auditors (Schneider et al., 2015). The difficulty of extracting useful information from a large amount of data could impede auditors from using analytics on a frequent basis. Understanding factors that impact the usage of audit analytics could provide insights to management, regulators, and audit analytics software vendors.

In this paper, we use the Technology-Organization-Environment framework (hereafter the "TOE framework") (Tornatzky et al., 1990) to examine the determinants and extent of audit analytics usage, as well as whether using audit analytics improves the performance of the internal audit process. Following prior literature (Harrison and Datta, 2007; Kim et al., 2009; Sun, 2012), we distinguish audit analytics usage at the application-level from that at the feature-level. Application-level audit analytics usage refers to the extent to which audit analytics software is used by auditors. For example, application-level audit analytics usage is considered high when software that enables audit analytics is used frequently in the majority of audit processes. Feature-level audit analytics usage, on the other hand, is a composite measure that considers specific audit analytics techniques (feature of software), such as summarization, regression, Benford's Law, etc., and the frequency of their usage. We hypothesize that technological competence, IT complexity, firm size, management support, standards, and professional help will have an impact on application-level audit analytics usage. Furthermore, this paper posits that application-level usage, professional help, and technological competence have positive influences on feature-level usage. Finally, the use of audit analytics at both levels improves the performance of internal audit. Our empirical results indicate that technological competence, management support, and standards are positively associated with application-level audit analytics usage, while application-level usage, professional help, and technological competence have positive impacts on feature-level usage. Both application and feature-level usage improve the performance of the internal audit process.

The main contributions of this study are threefold. First, we believe that this is the first paper to examine the determinants and extent of audit analytics usage, and whether it improves the internal audit function. Our results provide insights to management, regulators, and vendors to potentially facilitate the incorporation of audit analytics into internal audit. Second, new constructs are proposed to measure audit analytics usage. In our model, audit analytics is examined from two perspectives: application-level and feature-level (Harrison and Datta, 2007), which few prior studies (Kim et al., 2009) have accomplished. The paper is also consistent with recent IS research that emphasizes the importance of understanding the usage of application features (Sun, 2012). Third, this paper examines factors that influence audit analytics usage via an organizational approach. It fills a gap in the literature as few research studies have examined, at the organizational level, the acceptance and use of technology by the audit profession (Rosli et al., 2012; Vasarhelyi et al., 2012).

The remainder of this paper proceeds as follows: Section 2 provides background on information technology adoption. Section 3 reviews literature and develops hypotheses. Section 4 identifies data collection and the method employed. Empirical results are presented in Section 5. Discussion of results is provided in Section 6. The last section concludes this paper and identifies future research.

[3] CAATTs are defined as "any use of technology to assist in the completion of an audit. This definition would include automated working papers and traditional word processing applications as CAATTs" (Braun and Davis, 2003).

2. Background

2.1. Audit information technology acceptance and use

As information technology (IT) significantly influenced the audit profession, prior studies (Braun and Davis, 2003; Curtis and Payne, 2008, 2014; Janvrin et al., 2009; Mahzan and Lymer, 2008; Kim et al., 2009; Bierstaker et al., 2014; Vasarhelyi et al., 2012) have examined the acceptance and usage level of IT by internal or external auditors, as well as the perceived importance of IT usage. For example, Mahzan and Lymer (2008) studied CAATTs acceptance by UK internal auditors. They developed a theoretical model of successful CAATT adoption and claimed that influencing motivation, best practices of implementation, performance measurement criteria, and technical complexity are the main factors in a successful CAATTs implementation. Kim et al. (2009) found that internal auditors' adoption of audit software packages is influenced by organizational factors through perceived ease of use and individual factors through perceived usefulness. Gonzalez et al. (2012) surveyed 210 internal auditors worldwide on their use of Continuous Auditing (CA). Results indicated that CA usage varies by regions, and is significantly influenced by internal auditors' expectations of effort and social influences. Regarding the IT usage by external auditors, Janvrin et al. (2008) identified that external auditors extensively use a variety of audit applications, and the usage varies by firm size. Bierstaker et al. (2014) examined factors that influence the use of CAATTs by auditors from Big 4, national, regional, and local firms. Their study showed that outcome expectations, organizational pressure, and technical infrastructure support influence auditors' willingness to use CAATTs. While many studies focus on the acceptance and use of CAATTs and CA, there is limited research on the factors that influence audit analytics usage, and whether it improves the performance of the current audit process.

The majority of prior studies examined audit IT acceptance and usage at the individual level rather than the organizational level, mostly because interviewing key personnel in audit departments is difficult (Janvrin et al., 2008). Only a few studies investigate how audit firms or audit departments adopt and use technology. Rosli et al. (2012) developed a theoretical model to address the factors influencing CAATTs acceptance at organizational level; however, they were not able to collect real data to test the proposed model. Ahmi and Kent (2012) attempted to add several organizational factors and external factors in their model to investigate what influences external auditors to use generalized audit software, but the main model still focused on individual auditors. Vasarhelyi et al. (2012) assessed both the acceptance of CA by internal auditors individually and the degree to which CA has been adopted by internal audit departments. They argued that it is necessary to study IT acceptance and use at organizational level because "audit-aid technology implementation is initiated and supported by the head of the internal audit department or upper level management" (Vasarhelyi et al., 2012, page 18). Following this discussion, this paper uses an organizational approach to examine the usage of audit analytics and whether it improves the performance of internal audit.

It is important to note that we focus on the post-adoption usage, rather than the adoption of audit analytics. Many researchers focused on adoption versus non-adoption (intent to adopt) in information technology studies (Fichman, 2000), while a number of others studied post-adoption stage (Huh and Kim, 2008; Saeed and Abdinnour-Helm, 2008; Sun, 2012). Information Systems literature documents that information technology values come from the organizations' skills to leverage a particular technology, rather than the technology itself (Zhu and Kraemer, 2005; Ross et al., 1996). Similarly, when examining information technology used in the auditing domain, Janvrin et al. (2008) also indicated that the tool itself does not improve audit efficiency or effectiveness, but users do. Therefore, this paper exclusively focuses on the post-adoption usage, rather than the firm's intention to adopt audit analytics.

2.2. Application-level versus feature-level

We differentiate application-level audit analytics usage from feature-level audit analytics usage. Features are the building blocks of an application and reflect the core of the technology (Jasperson et al., 2005). Features correspond to tasks that an information system is designed to resolve (Sun, 2012). Specific to audit analytics, features are defined as vendor-created software tools for completing audit tasks on behalf of the auditors (Kim et al., 2009). Because different people may use different features even when using the same information technology (Sun, 2012), it is appropriate and essential to separately examine application-level usage and feature-level usage.

Application-level audit analytics usage is defined as the extent to which audit analytics software is used in the audit process. The frequency of performing audit analytics, the number of audit tasks to which the techniques are applied, and the scope of audit processes in which analytics is involved are all measures of application-level audit analytics usage. Feature-level audit analytics usage is defined as the extent to which specific audit analytics techniques are used in the audit process. It considers both the quantity of different audit analytics techniques being used and the complexity of different audit analytics techniques. To have a high level of feature-level audit analytics usage, auditors of the company should understand both basic and sophisticated techniques, as well as their strengths and weaknesses. Auditors should also be able to use the most effective ones to accomplish different audit tasks. It is possible for a firm to achieve greater application-level usage, but remain at a low feature-level usage. For example, internal auditors could use basic audit analytics throughout the audit process frequently, but not have the knowledge to use more advanced tools.

3. Hypotheses development

3.1. The Technology – Organization – Environment framework (TOE)

Several models can be used to study information technology usage, including the Technology Acceptance Model (TAM) (Davis, 1986; Venkatesh and Davis, 2000), theory of planned behavior (TPB) (Ajzen, 1991), unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), diffusion of innovation (DOI) (Rogers, 1995), and the TOE framework (Tornatzky et al., 1990). The first three models are used to study IT adoption at the individual level, while DOI and TOE operate at the organizational level. We choose the TOE framework for three reasons. First, the focus on the post-adoption stage requires the use of the TOE framework because it identifies aspects that have impacts on not only the adoption, but also on the implementation and use process of technological innovations (Zhu and Kraemer, 2005). Second, the TOE framework studies technology usage in an enterprise context, making it suitable for examining the determinants of audit analytics usage by the entire internal audit departments rather than individual auditors. Third, the TOE framework works as a generic theory for studying all types of innovation. Audit analytics can be considered as both type two innovation[4] (identifying fraud as administrative task tool) and type three innovation[5] (inferring operational inefficiency, and providing insights to the business as a strategic tool) (Swanson, 1994). Thus, it is appropriate to use the TOE framework in this study.

The TOE framework focuses on three contexts: technological, organizational, and environmental. The technological context refers to the existing technology in use and the available technology that can be used by a firm. The organizational context includes descriptive measures about the organization such as size or management attitude (Zhu and Kraemer, 2005). The environmental context describes the environment in which a firm conducts its business, including industry, competitors, and government relationships (Tornatzky et al., 1990). The TOE framework is consistent with DOI theory, but provides better explanatory power by including the environmental context, which presents both constraints and opportunities for technology adoption (Oliveira and Martins, 2011).

Based on the TOE framework, we develop a conceptual model to assess the usage of audit analytics as shown in Fig. 1. The left side of this model displays antecedents of audit analytics usage, i.e., factors influencing the utilization of audit analytics. The right side focuses on the performance improvement of the internal audit process because of the use of this technology.

3.2. IT complexity

IT complexity refers to the degree to which a firm uses highly computerized transactions. The AICPA states that in determining whether specialized skills are needed on the audit team to understand IT controls, or to design and perform tests of IT controls or substantive tests, the auditor should consider factors such as "the complexity of the entity's systems and IT controls and the manner in which they are used in conducting the entity's business" (AU SECTION 319 31). Janvrin et al. (2009) found that when client IT complexity is high, external auditors are more likely to use computer-related audit procedures. While limited research examines the relation between IT complexity and audit analytics usage by internal auditors, it is conjectured in this paper that they are positively associated. The underlying reason is that a firm's complex IT environment may put large burden on auditors to understand the complicated, firm specific business transaction issues (Vasarhelyi and Alles, 2008). Audit analytics can help to significantly reduce time and labor costs in the audit engagement. Furthermore, audit analytics not only broadens the audit scope, but also increases the efficiency and effectiveness in identifying potential fraud.

Hypothesis 1. Firms with greater IT complexity are more likely to achieve greater application-level audit analytics usage.

3.3. Technological competence

Technological competence consists of two parts: IT infrastructure and IT specialists (Zhu and Kraemer, 2005). IT infrastructure refers to the physical assets a firm possesses that can be used to facilitate technology adoption. IT specialists are personnel who have the knowledge and skill to conduct computer-related tasks. Technological competence is necessary for audit analytics software usage. It is infeasible to use audit analytics appropriately without the support of technical resources and competent personnel, the lack of which present barriers to CAATT implementation (Mahzan and Lymer, 2008; Vasarhelyi et al., 2012). As prior research shows that technological competence is a prerequisite for the adoption of technology innovation (Lin et al., 2007), it is expected that internal auditor departments with greater technological competence are more likely to be ready to adopt technology innovation and use it in the audit process.

Hypothesis 2. Internal audit departments with better technological competence are more likely to achieve greater application-level audit analytics usage.

3.4. Management support

Management support, or management commitment, is the degree to which a firm's management invests in technology innovation. Management literature suggests that support from upper levels plays a key role in the success of nearly all programs within an organization (Cohen and Sayag, 2010). Audit analytics is not an exception. Audit analytics requires management to dedicate resources to purchasing analytics software, implementing maintenance services, and training auditors.

[4] Type two innovations in information systems (IS) focus on the support of business administration (Swanson, 1994).

[5] Type three IS innovations refer to those embedded in the core of business (Swanson, 1994).

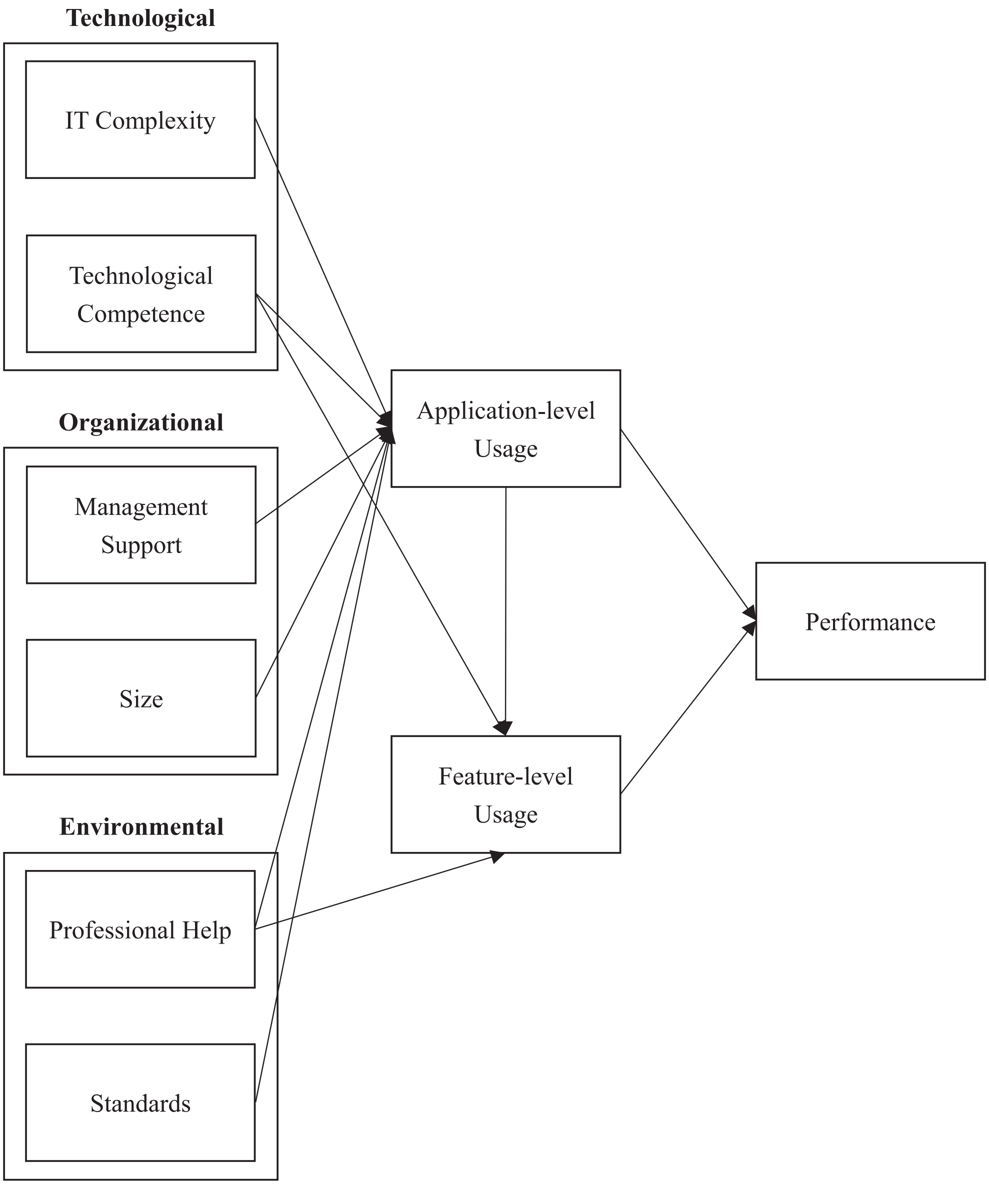

Fig. 1. A conceptual model of audit analytics use and value based on the TOE framework.

Hypothesis 3. Firms with stronger management support are more likely to achieve greater application-level audit analytics usage.

3.5. Size

Prior literature has widely debated on the impact of firm size on innovation adoption (Hannan and McDowell, 1984; Acs and Audretsch, 1987; Cohen and Klepper, 1996). The association between firm size and innovation diffusion depends on the definition of size, environmental uncertainty, and focus on technical innovations (Damanpour, 1996). A generally positive relationship between organizational size and IT innovation adoption is moderated by type of IT innovation, type of organization, stage of adoption, scope of size, and type of size measure (Lee and Xia, 2006). Nevertheless, in the current context, size is anticipated to have a positive impact on the usage of audit analytics for two reasons. First, large firms tend to have more resources available to facilitate the adoption process. A survey on audit analytics (AuditNet, 2012) revealed that cost of software and training is one of the main reasons for limited use of audit technology tools. Large companies usually have sufficient financial resources to purchase sophisticated software, as well as training and maintenance services, while small firms may only be able to afford basic functions and limited training courses. Second, on average, larger firms have more transactions and procedures to be audited than smaller firms. The benefit of using audit analytics is therefore more apparent for larger firms.

Hypothesis 4. Larger firms are more likely to achieve greater application-level audit analytics usage.

3.6. Professional help

Professional help refers to the ease of getting professional support for using audit analytics and the appropriateness of such support. Discussions with internal auditors suggest that a major obstacle that hinders the use of advanced audit analytics is the inability to get timely professional support. Ndubisi et al. (2003) found that systems are more successful when technical support is in place. Information regarding new features and products can also enhance the user's understanding of the software.

Although analytics software vendors provide online training classes and on-site training classes, this problem is only alleviated rather than eliminated. The high cost and limited duration of training classes may restrict their benefits and may limit task specificity of the training.

Hypothesis 5. Firms with better professional help are more likely to achieve greater application-level audit analytics usage.

3.7. Standards

Standards refer to the perceived level of encouragement from auditing standards of using audit analytics. While there is no mandatory requirement to use audit analytics, professional bodies and guidance encourage the use of technology-based audit and other data analysis techniques in performing internal audit (IIA, 2017). Firms that face different risks in their business and industries may have a different perception of how strongly standards encourage them to use audit analytics.

Hypothesis 6. Firms with higher perceived level of encouragement by auditing standards are more likely to achieve greater application-level audit analytics usage.

3.8. Application-level and feature-level audit analytics usage

Application-level and feature-level audit analytics usage are arguably not independent with each other. Sun (2012) and Jasperson et al. (2005) both suggest that users continue to explore and adopt new features after adopting information systems. While at the beginning users only see the need for a limited number of features, they eventually realize that a larger set of features is necessary as they gain more experience (Hiltz and Turoff, 1981). Although greater software use may not necessarily encourage the use of a wider set of audit analytics tools, it might help auditors develop confidence in using audit software. Compeau and Higgins (1995) conducted an experiment which reveals that individuals who are confident in their ability to use computers have higher expectations of outcomes of using computers and can indeed perform better than those who have less confidence. In addition, greater application-level audit analytics usage leads to more familiarity with audit software. Thus, auditors who use audit software more frequently are more likely to succeed in learning and using various audit analytics and achieve proficiency because of confidence and familiarity. Thus, there should be a positive relationship between application-level audit analytics usage and feature-level usage.

Technological competence and professional help are also expected to have impacts on feature-level audit analytics usage. Because advanced audit analytics tools are more difficult to use and require more expertise, technical support will have a direct impact on advancing audit analytics proficiency. For example, Vasarhelyi et al. (2012) interviewed internal audit managers and found that training is necessary in providing employees with basic information technology knowledge. Similarly, technological competence is the basis of using advanced audit analytics techniques. Firms with up-to-date IT infrastructure and skilled IT specialists have the capability and are more likely to perform advanced audit analytics, while those with low technological competence may only be able to utilize basic audit analytics tools.

Hypothesis 7. Firms with greater application-level audit analytics usage are more likely to achieve greater feature-level audit analytics usage.

Hypothesis 8. Firms with better technological competence are more likely to achieve greater feature-level audit analytics usage.

Hypothesis 9. Firms with better professional help are more likely to achieve greater feature-level audit analytics usage.

3.9. Internal audit function improvements

Facilitated by audit software, audit analytics can perform investigation upon a large population, save effort for auditors, and identify misstatements or fraud which would otherwise not be discovered. The increase in efficiency and effectiveness of the audit process will also enable auditors to conduct more frequent audits in high-risk areas and enhance the reliability of audit results. Similarly, if internal auditors are proficient in using various audit analytics tools, the likelihood of finding anomalies will increase, leading to improvements in the internal audit function. Therefore, the use of audit analytics is expected to improve audit efficiency, effectiveness and the ability to identify more exceptions. Thus:

Hypothesis 10. Firms with greater application-level audit analytics usage are more likely to achieve better performance in internal audit.

Hypothesis 11. Firms with greater feature-level audit analytics usage are more likely to achieve better performance in internal audit.

4. Research method, data collection, and instrument validation

An online survey was administered to test the hypotheses. Participants of the survey are clients of a major audit analysis software vendor. The survey was sent to the main contact of each firm by the software vendor. The selected sample meets the following criteria: first, to be able to evaluate audit analytics usage level, participating firms should own at least one audit analytics software package. Second, the respondent should have an understanding of the audit analytics usage of the whole audit department, because this study focuses on the organizational level. Since the recipients of this survey are the main contacts of their companies with the software vendor, and most of them hold high positions in their internal audit departments, we assume that they are knowledgeable regarding audit analytics usage in their audit department. This paper also overcomes the limitation of prior research that does not properly examine technology adoption at the organizational level because of inability to interview key personnel (Janvrin et al., 2008). Third, to assure participants provide accurate answers to our questions and present the best knowledge of their internal audit department, participants are allowed to consult their colleagues, if they are not able to answer the questions.

4.1. Instrument development

The questionnaire was developed by referring to prior literature and consulting experts. Because many constructs have not been examined before in the audit domain, four rounds of pilots were conducted to refine the instruments. First, several researchers who have expertise in audit analytics were asked to examine the instruments. Then, the questionnaire was sent to a sample of practitioners who use audit analytics in their business in order to refine the questions. Next, the third-round pilot was run among participants in a fraud seminar. Lastly, the survey was distributed to participants of a continuous auditing symposium for further refinement. The items used in the study are listed in Table 1.

Two constructs warrant further discussion: application-level and feature-level audit analytics usage. Application-level usage shows, in the overall audit process, how frequently a company uses audit analytics tools, regardless of what these tools are. It is measured by asking the participants to rate their agreement with four questions: a) we use audit analytics as supplement of audit function, b) we use audit analytics in every task, c) we use audit analytics as a basis of the audit function, and d) we use audit

Table 1
Construct measures.

Constructs	Item	Definition
Application-level audit analytics usage	AL1	We use audit analytics as supplement of audit function
	AL2	We use audit analytics in every task
	AL3	We use audit analytics as a basis of audit function
	AL4	We use audit analytics frequently
Management support	MS1	Management is supportive of using audit analytics
	MS2	Management is supportive in financing/approving a purchase of an audit software
	MS3	Management provides financial support in software training class
	MS4	Management is financially supportive when software maintenance is needed
Standards	SD1	Standards encourage use of various analytical methods to detect misstatement
	SD2	If AICPA provides guidance on how to use audit analytics tools in auditing procedures, I will be willing to use audit analytics
	SD3	Standards encourage use of advanced analytics methods to enhance internal audit function reliability
Professional help	PH1	The cost of attending training class is reasonable
	PH2	Content in training classes is appropriate and sufficient for my professional needs
	PH3	We can get professional support in a timely manner
	PH4	Professional support is helpful in building our knowledge in using audit software
Performance	VL1	Using audit analytics improves our ability to identify more exceptions
	VL2	Using audit analytics improves our audit efficiency
	VL3	Using audit analytics improves our audit effectiveness
	VL4	Using audit analytics reduces the likelihood of unintended errors in our business operations
Technological competence	TC1	Log of the number of computers in your internal audit department
	TC2	Log of the number of auditors who utilize at least one audit analytics software solution (excluding Microsoft Excel) in your internal audit department
	TC3	Log of the number of Information Technology (IT) auditors in your company
Feature-level audit analytics usage	FL1	Log of the aggregated dummies over all the 17 tools, where the dummy equals one for a particularly tool if the rating is at least 4 (on a seven point Likert scale), zero otherwise. Tools can be found in Table 9.
	FL2	Log of the aggregated dummies over all 5 advanced audit analytics tools, where the dummy equals one for a particularly tool if the rating is at least 4 (on a seven point Likert scale), zero otherwise. Tools can be found in Table 9.
	FL3	Log of the sum of participant's ratings (on a seven point Likert scale) over all 5 advanced audit analytics tools. Tools can be found in Table 9.
Firm size	SIZE	Log of the total number of employees in the company
IT complexity	IT	The degree of information technology usage in company's major business

Table 2
Sample selection.

4820 (4704)	Total number of surveys sent (total number of surveys delivered)
427 (9%)	Total number of responses collected (% of total number of surveys delivered)
25	Delete responses that did not pass validity check
193	Delete responses with missing values on any of the items used in the study
209	Total number of responses used in this study

analytics frequently. A scale of 1 (strongly disagree) to 7 (strongly agree) was used to measure the rate of agreement among participants. Feature-level audit analytics usage takes specific analytical tools into account, and differentiates basic tools and advanced tools.[6] This construct is measured by using three items calculated from participants' ratings over the 17 audit analytics tools[7] in the audit process on a scale of 1 (never) to 7 (every time).

4.2. Response rate and sample selection

The survey was distributed on December 15, 2014 to 4820 firms and 116 (2.4%) were not delivered due to invalid email addresses. All responses were collected from December 15, 2014 to January, 20, 2015. A total number of 284 responses were collected at this stage. On May 4, 2015, the survey was resent to those who didn't respond, and obtained another 143 responses. In total 427 responses were received, representing a response rate of 9%. The response rate is reasonable and has comparable response rates from prior studies in examining similar issues. For example, the Institution of Internal Auditors (UK) 2006 survey on internal audit software use to its members had a response rate of 7.9% (516/6500) (Mahzan and Lymer, 2008). Ahmi and Kent (2012) examined the utilization of generalized audit software by external auditors and achieved a response rate of 6.2% (205/3296).

A validity check was performed over the 427 responses received. The observations that are invalid due to obvious issues (such as the total number of internal auditors being larger than the total number of employees) were deleted, resulting in 402 observations in the sample. Finally, observations with missing values on any of the items listed Table 1 were removed. The final sample consists of 209 observations. The sample selection process is summarized in Table 2.

Table 3 shows the position titles of the respondents in the final sample. Consistent with the expectation, most respondents hold high ranks or have expertise in audit analytics, with more than half of the respondents (118) being audit managers or audit directors and 4 hold top positions in the firm.

With regard to industry, educational services accounts for the largest group (25.00%), followed by finance and insurance (18.27%) and public administration (14.42%). Table 4 lists the breakdown of industries.

4.3. Nonresponse bias

We examined whether there is any systematic bias in our sample. Responses are divided by the ranking of respondents: those who hold director/manager or higher positions and those whose ranks are relatively low, because one may have concerns that they have different perceptions regarding the questions we asked. Paired *t*-test shows that there is no significant difference. We also divided the responses into two parts: those finished earlier than the median completion time of all responses and those completed later than the median completion time. There is no significant difference in the responses, suggesting that nonresponse bias is not a major concern in our sample.

4.4. Instrument reliability and validity

We tested internal consistency reliability using Cronbach's alphas. Cronbach's alphas should be greater than or equal to 0.7 (Straub, 1989). Two items were deleted due to low internal consistency reliability: PH1 and TC1. Cronbach's alphas of the constructs using the remaining items are reported in Table 5.

Discriminant validity of item measures was tested by running factor analysis using maximum likelihood. As there may be high correlation between our constructs (e.g. application-level usage and feature level usage), we use direct oblimin rotation rather than Varimax rotation. Structure matrix is reported in Table 6. Four items were deleted at this stage due to low loadings on their intended constructs: AL1, MS3, SD2, and VL4. All the remaining items loaded much higher on their intended constructs than on any other construct, providing support for discriminant validity of items (Chin, 1998; Gefen et al., 2000; Grégoire and Fisher, 2006; Hair et al., 2012). Although several cross-loadings are slightly larger than 0.4, the difference between the primary and secondary factor loadings are sufficiently larger than the 0.3 threshold (Matsunaga, 2010). Therefore, we decide to keep these items as well.[8]

Convergent validity and discriminant validity were examined by running Confirmatory Factor Analysis (CFA) using AMOS with all the remaining items. The measurement model has acceptable fit, with SRMR = 0.043, Chi-square = 212.82, Degree of

[6] Several academic and professional experts were consulted on whether a tool is advanced or basic audit analytics. The category of a specific tool is determined by using majority vote. Five tools are considered to be advanced: duplicate detection, regression, clustering, text mining, and fraud detection.

[7] Tools are listed in Table 9.

[8] The potential effects and implications of high item cross-loadings on model estimation and results are discussed in the Limitations section.

Table 3
Breakdown of positions.

Respondent position	Frequency	Percent	Cumulative frequency	Cumulative percent
Internal audit manager/internal audit director	93	44.50	93	44.50
Junior auditor	36	17.22	129	61.72
Senior auditor	28	13.40	157	75.12
IT audit manager/IT audit director	25	11.96	182	87.08
Control and compliance specialist	10	4.78	192	91.87
Data analyst	6	2.87	198	94.74
CFO/president/vice president	4	1.91	202	96.65
Accountant	4	1.91	206	98.56
Fraud inspector	3	1.44	209	100.00

Table 4
Breakdown of industries.

Industry	Frequency	Percent	Cumulative frequency	Cumulative percent
Educational services	52	25.00	52	25.00
Finance and insurance	38	18.27	90	43.27
Public administration	30	14.42	120	57.69
Other services (not listed here)	27	12.98	147	70.67
Manufacturing	17	8.17	164	78.85
Health care and social assistance	10	4.81	174	83.65
Construction	6	2.88	180	86.54
Arts, entertainment, and recreation	5	2.40	185	88.94
Utilities	4	1.92	189	90.87
Retail trade	4	1.92	193	92.79
Accommodation and food services	4	1.92	197	94.71
Information	3	1.44	200	96.15
Wholesale trade	2	0.96	202	97.12
Transportation and warehousing	2	0.96	204	98.08
Real estate and rental and leasing	2	0.96	206	99.04
Agriculture, forestry, fishing and hunting	1	0.48	207	99.52
Professional, scientific, and technical services	1	0.48	208	100.00

Missing = 1.

Table 5
Cronbach's alpha, composite reliability, and average variance extracted.

Construct	Cronbach's alpha	Composite reliability	Average variance extracted
Technological competence	0.789	0.794	0.660
Management support	0.887	0.890	0.732
Standards	0.896	0.900	0.818
Professional help	0.758	0.764	0.520
Application-level audit analytics usage	0.880	0.881	0.713
Feature-level audit analytics usage	0.894	0.939	0.837
Performance	0.866	0.873	0.696

Freedom = 155, RMSEA = 0.042 (90% confidence interval 0.027-0.056), CFI = 0.976, and GFI = 0.911. We use three criteria following prior literature (McKnight et al., 2002): coefficient of individual item is greater than 0.6, each path is significant, and each path loading is greater than twice its standard error. All our items pass these criteria, with loading ranging from 0.647 to 0.965. Factor loadings, as well as descriptive statistics of each item used in the measurement model, are reported in Table 7. Skewness of each item is less than the threshold of 1.96 and none of the items has large standard deviation.

The correlations between all the constructs in the measurement model are presented in Table 8. None of the correlations is above the 0.85 threshold, and none of the squared correlation is larger than the Average Variance Extracted (AVEs) of either of the corresponding constructs (reported in Table 5), suggesting good discriminant validity of constructs (Fornell and Larcker, 1981).

5. Empirical results

5.1. Descriptive analysis of audit analytics tools

There are in total 17 tools examined in this study. Participants were asked to rate the usage frequency of different tools in the overall audit process on a scale of 1 (never) to 7 (every time). Table 9 lists the mean, median, and standard deviation of ratings for all

Table 6
Factor loadings.

	Factor						
	Feature-level audit analytics usage	Standards	Management support	Performance	Application-level audit analytics usage	Technological competence	Professional help
AL1	0.328	0.186	0.256	0.148	**0.480**	0.134	0.280
AL2	0.414	0.269	0.068	0.184	**0.786**	0.225	0.112
AL3	0.438	0.287	0.180	0.235	**0.858**	0.097	0.176
AL4	0.462	0.219	0.277	0.229	**0.835**	0.189	0.248
MS1	0.175	0.135	**0.769**	0.132	0.281	0.033	0.186
MS2	0.212	0.154	**0.886**	0.161	0.210	− 0.093	0.381
MS3	0.159	0.104	**0.653**	0.045	0.135	− 0.012	0.307
MS4	0.206	0.109	**0.884**	0.179	0.155	− 0.009	0.375
SD1	0.234	**0.910**	0.133	0.331	0.250	0.079	0.205
SD2	0.154	**0.470**	0.067	0.176	0.113	0.121	0.109
SD3	0.177	**0.883**	0.086	0.283	0.237	0.115	0.113
PH2	0.164	0.080	0.189	0.267	0.266	0.018	**0.666**
PH3	0.180	0.181	0.319	0.262	0.115	− 0.095	**0.687**
PH4	0.188	0.186	0.243	0.161	0.107	0.044	**0.800**
VL1	0.217	0.268	0.174	**0.776**	0.173	0.146	0.399
VL2	0.299	0.316	0.094	**0.803**	0.226	− 0.038	0.213
VL3	0.247	0.377	0.089	**0.885**	0.205	0.059	0.272
VL4	0.253	0.279	0.125	**0.602**	0.273	0.056	0.183
TC2	0.151	0.079	− 0.014	0.070	0.129	**0.818**	0.002
TC3	0.183	0.107	− 0.033	− 0.030	0.081	**0.796**	− 0.029
FL1	**0.833**	0.219	0.143	0.268	0.461	0.256	0.218
FL2	**0.979**	0.198	0.196	0.243	0.398	0.201	0.210
FL3	**0.894**	0.232	0.152	0.243	0.408	0.276	0.173

Cells in bold refer to factor loadings on each item's intended construct.

Table 7
Descriptive statistics and factor loadings of items.

Constructs	Item	Factor loading	Mean	Median	STD	Skewness
Application-level audit analytics usage	AL2	0.796	3.531	3.000	1.768	0.362
	AL3	0.887	4.172	4.000	1.681	− 0.146
	AL4	0.847	4.789	5.000	1.697	− 0.495
Management support	MS1	0.743	5.651	6.000	1.296	− 1.346
	MS2	0.946	5.325	6.000	1.326	− 0.929
	MS4	0.866	5.354	6.000	1.286	− 1.015
Standards	SD1	0.965	5.431	6.000	1.167	− 0.802
	SD3	0.840	5.311	6.000	1.178	− 0.875
Professional help	PH2	0.647	4.995	5.000	1.158	− 0.553
	PH3	0.743	5.455	6.000	1.083	− 0.570
	PH4	0.767	5.646	6.000	1.056	− 0.959
Performance	VL1	0.781	6.000	6.000	0.956	− 1.034
	VL2	0.801	5.900	6.000	0.988	− 0.885
	VL3	0.915	6.038	6.000	0.871	− 0.692
Technological competence	TC2	0.744	1.597	1.386	0.936	1.752
	TC3	0.876	0.874	0.693	0.958	1.655
Feature-level audit analytics usage	FL1	0.861	2.097	2.303	0.785	− 1.354
	FL2	0.965	1.008	1.099	0.581	− 0.386
	FL3	0.916	2.759	2.833	0.388	− 0.474
Firm size	SIZE		7.918	7.901	1.939	− 0.345
IT complexity	IT		5.761	6.000	1.148	− 0.849

tools. The most frequently used tool is summarize (5.00), followed by sampling (4.95) and duplicate detection (4.52).

The least used tools are regression (2.38), clustering (2.46), Benford's Law (2.79), and Exam Sequence (2.88). The most frequently used tools tend to be easy to use and serve as the starting point for follow-up analysis. Untabulated results in our study show that ease of use is rated as the most important factor by internal auditors when selecting tools. The least used tools are generally more complicated in terms of both usage and ease of understanding.

Overall, usage frequency ratings of different tools show that there is a gap between what practitioners are doing and what academia advocates. For example, current research has devoted efforts in applying clustering (Thiprungsri and Vasarhelyi, 2011) and data mining (Debreceny and Gray, 2010) into fraud detection and anomaly identification. While these advanced methods were shown to be effective by prior studies, practitioners are still reluctant to use them, possibly due to lack of knowledge.

Table 8
Correlation between constructs.

	Application-level audit analytics usage	Management support	Standards	Professional help	Performance	Technological competence	Feature-level audit analytics usage	Size	IT complexity
Application-level audit analytics usage		0.306	0.386	0.294	0.352	0.181	0.596	0.008	0.115
Management support			0.214	0.489	0.241	− 0.064	0.280	− 0.100	0.073
Standards				0.293	0.477	0.104	0.295	− 0.031	0.187
Professional help					0.423	− 0.028	0.304	− 0.040	0.096
Performance						0.040	0.365	0.003	0.023
Technological competence							0.266	0.422	0.050
Feature-level audit analytics usage								0.144	0.029
Size									− 0.049
IT complexity									

Table 9
Descriptive statistics of tool usage.

	Mean	Mean	Median	STD
Basic tools	summarize	5.00	5.00	1.57
	sampling	4.95	5.00	1.62
	stratify	4.01	4.00	1.69
	descriptive_statistics	3.86	4.00	1.71
	gap_detection	3.67	4.00	1.64
	aging_analysis	3.65	4.00	1.64
	cross_tabulations	3.54	4.00	1.73
	ratio_analysis	3.52	4.00	1.70
	exam_sequence	2.88	3.00	1.68
	trend_analysis	3.88	4.00	1.76
	data_visualization	3.62	4.00	1.80
	benford_law	2.79	2.00	1.64
Advanced tools	text_mining	2.91	3.00	1.67
	regression	2.38	2.00	1.42
	duplicate_detection	4.52	5.00	1.49
	fraud_detection_tool	3.74	4.00	1.81
	clustering	2.46	2.00	1.44

All responses are on a seven point Likert scale. 1: never; 2: rarely; 3: occasionally; 4: sometimes; 5: frequently; 6: usually; 7: every time.

The lower diagonal of Table 10 shows the correlation between these tools while the upper diagonal shows the correlations after deleting responses with the value of 1 (never use). All correlations are significant at 0.001 levels. This supports the argument that internal auditors will not use one specific analytics tool solely; instead they tend to explore various tools at the same time. As they accumulate knowledge and gain experience with audit analytics, the usage of different tools tends to increase simultaneously.

Highly correlated tools include gap detection and duplicate detection (0.677), data visualization and descriptive statistics (0.654), and trend analysis and ratio analysis (0.670). The results are within expectation; these tools tend to work on the same level. For example, gap detection and duplicate detection work with individual transactions to filter out highly suspicious transactions directly, while ratio analysis and trend analysis reveal the patterns in a time series and identify anomalies indirectly.

5.2. Structural equation model

The structural model shows acceptable fit: RMSEA is 0.044 (90% confidence interval 0.027 to 0.057), which is well below the commonly accepted threshold 0.08 (Browne and Cudeck, 1993; Barua et al., 2004). Chi-square = 230.579, Degree of Freedom = 165, SRMR = 0.065, CFI = 0.972, GFI = 0.905. These fit indexes suggest that the structural model is properly developed.

Fig. 2 displays the standardized paths. For application-level audit analytics usage, three of the six TOE factors are significant: management support, technological competence, and standards. They all have positive paths to the dependent construct. The coefficient of professional help is positive but is not statistically significant ($p = 0.11$). Thus, Hypotheses 2, 3, and 6 are supported while Hypotheses 1, 4, and 5 are not supported.

All hypotheses dealing with feature-level audit analytics usage are supported: application-level usage, technological competence, and professional help are shown to have significant positive association with feature-level audit analytics usage, with application-level usage showing the largest impact.

Both application-level and feature-level audit analytics usage have significant influence on improving internal audit. The impact of application-level usage (0.262) is larger than that of feature-level audit analytics usage (0.243). Hypotheses 10 and 11 are supported.

6. Discussion of results

The hypothesis test results are summarized in Table 11. Hypothesis 1 is not supported. While this seems to suggest that IT complexity has no impact on application-level audit analytics usage, cautions should be exerted that the insignificance of the construct could also result from the lack of variance for IT complexity as about 90% of the participating firms rate IT complexity higher than 4 on a seven point Likert scale.

Hypothesis 2 is supported, suggesting that more technologically competent internal audit departments will use audit analytics frequently throughout the audit process. By contrast, internal audit departments with fewer technologically competent auditors may rarely use audit analytics and are unable to take advantage of it. For firms that intend to expand audit analytics usage, our results demonstrate that they can hire auditors who are knowledgeable of technology and audit analytics.

Management support and standards are shown to be major facilitators of application-level audit analytics usage. Most participants indicate that management support and encouragement by standards are high (mean = 5.45 and 5.32, respectively). These two constructs have comparable magnitudes of effect and are more powerful than technological competence in enabling the usage of audit analytics software. It implies that the attitudes of both upper management and standard setters are critical in deciding whether

Table 10
Correlations between tools.

	descriptive_statistics	duplicate_detection	gap_detection	benford_law	summarize	aging_analysis	exam_sequence	cross_tabulations	stratify	sampling	ratio_analysis	data_visualization	regression	clustering	text_mining	trend_analysis	fraud_detection_tool
descriptive_statistics		0.330	0.476	0.399	0.474	0.324	0.421	0.572	0.461	0.348	0.515	0.539	0.369	0.275	0.398	0.516	0.420
duplicate_detection	0.485		0.691	0.265	0.589	0.324	0.348	0.389	0.571	0.304	0.253	0.471	0.234	0.232	0.328	0.393	0.495
gap_detection	0.539	0.677		0.455	0.519	0.471	0.496	0.472	0.681	0.458	0.522	0.521	0.378	0.351	0.480	0.492	0.517
benford_law	0.437	0.397	0.472		0.230	0.230	0.392	0.444	0.377	0.253	0.411	0.434	0.561	0.523	0.387	0.360	0.405
summarize	0.573	0.606	0.547	0.263		0.333	0.197	0.467	0.495	0.460	0.444	0.462	0.182	0.123	0.254	0.451	0.470
aging_analysis	0.496	0.520	0.585	0.391	0.447		0.273	0.345	0.466	0.284	0.467	0.338	0.283	0.229	0.151	0.397	0.450
exam_sequence	0.503	0.391	0.530	0.416	0.341	0.435		0.456	0.355	0.254	0.412	0.482	0.382	0.297	0.336	0.227	0.344
cross_tabulations	0.612	0.456	0.544	0.374	0.493	0.487	0.498		0.528	0.212	0.449	0.464	0.437	0.381	0.414	0.435	0.460
stratify	0.522	0.512	0.632	0.405	0.493	0.486	0.434	0.584		0.385	0.605	0.541	0.446	0.378	0.388	0.454	0.497
sampling	0.385	0.287	0.367	0.273	0.440	0.222	0.299	0.356	0.394		0.582	0.404	0.211	0.180	0.236	0.403	0.390
ratio_analysis	0.603	0.506	0.637	0.460	0.493	0.606	0.437	0.538	0.595	0.461		0.594	0.519	0.418	0.354	0.540	0.395
data_visualization	0.654	0.452	0.560	0.357	0.536	0.452	0.477	0.574	0.539	0.391	0.631		0.491	0.510	0.542	0.671	0.475
regression	0.522	0.340	0.516	0.540	0.295	0.501	0.514	0.547	0.492	0.297	0.612	0.545		0.878	0.526	0.475	0.357
clustering	0.472	0.312	0.510	0.450	0.287	0.447	0.487	0.565	0.458	0.316	0.574	0.564	0.853		0.533	0.508	0.350
text_mining	0.438	0.392	0.518	0.420	0.366	0.414	0.378	0.439	0.390	0.196	0.506	0.548	0.617	0.645		0.571	0.521
trend_analysis	0.550	0.472	0.560	0.382	0.492	0.563	0.356	0.546	0.494	0.384	0.670	0.622	0.554	0.628	0.653		0.566
fraud_detection_tool	0.473	0.453	0.511	0.400	0.386	0.506	0.411	0.419	0.446	0.209	0.445	0.457	0.461	0.465	0.525	0.597	

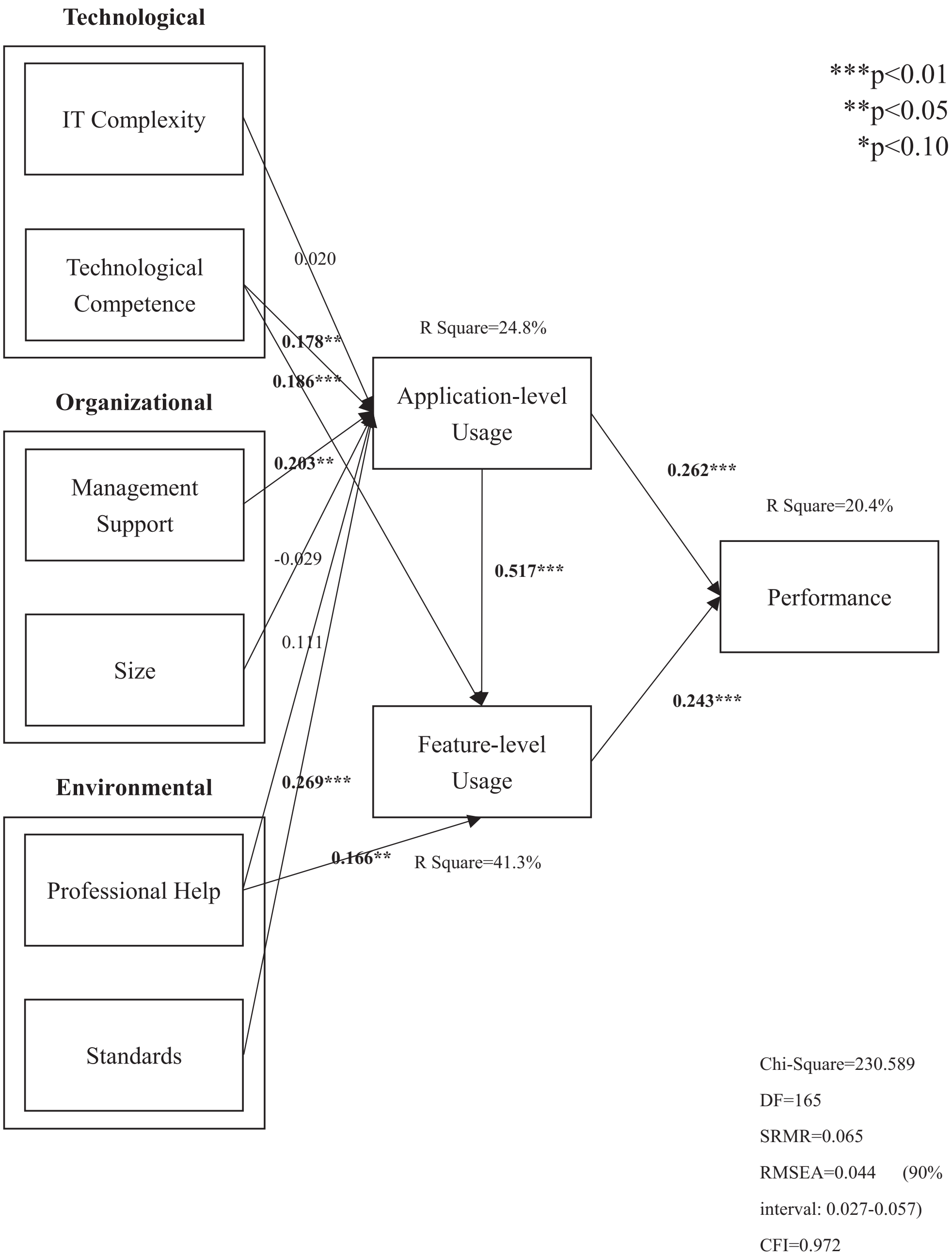

Fig. 2. Audit analytics use and value-results.

internal audit departments will frequently use audit analytics. Since audit analytics have been shown to be effective in improving efficiency and effectiveness in internal audit, management and regulators can be more active in emphasizing its importance and benefit, and providing financial and legal support for using audit analytics.

Firm size does not significantly influence adoption. One reason could be that this study focuses on the audit analytics usage of internal audit departments rather than the entire company. Since mixing the scope of size may introduce mixed results (Lee and Xia, 2006), the insignificance of firm size is not without expectation. Another reason could be that audit analytics software seems affordable even to small companies. For example, one license of CaseWare IDEA[9] was $1995 for a single user per year.[10] Therefore, firm size may not significantly drive application-level audit analytics usage.

[9] CaseWare IDEA is a widely-used audit analytics software for auditors and accountants.
[10] http://www.casewareanalytics.com/sites/default/files/uploads/caseware_idea_price_list_-usd.pdf.

Table 11
Hypotheses testing.

Hypothesis	Path coefficient	Supported?
H1: Firms with greater IT complexity are more likely to achieve greater application-level audit analytics usage.	0.020	No
H2: Firms with better technological competence are more likely to achieve greater application-level audit analytics usage.	0.178	Yes
H3: Firms with stronger management support are more likely to achieve greater application-level audit analytics usage.	0.203	Yes
H4: Larger firms are more likely to achieve greater application-level audit analytics usage.	− 0.029	No
H5: Firms with better professional help are more likely to achieve greater application-level audit analytics usage.	0.111	No
H6: Firms with higher perceived level of encouragement by auditing standards are more likely to achieve greater application-level audit analytics usage.	0.269	Yes
H7: Firms with greater application-level audit analytics usage are more likely to achieve greater feature-level audit analytics usage.	0.517	Yes
H8: Firms with better technological competence are more likely to achieve greater feature-level audit analytics usage.	0.186	Yes
H9: Firms with better professional help are more likely to achieve greater feature-level audit analytics usage.	0.166	Yes
H10: Firms with greater application-level audit analytics usage are more likely to achieve better performance in internal audit.	0.262	Yes
H11: Firms with greater feature-level audit analytics usage are more likely to achieve better performance in internal audit.	0.243	Yes

Hypothesis 5 is not supported, indicating that proper technical support does not influence application-level audit analytics usage by the audit department. However, professional help has significant positive impact on feature-level audit analytics usage. The seemingly counterintuitive results can be explained as follows: internal auditors are able to perform some simple audit analytics tools without professional help. Examples of such techniques include summarization, stratification, and sampling. However, professional help is necessary for using advanced audit analytics tools. Since the application-level usage construct does not differentiate between simple and advanced tools, professional help should not have a significant impact on it. In contrast, the feature-level audit analytics usage construct considers specific tools and accounts for the complexity of those tools. Internal auditors who can obtain professional help are better able to use advanced tools appropriately, while auditors without technical support are less likely to use them.

Application-level audit analytics usage has the largest impact on feature-level audit analytics usage. This reveals that using audit software frequently increases the likelihood of using more audit analytics tools. Hypothesis 8 demonstrates that for firms to explore more analytical tools, competence in technology is a key factor. Since technological skill is critical for both application and feature-level audit analytics usage, hiring competent auditors seems to be an efficient way to equip the audit department with audit analytics.

Finally, both application and feature-level usage are shown to improve the performance of the internal audit process, with application-level usage having a larger effect. The results demonstrate that using either basic or advanced analytics tools can increase the efficiency and effectiveness of audit work. It thus encourages internal audit departments to engage in audit analytics, because they can benefit even if they only use basic analytics techniques.

7. Conclusion, limitations, and future research

This paper examines factors that influence post adoption usage of audit analytics, as well as whether using audit analytics improves the performance of the internal audit function. We identified factors from an organizational level rather than an individual level to fill the gap in the prior literature. By adopting the TOE framework, we hypothesized several constructs that could facilitate application-level and feature-level audit analytics usage, and empirically examined whether using analytics improves the performance of the internal audit process.

The results indicate that application-level audit analytics usage by internal auditors is driven by their perceived level of importance and technological capability. Encouragement by management and regulators are the most important factors in shaping how internal auditors use audit analytics. Factors that relate to firm's characteristics, such as IT complexity and firm size, do not have significant influence.

Feature-level audit analytics usage is influenced by professional help, technological competence, and application-level audit analytics usage. It supports the argument that advanced audit analytics tools require expertise in statistics and technology, which can be acquired by frequently using audit analytics throughout the audit process, or by enhancing technological competence and seeking assistance from vendors. Finally, both application-level and feature-level audit analytics usage improve the performance of the internal audit process.

The results in this paper should be valuable to both practitioners and regulators. Software vendors can use the factors identified in our model to promote their products efficiently. They may also consider improving the quality of customer support to expand audit analytics usage by their customers. Additionally, our findings can help firms acknowledge that the most effective ways to encourage audit analytics usage is by hiring competent auditors and providing financial support. Lastly, since standards are shown to be a powerful driver, regulators can develop rules or guidance to encourage the use of audit analytics.

7.1. Contributions

This paper contributes to the literature in at least three ways. First, we are among the first to study actual usage of audit analytics by internal auditors in an organizational setting. Prior research that examines internal audit technology adoption mostly focuses on individual factors. The only known exception is Rosli et al. (2012), who proposed to investigate Generalized Audit Software (GAS) from an organizational level and call for further empirical research. Second, we study the actual usage of audit analytics, rather than the intention of using it. As Janvrin et al. (2008) suggested, the tool itself does not improve efficiency or effectiveness, but users do. It is thus relevant and important to study actual usage behaviors. Third, we are among the first to separate application-level and feature-level audit analytics usage. Prior research does not distinguish analytics software, basic analytics tools, or advanced tools. Our study shows that at the current stage, it is mostly the usage of basic audit analytics tools that improve audit efficiency and effectiveness.

7.2. Limitations

Our study has several limitations. First, due to the limited sample size, it is impossible to test the interaction effect between firm size and the public or private binary. Tests like this will reduce our sample to a level that cannot generate statistically robust results. Further research could address this issue with enough observations. Second, the survey participants are clients of one audit software vendor, which may limit the generalization of the findings in this paper. However, this limitation is not going to significantly influence the results, as the vendor is one of the largest players in the market. However, if an audit analytics tool is not included in the vendor's product, it could be difficult to obtain an accurate result of its usage. Third, the vendor reveals that they do not know whether the clients are using its products exclusively, or use it in combination with other audit software packages, which could possibly induce bias in our sample. Further research could conduct similar research on a larger sample that includes clients of multiple audit software vendors. Fourth, this paper measures whether audit analytics improves the performance of the internal audit function using respondents' perceptions. Obtaining objective measures would increase the validity of this study. Similarly, respondents were asked to self-rate their usage of different audit analytics tools. A more accurate measure could be the actual usage of each tool from log files. However, the software vendor indicates that they do not collect such information due to privacy concerns. Fifth, the high item cross-loadings between feature-level and application-level constructs may indicate that there exists multicollinearity, which could result in inaccurate parameter estimates, large standard errors of estimates, and a high probability of Type 2 errors (Grapentine, 2000; Grewal et al., 2004). Grewal et al. (2004) states that the problem becomes severe when the multicollinearity is extreme (larger than 0.9) and when the composite reliability is low (smaller than 0.7). Because the correlation between feature-level and application-level constructs is 0.596, and because composite reliability of feature-level and application-level constructs is 0.939 and 0.881, respectively, it appears that high item cross-loadings are not a major concern in this study.

7.3. Future research

There are several opportunities for future research. First, the interaction effect of technological competence and professional help could be examined. Since help from vendors has a differential effect on application-level and feature-level audit analytics usage, it would be interesting to explore whether its impact is conditional on technological competence. Second, it is worthwhile to examine how the nature of analytical tools could affect their usage. Some analytical tools deliver intuitive information that is easy to understand, while others operate as "black boxes" with oblique underlying methods. Auditors may have preferences on different analytical tools due to their conservative nature and constraints from regulations. Third, the extent of external auditor reliance on the analytical results from internal auditors, and whether internal auditors' analytical work could improve external audit quality, are still unknown. As internal auditors usually have more frequent access to companies' financial or operational data, they could discover risks and exceptions in time by using appropriate analytics. External auditors may utilize such information to expand the audit scope and enhance accuracy. Fourth, it would be interesting to investigate how the analytical work performed by internal auditors could affect external auditors' workload, and further impact audit fees. Internal auditors' analysis could provide valuable insights to external auditors on risk assessment by locating high-risk processes or transactions, reducing external auditors' workload. Last, future research could track operation logs of analytical software to measure actual audit analytics usage, and examine whether the results in this study hold. A comparison between self-reported usage and actual usage would also add great value to the audit analytics literature.

Appendix A. Questionnaire

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