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What Makes AI Different? Exploring Affordances and Constraints - The Case of Auditing

Jiaqi Yang
Macquarie University, jiaqi.yang@students.mq.edu.au

Mauricio Marrone
Macquarie University, mauricio.marrone@mq.edu.au

Alireza Amrollahi
Macquarie University, ali.amrollahi@mq.edu.au

WHAT MAKES AI DIFFERENT? EXPLORING AFFORDANCES AND CONSTRAINTS - THE CASE OF AUDITING

Research Paper

Jiaqi Yang, Macquarie University, Sydney, Australia, jiaqi.yang@hdr.mq.edu.au

Mauricio Marrone, Macquarie University, Sydney, Australia, mauricio.marrone@mq.edu.au

Alireza Amrollahi, Macquarie University, Sydney, Australia, ali.amrollahi@mq.edu.au

Abstract

This study aims to gain a comprehensive understanding of the differences between classic IT and AI artefacts. To achieve this objective, the study employs a grounded theory literature review approach and analyses 81 papers related to the application of classic IT and AI artefacts in the auditing industry. Drawing on the Technology Affordances and Constraints Theory, we examine the actions that can be potentially enabled or restricted by using classic IT and AI artefacts. This analysis allows us to conceptualise and compare the affordances and constraints associated with these two types of artefacts. The study addresses the need for more research on AI from both social and technical perspectives. Our findings may facilitate practitioners in improving their business processes and promoting effective collaboration between humans and AI.

Keywords: AI, Auditing, Technology Affordances and Constraints Theory, Literature Review

1 Introduction

The integration of AI into various aspects of society has significantly disrupted people's lives. The disruption caused by AI is considered to be critically different from that caused by other forms of IT because it changes how information is processed in people's decision-making (Balasubramanian et al., 2022, Brynjolfsson and McAfee, 2014). Backed up by massive volumes of data, fine-tuned algorithms and strong computational capacity, AI has become an integral component of modern society (Dwivedi et al., 2021). The application of AI has been extended to many areas, including agriculture (Spanaki et al., 2021) and manufacturing (Demlehner et al., 2021). It has even created a surgent discussion about the impact of AI instantiations like ChatGPT on academic integrity (Graham, 2022).

The significant impact of AI on society, however, warrants more research from the *socio-technical* perspective into how social entities and AI artefacts intertwine to create new avenues for contemporary social and organisational practice. Nevertheless, this kind of study is limited, and scholars have called for more research on AI from both social and technical aspects (Berente et al., 2019). We especially lack a comprehensive understanding of the difference between classic IT and AI artefacts. This gap can have negative consequences for both research and practical applications, as researchers are inhibited from articulating the distinct AI-human interaction model and further studying the impact of the interaction. Additionally, without such understanding, individuals and organisations may have unrealistic expectations of AI and disregard the critical skills required to utilise AI. To address these gaps, we propose that the Technology Affordances and Constraints Theory (TACT) can be utilised to differentiate AI artefacts from classic IT (Faraj and Azad, 2012). Technology affordance refers to what individuals or organisations with particular goals (hereafter referred to as social actors) can do with technology, while technology constraint refers to limitations imposed by technology on social actors (Majchrzak and Markus, 2012). TACT offers a lens to understand how technologies enable and limit particular actions, providing the basis for highlighting the capabilities and limitations of AI artefacts, in contrast to classic IT, when used to achieve certain goals.

TACT theorists cautioned that the study of affordance and constraints must be situated within specific contexts and boundary conditions. In the extant literature, the TACT is usually used as a mid-range theory to study the interaction between technology and social actors in a particular context (Strong et al., 2014, Burton-Jones and Volkoff, 2017). This is because the same artefact may exhibit different affordances when the users are driven by different goals (Faraj and Azad, 2012). For instance, studies reveal that the affordance of AI in HR services may be quite different from that of car manufacturing (Demlehner et al., 2021, Trocin et al., 2021). Because the research interest is to compare the various affordances and constraints associated with AI and classic IT, the research subject should be a social group undergoing significant technological changes. Following this consideration, we select the auditing profession as it has a long and sustaining tradition of relying on IT to deliver its services, from a series of computer-assisted auditing tools in earlier years to AI-enabled artefacts more recently (Sutton et al., 2016, Goto, 2022). Auditing is a professional service that assures the reliability of the information in the financial reports prepared by management (Knechel and Salterio, 2016). The impact of AI on the auditing profession is significant, with various types of AI artefacts involved in service delivery (Munoko et al., 2020). Selecting auditing as the research context, this study sets out to provide an understanding of the affordances and constraints associated with AI compared to classic IT without an AI component. We accordingly pose the following research question:

RQ. In terms of affordances and constraints, what are the differences between classic IT and AI artefacts utilised in the auditing industry?

Our research used a systematic literature review approach to analyse existing studies on classic IT and AI artefacts in auditing (Wolfswinkel et al., 2013). This method enabled us to compare the material properties of these tools, including functionality and other properties such as packaging, arrangement, and appearance (Markus and Silver, 2008). Such comparison forms the basis for identifying AI's distinct affordances and constraints. This study was motivated to make theoretical and practical contributions by developing an understanding of the unique material properties of AI that enable or limit individual and organisational actions. Our findings offer a theoretical perspective on the socio-technical aspects of AI and may be helpful for future research examining the interaction between AI's material properties and actors' goal orientation. The study's insights may also be useful for firms seeking to improve their business processes and promote better human-AI collaboration.

The paper is structured as follows. In the next section, we provide the background of classic IT and AI usage in the auditing industries and an overview of affordance theory. Next, we present the study's methodological approach to conducting a systematic literature review. This is followed by findings and discussion that synthesise and critically analyse extant literature on classic IT and AI in auditing. Finally, we elaborate on the study's contributions and implications.

2 Research Background

2.1 Evolution of auditing tools from classic IT to AI

Given that the auditing industry is the focal research context, it is imperative to glance at auditing tools' progression from classic IT to modern AI artefacts. In this study, the term 'classic IT' denotes the conventional software systems that are programmed using explicit instructions and algorithms to be executed by computers. This stands in contrast to the data-driven and autonomous decision-making approach of AI. We acknowledged that reviewing all classic IT used in auditing within a single review is not feasible. Thus, a representative group, Computer-Assisted Auditing Tools and Techniques (CAATTs), is selected to analyse classic IT in auditing. The umbrella term CAATTs includes general-purpose software such as spreadsheet and word processors and generalised auditing software such as CaseWare IDEA (Ahmi and Kent, 2013). The term CAATTs was created in the 1980s when the auditing profession had just popularised computers. Professionals and researchers use this term to distinguish paper-based auditing and computer-assisted auditing. Initially, researchers prototyped Audit Command Language to consolidate the audit support functions into a common language of management information systems (Will, 1983). Later, CAATTs have broad applications in performing auditing tasks, such as detecting material misstatements, control deficiencies, and fraud (Bradford et al., 2020).

As early as the 1980s, researchers discussed AI's potential to change audit methodologies (Elliott, 1986). At the primitive stage, researchers frequently referred to AI as a series of expert systems and decision support systems (Hansen and Messier, 1986, Elliott, 1986, Elam and Mead, 1990). These artefacts were claimed to have intelligence because they could use a network of decision rules to describe a complex system and converse meaningfully with auditors. The application of expert systems and decision support systems was limited to some structured and semi-structured tasks (Abdolmohammadi, 1991). Despite the above developments, the profession's understanding of AI was very limited in those early days, and it evolved with the advancement of technology. In the late 1990s and early 2000s, for example, researchers explored the opportunity to use machine learning-based data analysers, such as Neuro Shell 2, to classify and predict management fraud and bankruptcy (Green and Choi, 1997). This research stream flourished in the 2010s when researchers attempted different machine learning algorithms with various parameters to improve classification accuracy. The algorithms include artificial neural networks, Bayesian networks, decision tree models, support vector machines, and ensemble methods (Perols, 2011). For example, the Bayesian belief network enables calculating the probability of financial statement fraud, while the Naïve Bayes hybrid model offers a set of decision rules to detect fraudulent firms (Hajek and Henriques, 2017). The types of data that machine learning can process also expanded as the technology matures, from only five financial ratios in Green and Choi (1997) to 84 financial ratios and 21 social media and disclosure with sentimental, topical, emotional, and linguistic features in Dong et al. (2018). The auditing industry has experienced a surge in the utilisation of AI since the 2010s, and it is anticipated that this trend will persist in the foreseeable future (Sutton et al., 2016). Nowadays, AI applications are increasingly integrated into the grand auditing platform. For instance, Deloitte has developed the AI-enabled auditing system 'Argus' to recognise key contract terms, trends, and outliers.

In this paper, we established criteria to distinguish AI artefacts from classic IT. CAATTs are considered classic IT without an AI component because they are limited to the functionality that has been programmed into them, such as data analysis and report generation. Their operational capabilities are limited to executing the tasks that have been specifically defined, and they do not possess the ability to learn from data or make decisions based on insights generated from the data. These features distinguish them from AI artefacts, which possess higher intelligence and autonomy. We followed the definition by Russell et al. (2010, p. 31), referring to AI as the technology that "enables the machine to exhibit human intelligence, including the ability to perceive, reason, learn, and interact." The AI Tree by Sutton et al. (2016) informed this study about taking a broad lens in considering AI applications, including various machine learning algorithms and knowledge-based expert systems and decision support systems. We also referred to other research which expands the AI spectrum by adding deep learning, natural language processor, computer vision, and robotic process automation (Tiron-Tudor and Deliu, 2022). This classification is close to the widely accepted AI typology in the IS discipline that AI refers to machine learning, machine vision, natural language processor, expert systems, and robotics (Collins et al., 2021).

2.2 Technology Affordances and Constraints Theory

We utilised the TACT to answer our research question considering its power in explaining the process and consequence of the human-IT interaction at multiple societal levels. The concept of affordances, initially introduced in ecological psychology by Gibson (1977), describes what is offered, provided, or furnished to someone by an object. Subsequently, the concept gained attention in the IS field. We draw on prior literature and adopt the following definition of technology affordances and constraints: "The concept of technology affordance refers to an action potential, that is, to what an individual or organisation with a particular purpose can do with a technology or information system; technology constraint refers to ways in which an individual or organisation can be held back from accomplishing a particular goal when using a technology or system" (Majchrzak & Markus, 2012, p. 1). That means affordances and constraints exist as a relationship between goal-directed actors and the artefacts, where artefacts enable and constrain potential actions to achieve goals. Pozzi et al. (2014) explained the relationship by making a good example of an actor who desires to enter another room by passing through a door. The door's affordance is determined by its width and the actor's physical capability to pass through it. However, the door may become a constraint for an actor whose width exceeds the door size. TACT has been widely accepted by IS scholars. For example, in the context of tensions in crowdsourcing for innovation, TACT has been used to identify design affordances and constraints that can increase the possibility of co-creation among strangers (Majchrzak and Malhotra, 2013). In other studies, TACT has helped researchers address assumptions about the differentiation between innovation process and outcome, specifically addressing complex, dynamic interactions and duality between digital innovation processes and outcomes (Nambisan et al., 2017).

We were guided by prior research advocating the use of materiality as a theoretical lens for studying IS phenomena (Faraj and Azad, 2012). A typical Cartesian perspective may differentiate classic IT and AI by characterising the features and functions of the two types of artefacts. However, scholars have emphasised the dangers of viewing technology as a bundle of features and product classes, which leaves researchers unable to distinguish between taken-for-granted features and emergent technology-in-use when users encounter IT in a situated context (Faraj and Azad, 2012). For example, both AI and classic IT possess data analysis functions, which do not indicate a substantial difference between these two artefacts. Therefore, to overcome such limitations, we adopt TACT to differentiate AI from classic IT by comparing the action potential offered and constrained by these two artefacts. The analysis of affordances and constraints is rooted in the mutual relations between actors and artefacts. As such, we are able to gain rich insights into the difference between classic IT and AI, not only from the perspective of functionality but also from the angle of actors with evolving goal orientations.

3 Research Methodology

This study adopts the literature review method to address the research question, informed by the grounded theory literature review approach by Wolfswinkel et al. (2013). The approach involves selecting a set of articles as the data source for exploring and extracting relevant 'excerpts' that can be used to generate the theory (Rowe, 2014). It should be emphasised that a "grounded theory approach" in this context does not mean that this review creates a brand-new theory from the very sketch. Instead, it relies on TACT to conceptualise the distinct properties of AI artefacts affording and constraining specific actions. The grounded theory literature review approach is appropriate in this research context because it offers a comprehensive and in-depth analysis of a novel and evolving phenomenon. For example, prior research reviews the literature to theorise the affordance of social media regarding organising (Leonardi and Vaast, 2017). In another study, the authors conducted a review to provide an affordance-based institutional logic on IT and social changes (Faik et al., 2020).

Following the grounded theory approach to the literature review (Wolfswinkel et al., 2013), we first defined the inclusion and exclusion criteria for selecting articles. This review applies the quality threshold by referring to two widely recognised journal ranking guides, the Academic Journal Guide 2021 (ABS list) and the Australian Business Deans Council 2019 (ABDC list). We included journals ranked 4*, 4, or 3 on the ABS list or A* or A journals on the ABDC list. As an inclusion criterion, the articles must discuss either CAATTs or AI used in auditing. The exclusion criteria applied to papers were that 1) discuss other types of technology, such as cloud and blockchain, and 2) the context other than external financial statement auditing, such as internal and sustainability auditing.

Next, we identified the appropriate journals and relevant research fields. In the initial search, the Scopus Meta Database was used to conduct the keyword-based search, such as the combination of CAATTs & auditing and AI & auditing. Though the database identifies several research fields, after screening out the irrelevant ones, all the papers were found to be published in journals from three subject areas: Accounting, Management, and Information Systems. Accordingly, 357 journals were selected.

Subsequently, we decided on the specific search terms. This was challenging because AI and CAATTs are broad and generic terms with many sub-categories. Thus, we first searched the existing literature review focusing on AI and referred to their search terms. We found that the search terms used by Collins et al. (2021) and Borges et al. (2021) are the most current and comprehensive, covering most of the search terms used in other papers. We decided on the following search terms for AI artefacts in auditing: *("AI" OR "artificial intelligence" OR "machine learning" OR "neural networks" OR cognitive* OR automation* OR robot* OR augment* OR "Deep Learning" OR "Represent* Learning") AND (audit OR auditing OR auditor))*. Regarding CAATTs, unfortunately, there is no recent literature review on this topic. Therefore, we selected several influential articles discussing CAATTs and generated a set of keywords from the content (Curtis and Payne, 2014, Braun and Davis, 2003, Bierstaker et al., 2014, Janvrin et al., 2008). The following search terms were determined for CAATTs: *("Generalised Audit Software" OR "Computer Assisted Audit Tools and Techniques" OR "CAATTs" OR "Computer Assisted Audit Techniques" OR "CAATTs" OR "Computer Audit Software" OR "Computer Audit Package" OR "audit command language" OR "ACL" OR "interactive data extraction and analysis" OR "Test Data" OR "integrated test facility" OR "Utility program" OR "Specialized audit software") AND (audit OR auditing OR auditor))*.

We executed the search protocol in April 2022. The literature search first explored the entire Scopus Database using the defined search terms in the title, abstract and keywords. We did not limit the timeframe, as we aimed to include a comprehensive literature set in the initial literature pool. This allowed us to gain a holistic understanding of the evolution and advancement of CAATTs and AI in auditing. Following the initial search, the qualitative threshold was applied to limit the papers to 357 high-ranking journals. Finally, we screened the title, abstract, and full text based on the inclusion and exclusion criteria, ending up with 81 papers in the final pool. Figure 1 shows the literature selection process.

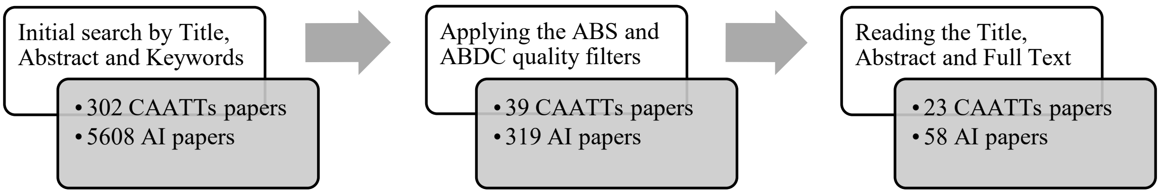

Figure 1. Literature selection process.

Informed by prior studies, the literature analysis commenced with the reading of ten randomly selected articles on AI and the CAATTs categories, which allowed us to become fluent with the subjects and to form the initial concepts regarding the affordance and constraints (Wolfswinkel et al., 2013, Hund et al., 2021). During the open coding stage, the authors extracted the ideas behind the excerpts and attached a label. Subsequently, these codes and concepts provided the foundation for conducting axial coding, where various relationships were identified. The open codes of the sample excerpts were categorised, and some relations between these categories emerged, such as the central phenomenon, context, actors, artefacts, and their interactions. The pilot excerpt analysis generated a codebook all authors reviewed and agreed upon. Based on the codebook, all the remaining articles were coded, and the relationships between codes were constantly challenged and modified. As the relations and categories were continuously refined and integrated, the selective coding generated a core category that explains the difference between CAATTs and AI artefacts regarding the affordances and constraints on actors' action possibilities. The following section presents the main findings.

4 Findings

We identified two sub-categories of CAATTs, and five sub-categories of AI artefacts studied in extant literature. We acknowledged that there might be an overlap between AI and CAATTs. For instance, prior studies might use the term 'AI' but actually refer to some classic IT. To address this issue, we constantly compare the described features and properties of the artefacts against the criteria we established in the literature review section to differentiate CAATTs from AI. This ensured that our categorisation was accurate and not solely based on the terminology in the manuscripts. Applying the TACT lens, we identified nine affordances and five constraints associated with CAATTs and AI artefacts. These findings formed the basis for further analysing how the affordances and constraints emerged from the interactions between the artefacts and actors.

4.1 A description and category of CAATTs

We identified two groups of CAATTs used in auditing, including Generalised auditing software (GAS) and continuous auditing system (CAS) (Lin and Wang, 2011, Braun and Davis, 2003, Ahmi and Kent, 2013). Generalised auditing software is auditing software with multiple data functions such as display, reading, analysis, manipulation, sampling, and extraction (Bradford et al., 2020). ACL and CaseWare IDEA are the two most frequently discussed generalised auditing software packages, but other packages with similar functions are available, such as ProAudit, CCH, IRIS and Mersia (Ahmi and Kent, 2013). Most generalised auditing software can only perform some fundamental data analysis based on the output of clients' ERP systems. By contrast, a continuous auditing system is an automated system that allows auditors to conduct controls and substantive tests on transactions throughout the year to detect abnormal transactions and to ascertain whether any modifications have been made to the computer program (Li et al., 2007). A continuous auditing system examines the accounting process rather than the accounting output. Based on the system architecture, it can be either an embedded audit module in the ERP system or an independent monitor and control layer owned and operated by the auditors (Singh et al., 2013). Table 1 summarises and categorises the CAATTs discussed in the literature.

Categories	Example artefacts	Exemplar research
GAS	ACL and CaseWare IDEA	Lin and Wang (2011), Braun and Davis (2003), Ahmi and Kent (2013)
CAS	SAPSECURE, CAMAP, and Bagheera-S modules	Li et al. (2007), Farkas and Hirsch (2016)， Singh et al. (2013), Alles et al. (2004)

Table 1. Category of CAATTs.

4.2 A description and category of AI artefacts used in auditing

We identified five groups of AI artefacts used in auditing, including computer vision (CV), robotic process automation (RPA), natural language processor (NLP), machine learning number analytics (MLNA)[1], expert systems and decision support systems (E/DS). Computer vision used in auditing is a system based on a computer expression recognition toolbox that can automatically detect untruthful information by performing facial rigidity analysis. Robotic process automation is an application that allows users to configure one or more scripts (sometimes referred to as "bots") to activate specific keystrokes in an automated fashion. A natural language processor is a toolkit based on machine learning algorithms that can process and analyse natural language with the capability of 'understanding' the content and contextual nuances. Machine learning number analytics contain a single or a collection of

1 We use the term 'number' rather than 'data' on purpose. While numbers, text, images, and even voice can be regarded as data, this artefact category can only process numerical data. We do this to differentiate this group of artefacts from others, such as natural language processors and computer vision.

machine learning algorithms that can be used for numerical data analysis and predictive modelling, usually with a graphical user interface that allows researchers to set up and tune the functions and key parameters. Decision support systems contain data and model subsystems with user interfaces, providing users access to data and models to support decision-making. In contrast, expert systems contain a knowledge base, database and inference engine that provides conclusions requiring specific knowledge.

Regarding categorisation, it is imperative to acknowledge that artefacts may exhibit overlaps, such as the WEKA software, which possesses the capability to process numerical data and natural language. Therefore, we have placed WEKA in both categories. Additionally, some advanced decision support systems have been reported to incorporate machine learning algorithms (Kratzwald et al., 2018). However, despite these observations, we have not found any instances of such systems discussed in the extant auditing literature. As a result, our categorisation is limited to the application of AI in the auditing industry. Table 2 summarises and categorises the AI artefacts used in auditing. Noteworthily, some machine learning-based auditing systems developed by large accounting firms, such as Argus and GL.ai, are excluded from the list. The reason is that the systems with a commercial license and IP protection have prevented researchers from accessing them, resulting in little insightful discussion over those systems.

Categories	**Example artefact**	**Exemplar research**
CV	Video-based screening system	Pentland et al. (2017)
RPA	Automation Anywhere; Blue Prism; UiPath	Eulerich et al. (2022), Huang and Vasarhelyi (2019), Werner et al. (2021)
NLP	Word2vec; Stanford CoreNLP toolkit; Wordnet Stemmer; GPT-2; WEKA	Dong et al. (2018), Craja et al. (2020), Brown et al. (2020)
MLNA	Brainmaker; Neuralyst; Neural Works Professional IV Plus; NeuroShell 2; N-NET; WinNN; InTrees; WEKA	Bhattacharya et al. (2011), Etheridge et al. (2000), Green and Choi (1997), Koh and Tan (1999), Bertomeu et al. (2021), Perols (2011)
E/DS	Analytical diagnostic tool; Client risk assessment tool; Fraud assessment tool; Audit Checklist; Decision rule; Statistical decision aids; Audit expert system	Abdolmohammadi (1991), Elam and Mead (1990), Baldwin-Morgan (1995), Nelson et al. (2000), Sutton et al. (2016), Dowling and Leech (2007)

Table 2. Category of AI artefacts used in auditing.

4.3 Affordances associated with CAATTs and AI artefacts

As mentioned earlier, affordances are action potential, a relational concept and a joint product of goal-oriented actors and the material properties of the artefacts (Faraj and Azad, 2012). Following this thought, we generated a list of affordances based on the mapping between auditors' goals and the material properties of the CAATTs and AI artefacts, referring to their functionalities and the consequences of usage. For instance, during an auditing interview, auditors strive to differentiate between veracious and deceptive responses; the material property of a video-based screening system facilitates the identification of dubious information by performing facial rigidity analysis (Pentland et al., 2017). In this context, a video-based screening system yields valuable insights to resolve decision-making intricacies, offering the potential for informed decision-making based on data rather than intuition. Accordingly, we code this affordance as 'data-informed decision making'. Table 3 explains the affordances with reference to the exemplar in literature.

Affordance	**Explanation**	**Exemplar**
(1) Data-informed decision making	Artefacts offer data insights into complex decision-making tasks, usually involving high judgement, contradictive evidence, and massive amounts of information.	*Because of deep learning's information identification function, the audit data warehouse covers semi-structured and unstructured data, describing the company from a variety of aspects and providing a wide range of audit evidence for decision-making (Sun, 2019, p. 98).*

(2) Upgrade work content	Artefacts afford a work content upgrade by reducing the effort on mundane, repetitive tasks, thus allowing expertise, judgement, and experience to be better utilised.	*Companies are finding that auditors are burdened by repetitive activities in audit processes and that RPA may help reduce this burden while simultaneously freeing up auditors to focus on value-enhancing tasks that require problem-solving, creativity, and human judgment (Eulerich et al., 2022, p. 965).*
(3) Structuralise process	Artefacts organise data, information and procedures into a structure, creating a path that is consistent with the prescribed methodology. This further offers standardisation of service and quality control.	*…provide an example of Deloitte's 'Cognitive Audit' strategy, which involves first standardising the audit process, after which, the standardised processes are digitised. Then the digitised tasks are automated, followed by employing advanced analytics to the audit. Finally, cognitive (augmented) technology is used to transform the audit (Munoko et al., 2020, p. 213).*
(4) Automate process	Artefacts offer opportunities for replacing labour-based procedures with machine-based procedures, achieving better efficiency by reducing the input and/or increasing the outputs.	*RPA tools help businesses improve the efficiency of processes and the effectiveness of services. First, replacing the human workforce reduces the cost and processing time for high-frequency tasks. The running cost of an RPA software is around one ninth that of employing a human being (Huang and Vasarhelyi, 2019, p. 3)*
(5) Close knowledge gap	Artefacts close the knowledge gaps for juniors with low experience and expertise when performing demanding tasks	*Moreover, Big four companies implemented chatbots that assist junior auditors in their tasks. Digital aid may also be offered to auditors, as well. A chatbot may be enabled in audits to be used as a search tool for an online technical library (Deloitte, 2018) (Tiron-Tudor and Deliu, 2022, p. 266).*
(6) Diversify workforce	Artefacts offer opportunities for firms to diversify the workforce by reducing the reliance on experts from a single background and expanding the talent pool with IT experts.	*This change contrasted with the more traditional view that auditors are isolated specialists in a homogeneous culture that lacks diversity…, '[audit firms had only] an extremely narrow range of people, or one could call them very unilinear', as most auditors joined the firms…having experienced only the same CPA examination'(Goto, 2021, p. 96).*
(7) Develop new business models	Artefacts afford the development of a new business model, such as the change of billing model from labour-driven to technology-driven, as well as offering new value-adding services.	*These technologies can drastically improve the audit quality and evolve the audit offer towards services with stronger added value as customers could correct these errors, prevent risks and continuously improve their systems (Manita et al., 2020, p. 6).*
(8) Re-acquire legitimacy	Artefacts offer opportunities to create a rhetoric that can meet social expectations, restore creditability and re-acquire legitimacy	*Sceptical public views regarding the legitimacy and sustainability of their profession posed a significant threat…and the professional association had published visionary reports delineating full utilisation of it (Goto, 2022, p. 86).*
(9) Create new knowledge ecosystems	Artefacts provide the profession with a new way to acquire, enhance, revise and reposit knowledge.	*A deep neural network gathers knowledge and learns the underlying data patterns by automatically identifying features from the data itself (Sun, 2019, p. 89).*

Table 3. Explanation of affordances.

4.4 Constraints associated with CAATTs and AI artefacts

Like affordance, technology constraint is a relational concept that the technology with particular features hinders the potential actions of social actors (Majchrzak and Markus, 2012). Technology constraints may arise because actors shift their goals or cannot figure out how to use the artefacts to achieve their goals (Leonardi and Vaast, 2017, Leonardi, 2011). In our research context, we found that some features of CAATs and AI artefacts create action hurdles for actors in achieving their goals. For a simple instance, actors are not able to use CAATTs to generate sentimental meanings of text because it lacks natural language processing features. Thus, it limits actors' actions, namely, making decisions based on multiple sources of information, where the constraint 'information abandonment' emerge. Table 4 explains the constraints with reference to the exemplar in the literature.

Constraints	**Explanation**	**Exemplar**
(1) Information abandonment	Artefacts restrict actors' decision-making because they can only process certain types of information, while actors have to forgo actions resulting from other information	*An important factor is the possibility of collusion or off book frauds…. Any activity occurring outside SAP, that does not leave a 'footprint' within the system, cannot be investigated using this approach (Singh and Best, 2015, p. 314).*
(2) Information overload	Artefacts produce too much information, such as alarm floods or high false negative results, limiting actors' ability to act properly.	*If the number of alarms generated by the CMBPC system explodes, then it will hamper the ability of auditors and other enterprise personnel to react (Alles et al., 2006, p. 157).*
(3) Black-box decision making	Artefacts are featured with a black-box decision-making model that actors do not understand how the artefacts reach a conclusion or decision. This further constrains actors' ability to interpret and document their decision.	*However, the majority of systems designed to detect fraud reported by researchers aim to maximise the prediction accuracy, while disregarding how transparent they are. This factor has particular significance as the development of interpretable models (Craja et al., 2020, p. 4)*
(4) Encroach other procedures	The artefacts only operate with high resource input, like labour hours and financial investment, on tuning, testing, and setting up. This constrains auditors from spending resources on other procedures or using other tools.	*One shortcoming of a traditional textual analysis is that it requires handcrafted data features: human engineers need to manually select or design data features for an algorithm to analyse… leads to numerous features per word and requires a priori knowledge of human engineers (Sun, 2019, p. 94).*
(5) Decision restrictiveness	The artefacts restrict the actors to some subset of the full-range possible decision-making process, or the actors treat the results of the artefacts as conclusive and prescriptive.	*However, the long-term use of decision aids may lead to the auditor only focusing on the issues that are identified by the decision aid and not consider other factors or issues not identified by the system (Munoko et al., 2020, p. 221).*

Table 4. Explanation of constraints.

4.5 Mapping of affordances and constraints to CAATTs and AI artefacts

The findings show that the affordances and constraints vary when actors interact with different artefacts. While some affordances and constraints are exclusive to AI artefacts, such as data-informed decision-making and black-box decision-making, other affordances and constraints are associated with both CAATTs and AI artefacts. On average, AI affords more action potential than CAATTs. Among AI artefacts, robotic process automation, expert systems and decision support systems share relatively more affordances with CAATTs, while the affordances of computer vision, natural language processors and machine learning number analytics are relatively more distinctive. The findings also reveal that decision restrictiveness is the most prevalent constraint imposed by CAATTs and AI artefacts. When actors use those artefacts in their decision-making process, they are unavoidably restricted to some subset of the full-range action potential. Other constraints are closely aligned with the artefacts' material properties and features. For instance, continuous auditing software, computer vision, natural language processor and machine learning number analytics are all featured with high resource consumption, resulting in the common constraint "encroach other procedures." Similarly, continuous auditing systems, natural language processors and machine learning number analytics usually produce a high volume of information and false negative classifications, creating "information overload". Table 5 maps the affordances and constraints of CAATTs and AI artefacts.

	CAATTs		**AI Artefacts**				
Affordances	**GAS**	**CAS**	**CV**	**RPA**	**NLP**	**MLNA**	**EDS**
(1) Data-Informed decision making			•		•	•	
(2) Upgrade work content	•			•			•
(3) Structuralise process	•	•		•			•
(4) Automate process	•	•		•			
(5) Close knowledge gaps			•		•	•	•
(6) Diversify the workforce		•	•	•		•	
(7) Develop new business models		•			•	•	
(8) Re-acquire legitimacy		•	•		•	•	
(9) Create new knowledge ecosystems			•		•	•	
Constraints							
(1) Information abandonment	•	•					•
(2) Information overload		•			•	•	
(3) Black-box decision making			•		•	•	
(4) Encroach other procedures		•	•		•	•	
(5) Decision restrictiveness	•	•	•	•	•	•	•

Table 5 mapping of affordances and constraints to CAATTs and AI artefacts.

5 Discussion

This study sets out to better understand the difference between AI and classic IT artefacts in terms of their affordances and constraints. Selecting auditing as the research context, we identified the variation of nine affordances and five constraints among CAATTs and AI artefacts. This section discusses the implications of the findings.

5.1 Common affordances shared by CAATTs and AI artefacts

Unsurprisingly, we found that CAATTs and AI artefacts share some common affordances. However, the presence of commonality does not imply that AI and classic IT artefacts are indistinguishable. For example, both generalised auditing software and robotic process automation allow users to enhance their work content by reducing clerical tasks and increasing involvement in managerial tasks (Eulerich et al., 2022). However, robotic process automation affords a much broader scope of work content enhancement than generalised auditing software. This is because most off-the-shelf generalised auditing software has a relatively fixed functionality, limited to predefined procedures and administrative tasks (Abou-El-Sood et al., 2015). When a particular function is not included in the software package, actors have limited options to add the function to the software. In contrast, the work content enhancement by robotic process automation is not restricted by pre-designed functions, as it uses scripts to emulate the tasks carried out by human actors. The high configurability of robotic process automation allows users to delegate repetitive and well-defined tasks to it, provided that it is technically and economically feasible. The configurability also implies adaptability, enabling actors to enhance their work content in an evolving environment where job requirements may change (Eulerich et al., 2022).

Another example is that CAATTs and AI allow new business model development in different measures. Continuous auditing systems allow organisational actors to develop new business models by altering how their existing services are delivered. Its system architecture enables a shift from point-in-time to continuous delivery, from reactive to proactive measures, and from post-event to real-time processing

(Singh and Best, 2015, Chan and Vasarhelyi, 2011). Nevertheless, the essence of the service remains focused on ensuring the reliability of financial statements. By contrast, AI artefacts afford new business models by enhancing existing services and making the provision of new services visible. The AI-powered data models, such as those developed through machine learning number analytics and natural language processor, can be used for multiple purposes. They can be leveraged as auditing tools to identify potential misstatements in clients' databases. Meanwhile, the data models provide insights into a client's business operations, offering numerous opportunities for firms to expand their service ranges, including consultancy, advisory, and risk management services (Tiron-Tudor and Deliu, 2022). This aligns with multidisciplinary research on AI affording value creation through new products and services (Borges et al., 2021). Therefore, we argue that although classic IT and AI offer some common affordances, AI artefacts are distinguishable from classic IT due to their ability to provide more visible, convenient, versatile, flexible, adaptable, and scalable measures to achieve goal-directed outcomes.

5.2 Distinct affordances of AI artefacts

We noticed that certain affordances, such as 'data-informed decision-making' and 'new knowledge ecosystems', are exclusive to computer vision, natural language processing, and machine learning number analytics. These affordances are distinctive because they are built on machine learning algorithms, allowing multiple data functions without explicit programming (Sun, 2019). Machine learning algorithms enable the development of more advanced functions, such as 'understanding' text and facial expressions, based on their ability to identify abstract data features. These features transform how decisions are made. A comparison can be made between the IT-assisted decision-making model and the AI-empowered, data-informed decision-making model. Classic IT, including statistical software, supports decision-making using a hypothesis-testing approach. However, the process of formulating hypotheses is dominated by humans, while IT tools perform data analysis to validate the hypothesis. In contrast, AI can explore relationships between data and formulate hypotheses, surpassing the cognitive limitations of humans in understanding complex phenomena, such as the correlation between facial stiffness and deceitful behaviours (Pentland et al., 2017). Therefore, we argue that machine learning algorithms provide actors with unique opportunities for data-informed decision-making by analysing vast amounts of data, identifying patterns, and making predictions. This affords actors insights from various forms of data that would not be possible with classic IT.

At the professional level, only artefacts with machine learning algorithms offer a new knowledge ecosystem where machines can create, enhance, revise, and store knowledge based on data. Machine learning algorithms explore data and reveal patterns without relying on existing theory or knowledge, making it particularly effective for creating new knowledge grounded in data and overcoming cognitive limitations associated with knowledge production based on experience (Bertomeu et al., 2021). Knowledge is stored in the data model and can be used further. Machine learning algorithms also have the ability to self-learn and evolve in response to new data without explicit programming by humans. This allows machine learning algorithms to adapt to a changing world and refine previous knowledge, forming a new knowledge ecosystem. We can effectively compare the knowledge ecosystem between machine learning-powered artefacts and non-machine learning artefacts, such as traditional expert systems. The architecture of expert systems is a rule engine and knowledge base, which affords knowledge preservation, replication and distribution (Davis et al., 1997), where the creation and refinement of knowledge heavily rely on humans. Our findings highlight that computer vision, natural language processors, and machine learning number analytics offer unique opportunities to transform the knowledge ecosystem within the profession fundamentally.

The distinct affordances of machine learning-powered artefacts also remind us of the difference between strong AI (rule-following) and weak AI (rule-based) discussed in prior research (Wolfe, 1991, Collins et al., 2021). Weak AI tools assist actors by providing recommendations or advice and are intended to help with repetitive decisions and complex problems without taking over cognitive tasks from humans (Coombs et al., 2020). Strong AI, on the other hand, has more engagement in cognitive tasks and active decision-making. Our findings suggest that weak AI, such as robotic process automation, expert systems, and decision support systems, shares more affordances with classic IT. Conversely, strong AI tools like computer vision and natural language processing may not produce those affordances. For example, weak AI and CAATTs can 'structuralise process' by applying existing *rules* through automation, workflow monitoring, and decision standardisation. By contrast, machine learning-powered artefacts discover new *rules* rather than assuming explicit *rules*; as such, they do not afford business process structuralisation. Our finding supports prior literature discussing the different levels of digital labour, asserting that weak AI primarily contributes to automation while strong AI has more cognitive engagement (Collins et al., 2021, Tiron-Tudor and Deliu, 2022). Noteworthily, we acknowledge that the observed similarity between CAATTs and weak AI, as well as their distinction from strong AI, may be attributed to the evolution of terminology and language over time. This consideration suggests the need for investigation in future research.

5.3 Constraints removed and imposed by AI artefacts

We found that strong AI artefacts can possibly remove one significant constraint imposed by CAATTs. The lack of multi-type data processing capacity in generalised and continuous auditing software creates the constraint of 'information abandonment'. These artefacts can perform functions on numerical and text data, including sampling and exception reporting, but they do not support the analysis of other forms of data, such as video and images (Huang et al., 2009). This shortcoming can lead to the neglect of relevant information and hinder effective decision-making. However, we found that strong AI artefacts, such as natural language processing and computer vision, can overcome this constraint by processing various forms of data, including textual sentiment and facial rigidity (Huang et al., 2022, Pentland et al., 2017). Unlike CAATTs, which can only handle numerical and text data, AI algorithms can be trained to process different types of data, thus providing a more comprehensive and accurate input for decision-making. Consequently, those strong AI artefacts offer a promising solution to the information abandonment problem associated with CAATTs.

The finding suggests that AI cannot be regarded as an all-encompassing solution for all the constraints arising from classic IT. We found that AI may even give rise to more stringent constraints in some cases. A typical example is decision restrictiveness. The artefacts restrict the actors to some subset of the full-range possible decision-making process, or the actors treat the results of the artefacts as conclusive and prescriptive (Silver, 1988, Dowling and Leech, 2014). Compared with CAATTs, the results generated by AI artefacts tend to be more conclusive, especially when they provide a dichotomous classification of fraudulent firms and prediction of bankruptcy (Dong et al., 2018, Craja et al., 2020). Actors are restricted to a narrow range of options, either fraud or no fraud, which may not reflect the complexity and nuance of the situation. This oversimplification may lead to over-reliance on AI-generated outcomes while ignoring other relevant information, resulting in suboptimal decision-making. Although some researchers claim that actors may demonstrate algorithm aversion and place limited reliance on AI artefacts (Commerford et al., 2022), others believe that algorithm appreciation is far more common than algorithm aversion (Logg et al., 2019). This study supports the latter view, arguing that AI artefacts may result in overreliance on the results generated by the artefacts and neglecting information suggesting otherwise, thus restricting actors' decision-making process.

Furthermore, AI artefacts may impose new types of constraints on actors. Typical examples are "black-box decision making" and "encroach other procedures", largely attributed to machine learning algorithms' material properties. Some machine learning algorithms, such as artificial neural networks, may produce accurate classification but lack interpretability in decision-making processes (Sun, 2019, Li et al., 2021). This imposed significant constraints on actors to interpret, document, and explain their actions when using the artefacts. Additionally, the functional accuracy of many algorithms relies on significant resource input, such as collecting the training data, tuning the parameters, testing the correctness, and application setup (Krieger et al., 2021, Bertomeu et al., 2021). This imposes constraints on actors to allocate resources to other necessary procedures. In summary, while AI artefacts can remove some of the limitations imposed by traditional IT artefacts, their material properties can also introduce new types of constraints, limiting the flexibility and adaptability of decision-making processes.

6 Conclusion

This study adopts the TACT lens and conducts systematic literature on the technology used in the auditing industry to understand the distinctive nature of AI compared with classic IT artefacts. Based on 81 papers reviewed, we identified nine affordances and five constraints that emerged due to the interaction between actors and artefacts. We noticed that the affordances and constraints vary between classic IT and AI artefacts, which the distinct material property of machine learning algorithms can partially explain. This property features versatility and offers new action potential for actors to make the data-informed decision. At the professional level, AI artefacts offer the potential to re-acquire legitimacy and create a new knowledge ecosystem. We also noticed that AI is not the silver bullet to remove all the constraints imposed by classic IT artefacts. Instead, because of the machine learning property featured with a black-box decision model and high resource dependency, AI artefacts may impose new constraints on actors to achieve their goals.

This study has several theoretical implications. It synthesises extant literature on AI and classic IT artefacts in the auditing industry, explaining the material difference between these two kinds of artefacts from the TACT perspective. The finding contributes to a better understanding of the socio-technical aspect of AI technology which both affords and constrains the action potential of social actors. It addresses the gap in the existing literature by providing an in-depth discussion of the difference between classic IT and AI artefacts. This study can be situated alongside existing literature to provide an understanding of the strategic impact of AI on social actors (Borges et al., 2021, Coombs et al., 2020). Additionally, this study extends the applicability of TACT to a broader context. Prior literature has primarily employed TACT to study the consequences of using IT artefacts in organisations and the related organisational changes (Zammuto et al., 2007). This study is among the first to apply TACT to investigate the distinctions between two types of artefacts. The study may provide useful insights for future research to distinguish one specific group of IT artefacts from others.

This study has practical contributions by shedding light on the affordances and constraints of AI artefacts on individuals and organisations. While recognising the potential benefits of AI in offering new practices and knowledge ecosystems, it also highlights potential constraints that may hinder actors' decision-making processes, including information overload, high resource consumption, and black-box decision-making models. To minimise these negative impacts, organisations should consider various measures. For instance, they can address the black-box problem and enhance interpretability by selecting highly transparent machine-learning models or adopting post hoc explainable AI techniques (Barredo Arrieta et al., 2020). Additionally, organisations can adopt more cost-effective measures, such as transfer learning, to reduce the resource consumption problem (Weiss et al., 2016). Transfer learning involves utilising a pre-trained machine learning model on a large dataset as a starting point to solve a different but related problem, which can significantly reduce the cost of acquiring data and tuning parameters for firms with limited resources. Together with previous research, this study provides practical insights for organisations to actualise the affordances of AI while reducing its constraints, ultimately leading to better outcomes for individuals and organisations.

The study provides avenues for future research. While we believe that the findings apply to a wider context, their generalisability is not guaranteed. Differences across industries and technologies should be taken into consideration. Future research may need to validate the findings by collecting data from other contexts and technologies to better understand the focal technology's affordances and constraints. We also recognise that identifying affordances and constraints is merely the first step in examining the interaction between social actors and AI artefacts. Future research, particularly field studies, is necessary to understand how social actors actualise the affordances and overcome the constraints of AI, as well as the consequences of usage. In addition, while the grounded theory approach to the literature review is rigorous and systematic, it is not free from human error (Wolfswinkel et al., 2013). We attempted to mitigate the errors as much as possible by constantly cross-checking the results during the open, axial, and selective coding stages. The findings were based on a shared understanding of the literature and consensus among all three authors.

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