Artificial Intelligence Affordances for Organisational Change: Perspectives from South African Artificial Intelligence Practitioners

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by

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Publications

This Masters study resulted in the publication of a conference paper (Achmat & Brown, 2019) which was a requirement that formed part of the Masters coursework. The conference paper highlighted the affordances related to artificial intelligence through a systematic review of literature. The systematic literature review therefore formed part of the broader literature review for the Masters study, and is therefore integrated into the dissertation. The aim of the conference paper was to analyse literature as an empirical data source where affordances for business innovation emerged as an implication of artificial intelligence technologies. The broader study paid greater attention to affordance theory in addition to the explicit identification of affordances by analysing primary interview data, with the intent of exploring how artificial intelligence-related affordances influence organisational change from the perspective of the artificial intelligence practitioner.

Reference: Achmat, L., & Brown, I. (2019). Artificial intelligence affordances for business innovation: a systematic review of literature. In *Proceedings of the Fourth International Conference on the Internet, Cyber Security and Information Systems* (Vol. 12, pp. 1-12). Johannesburg, South Africa.

Abstract

Artificial intelligence (AI) technologies have been in use for several decades, but have seen substantial growth and commercialisation in the last decade, largely due to the available and growing ubiquitous access to more affordable computing resources. While some organisations have adopted these technologies fairly quickly, others grapple with understanding how these technologies would strategically benefit the organisation. The purpose of this research is to address this gap by theorising how AI could be positioned to influence strategic organisational change. It does so by delineating the AI features and drawing on affordance theory to explicitly identify the affordances, the types of organisational change and the constraining conditions under which such AI-related affordances may influence organisational change. This qualitative study adopts an interpretive epistemology, while lending itself towards a constructivist ontology. By adopting a qualitative interview strategy for data collection, and a thematic analysis to analyse the data, this study abductively theorises how AI affords organisational change from the perspective of the AI practitioner. It uses the Trajectory of Affordances as the underpinning lens to explore this phenomenon. Eight key affordances are identified: (i) Analysing risk, (ii) analysing needs, (iii) forecasting, (iv) assessing efficiency and effectiveness, (v) providing prediction criteria, (vi) translating information, (vii) tailoring information, and (viii) improving predictability as an affordance that results from an outcome or organisational change influenced by one or more of the other affordances.

Keywords: artificial intelligence, affordances, AI practitioner

Table of Contents

1. Introduction

Artificial intelligence (AI) is not a new technology, but its recent adoption and interest have seen a significant uptake over the last decade, revealing it as an emerging, but also ubiquitous technology in everyday life. The annual AI index report was introduced in 2018 to provide a better understanding of AI developments to the general public (Zhang, Maslej, Brynjolfsson, Etchemendy, Lyons, … & Perrault, 2022). In 2022, it reported that the investment in AI in the global private sector doubled between the years 2020 and 2022 to more than ninety-three billion US dollars (US$93bn). Compared to a recent Microsoft survey, in one hundred and twelve companies based across five countries in the Middle East and Africa, a total of over nine billion US dollars (US$9bn) was invested in AI between 2008 and 2018 in the region, South Africa (SA) being cited as one of the countries where AI investment activity is highest (Ernst & Young, 2019). This progression in AI has seen the cost of AI reduced substantially, and the technology itself showing vast improvements in its run-time efficiency (Zhang et al., 2022).

Established AI use cases already exist in sectors like the automotive, healthcare, legal, finance and military to name a few (Adadi & Berrada, 2018). From a global perspective, AI offers organisations better insight and fast, effective decision-making capabilities that allow them to effectively compete in their industries (Borges, Laurindo, Spínola, Gonçalves & Mattos, 2020; Raisch & Krakowski, 2021). These AI-based interventions include improvements in customer service through improved lead times and reliability, improved productivity, and improved inventory management (Blanco, 2018; Wamba-Taguimdje, Wamba, Kamdjoug & Wanko, 2020). These AI-related benefits also allow organisations to focus more on innovation, drive business growth, and better manage risks and costs (Mikalef & Gupta, 2021).

South Africa is a key player in the discussion about AI in Africa. The country is known as a strategic business centre in Africa because of its key geographical position for the import and export of goods. It also houses good basic infrastructure such as the busiest harbour in Africa (Economist, 2016), while also finding favour in the international business market (Scholvin & Draper, 2012; Bankole et al., 2015). In 2018, 44 out of the 55 member states of the African Union (AU)[1] signed the African Continental Free Trade Area (AfCFTA) agreement which will see the majority of intra-Africa trade tariffs being scrapped. It is seen as the largest trade agreement since the establishment of the World Trade Organisation and is expected to significantly accelerate intra-African trade (Luke, 2019), with South Africa being a major beneficiary (Wasserman, 2019). In addition, South Africa was ranked in 2021 as the top country in Africa for the overall tech ecosystem of the future, with one of its cities ranking first for "economic potential, start-up status and business friendliness" (fDiIntelligence, 2021, p. 28). This means that the country is seen as one with promising technology-based innovation through a number of progressive technology hubs and incubators.

[1] The main objective of the AU is to promote development and improve relations amongst African States; https://au.int/en/overview

The response of South African companies to opportunities like these may not always effectively materialise or sustain. One of the obstacles is the access to relevant skills that drive these economic opportunities. Ironically, SA's digital drive is viewed as an opportunity to revolutionise the economy, but it is also plagued by several challenges, one of them being the sourcing of skills required to drive the digital economy (Downie, 2019). This opportunity is accompanied by the threat of job security that AI brings, particularly to the lower skilled workforce (Rapanyane & Sethole, 2020), to an economy with one of the highest unemployment rates in the world (Naidoo, 2021) and exacerbated by the Covid-19 pandemic (Köhler, Bhorat, Hill & Stanwix, 2021). While recent literature has highlighted skills and relevant resources as an important factor in the adoption of AI (Kordon, 2020; Schaefer, Lemmer, Samy Kret, Ylinen, Mikalef & Niehaves, 2021), SA has been suffering a technology skills shortage for some time. This was emphasised in the country's National Planning Commission (2011). Furthermore, information technology (IT) skills are on the national list of occupations in high demand (Capazario & Venter, 2020). The high demand and shortage of IT skills threaten the country's economic development in the digital era (Sutherland, 2020). Add to this, the SA government's poor and slow track record for creating the policies and frameworks that are known to be crucial factors in the proliferation of new technologies such as AI (Kruse, Wunderlich & Beck, 2019; Pumplun, Tauchert & Heidt, 2019). An example is the wireless spectrum allocation which the SA government has had limited capacity and competency to implement sustainably and fairly, leaving the issue of spectrum allocation entangled in court cases for several years (Klein, 2021; Malinga, 2021).

As is experienced globally, South Africa is further burdened by the challenges related to the Covid-19 (also called 'corona') virus pandemic announced on 11 March 2020 (World Health Organisation, 2020). The pandemic escalated the global need for businesses to transact digitally instead of via physical face-to-face interaction (Schrage, 2020). For example, Covid-19 drove a significant global increase in e-commerce transactions (Bhatti, Akram, Basit, Khan, Raza & Naqvi, 2020; Veeragandham, Patnaik, Tiruvaipati & Guruprasad, 2020; Ungerer, Portugal, Molinuevo & Rovo, 2020). This accelerated shift from traditional business to digital business also paves the way for strategic differentiation using emerging technologies like AI (Evans, 2020). Covid-19 also arrives against the backdrop of an already-ailing South African economy; prior to the announcement of the Covid pandemic, the World Bank already cut the country's growth forecast for 2019 through to 2021 (Smith, 2019).

The introduction of emerging technologies like AI may further deepen the adverse impact of the technologies on the already-high unemployment rate in South Africa if the issue of the lack of local skills and adequate governmental support is not effectively addressed. Many of the much needed digital skills are based or sourced in developed countries and many of the technologies like AI are being developed in these economies and exported to developing economies like South Africa (Burbidge, 2022). Already enacted in many developed economies, in sub-Saharan Africa, governments are required to proliferate affordable internet access, provide the necessary policy and regulatory support to accommodate digital changes and workforce impact, and raise the awareness of digital work opportunities to persuade the public to upskill and seek out digital work (Daramola & Etim, 2022). Although uncertain about how progressive the impact of AI will be on the workforce, there is some consensus that it will be significant in the long term (Bresnahan & Yin, 2017; Plastino & Purdy, 2018; Kaplan & Haenlein, 2019).

Problem Statement

Considering the challenges faced by South Africa in the wake of the pandemic, an economic crises and business uncertainty, AI can be leveraged to aid economic growth (and therefore job growth) through both local and international markets, but would need to be appropriately positioned to reflect the specific needs of the organisation, and the effects and consequences would need to be fully understood (Mahomed, 2018). In the absence of such strategies, traditional techniques and technologies may become redundant as competitors and their technologies evolve with the ever-changing and demanding economic environment (Salam & Khan, 2018). AI can therefore play a pivotal role in IT-associated organisational change (Plastino & Purdy, 2018; Calatayud, Mangan & Christopher, 2019). By strategically positioning AI and navigating the hype around the technology (Brynjolfsson, Rock & Syverson, 2018), organisations are better equipped to respond to challenges and opportunities such as those mentioned in this study.

There are limited studies that explore AI in order to better understand the potential with which AI can enable or drive such change. One approach for South African organisations to explore such opportunities, is to begin to understand what the AI technologies offer such organisations by (i) exploring its features, and (ii) gaining an understanding of how AI technologies (with these identified features) can be positioned as an opportunity for strategic organisational change. By delineating the features of AI, organisations and its actors gain clarity around the technology, aiding its adoption in the case for digital innovation (Trocin, Hovland, Mikalef & Dremel, 2021). One way to grow understanding of how AI can be positioned as an opportunity for strategic organisational change is by exploring the AI-related affordances. Affordances are the actionable possibilities made available as a consequence of the relationship between the goal-oriented actor and the IT artefact in a particular social context (Markus & Silver, 2008). This pragmatic approach, underpinned by theory, is beneficial to organisations wanting to position AI in a strategic sense; i.e. positioning AI with an objective in mind, such as to explore opportunities or to address challenges or threats. Using affordance theory as a lens to explore this phenomenon provides a practical means to identify possibilities for action, and understand the relationship between the AI technology (and its features) and the AI practitioner in order to effect strategic organisational change. By considering affordances as the theory underpinning this study, it also answers the call for more studies to use the affordance lens in IS research (Volkoff & Strong 2017; Fromm, Mirbabaie & Stieglitz, 2020). However, there is paucity of affordance research concerning AI, particularly considering the context of the actors, goals and social contexts (Trocin, Hovland, Mikalef & Dremel, 2021). This study uses the AI practitioner as the actor representing the South African organisation, the AI practitioner taken as sharing common goals with the organisation.

This study explores the affordances related to AI that result in IT-associated organisational change from the perspective of AI practitioners that implement or configure such technologies. The research question and related objectives therefore are:

How do artificial intelligence technologies afford change in South African organisations, from the perspective of the AI practitioner?

> Objective 1: Identify the key AI features that play a role in its affordances in South African organisations.
>
> Objective 2: Identify the AI-related affordances in South African organisations.
>
> Objective 3: Identify the types of organisational change effected by such AI-related affordances.
>
> Objective 4: Identify the constraining conditions under which such AI-related affordances result in achieving organisational change.

The following chapters offer a literature review on AI and affordances as the theory underpinning this study. The research methodology, data collection and analysis, and discussion follows as subsequent chapters. This paper then concludes with theoretical and practical contributions, and future research opportunities.

2. Literature Review

Background of Artificial Intelligence

The term 'Artificial Intelligence' was first coined in 1955 by American scientist John McCarthy, where he refers to AI as an 'intelligent' machine when it exhibits human behaviour by performing typical human tasks (McCarthy, Minsky, Rochester & Shannon, 2006). Although it remained an area of interest over the decades after McCarthy first coined the term, it wasn't until the 1990s when interest and research in AI started to accelerate (Ertel, 2018), popularised by the 1997 defeat of the world chess champion, Garry Kasparov, by an IBM computer called Deep Blue (McCorduck & Cfe, 2004). One of the main challenges during the 1990s was the ability to efficiently compute large volumes of data. This rapidly began to change as computing resources advanced, improved in quality, became more readily available and significantly more affordable (Bauer, van Dinther & Kiefer, 2020). As a result, the 2010s saw the exponential propagation of AI applications across multiple industries and markets, ushering in a new era for business (Agrawal, Gans & Goldfarb, 2018) and research (Shoham et al., 2018). Coincidentally, the popularisation of AI in the 2010s was also made so by a program called AlphaGo (developed by a Google company) defeating human world champions in a popular strategic board game called "Go", thanks to the supervised and reinforcement learning techniques offered by AI (Silver et al., 2017).

AI as an Emerging Technology

AI is perceived as an emerging technology because of its escalating importance and ubiquitous nature, and the amount of uses cases in the world have grown substantially in the last decade. Popular consumer examples are search engines, voice and image recognition (Varian, 2019). Google has for the last several years used AI systems to continuously improve its language understanding and search results (Theodoridis & Gkikas, 2019). Millions of users use AI-enabled voice recognition applications such as Google, Apple's Siri or Amazon's Alexa (Kim, 2020), and AI-enabled image recognition using a smartphone camera. Although voice and image recognition saw a difficult adoption because of their high error rates, these error rates have drastically reduced over the last decade; the year between 2016 and 2017 alone saw the voice recognition error rate nearly halve (Brynjolfsson & Mcafee, 2017). This is interesting to note because Statista, a global provider of economic and consumer data, reported 728 million iPhones in global active use by early 2017 (O'Dea, 2021). In business, AI serves as a key enabler in the financial services industry, offering a significant improvement in fraud detection, automated customer service, automated trading, loan applications, credit scoring, risk management, insurance underwriting and in general lowering the cost of doing businesses, to name only a few (Giudici, 2018; Buchanan, 2019). In telecommunications, AI is used to automatically manage network configurations, detect network anomalies and identify network failures without the need for human resources; Balmer, Levin & Schmidt (2020) use the example of a distributed denial of service (DDOS) cyber-attack, in which the AI engine can detect and automatically react to. During the Covid-19 pandemic, retailers considered applying AI technologies in new ways to accommodate the change in consumer behaviour (Iansiti & Lakhani, 2020; Purcărea, Ioan-Franc, Ionescu & Purcărea, 2021). AI technologies in this sector offer personalised experiences (Wilson & Daugherty, 2018), predict customer demand, automate operations (Bughin, Hazan, Ramaswamy, Chui, Allas, Dahlstrom, Henke & Trench, 2017) and augment brick and mortar store human resources resulting in greater revenue through AI-based recommendations (Iansiti & Lakhani, 2020). These initiatives seem promising because of the reported potential economic opportunities that arise from AI, including an increase in global gross domestic product (GDP) by 15.7 trillion United States Dollars (USD) by the year 2030 (Rao & Verweij, 2017).

Africa and Oceana are predicted to see an approximate 1.2 trillion USD increase in GDP by 2030 resulting from AI adoption (Rao & Verweij, 2017). So it is not surprising that in addition to the advantages globally, countries with developing economies (often referred to as "developing[2] countries") also leverage AI in several other industries. For example, the farming and agricultural sector in Brazil uses AI to improve farming efficiency and predict harvest size; Chile's mining and energy industry uses AI to monitor machines for potential maintenance; China's transportation industry uses AI technologies to predict traffic congestion for ride-sharing services that allow it to better predict customer demand (Kshetri, 2020). In the Kenyan health sector, AI not only complements the decision-making in business processes, but also improves efficiency in the collection and analysis of high-volume data in an effort to prioritise patient needs; these AI-derived benefits proactively allow for lifesaving supplies to be made more readily available (Mahomed, 2018). In the South African agricultural industry, Artificial Neural Networks (ANN) are used for predicting maize production (Adisa, Botai, Adeola, Hassen, Botai, Darkey & Tesfamariam, 2019). AI use cases such as these have

[2] While there is no globally accepted definition of the term "developing country", the reference made here refers to countries where there are a less than advanced economic industry, and lower life expectancy, education and per capta income when compared to developed countries (O'Sullivan & Sheffrin, 2003; International Monetary Fund, 2022; United Nations, n.d.).

therefore been the subject of upcoming and evolving trends (Mzekandaba, 2018), so much so that Gartner began tracking a hype cycle specifically for AI (Sicular & Brant, 2018).

AI in South Africa

South Africa (SA) has taken a progressive approach on AI. South African president, Cyril Ramaphosa, announced in his first ‘state of the nation address’ (SONA) that the “digital industrial revolution” would be incorporated into the country’s economic policy (Ramaphosa, 2018). A few additional SA-based examples are shared here to offer a glimpse at AI use cases in SA. AI-enabled virtual agents or chatbots have been widely adopted in recent years in South African organisations to service customers, service providers and staff alike (Schoeman, Moore, Seedat & Chen, 2021). One example is where chatbots support organisations by facilitating customer queries and other business transactions between service providers (e.g. “gig workers[3]”) and customers (Daramola & Etim, 2022). Financial Technology (FinTech) companies in SA have multiplied in recent years and have largely incorporated emerging technologies such as AI and blockchain into their operations and offerings (Coetzee, 2018). The companies disrupt conventional banking by offering a range of blockchain and AI-enabled digital services at a very low cost; digital mobile payment services, mobile wallet services as a replacement for traditional bank accounts, cash withdrawals, loans, remittances and money transfers are a few examples (Alexander, Shi & Solomon, 2017). In healthcare, in the midst of the Covid-19 pandemic, Mashamba-Thompson & Crayton (2020) offer a blockchain and AI-based technology for analysing information through self-testing. Their proposal offers AI as a way to collect and analyse Covid-19 related test information to gain early insights on the data, and reduce reliance on time-affected traditional logistics to obtain meaningful information. They further claim that their AI-based solution can be used in similar scenarios for other infectious diseases. The use of AI in SA healthcare is not uncommon. Among other uses in healthcare, the country has also seen the application of AI to predict health workers’ length of service (Owoyemi, Owoyemi, Osiyemi & Boyd, 2020), AI-enabled telemedicine to connect remote health workers to doctors (Sallstrom, Morris & Mehta, 2019), and AI-enabled medical and lifestyle assessments by corporate Discovery Health’s application called DrConnect (Singh, V., 2020).

While AI may be leveraged for opportunities such as aiding economic growth in South Africa, it is not without challenges. The threat of job security, particularly to the lower skilled workforce, is one such challenge (Rapanyane & Sethole, 2020). The government and private sectors are being called on to prioritise the regulatory environment and upskilling of the workforce in order to realise a positive economic impact in the country by the year 2035 (Schoeman, Moore, Seedat & Chen, 2021). The skills threat is worsened by the technology skills shortage which was emphasised in the country’s National Planning Commission (2011).

Technologies, including those incorporating AI, depend on a sustainable source of energy. One of South Africa’s biggest challenges is a lack of sustainable energy supply, severely affecting economic growth (Heinemann, 2019). The energy crisis has been in existence for more than a decade with little hope of short term recovery (Masondo, 2022) as

[3] Gig workers may be classed as a “category of workers [who] provides offline services such as ride-hailing, grocery/pharmacy/food delivery, home maintenance, and care workers” (Daramola & Etim, 2022, p. 4).

the number of rolling power outages across the country amount to more than three thousand hours in 2022 (Mtembu, 2022).

Without the necessary governmental support and appropriate digital upskilling programs, these challenges are particularly problematic for South Africa where economic growth has been severely stunted by the impact of Covid-19 and the energy crisis.

Concepts and Definitions of AI

Although not a new concept, a global and consistent definition of AI has not been grounded in literature. In fact, much of the extant literature considers the concept of AI a very broad and an evolving one (Nguyen & Sidorova, 2017; Alsheibani, Cheung & Messom, 2018; Hamm & Klesel, 2021). AI has also often been conceptualised as a 'black box' (Davenport & Ronanki, 2018; Leyer & Schneider, 2019; Pumplun, Tauchert & Heidt, 2019; Arrieta et al., 2020). In addition, the terms 'Artificial Intelligence' and 'Machine Learning' (ML) are often used together or interchangeably, while not distinguishing between the two terms (Burgess, 2018; Bauer, van Dinther & Kiefer, 2020). This is confusing for researchers wanting to explore the concept of AI, even in the field of software engineering (Feldt, de Oliveira Neto & Torkar, 2018). Illustrating an example from Karacay (2018, p. 124) when discussing lean production in the age of digital transformation, they state that "developments in robotics, artificial intelligence, and machine learning are channeling through a new phase of automation of work processes…". Likewise, "infused with artificial intelligence and machine learning ability, robots have become smarter and more autonomous…" (Xu, David & Kim, 2018, p. 94). This can be challenging in practice too as organisational leaders face confusion about what AI is and how it may contribute organisational value, especially while trying to navigate the marketing hype (Burgess, 2018); in the retail industry, "many AI applications, already available or under development, contribute to retailers' confusion and frustration with regards to which AI technologies to invest in." (Oosthuizen, Botha, Robertson & Montecchi, 2021, p. 267).

Recent literature refers to AI as a broad, overarching concept, implying that a finite definition may never emerge because of its evolving nature (Nguyen & Sidorova, 2017; Kruse, Wunderlich & Beck, 2019; Hamm & Klesel, 2021). More consistently, subfields and techniques are often referred to. Nguyen & Sidorova (2017, p. 2) refer to "subfields that generally fall under the AI umbrella include automated reasoning, natural language and image processing, knowledge representation and machine learning". Similarly, Nascimento, da Cunha, de Souza Meirelles, Scornavacca & de Melo (2018) find nine AI subfields and seven AI-related techniques, represented in table 1.

Attempting to tightly define AI subfields may be problematic as AI evolves over time. This problem is reflected in the inconsistent terms used between Nguyen & Sidorova (2017), Nascimento et al. (2018) and other authors. For example, 'general artificial intelligence' is viewed as a progression of the AI concept in a broad sense rather than a subfield at any particular point in time (Kaplan & Haenlein, 2019). Referring to table 1, 'Big data' [analytics] and 'data mining' have more recently become synonymous terms related to AI (Nascimento et al., 2018). Bawack, Wamba & Carillo (2019) offer a practitioner's perspective where terms such as ‘subfields’ and ‘techniques’ are conflated with other interchangeable terms by referring to the group of terms as ‘AI technologies’. This may be a more appropriate reflection on the *broad* concept of AI because the notions of AI subfields and techniques blend and evolve as AI advances (Nascimento et al., 2018).

Table 1 - AI Subfields and Techniques, source: Nguyen & Sidorova (2017); Nascimento, da Cunha, de Souza Meirelles, Scornavacca & de Melo (2018)

AI Subfields	AI Techniques
1. Expert Systems 2. General Artificial Intelligence 3. Knowledge based system 4. Decision Support 5. Big Data [Analytics] 6. Data Mining 7. Predictive Models 8. Machine Learning 9. Collaborative Information Systems	1. Artificial Neural Networks 2. Regression based models 3. Genetic Algorithms 4. Fuzzy Logic 5. Complex Adaptive Systems 6. Analytic Hierarchy Process 7. Cluster Analysis

Categories of AI. The concepts of ‘Weak’ or ‘Strong’ AI classes have been discussed for the past few decades (Sloman, 1986; Searle, 1990; Bringsjord & Schimanski, 2003). In more recent years, the definitions of these classes have evolved into categories or stages (Urban, 2015; Siau & Yang, 2017). Based on these concepts of ‘weak’ and ‘strong’ AI, Urban (2015) first categorised AI into three stages: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). Most AI applications are considered ANI and are applied to a specific task or area, such as Amazon Alexa’s ability to recognise a human voice and respond or act on a command. Gurkaynak, Yilmaz, & Haksever (2016) argue that ANI applications are becoming smarter, with many ambitious initiatives and projects being funded by major corporations such as Microsoft, Google and IBM; many of these projects involve blending the physical and biological world with the virtual, AI-incorporated world. There is also a growing trend to move from ANI to AGI, if not already employed by organisations (Calatayud, Mangan & Christopher, 2019). The second category of AI known as AGI is an evolution of ANI in that it can be applied to multiple areas instead of a specific area or task. It can perform any human task (Urban, 2015) and is also able to autonomously solve complex problems or challenges it may encounter (Gurkaynak, Yilmaz, & Haksever, 2016). Accenture’s research into AI strategies shows how Bosch is looking to use A[G]I in its automotive plants to autonomously solve technical failures (Plastino & Purdy, 2018). Urban (2015) refers to the third AI stage as ASI. This stage is considered to be more intelligent than humans. Kaplan & Haenlein (2019) consider this stage a significant extension or evolution from AGI; ASI is considered to be AI that is fully self-aware and self-conscious. In any of the three stages, AI will ultimately be integrated into human daily life the more pervasive and ubiquitous it becomes (Haenlein & Kaplan, 2019).

AI Learning Types. AI employs one of three learning types; supervised learning, unsupervised learning and reinforcement learning (Kaplan & Haenlein, 2019). Machine Learning (ML), a subset of AI, employs the same learning types. Supervised learning is where a system or 'machine' is provided with input data and output data that requires mapping or linking by the machine. The machine then learns to connect the input data with the desired output data. In unsupervised learning, the output is unknown, and the machine makes sense of input data to provide structured and linked output (L'heureux, Grolinger, Elyamany & Capretz, 2017). Reinforcement learning does not necessarily require input data to be linked to output data. It relies on the state of the environment and any input data. It then takes actions based on these variables and the action changes the state of the environment, of which the result is communicated as input to the machine. It continues this in a cyclical fashion and learns in this process (Kaelbling, Littman & Moore, 1996).

This study explores the 'broad' concept of AI rather than the specific fields or techniques in detail. It does so to allow clarity and generalisability when referring to AI in practice and theory. It is therefore appropriate to consider the concepts and definitions that encompass the 'broad' construct of AI. For instance, five themes that help clarify the broad concept of AI are "solving complex problems", "human-like processing", "degree of intelligence", "technology focus" and "handling of external data"; "they help to better understand the main characteristics of AI and how they can be distinguished from other technologies." (Hamm & Klesel, 2021, pp. 2-3). In summary, AI can be defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific [human] goals and tasks through flexible adaptation." (Kaplan & Haenlein, 2019, p. 17).

AI Influence on Organisational Change: A Capabilities Approach

AI studies in organisations have been ongoing for decades. While some of the recent literature focusses on the adoption of AI technologies (Alsheibani, Cheung & Messom, 2018; Eljasik-Swoboda, Rathgeber & Hasenauer, 2019; Demlehner, & Laumer, 2020), or on understanding human interaction with AI technologies (Siau & Wang, 2018; Glikson & Woolley, 2020; Makarius, Mukherjee, Fox & Fox, 2020), others such as the impact or influence of AI on organisations are underdeveloped research areas (Öztürk, 2021); these studies attempt to make sense of how organisations could position AI as an opportunity for innovative organisational change. Schmidt, Zimmermann, Möhring & Keller (2020) attempt to do so by linking AI and business value, specifically focussing on AI capabilities, defining it as "the ability of organizations to use data, methods, processes and people in a way that creates new possibilities for automation, decision making, collaboration, etc. that would not be possible by conventional means" (Schmidt, Zimmermann, Möhring & Keller, 2020, p. 3). Schmidt et al. (2020, p. 4) present a "business value framework" that considers "deep learning systems as Information System asset, that impacts process performance which in turn drives the organizational performance.". The framework includes the identification of "assets" (features) which play an integral role in AI's basic and process-related capabilities in order to generate organisational value.

Despite the claim by Schmidt et al. (2020) that there is no guidance provided to link AI capabilities and organisational value, there is extant recent literature that does provide such guidance (Burgess, 2018; Mikalef, Fjørtoft & Torvatn, 2019; Wamba-Taguimdje, Wamba, Kamdjoug & Wanko, 2020; Papagiannidis, Enholm, Mikalef & Krogstie, 2021). A few examples from recent literature are briefly discussed here. Burgess (2018) offers an AI framework which breaks AI down into eight core capabilities that either collects information or attempts to make sense of "what is happening" with information that has been collected, and uses that information to achieve specific organisational goals (Burgess, 2018, p. 3). Another example highlights AI capabilities as a key contributing factor to organisational performance, not only from a financial perspective, but also at a broader process level (automation, information and transformation) and broader organisational level (financial, marketing and administrative) (Wamba-Taguimdje, Wamba, Kamdjoug & Wanko, 2020). Mikalef, Fjørtoft & Torvatn (2019) adopt a resource based approach to develop an AI capabilities and competitive performance framework, with the aim to highlight the key resources that make up an organisation's value-driving AI capability. Papagiannidis, Enholm, Mikalef & Krogstie (2021) expand on this theory to develop a conceptual framework that outlines how resources could be 'orchestrated' to deliver organisational value using AI.

The common thread in these approaches is the significant role that AI capabilities play in organisational change; i.e. achieving organisational value in the form of innovation or organisational performance. Figure 1 represents a summation of how AI capabilities influence such change (Burgess, 2018; Mikalef, Fjørtoft & Torvatn, 2019; Schmidt et al., 2020; Wamba-Taguimdje et al., 2020). It refers to AI capabilities enabled by AI features such as algorithms, computing, image recognition etc. These AI capabilities influence organisation- or process-based capabilities (e.g. automation, augmentation, service enhancement), which in turn influences organisational change such as predictive maintenance (as an intended organisational outcome), and financial, marketing and administrative performance.

Compelling theoretical approaches with the aim of understanding how organisations can position AI as an opportunity for organisational change are offered by Enholm, Papagiannidis, Mikalef & Krogstie (2021) and Mikalef & Gupta (2021). Through a review of literature, Enholm et al. (2021) develop an AI and business value research framework, which may be considered an elaboration of the framework illustrated in figure 1, with the aim to understand how organisations can adopt AI capabilities as a strategic enabler. Using this capabilities-based framework, researchers may explore up to five research themes in order to understand how AI influences strategical organisational change, thereby offering several ways to expand such knowledge. Similarly, Mikalef & Gupta (2021) use a resource-based approach to develop an organisation's AI capabilities to influence its performance. Their study categorises technical and nontechnical resources into three categories that make up an organisation's AI capability, namely tangible, human skills and intangible.

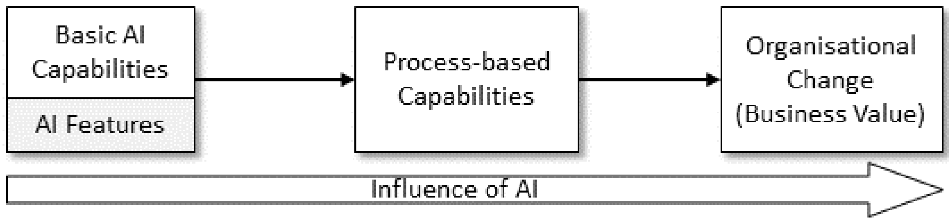


Figure 1. AI-Based Business Value Framework (Burgess, 2018; Mikalef, Fjørtoft & Torvatn, 2019; Schmidt, Zimmermann, Möhring & Keller, 2020; Wamba-Taguimdje, Wamba, Kamdjoug & Wanko, 2020)

A capabilities-based approach is therefore considered in recent literature to understand the link between AI and organisational value creation (i.e. organisational change) (Burgess, 2018; Mikalef et al., 2019; Wamba-Taguimdje et al., 2020; Schmidt et al., 2020; Enholm et al., 2021; Mikalef & Gupta, 2021). However, Schmidt et al. (2020) admits that the capabilities-based approach may be inadequate to fully understand the impact to strategic organisational change, so it may be useful to consider an alternative approach in theory and practice. Second, Burgess (2018) has largely drawn on personal working experience to develop the capabilities framework with limited critical and empirical assessment. Third, Wamba-Taguimdje et al.'s (2020) study is based on archival (secondary) data from case studies by a variety of AI solution providers and recommend further studies involving tools such as interviews and questionnaires to complement their research. Similarly, the remaining capability-based studies by Mikalef et al. (2019), Enholm et al. (2021) and Mikalef & Gupta (2021) are largely theoretical with limited empirical consideration, perhaps due to the novel nature of frameworks related to the understanding of AI in practice.

The AI-human integration approach is also briefly considered here to understand how AI influences organisational change (Makarius, Mukherjee, Fox & Fox, 2020; Murray, Rhymer & Sirmon, 2020), but studies such as these are claimed to perpetuate a broad research approach that distinguishes between human and AI machines instead of the call to "focus on the *interdependence* of these two actors interacting on the same or closely related tasks" (Öztürk, 2021, p. 283). For instance, the AI-employee integration model at its core is about people change management that assists or enables, for example, the adoption of AI technologies.

AI Influence on Organisational Change: An Affordances Approach

Affordance theory has in recent years attracted greater research focus in IS to understand how technology is used and integrated into social structures (Volkoff & Strong, 2017; Hacker, vom Brocke, Handali, Otto & Schneider, 2020). Affordances refer to the actionable possibilities made available as a consequence of the relationship between the goal-oriented actor and the IT artefact in a particular social context (Markus & Silver, 2008; Bernhard, Recker & Burton-Jones, 2013). The topic of affordance has also attracted greater interest in recent studies concerning emerging technologies (Lehrer, Wieneke, vom Brocke, Jung & Seidel, 2018; Du, Pan, Leidner & Ying, 2019; Trocin, Hovland, Mikalef & Dremel, 2021).

Even though there is a growing body of knowledge on affordance in IS research, there are limited studies concerning AI-related affordances and its impact on organisations. For example, May, Sagodi, Dremel & van Giffen (2020) explore digital innovation as a product of AI; they use affordance theory to adopt a perspective of AI as a feature of a digital technology. However, the AI affordances are not sufficiently exposed because their research question, at its core, is focussed on digital innovation as a realisation of digital ventures. In another example, while Canhoto (2021) applies the theory of affordance to explore how machine learning combats money laundering, but does not explicitly identify the affordances of machine learning and instead provides a descriptive overview of artificial intelligence, specifically machine learning. The literature surveyed therefore highlights gaps in identifying affordances related to AI and how it is used to influence organisational change.

While an affordances approach provides some guidance to position AI as an opportunity for strategic organisational change, this study pays greater attention to affordance theory in addition to affordance identification and exploration. By doing so, decision-makers can begin to practically understand the role and influence of AI in their organisations. Affordance theory is explored and elaborated in the next section as the lens underpinning this study.

Literature Review Summary

This study reviews relevant literature on the concept of AI as an emerging technology. It acknowledges that AI is an important, strategic and ubiquitous technology, and will progressively play an integral role in South Africa. Various approaches are considered when exploring how AI can be positioned as an opportunity for strategic organisational change. There is extant literature that puts forward a capabilities or AI-human integration approach when exploring AI as an opportunity for organisational change. However, there are some limitations highlighted by the use of these approaches. For example, focussing on capabilities alone or an actor's ability to incorporate technologies such as AI effectively into an organisation do not necessarily ensure success such as an intended organisational change (Nguyen & Sidorova, 2017). Instead it is the relations between the actors and technologies that better determine the success of such technologies (Markus & Silver, 2008; Volkoff & Strong, 2017). An alternative approach is to adopt the theory of affordances as a lens through which to explore how AI can be positioned as an opportunity for organisational change. By doing so, it explores the AI features, AI-related affordances and relations that result in intended organisational outcomes. Such an approach therefore provides a pragmatic perspective on the relations between the goal-oriented AI practitioner and the AI technology in a particular social environment. An affordances approach would be underpinned by theory that brings into focus the relationship between the actor (AI practitioner) and the technology (AI). This relationship focus not only serves as a key feature for determining the success of such technologies, but also satisfies the urgent need to understand these relations and the role they play in contributing to strategic organisational value (Trocin, Hovland, Mikalef & Dremel, 2021). Affordance theory is explored in detail in the following chapter.

The research question is: How do artificial intelligence technologies afford change in South African organisations, from the perspective of the AI practitioner? To help answer the research question, this study intends to achieve the following objectives. First, it contributes to the call to explore the key AI features that play a role in its affordances (Wang, Wang & Tang, 2018; Leidner, Gonzalez & Koch, 2018; Karahanna, Xu, Xu & Zhang, 2018; Canhoto, 2021) in South African organisations. Second, there is limited literature which explicitly identifies AI affordances and therefore addresses this gap. Third, it identifies the types of organisational change or outcome that takes effect as a result of such affordances. Fourth, it explores a less developed research area entailing the constraining conditions (Volkoff & Strong 2017; Fromm, Mirbabaie & Stieglitz, 2020; Canhoto, 2021) under which AI affordances influence organisational change. The next section discusses affordance theory as the theoretical lens through which AI is explored as an opportunity for organisational change.

3. Theoretical Underpinnings

Affordances

The concept of 'affordance' was first introduced by ecological psychologist, James Gibson (1977). Affordance is a term derived from the word 'afford', which reflects an individual's ability to provide something; for example, a father's ability to purchase a birthday gift for his child. Similarly, in academia, affordance is about what the environment offers to someone[4] and must be perceived to achieve an intended outcome (Gibson, 1977). Gibson (1977) also states that affordances exist regardless of whether the observer (actor) perceives it or not. An example may be a coffee mug which affords a human actor to contain coffee, but also affords the same human to pick the mug up with the intention of drinking that coffee. Although the features of the mug allow it to hold coffee and to be picked up by human hand, these affordances exist regardless of whether the observer perceives them for those purposes or not.

The concept of affordance has been a much debated topic in literature since Gibson first introduced it (Jones, 2003; Volkoff & Strong, 2017). This resulted in some variations and contradictions in the understanding of the concept. For example, Turvey (1992) argued that affordances are the properties of the *environment* in relation to the observer, while Stoffregen (2003) consider affordances as properties of the *relationship* between the environment and the observer. The nuances are evident in Norman's (1998) adaptation of Gibson's original affordance theory in one of the early technology related studies concerning human-computer interaction (HCI), where affordances are directly related to the technology and not the observer or the relationship between the two. However, recent affordance literature shows a shift toward a shared understanding of the affordance concept more closely aligned to that of Gibson (1977) (Heft, 2001; Chemero, 2003; Michaels, 2003), where affordances are seen as "possibilities for *action* provided to an animal by the environment" (Rietveld & Kiverstein, 2014, p. 327).

Affordance as a Lens in Information Systems Research

[4] Gibson (1977) refers to living beings as 'animals' who have the ability to perceive; e.g. human beings.

The topic of affordance is a growing focus in information systems (IS) research and used as a lens with which to study the relationship between information systems and goal-oriented actors (Wang, Wang & Tang, 2018; Fromm, Mirbabaie & Stieglitz, 2020). Hutchby (2001) argued the appropriateness of using the theory of affordance in the field of information systems because of the inexorable interaction between the technology artefact and the goal-oriented human actor. Information systems literature has since largely adopted the definition of affordance as "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus & Silver, 2008, p. 622) and the shared view that affordances emerge "from the relation between an artifact and a goal-oriented actor or actors" (Strong, Volkoff, Johnson, Pelletier, Tulu, Bar-On, Trudel & Garber, 2014, p. 69). Affordances are not simply highlighting technology features, but rather reflect the possible social *practices* made available to the actor/s (e.g. personalising customer communication, improving inventory efficiency) by the relation between such features and the goal-oriented actor/s (Fayard & Weeks, 2014).

Components of affordances in IS research. The affordance theoretical framework in figure 2 by Pozzi, Pigni & Vitari (2014) is adapted from Bernhard, Recker & Burton-Jones (2013). It shows how affordances are brought into existence by the relationship between the IT artefact and actor. The adaptation by Pozzi, Pigni & Vitari (2014) is primarily concerned with the relationship between the IT artefact (and its features) and the actor, that gives rise to the existence of affordances. This relationship is absent from the framework presented by Bernhard, Recker & Burton-Jones (2013), where affordance existence is influenced either by the object (IT artefact) or by the user (actor), or both. The constructs removed from Bernhard et al. (2013) in the adaptation by Pozzi et al. (2014) are the information about affordances in order to perceive it, and the effort taken to actualise the perceived affordance. Instead, Pozzi et al. (2014) claim that the factors that influence this actualisation process "depends on the presence of appropriate enabling, stimulating, and releasing conditions" (Volkoff & Strong, 2013, p. 828).

In addition, figure 2 incorporates the terms as described in the definition of affordance by Markus & Silver (2008). Using this definition, the IT artefact in this study is the AI technology and the actor the goal-oriented AI practitioner representing an organisation. The actor concerned in this study may not necessarily be *directly* employed by an organisation, but is a goal-oriented representative of such an organisation; such an actor may be an outsourced or contracted individual or organisation, or they may be an internal human resource. Understanding the AI practitioner's perspective as a representative of the organisation in how artificial intelligence technologies afford change in organisations is therefore useful in theorising the relationship between the actor as a 'practitioner' and the AI technology (Bawack, Wamba & Carillo, 2019). In addition, as organisations and systems advance, the human-AI system becomes more entangled in order to achieve organisational goals (Murray, Rhymer & Sirmon, 2020). In fact, advances in the field of AI allow AI to create AI, with such advances calling for a renewed perspective on organisational theories (Lindebaum, Vesa & Den Hond, 2020; van Rijmenam & Logue, 2021). This entangled socio-technical phenomenon (the human-AI system) therefore offers an opportunity to understand the perspective from the AI practitioner as one who has a deep understanding of the developments in the AI field and its potential influences on social organisation. The affordance existence therefore refers to the possibilities that emerge as a result of the relationship and interaction between the AI practitioner (with consideration of an organisation's goals) and the AI technology.

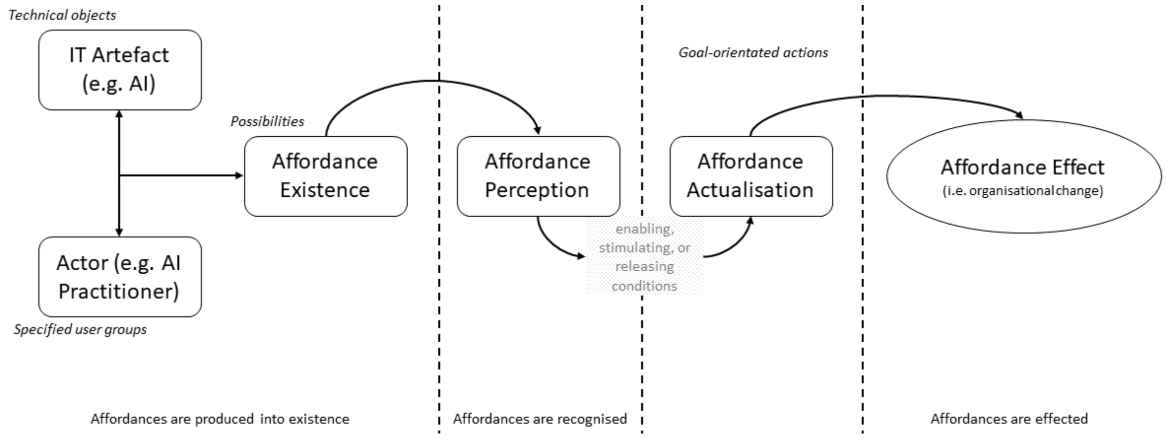


Figure 2. Affordance Theoretical Framework as adapted by Pozzi, Pigni & Vitari (2014), incorporating the definition of affordance by Markus & Silver (2008) and conditions by Volkoff & Strong (2013)

Affordance perception and actualisation. The mere fact that AI affordances are produced and exist does not mean that the intended outcomes will be achieved. The affordances would need to be perceived and actualised to realise its effects (Bernhard, Recker & Burton-Jones, 2013; Pozzi, Pigni & Vitari, 2014; Stöckli, Dremel, Uebernickel & Brenner, 2019). To illustrate using the mug example once more, the mug ear affords a human hand to pick up the mug. The affordance offered by the mug ear therefore exists but may not be actualised if not perceived and picked up by the human hand to drink the coffee contained in the mug. Instead, the cylindrical feature of the mug also affords a human hand to grasp the mug and actualise the affordance offered by this feature, in order to achieve the same goal. The question about whether affordances need to be perceived to be actualised has also been debated in literature. One argument is that this is primarily because of the misuse of the word 'perceive' when it comes to the theory of affordances, and Volkoff & Strong (2017, p. 239) suggests that the term "perceived affordances" should not be used at all in order to avoid confusion. The explanation for this confusion is because (i) 'perception' can take on several meanings and therefore requires meticulous definition when used, and (ii) affordances may be actualised without any awareness of its existence, especially where such affordances may be a subset of another/others (Bernhard, Recker & Burton-Jones, 2013); "this is particularly true when the artifact in question is complex and somewhat opaque, such as an information system" (Volkoff & Strong, 2017, p. 239) like AI.

Affordance-actualisation theory. Consequently, an increase in the adoption of affordance-actualisation theory is observed in more recent literature. For instance, Du, Pan, Leidner & Ying (2019, p. 35) adapts affordance-actualisation theory to examine the strategic value of blockchain in financial technology companies, defining the affordance actualisation process as "the goal-oriented actions taken by actors as they use a technology to achieve an outcome", derived from the definition by Strong et al. (2014). A similar adaptation by Keller, Stohr, Fridgen, Lockl & Rieger (2019) explores the affordances offered by an AI-enabled predictive maintenance system, by expanding affordance-actualisation theory to focus on the experimentation of such an IS to enable strategic business value. Furthermore, other than at an individual level, affordances are also studied at organisational levels, and the actualisation process can happen at either (Du, Pan, Leidner & Ying, 2019), creating the same or new affordances for different actors (Leidner, Gonzalez & Koch, 2018); this study focusses on actualisation at an organisational level, with the AI practitioner representing organisational goals. While many studies distinguish between affordance existence, perception and actualisation, the AI practitioner as the implementor of the IT artefact (AI technology) may already consider the affordances as actualised. This enables the AI practitioner to specify how to effect organisational change (Seidel, Recker & Vom Brocke, 2013) and make them more effective actors of the technology (Volkoff & Strong, 2017). This claim is also echoed by Lanamäki, Thapa & Stendal (2016) who suggest that affordance studies typically adopt one of four stances; most studies, including those studies cited earlier in this paper, are concerned with the stance 'potential affordances' which "follows a relational ontology between artifact and actual users (individual or collective). From a temporality view, affordances remain latent until they are perceived and actualized by an individual or group of users, and the affordance can be realized time and time again." (Lanamäki, Thapa & Stendal, 2016, p. 132).

Thapa & Sein (2018, p. 810) propose "that the emergence and actualisation of affordances are interdependent and connected processes". An example of this is how an emerging technology, big data analytics, affords service innovation. Lehrer, Wieneke, vom Brocke, Jung & Seidel (2018, p. 29) explore how the key features of big data analytics (BDA) influence service innovation across four different companies, and the affordances referred to in their theoretical model are actualised affordances not distinguished from its perception; for example, the affordance of the "automation of customer-sensitive service provision" is an action taken by an actor/s to provide a tailored service (organisational goal). The BDA technology is implemented by the practitioner with this organisational goal in mind. Similarly, actualised BDA affordances such as "establishing customer-centric marketing" are discussed by Dremel, Herterich, Wulf & Vom Brocke (2020, p. 10) without distinguishing between the existence, perception and actualisation of the affordance. AI affordance actualisation may therefore be influenced not only by the features of the AI technology and the actor, but also the organisation's goals or problems to be solved (Canhoto, 2021).

Affordance as a Lens in AI Research

To explore the concept of affordances related to AI, this Masters study analysed key literature to highlight potential high-level affordances for business innovation that emerged from the implementation or use of an AI technology. A systematic six-step literature review methodology (as shown in Appendix F) was conducted with an iterative disposition. Seven key affordances of AI for business innovation were identified through an analysis of this literature. The affordances are labelled as action-associated gerunds as suggested by Strong, Volkoff, Johnson, Pelletier, Tulu, Bar-On, Trudel & Garber (2014) in order to distinguish the affordances from the technology features and organisational outcomes based on the use of such technologies. The affordances are (i) automating business processes, (ii) individualising engagement, (iii) providing predictive analytics, (iv) augmenting human workforce capacity and skills, (v) supporting decision-making, (vi) introducing efficiencies, and (vii) managing knowledge.

Automating business processes. This involves the automation of manual organisational processes. For example, the automatic updating of customer information such as address changes, or communication updates when an event (such as a lost credit card) is triggered (Davenport & Ronanki, 2018). This could also involve the automatic search and selection of job applicants (Daugherty, Wilson & Chowdhury, 2019; Trocin et al., 2021) and the automatic assignment of tasks to workers, including the assessment of their work (Dhir & Chhabra, 2019). These examples reflect how the concept of AI-based automation is evolving from simple task-based automation to more complex, contextual based automation (Davenport, Guha, Grewal & Bressgott, 2020).

Individualising engagement. Automation may also be accompanied by individualised engagement to the end user, be it a customer, supplier or employee. For example, systems may include health treatment recommendations based on an individual's specific health habits, age and medical history (Davenport & Ronanki, 2018); chatbots are able to "analyze words, phrases and sentence constructions of customers so they can predict customer personality" in order to improve customer service (Nguyen & Sidorova, 2018, p. 2). Similarly, individualised engagement may refer to customised employee (or other stakeholder) engagement that in turn improves such engagement with the intent to improve their productivity (Brachten, Kissmer & Stieglitz, 2021).

Providing predictive analytics. A third affordance illustrated by the reviewed literature is predictive analytics. These include financial time series forecasting, market predictions and fraud detection (Nascimento et al., 2018). Other examples in the literature include the affordance of providing predictive analytics in order to perform predictive maintenance as an outcome (Keller, Stohr, Fridgen, Lockl & Rieger, 2019); the ability to "analyze warranty data to identify safety or quality problems in automobiles and other manufactured products" (Davenport & Ronanki, 2018, p. 110).

Augmenting human workforce capacity and skills. An affordance for business innovation is by way of addressing human capacity. For example, AI can be used to perform low complexity tasks and free up capacity of the human to focus on more complex tasks that require human intuition or a specific experience requirement (Traumer et al., 2017; Makarius, Mukherjee, Fox & Fox, 2020).

Supporting decision-making. Decision support is also cited in literature as an affordance of AI (Murray, Rhymer & Sirmon, 2020). AI-based decision-making may be fully automated or simply 'assisted' decision-making where humans make the decision based on suggestions the AI-based technology provides (Maedche et al., 2019); e.g. The AI technology uses algorithms and historical information to make suggestions to humans when making organisational decisions (Rzepka & Berger, 2018). How AI is implemented (fully automated or assisted decision-making) would depend on the context of the application (Maedche et al., 2019).

Introducing efficiencies. AI also affords efficiencies within business processes. For example, General Electric used AI "to integrate supplier data and has saved $80 million in its first year by eliminating redundancies and negotiating contracts that were previously managed at the business unit level" (Davenport & Ronanki, 2018, p. 111). While several examples have been illustrated in the context of AI affordance through business systems or processes, there is some paucity in AI affordance in the context of IT infrastructure. Pike & Pike (2019) offer an example where AI is used to create efficiencies in a highly virtualised IT environment, thereby also maximising the availability of crucial business systems. Another example they offer is the adaptive nature of IT security infrastructure by using AI to "analyze the ingested data to ensure that activities on the systems are consistent with the organizations policies, develops compliance reports and sends alerts when activities deviate from expected outcomes" Pike & Pike (2019, p. 2).

Managing knowledge. Knowledge Management is another way in which AI affords business innovation. This can be performed in a variety of ways. One method is through chatbots which can be used to generate, challenge and store work related knowledge such as software engineering requirements or training material (Maedche et al., 2019; von Wolff, Masuch, Hobert & Schumann, 2019; Brachten, Kissmer & Stieglitz, 2021).

Further examination of the literature shows that there are links and influences between the affordances themselves. *Automating business processes*, for instance, is an overarching affordance theme, since any one of the seven affordances have some degree of automation to be able to perform tasks faster, and with limited or no human intervention (Davenport, Guha, Grewal & Bressgott, 2020; Trocin et al., 2021). It can also be argued that automation is a form of introducing efficiency (Jarrahi, 2019; Brachten, Kissmer & Stieglitz, 2021). Using another example, *supporting decision-making* may be considered an affordance as a consequence of actualising both affordances *providing predictive analytics* and *automating business processes*. This implies that an affordance may be a consequence of another actualised affordance. To illustrate this, table 2 shows the results of an analysis by Trocin et al. (2021) which focusses on affordances specific to their human resource (HR)-related processes, more specifically the recruitment and onboarding processes. It is integrated here with the affordances highlighted by the systematic literature review as part of this study.

Table 2. First- and Second-level HR-related Affordances Trocin et al. (2021, pp. 5-7) integrated with the systematic literature review (in parentheses)

First-Order Affordances	Second-Order Affordances
AB-testing[5] Ranking candidates Setting a threshold value (Automating business processes)	Fine-tuning algorithms (Individualising engagement) (Introducing efficiencies)
Collecting online behavioural information Creating clusters of online job advertisements	Identifying patterns in users' interests (Individualising engagement) (Introducing efficiencies)

[5] A/B testing is a form of controlled experiment or statistical test (Kohavi & Longbotham, 2017), in this case used in the field of human resources in their recruitment process.

(Automating business processes) (Managing knowledge)	
Suggesting keywords Targeting job listings with users (Automating business processes)	Recommending online job listings (Individualising engagement) (Introducing efficiencies)
Parsing information Matching profiles with job listings (Automating business processes) (Providing predictive analytics)	Facilitating job application (Individualising engagement) (Introducing efficiencies)
Parsing job requests Reviewing the pool of available candidates Matching candidates with open positions Ranking candidates for open positions (Automating business processes) (Providing predictive analytics)	Optimising online recommendations (Individualising engagement) (Introducing efficiencies)
Providing introductory information Asking questions about competence Transcribing responses (Automating business processes)	Androgynous robot for interviews (Individualising engagement) (Augmenting human workforce capacity) (Introducing efficiencies)
Competence based evaluations (Automating business processes) (Providing predictive analytics)	Assessing objectively candidates (Supporting decision making) (Introducing efficiencies)
Unbiased information analysis (Automating business processes)	Data-driven decision making (Supporting decision making) (Introducing efficiencies)

While the systematic literature review potentially highlighted affordances for business innovation, this Masters study aims to also explore and explicitly identify AI-related affordances in a broad fashion (not limited to HR processes). It does so by adopting the Trajectory of Affordances as a lens through which to explore AI-related affordances, thereby developing a richer body of knowledge and theory proposition.

Trajectory of Affordances as a Lens

Thapa & Sein (2018) develop the concept of the 'Trajectory of Affordances' (figure 3) in which affordances that arise from the relation between an IT artefact and actor, may result in multiple other affordances. Similarly, in their study of big data analytics (BDA) affordances for smart cities, a cascading affordances model proposed by Zeng, Tim, Yu & Liu (2020) suggest that multiple affordances 'cascade'. In other words, affordances may result in an outcome that leads to more affordances. Another similar model involving AI is in the case of the first- and second-level affordances in the study by Trocin et al. (2021) about how AI affords digital innovation; machine learning in a human resource services organisation affords "collecting online behavioural information" which leads to another affordance of "identifying patterns in users's interests" (Trocin et al., 2021, p. 5). Thapa & Sein's (2018) Trajectory of

Affordances encapsulates both models by Zeng et al. (2020) and Trocin et al. (2021) because it not only explains how multiple affordances come about, but it also identifies each affordance path [organisational] outcome, and includes the relationship between the actor and IT artefact as a key component. Furthermore, it explicitly identifies the affordances that emerge as a result of these relations and considers the 'clustering' of multiple affordances (i.e. multiple events happening at the same time) in addition (and separate) to multiple affordances emerging as mutually exclusive events.

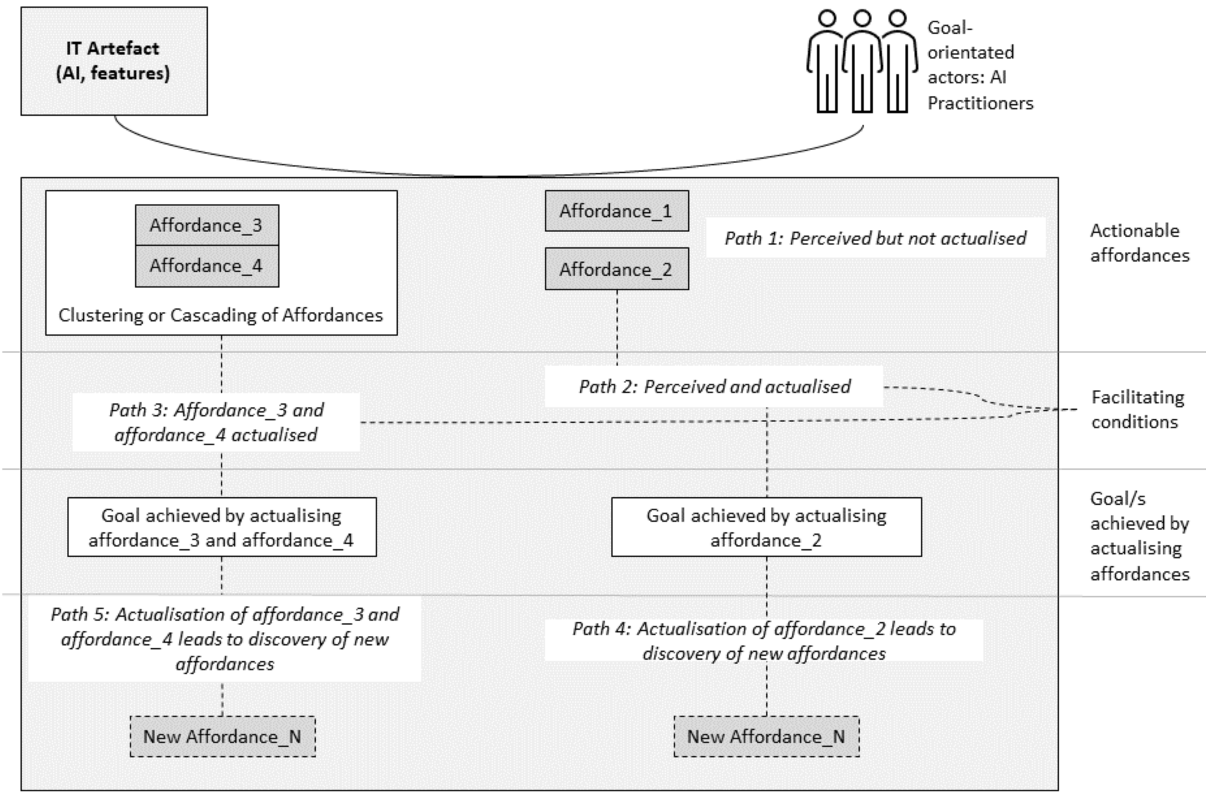


Figure 3. Adaptation of the Trajectory of Affordances from Thapa & Sein (2018, p. 810); Zeng, Tim, Yu & Liu (2020); Trocin, Hovland, Mikalef & Dremel (2021)

The concept of affordance has been a much debated topic over the last few decades and a useful tool to theorise how an information system such as AI is involved in organisational change (Leonardi, 2011; Fayard & Weeks, 2014; Lehrer, Wieneke, vom Brocke, Jung & Seidel, 2018). It builds on recent research, and begins to close the gap between (i) human and machine as separate agencies, towards (ii) entangled human-machine agents where the outcomes are as a result of their relations and/or interaction (Raisch & Krakowski, 2021). Using Thapa & Sein's (2018) Trajectory of Affordances as a lens with which to explore how AI can be positioned for strategic organisational change, it assists one's understanding of AI from various perspectives and provides a practical approach to understand the relationship between AI (IT artefact), the AI practitioner (goal-oriented actor) and their actions (Mesgari & Okoli, 2019, Trocin et al., 2021). It also follows the recommendations to (i) study affordances as a result of the relation between the AI (IT artefact) and the AI practitioner (the social construct), (ii) use affordance theory for exploring the influence of technology on organisational change, (iii) distinguish between technology features and outcomes, (iv) understand the relationships between multiple affordances, and (v) examine the constraining conditions for affordance actualisation (Volkoff & Strong 2017; Fromm, Mirbabaie & Stieglitz, 2020, Trocin et al., 2021). The following section discusses the research methodology of this study, which includes the philosophical considerations, research strategy, timeframe of the research, data collection and analysis.

Summary of Theoretical Underpinnings

Affordances can be defined as "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus & Silver, 2008, p. 622) and they emerge "from the relation between an artifact and a goal-oriented actor or actors" (Strong, Volkoff, Johnson, Pelletier, Tulu, Bar-On, Trudel & Garber, 2014, p. 69). Examples of affordances from literature are (i) automating business processes, (ii) individualising engagement, (iii) providing predictive analytics, (iv) augmenting human workforce capacity and skills, (v) supporting decision-making, (vi) introducing efficiencies, and (vii) managing knowledge. There are also links and influences between affordances such as affordances happening at the same time or affordances that lead to more affordances. Using the Trajectory of Affordances as a lens, the relations between the AI technology, the goal-oriented AI practitioner and the social context are explored as an opportunity for strategic organisational change. In doing so, it begins to describe how AI technologies afford change in South African organisations, from the perspective of the AI practitioner. The following chapter outlines the research methodology used by exploring the philosophical paradigms, research approach, research strategy, timeframe, data collection technique and data analysis technique.

4. Research Methodology

Philosophical Considerations

This research adopts an interpretive approach and lends itself towards a constructivist ontology. Data are collected through interviews and analysed using thematic analysis. This research contributes to the body of knowledge on AI and affordances. The following section explores the ontological and epistemological considerations as applied by this research.

Ontology is the philosophical study of *being* (reality) or the "assumptions that we make about the nature of reality" (Bahari, 2010, p. 23). The typology by Morgan & Smircich (1980) illustrate various ontological approaches to social science, each extreme end of the continuum representing pure objectivism versus pure subjectivism (or constructionism/constructivism). Historically, much of the research in IS adopt an objectivist ontology and positivist epistemology (Orlikowski & Baroudi, 1991; Liu & Myers, 2011). Objectivists assume knowledge, theories and reality already exist, independent of the researcher and with a high degree of objectivity. Data are therefore collected and analysed objectively. Constructivists on the other hand do not assume that reality exists independently of the researcher. Instead, knowledge is constructed through shared understanding and what knowledge emerges depends on the social context (Easterby-Smith, Thorpe & Lowe, 2002). Contrary to objectivism, constructivism accepts that multiple realities may exist (Saunders, Lewis & Thornhill, 2019).

Epistemology is about the assumptions made about knowledge (Burrell & Morgan, 2016); "what constitutes acceptable, valid and legitimate knowledge, and how we can communicate knowledge to others" (Saunders, Lewis & Thornhill, 2019, p. 133). There are three epistemological paradigms widely employed in IS literature over the last few decades: positivism, interpretivism and critical research (Orlikowski & Baroudi, 1991; Myers & Klein, 2011). Stemming from methods used in natural sciences, "positivist studies are premised on a priori fixed relationships within the phenomena which are studied with structured instrumentation" (Orlikowski & Baroudi, 1991, p. 6). Positivist research assumes one truth, a single reality, and take the objective stance that reality (and hence phenomena) exists independently of the researcher (Bahari, 2010). This means that researchers do not influence the phenomena being studied. With a typical focus on the explanation of cause-effect relationships (Bryman & Bell, 2007), in most cases they test hypotheses about phenomena through deductive reasoning and quantifiable means, using a representative sample in a given population (Orlikowski & Baroudi, 1991). Positivist research may also be qualitative, such as case studies (Dubé & Paré, 2003). Positivist researchers may also adopt an inductive approach instead of deductive (Paré, 2004). Positivism demands rigour in research, reliability of observations and generalisability of findings. Positivist researchers believe that knowledge has no value if it cannot be observed or measured directly (Dubé & Paré, 2003; Lee & Baskerville, 2003).

In contrast to positivism, interpretivist research aims to understand human behaviour in the context of the social organisation and phenomena being studied, and does not require the discovery of universal laws in order to be considered scientific (Lee & Baskerville, 2003). Reality is not independent of the researcher and the "knowledge of reality is gained only through social constructions such as language, consciousness, shared meanings, documents, tools, and other artifacts" (Klein & Myers, 1999, p. 69). Therefore interpretivism does not assume objectivity and instead develops deep insight into phenomena by immersing the researcher in the social processes (Orlikowski & Baroudi, 1991; Gregor, 2006). Through these interpretations and perceptions, interpretivists discover novel understandings about phenomena.

The paradigm of *critical research* refers to "*socially critical* research . . . often enabled and supported by IS" (Cecez-Kecmanovic, 2011, p. 442). Critical researchers in IS are involved with ethical and social concerns such as emancipation and power, especially where historical beliefs and social practices are embedded in society. It seeks to challenge these instituted assumptions to enhance understanding and evolve such circumstances into new norms (Myers & Klein, 2011). Although critical research sees many similarities with interpretive research, it is argued as an emerging, yet distinct, paradigm in IS research when compared to interpretivism or positivism (Myers & Klein, 2011).

An ontological paradigm more recently adopted in IS is that of critical realism (CR). Critical realism considers an objective reality, an understanding which can be gained through interpretive investigation (Wynn & Williams, 2012). This means that for critical realists, reality may exist independent of the researcher, but may not be directly accessible by the observer. CR may therefore be considered an appropriate research paradigm when using the theory of affordances because of the philosophical underpinning of affordance theory in critical realism (Volkoff & Strong, 2013) and the call to apply critical realism to affordance studies concerning IS (Mingers, Mutch & Willcocks, 2013; Mesgari & Okoli, 2019; Fromm, Mirbabaie & Stieglitz, 2020). However, the use of CR as paradigm is beyond the scope of this Masters study, and so using affordance theory as a lens, this study adopts an interpretive epistemology, while lending itself towards a constructivist ontology, as an appropriate approach to understand the AI phenomenon from the perspective of the AI practitioner. The constructivist position of this study means that knowledge is constructed through social interaction (Crotty, 1998) between the researcher and the AI practitioner representing an organisation. An interpretive approach enables the researcher to gain an in-depth understanding of the goal-oriented AI practitioner in the organisational context and their relationship to the AI phenomenon being studied. The researcher involved in this study is an IS practitioner and therefore able to gain knowledge through shared meanings with the goal-oriented AI practitioner as well as the organisational setting (Klein & Myers, 1999). This socio-technical perspective is also considered an appropriate one when considering affordance theory as a lens for such IS research (Volkoff & Strong, 2017).

Research aiming to provide an in-depth explanation of why and how AI technologies afford change in organisations may find the approach in this study limiting. This study does not intend to understand the unexplained AI-related generative mechanisms that cause events and experiences. For the most part, this study explores AI technologies which are implemented with specific outcomes in mind. It analyses and describes (Gregor, 2006) the AI technology features and the goal-oriented AI practitioner, to gain a rich understanding of the interaction between the two and the consequent affordances. Through this exploration, it also *begins* to explain the phenomenon by identifying relationships between the constructs (hence the research question), but does not offer deep insight into mechanism-based causal explanations. For example, one of the objectives of this study is to identify the AI affordances as a result of the relationship between the goal-oriented AI practitioner representing the organisation and the AI technology. This potentially allows the positioning of AI for strategic organisational change. There are several examples of other IS studies using affordance theory as a lens and an interpretive approach; some emerging technology examples are big data analytics affordances (Lehrer, Wieneke, vom Brocke, Jung & Seidel 2018; Zeng, Tim, Yu & Liu, 2020), AI-based digital innovation (May, Sagodi, Dremel & van Giffen, 2020) and wearable information systems (Benbunan-Fich, 2019). It is therefore acknowledged, at least from the perspective of achieving in-depth causal explanations within the evolving nature of the social system (Wynn & Williams, 2012), that this is a limitation of this study.

Research Approach

There is paucity in literature about how AI technologies afford change in organisations from the perspective of the AI practitioner. AI is considered an emerging technology and its strategic organisational use is considered novel or not well understood (Davenport & Ronanki, 2018). This study explores this novel phenomenon through a qualitative research approach (Myers, 2019). As opposed to quantitative research where data is numerical in nature, data in qualitative research is typically textual and focus is placed on the description and deep understanding of the phenomenon within a particular social context (Chen & Hirschheim, 2004). In order to develop theory about the AI phenomenon and the social context within which it interacts, a qualitative method for data collection and analysis is appropriate (Myers, 2019) and aligns well to the constructivist ontological and interpretivist epistemological assumptions (Bryman, 2004).

Deductive reasoning involves starting with a general theory about the topic and developing hypotheses about the topic, which is either confirmed or unconfirmed through testing and analysis of collected empirical data (Myers, 2019). It typically answers 'why' research questions to explain "an association between two concepts by proposing a theory, the relevance of which can be tested" (Blaikie & Priest, 2019, p. 109). Conversely, inductive reasoning starts 'bottom-up' and begins by collecting data about the topic. Patterns emerge through analysis of the data, which leads to the development of hypotheses and ultimately a general theory (Mitchell, 2018; Myers, 2019). Inductive reasoning answers the 'what' research questions and may be influenced by knowledge, culture and past experiences (Blaikie & Priest, 2019). Abductive reasoning is a third type of reasoning. It is "the form of reasoning through which we perceive an observation as related to other observations" (Tavory & Timmermans, 2014, p. 44). It may be used to answer both 'what' and 'why' questions with the aim to gain understanding rather than explanation (Blaikie & Priest, 2019). Abductive reasoning is a pragmatic approach that is used to generate or modify theory by using existing theory where appropriate (Mitchell, 2018).

The deductive approach is not appropriate for this study because it does not start with a general theory against which to test hypotheses. Furthermore, while deductive reasoning is confirmatory in nature, this study is explorative in nature. Inductive reasoning may be more appropriate because theory is developed through the empirical collection and analysis of data about the topic (Myers, 2019). This aligns with the constructivist ontology where knowledge is 'constructed'. However, the concept of AI and its related affordances are considered novel, and some theories about the phenomenon already exist. Moreover, this study seeks to gain an understanding of one observation in relation to others. An abductive approach is therefore more appropriate than an inductive one. It involves "piecing together all the evidence and coming up with a probable solution" (Myers, 2019, p. 49). Using abduction, this study provides an understanding of how AI affords organisational change using the theoretical lens of affordance to propose a theory (Okoli, 2021). This approach begins by collecting information from participants and developing this information into themes which, in turn, is developed into patterns or theories (Mitchell, 2018); these emergent patterns are observed and interpreted through the lens of affordance.

Strategy

Based on phenomenological research which "attempts to understand participants' perspectives and views of social realities" (Leedy & Ormrod, 2010, p. 108), this study follows a qualitative interview strategy with AI practitioners to explore the AI features and related affordances that result in South African organisational change. Interviews are conducted with professionals who deliver an AI service or product to - or on behalf of - South African organisations. The AI practitioners as the implementers or configuring agents, as well as having interactions in the context of the organisation they represent, are therefore the units of analysis in this study. Interactions are considered together with the AI practitioner as a unit of analysis because of how intertwined the AI technologies are with their AI implementers and their organisational application, and it is these interactions from which knowledge emerges (Edwards & Holland, 2013).

Timeframe

AI in South African organisations is a novel phenomenon. Due to the growing interest in AI in recent years, the phenomenon and perceptions thereof may evolve, making a cross-sectional study a more appropriate one, considering the research objectives to identify affordances, features and effect on organisations within a particular timeframe (Bryman & Bell, 2007).

Data Collection Technique

There are several possible choices for data collection. These could be observations, documents or interviews as examples of some of the options, but interviews are considered a key method for data collection in interpretivist research (Walsham, 2006; Creswell, 2014). A qualitative method for data collection was used in this study based on a semi-structured interview guide (Appendix A) as the primary instrument. However, due to the Covid-19 pandemic, certain options were limited, such as face-to-face interviews, group-based interviews, or on-site observations. All interviews were therefore conducted via video or audio call using the software collaboration tool Microsoft Teams. Each interview was scheduled for one hour, except where interviewees requested otherwise.

To develop a semi-structured interview guide, five phases were followed (Kallio, Pietilä, Johnson & Kangasniemi, 2016, p. 2959): (i) “identifying the prerequisites for using semi-structured interviews”; (2) “retrieving and using previous knowledge”; (3) “formulating the preliminary semi-structured interview guide”; (4) “pilot testing the interview guide”; and (5) “presenting the complete semi-structured interview guide”.

Role of the researcher. Walsham (2006) proposes that the level of involvement of a researcher in a qualitative study be represented on a spectrum whereby at one end, the involvement of the researcher is considered to be closely aligned to the goal/s of the organisation or subject/s being interviewed (close involvement). One may label this type to be a full action-based researcher. Conversely, the other end of the spectrum sees a ‘neutral’ researcher as one that is very ‘distant’ from the subject/s being interviewed, where there is no goal alignment between the researcher and the subjects being interviewed. The role of the researcher in this study leaned toward the neutral observer. However, there was also some shared understanding of the technology industry between the researcher, the subject/s being interviewed and the industry. This role position drew on some of the advantages typically benefitted by a closely involved researcher role where interviewees may see the researcher as someone wanting to make a valid contribution to the industry. The role of the researcher at this point on the spectrum allowed for a degree of reflexivity during dialogue and interpretation, which further enriched the data collected. This aligns closely to Klein and Myer's (1999) interpretive principle of interaction between the researcher and the subjects.

Ethics and data integrity. This study followed the protocols for ethics approval by the UCT Ethics in Research Committee prior to engagement of interviewees. The researcher regards ethics and the confidentiality and privacy of interviewees of key importance. Careful attention was paid to protect the privacy and security of any personal and company information. Participants of the study were adults over 18 years of age who were part of the general public and each interviewee was asked for consent to be interviewed; a consent form for being interviewed was signed by the interviewee. They were asked for permission for the audio or video call to be recorded using Microsoft Teams. Each participant was given the option to discontinue or postpone the interview at any time during the interview process. Quality of internet connectivity and sound during an interview was of utmost importance so that interviews could be transcribed after the interview completed. All data were stored in a secure digital database. This data included interview audio and video recordings, recording transcriptions, notes and files generated by the computer-assisted qualitative data analysis software (CAQDAS), NVivo. Only the researcher had access to the database. Data collected during this research was appropriately protected during the research process and personally identifiable information was anonymised; interviewee names were replaced by 'interviewee n'; for example 'John Doe' replaced by 'interviewee 3'. All data would be destroyed after the submission to the university.

AI is a novel phenomenon in South African organisations. The impact of AI on the South African workforce is unclear and leaves organisations and individuals uncertain about the future of such a workforce (Bresnahan & Yin, 2017; Wright & Schultz, 2018). Care was therefore be taken to avoid raising of such concerns.

Data Analysis Technique

Interviews were transcribed and the resulting data were analysed using thematic analysis (TA) in order to identify AI features, affordances, types of organisational change and constraining conditions for affordance actualisation. TA with abductive theorising complements the constructionist paradigm through in-depth interpretation of information, by identifying patterns (themes) to develop rich meanings (Patton, 1990; Braun & Clarke, 2006). This analytical approach provided flexibility and relatively easy access to the data, themes and meanings (Braun & Clarke, 2006). This was particularly useful when analysing information related to a novel IS phenomenon like AI in its social setting. This study followed the six phases of TA proposed by Braun & Clarke (2006, p. 87), namely (i) familiarisation of the data, (ii) "generating initial codes", (iii) "searching for themes", (iv) "reviewing themes", (v) "defining and naming themes", and (vi) alignment with research question and literature to produce the report. The phases involved an iterative process of reviewing the data, codes and themes, along with the taking of notes throughout the analysis. This iterative process of consideration and examination of the parts and the whole they make up is a fundamental principle of the hermeneutic circle proposed by Klein and Myers (1999). Each cycle provides an opportunity to potentially new understandings and/or support interpretations already formed (Paterson & Higgs, 2005).

Data Collection and Analysis Limitations

The main limitation in progressing this study was access to respondents. During the year 2020 when the Covid-19 pandemic first caused country-wide lockdowns and limited movement of persons, respondents were less interested to meet, physically or virtually. Second, AI is a novel development in South African organisations and there were limited practitioners available to interview, for those who agreed to interview. Third, much of the intellectual property (IP) developed using AI could not easily be shared by AI practitioners or limited information was shared in order to protect such IP. One of the ways to work around these limitations were through the networks of the University of Cape Town. This led the researcher to the AI Expo Africa and its community network, through which several AI practitioners eventually agreed to interview. AI Expo Africa "brings together numerous community members, speakers, sponsors, and many others for the largest business-focused AI and Data Science community event in Africa" (Girasa, 2020).

Generalisability

Generalisability "refers to the validity of a theory in a setting [*to* general notions] different from the one where it was empirically tested and confirmed [*from* particular instances]" (Lee & Baskerville, 2003, p. 221). The issue of generalisability in qualitative research has been much debated because of its association in quantitative research; quantitative studies are typically based on statistical sampling and this is often assumed as limiting generalisability in qualitative research (Lee & Baskerville, 2003; Myers, 2019). However, this is not necessarily the only form of generalisability in qualitative studies. One of the four types of generalisability offered by Lee & Baskerville (2003) include the generalisability *from* description *to* theory, which aligns to the approach adopted in this study. This study applied generalisability *from* empirical statements or descriptions about the AI technology and social context (including the AI practitioner as the actor) *to* a proposition (theory) about how AI affords organisational change. In doing so, the study also adopted Klein & Myers' (1999, p. 72) principle of abstraction and generalization: "Requires relating the idiographic details revealed by the data interpretation through the application of principles one and two to theoretical, general concepts that describe the nature of human understanding and social action".

5. Data Collection and Analysis

5.1. Data Collection

Data were collected from fourteen AI practitioners interviewed over a twelve month period between April 2020 and March 2021, through semi-structured interviews with open ended questions (Creswell, 2014). Not included in the fourteen interviews were two that were abandoned. One interviewee admitted being an AI practitioner based outside of South Africa and representing an organisation outside of South Africa. The second interviewee (interviewee 2) failed to provide adequate consent for the use of their data. Neither of these two interviewee data were ultimately used. The remaining fourteen interviews were conducted and recorded in video or audio format, and transcriptions completed by April 2021. These transcriptions were imported into NVivo. Notes made during data collection (and analysis) were also captured in NVivo as annotations. The average time used for the interviews was forty-seven (47) minutes; the shortest interview was conducted in twenty-three (23) minutes (due to the interviewee's time constraints) and the longest interview was conducted in one (1) hour and seven (7) minutes. The interviewees were goal-oriented South African AI practitioners who represented South African organisations, either as an internal employee or as a contractor (service provider) to the organisation with the goal of achieving specific organisational outcomes. Their profiles are illustrated in table 3.

Affordances refer to the actionable possibilities made available as a consequence of the relationship between the goal-oriented actor and the IT artefact, but also considers the social context as an important element in this relationship (Markus & Silver, 2008; Bernhard, Recker & Burton-Jones, 2013; Volkoff & Strong, 2017). The social context includes the socio-cultural and historical contexts (Thapa & Sein, 2018). For instance, the science and technology fields have been struggling with gender inequality concerns, resulting in these fields being dominated by male practitioners (Moss-Racusin, Sanzari, Caluori & Rabasco, 2018; Leaper & Starr, 2019), including in South Africa (Malinga, 2022). South Africa's social setting is also influenced by its history in racial discrimination known as 'apartheid'. The Broad-Based Black Economic Empowerment Act (B-BBEE) was introduced in South Africa in 2003 to redress the impact of apartheid in the years preceding South Africa's first democratic election in 1994 (Republic of South Africa, 2003). This programme attempts to redress past inequalities in the workforce (where the white population was advantaged) by ensuring proportionate representation of the workforce based on demographics such as race, ethnicity and gender. However, race and racial inequality still play a role in South Africa (Francis & Webster, 2019) and Black individuals continue to be underrepresented in the science and technology fields (Idahosa & Mkhize, 2021). The gender and race of each interviewee were therefore also included in table 3. All interviewees were male which further confirms a lack of female [IT] AI practitioners in South Africa. Furthermore, the majority of interviewees were white, which is a significant disproportion of the demographic of South Africa.

Considering that the AI practitioner plays a key role in this study, it needs to be noted that ten out of the fourteen interviewees represented senior AI-related roles within their organisation (e.g. a department within the organisation). The remaining four interviewees represented executive roles within service providers providing an AI-related service to organisations. Both employees and executives of the service providers shared common goals with the respective organisation/s they serve. Due to their senior roles, all interviewees were able to interview authoritatively on the subject of AI and the organisations' goals.

Table 3. Interviewee Profiles

Interviewee	Gender	Ethnicity / Race	Role	Organisation Representation
Interviewee 1	Male	White	Chief Data Officer	Service Provider
Interviewee 3	Male	White	Chief Executive Officer	Service Provider
Interviewee 4	Male	Black	Head of Digital Research and Development	Employee
Interviewee 5	Male	Coloured	Head of Artificial Intelligence	Employee
Interviewee 6	Male	White	Technical Lead for Artificial Intelligence	Employee
Interviewee 7	Male	White	Senior Manager - Business Consulting	Employee
Interviewee 8	Male	White	Manager of Artificial Intelligence Business Unit	Employee
Interviewee 9	Male	Black	Data Scientist	Employee
Interviewee 10	Male	White	Principal for Artificial Intelligence	Employee
Interviewee 11	Male	White	Data Analytics and AI Engineering Lead	Employee
Interviewee 12	Male	Black	Lead for Artificial Intelligence	Employee
Interviewee 13	Male	Asian	Chief Technical Officer	Service Provider
Interviewee 14	Male	White	Chief Executive Officer	Service Provider
Interviewee 15	Male	White	Solutions Architect	Employee

The interviews were conducted based on the focus area of the interviewee where the interviewee was involved in a specific AI project or initiative. Although the open ended questions were used to guide the discussion, several interviewees did not initially fully grasp the understanding of the concepts around AI features or affordances. In addition to this, some of the interviewees were not comfortable sharing intellectual property, which was not required from them in any case. In both cases, and in exercising an abundance of caution, the open ended questions were adjusted and reordered; for example, the outcomes were first discussed in order to gain a shared understanding of the organisation's objectives. This was followed by questions about AI affordances and then features. Once the features were discussed and clarified, further clarification about the affordances and outcomes were then explored where necessary. This back-and-forth approach stimulated the use of several examples and elaborations on their area of focus, and assisted the researcher interpretations.

Interviewees were accommodated as far as possible to be able to collect adequate, rich data from the interview. However, in one case, this also limited the data collection where the interviewee only agreed to a maximum of thirty minutes for conducting the interview. In another case, the interview was conducted while the interviewee was in transit and experienced heavy rain in the location of the interviewee, inhibiting a good quality interview.

5.2. Data Analysis

The subject of AI is a broad one (Nguyen & Sidorova, 2017) and the concept of affordance is often debated about in literature and in practice (Volkoff & Strong, 2017). A thematic analysis was followed at a latent level in order to "identify or examine the underlying ideas, assumptions, and conceptualizations" (Braun & Clarke, 2006, p. 84), particularly in developing themes. Assistance was sought to transcribe the interview data and the data analysis started when the majority of transcriptions were completed. This also allowed greater familiarisation with the collected data (Braun & Clarke, 2006).

Initial concepts were derived from the data by identifying these using *In Vivo* codes (verbatim) or by developing labels (Creswell, 2014). These codes were labelled based on the research question and objectives, including interesting concepts that may be related to the research such as the industries the AI practitioner is exposed to. It is therefore relevant in this chapter to revisit the research question and objectives:

RQ: ***How do artificial intelligence technologies afford change in South African organisations, from the perspective of the AI practitioner?***

Objective 1: Identify the key AI features that play a role in its affordances in South African organisations.

Objective 2: Identify the AI-related affordances in South African organisations.

Objective 3: Identify the types of organisational change effected by such AI-related affordances.

Objective 4: Identify the constraining conditions under which such AI-related affordances result in achieving organisational change.

The process initially yielded a total of six hundred and ninety one (691) initial codes. Using TA with abductive logic, the codes were reviewed in an attempt to interpret themes or categories while also referring to the interview data. During this cyclical process, labels were consequently renamed and/or consolidated based on the research question and some codes were discarded because meaningful themes in the context of this research could not be generated (Byrne, 2021). For example, "linking related information" was later relabelled as "identify and classify information", but codes such as "menial work" were discarded as not having any value in generating meaningful themes. As a result of this iterative process, 403 codes related to the research objectives were coded, as shown in figure 4. Codes concerning general statements about business outcomes (organisational change), constraints or affordances were considered 'miscellaneous' and coded into a theme identified using the term 'general' as part of the theme's label (Braun & Clarke, 2006). In addition, as interpretation evolved and provided further clarity, more notes were added as annotations to the data and recorded in NVivo.

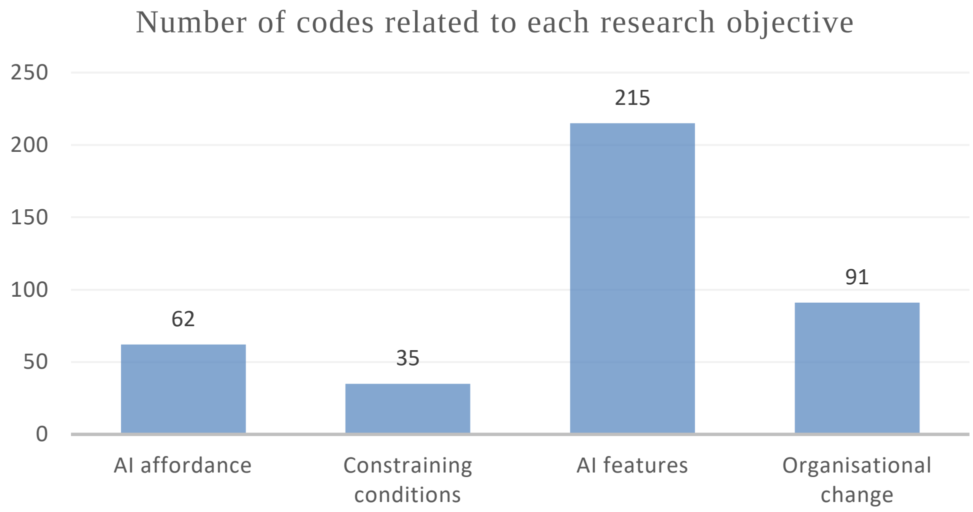


Figure 4. Number of codes related to each research objective

5.2.1. Themes

Themes were formed when codes with shared meanings in relation to the research were grouped together. Some themes were split into sub-themes where common concepts were shared between the subthemes (implying a relationship with the main theme), and with each subtheme representing a distinct meaning in the broader thematic structure (Braun & Clarke, 2006). Relationships between themes were also documented in NVivo when (i) extracted data were coded to more than one theme, and/or where (ii) interviewees implied a relationship between two or more concepts that were later coded into themes or subthemes.

The themes that emerged from the analysis are illustrated in figures 5 through 13. Several other themes were coded, but subsequently excluded from further analysis because they provided no further relevance to the research.

AI Features

Figure 5 shows the themes and subthemes related to AI features, the parent themes being: *prediction*, *accessibility to resources*, *train & learn*, *speed*, *computation*, *identify and classify information*, *data input*, *human sensory*. Features in the context of this research means "a typical quality or an important part of something" (Cambridge Dictionary, n.d.). The features of AI, in the broad sense, therefore refers to the distinct characteristics of the AI technology.

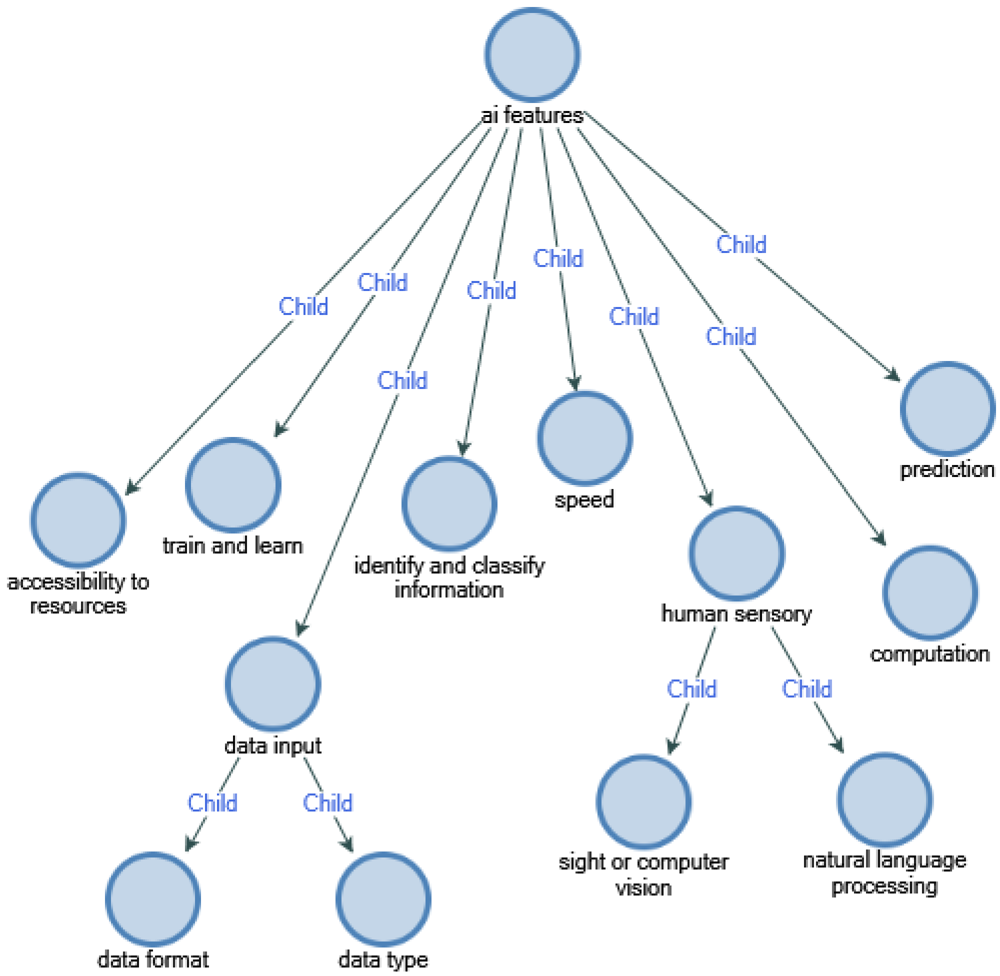


Figure 5. Themes and subthemes related to AI features

Prediction. The first interesting theme related to AI features is the concept of prediction. Prediction emerged as an overarching theme throughout the iterative analysis of data, codes and themes related to AI affordance. As shown in Appendix C, a NVivo word frequency query shows that the word "predict" is one of the top five most frequently quoted words.

"… it's still a machine with that calculating capability that can predict fairly accurately." (Interviewee 10)

"… and in doing so through these artificial intelligence um we can then um accurately predict you know what's um peoples categorization of spend is based on a limited set of inputs…" (Interviewee 11)

"You know the, a very simple, a very simple definition we, we use um for AI as, as let's say as a commodity is a prediction machine. We get inputs, you learn from those inputs and you make predictions." (Interviewee 14)

However, some interviewees grappled with the concept of AI features and similarly did not seem to understand the concept of affordance, struggling to distinguish between the two during the interview.

“I think the other feature is um prediction um from a machine learning perspective, then I think prescription would be the other one.” (Interviewee 8)

“I think you could say um well ya maybe I'm struggling with this affordance thing.” (Interviewee 12)

“Um the prediction, prediction is a, is a feature of AI and the affordance is that you can see into the future.” (Interviewee 14)

This was an opportunity for the interviewer to reorder the questions and restructure the interview to accommodate the interviewee, starting with the intended business outcome, in order to provide further clarification to the interviewee. In addition, the interviewer provided the interviewee with the simple analogy of a coffee mug also described earlier. The features of the mug *afford* the user to pick up the mug and drink the coffee (AI outcome). Similarly, the features of AI (e.g. computation, human senses, data input, identify and classify information, prediction, etc.) *afford* translating information, tailoring information etc. The following quotes are some responses to the mug analogy:

“Ya OK. So I would then under, under that kind of definition I would say um a feature um is certainly data location [access to resources].” (Interviewee 3)

“I must admit I, I haven’t thought about AI in that way before um in, but in, in your example, I think it’s a, it’s an excellent example as a coffee snob. Um I can relate to a coffee mug um [chuckles] and I think ya to, to, to um to continue from our, our previous sort of um short discussion.” (Interviewee 14)

Accessibility to resources. The theme of *accessibility to resources* refers to the feature or ability to access computing resources. Cloud-based computing enhances AI’s ability to use computing resources not limited by geographical boundaries. It also allows access to the AI technology without geographical boundaries.

“I mentioned cloud and the access and the accessibility to cloud. There’s no doubt in my mind that that has made AI more pervasive than ever before.” (Interviewee 3)

Whether resources are local (on-premises) or on cloud, it is a feature of AI required to build AI models. However, on-premises resources may be limiting. For example, on-premises computing resources may take longer to deploy. Using cloud computing resources to train AI models allow AI practitioners to use a try-before-you-buy approach before committing to purchasing such resources (such as on-premises), which is conducive to experimentation, evaluation and testing, particularly with novel technology like AI. This means that cloud based computing resources allow AI technologies to rapidly scale in order to process data in greater volumes and/or at greater speed.

“so when deploying um or building or um training a model um it requires um significant resources depending on the complexity of the model. Um and a lot of the time you’re dependant on an on premise system um to enable that functionality. Um what tends to happen is that you then um sort of um constrained from a resource perspective of physical CPU’s / memory perspective. Um this is obviously alleviated now days by the access to the cloud especially now we’ve got cloud providers in South Africa.” (Interviewee 11)

“And we build a model to sort of um predict or analyse what the future state would be. But getting to that stage is not a quick journey . . . So the three main cloud providers in South Africa. So generally what happens um we get it to that um, we move clients from on-prem to the cloud and this enables us to use a wide variety of tools um from the cloud…” (Interviewee 13)

Train & learn. Another theme emerged as a key AI feature is *train & learn*. The concepts of training and learning are grouped in this interpretation because an AI model that can learn means that it can be trained either through static input data or changing input data such as a changing environment.

“AI um leverages um learning strategies to be able to convert um, um certain data into insight um that it can then base um necessary actions upon.” (Interviewee 4)

“training those models . . . In other words a task would be um something which you’re trying to teach the machine.” (Interviewee 12)

“… it builds an algorithm so that whatever input you put in it will closely match to what it has been trained on.” (Interviewee 13)

An example of static methods of training is providing specific inputs to the AI model:

“So this algorithm what it does, what we actually, we were actually trained it using um people’s um, what you call it um, um people skills.” (Interviewee 9)

“… image classifiers sort of being trained to classify or detect um cats and horses and dogs and other physical objects.” (Interviewee 10)

“… it's learning from customer responses based on specific input from card data.”

An example of an input data feature is input data that changes. The AI model would learn and then ultimately predict improved outcomes based on the changing input data. An example is customer behaviour:

“… so something we would typically do um on a repetitive basis is, is learn about different data points around that customers behaviour.” (Interviewee 8)

To expand on this example, a customer at the end of a customer service call would be provided with the option to rate the customer service agent’s service. Depending on the rating, the AI model would *learn* that the specific agent managed the customer’s query well, in which case should the customer call on the customer service centre again, the AI model would route the call to the same agent, or perhaps route similar type queries to the same customer service agent. Similarly, an unfavourable rating by the customer may result in the opposite response from the AI model.

“… the customer survey at the end of the call would add feedback back to the model. So the model needed to be trained and retrained as time went by.” (Interviewee 13)

Another example of changing input data is that from appliances such as geysers or other Internet Of Things (IoT) devices.

"… in order to do that obviously you've got to have a model that's being trained on a series of data that's you know, say you've been able to get a whole host of data from various geysers and have the model trained on this." (Interviewee 3)

The output of the AI technology is therefore based on what and how the AI model is trained based on its input data. This implies that the AI technology's ability to learn (and be trained) is a key feature of such technology and is closely related to its prediction feature; by having the ability to be trained and to learn, an AI technology's prediction feature is improved.

Speed. An obvious key feature of AI technology is the speed in which it processes data. However, speed is widely known as a feature of electronic computation. Comparing a human mentally calculating arithmetic to a computer doing the same would obviously prove that the computer has the noticeable advantage of speed. AI models, however, are often comprised of much more complex mathematical or statistical models and so the speed advantage gap between human and computer is much more extensive.

"And you might need a team of ten people to, to, to do that within a reasonable amount of time because you know they didn't have a lot of time to do this." (Interviewee 10)

"… even if we had an army of a 100 people I don't think we would have got – and we had three weeks to do this. So there would have been close to no way um in which we could have actually done it when in reality it was two of us." (Interviewee 15)

"… computational capability, you can process a hell of a lot of data in a really quick amount of time." (Interviewee 6)

What is being acknowledged here is that the feature of speed, although key to AI, is not only a feature of AI per se, but also of general electronic computation. Take for example the 'reading' of email messages.

"So having a human doing something as tedious as that, reading 500 emails a day and just sending it to the relevant per-it might be a bit tedious." (Interviewee 10)

Computation. The ability to compute is another obvious feature. *Computation* for an AI model involves the computation of a statistical or mathematical model. The examples that emerged in this study are Euclidean, probability or regression modelling. This is not an exhaustive list because the research does not intend to identify the types of computation or statistical models involved in the development of an AI technology. Instead, this study explores AI in a broad sense and computational models therefore do not play a significant role in achieving its research objectives.

Identify & classify information. The ability to *identify and classify information* is a significant theme in terms of the number of files or references to the theme. The concept of classifying information is core to AI. The concept of identification of information is included in the interpretation of this feature because an AI model would need to be able to identify that information in order to classify it; for example, identifying specific information in large volumes of email messages in order to recognise any pattern (i.e. classify).

"ability to detect anomalies in large quantities of data" (Interviewee 5)

“… if I look at your specific personality profile, your strengths and weakness and the kind of job that you do. And I use models to, to, I can use models to determine the best way to train you. So some people are more visual, some are more auditory, some are more hands-on for instance.” (Interviewee 7)

“… or whether it's predicting an email belongs to a complaints or a claims or a new business category.” (Interviewee 10)

In order to classify information, AI can also identify such information that is not electronically generated (nor processed in it’s original ‘raw’ format) such as a picture of an object, logo or brand.

“So for instance, the contract would have been signed in Midrand, but it, the handwriting might look like Midfields. But because of the context of the rest of the contract, it was a Midrand store, Midrand address for instance.” (Interviewee 7)

“… one thing we were able to do for example is create a system that kind of does an automated audit of where the brands are used. So if you throw documents or images of places at the system it can I, automatically identify the brand and tell you that you know there’s still a brand usage is this specific document.” (Interviewee 10)

The information being identified need not only be content, but also related to the structure of the data to be able to classify it.

“… it looks at the structure of the data and um clusters it based on the similarities in the structure of the data.” (Interviewee 9)

For example, where AI technologies process data that are structured around a specific timeframe or customer profile, the AI technology is able to classify that information based on that timeframe or customer profile:

“Eventually you can look at the patterns in the time series data and connect it to the real world events in that transactional data. So we could see that as the temperature increased in the engine, it probably meant the oil was running low and something was wearing out.” (Interviewee 6)

“… it's aggregating the information and its finding patterns about a customer on a customer level, so very personalized. Um and based on those patterns its enable, its enabling you to potentially in the case of [application] to create new products that are personalized to that individual.” (Interviewee 8)

The feature of *identify & classify information* is a key AI feature because it allows AI to (i) recognise human-identifiable information, and (ii) classify that information (e.g. through pattern recognition) into human-labelled categories. The feature is also closely linked to the feature of *prediction*. The relationship between the feature of *prediction* and *identify & classify information* is a two-way influential relationship; prediction is used to identify and classify information (interviewee 10 below), and information that is identified and classified is used by the prediction feature to give rise to specific affordances or outcomes (interviewee 11 below).

"… image classifiers sort of being trained to classify or detect um cats and horses and dogs and other physical objects…" (Interviewee 10)

"… gives the customer insights into how they're spending their money um and it also gives them insights into how their peers for example are spending um their money um as well." (Interviewee 11)

Data input. Before an AI model can identify or classify information, it must be able to receive such information. *Data input* is therefore another key feature of AI. Figure 6 shows the *data input* theme and subthemes *data format* and *data type*. The *data format* subtheme refers to the format of the data the AI technology can receive. The *data type* subtheme refers to the type of data AI can receive.

Data formats that emerged from the data extract were general text, speech, images, documents and tones[6]. Data types that emerged from the data extract were profile, historical, device input, social media, uses cases and ai output as feedback. Using the example of profile, it refers to the ability to receive types of information related to a particular subject (e.g. person). The information is then processed by AI with the intention to tailor outputs; e.g. for the customer, supplier or application end user.

"… But if I look at your specific personality profile, your strengths and weakness and the kind of job that you do . . . I can use models to determine the best way to train you." (Interviewee 7)

"… that's to sort of create a segment of one based on um you know um defining what um a customer is um through AI and using a variety of inputs. Um such as for example um a customer's age um their financial status um their marriage states um their nationality and heritage and things like that to sort of drive out um a, a single view of what a customer looks like um to assist with marketing potential. So in that cases um what we'll do is, is there is a system that is um being built that would define these characteristics um, characteristics of customer um and in attempt to classify um customers within a specific segment…" (Interviewee 11)

The data type could also be transactional in nature. One example is a customer choosing to select a specific type of input such as a numbered option or one-time password (OTP) sent to such a customer's mobile device.

"… what our customer would do, would be to phone, route to a call centre and they would choose option one to resolve um resolve, I mean resolve change of a pin number. Let's put change of pin number, press 1 change of pin number and it would go to this agent." (Interviewee 13)

"… people's actual transactional information, so what you actually use your card on. Um where you buy, where you shop um what are more or less, what is your behaviour?" (Interviewee 15)

[6] Tones such as dual tone multi-frequency (DTMF) refer to the signals generated by a device (typically a telecommunications device) to other communications devices (Dodd, 2012).

What can also be considered a type of transactional data input is feedback from an AI output; when AI processes information, the resulting output that can be used as input, either to the same AI model or another.

"… we used three AI approaches, all unsupervised initially . . . And then once we actually got that we were able to train a model to say cool, um if these are, if these are the, if these are the aspects of the competency [initial AI output], that you get these are the courses that map to it [initial AI output] . . . when there was new courses that came in we could analyse the courses in the same way and put it through this model [AI output as AI input] and try and see if any of our competencies um, whether this course actually would fulfil any of the competencies that um, that we were after." (Interviewee 15)

The AI feature for receiving data (theme *data input*) includes the ability to input several types of data and/or in multiple formats. The excerpt below shows that the AI technology used the data format 'tone' as well as data type 'historical data' to predict whether the customer query was successfully resolved to that particular customer's satisfaction.

"So um what our customer would do, would be to phone, route to a call centre and they would choose option one to resolve um resolve, I mean resolve change of a pin number [tone] . . . And this agent would be able to help or not able to help. And the customer would be able to um say at the end of the call to, you know there's a customer survey, if this person assisted you press 1 or press 2 [tone]. Using that data and also the length of the phone call [historical] so, um if the length of the phone call was, it was an arbitrary number then say it lasted 10 minutes it would be, it would signify as the call being resolved um if and only if, if that same number doesn't phone again in the next 7 days [historical]." (Interviewee 13)

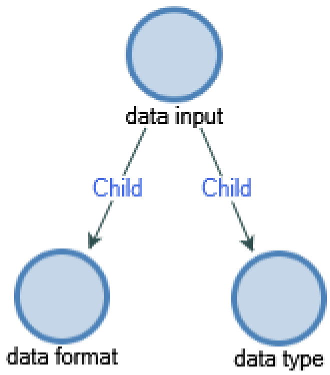


Figure 6. Data input theme and subthemes

Human sensory. Another theme that emerged was that of human sensory (see figure 7). This theme refers to AI features that mimic human attributes or 'senses' such as the ability to 'see', 'hear' and 'talk'.

"So a model should be able to hear, like a human would be, to understand, to hear, to um taste and to see the world around them." (Interviewee 13)

"… the ability to sense . . . and being able to act dynamically based on that sensing. Um and then in recent times being able to kind of then generate new outcomes I suppose. Um which is, which is this more kind of generative AI I think where it's moving. Um that is what I'd probably say are features that are distinct um to AI." (Interviewee 4)

"… the idea is that it has the ability to kind of sense and act based on what it senses in the environment. So, and that sense can be sight, that sense can be hearing, that sense can be um, um kind of um feeling. Um so in ambient computing it's more feeling, kind of hearing is more like your speech recognition, your speech um analytics your, your um your, your precede analytics um and other capabilities like that. But it's effectively sensing but not just being able to sense, being able to act based on the sensing." (Interviewee 4)

"And AI I like to say is giving that human quality to what um a model should behave. So a model should be able to hear, like a human would be, to understand, to hear, to um taste and to see the world around them." (Interviewee 13)

By mimicking human attributes, some AI technologies are not only able to receive and 'understand'/process human-sense information such as sight and speech, but also able to generate human-senses such as sight/vision, speech and language. The speech and language sense may be referred to as natural language processing (NLP) (Chowdhury, 2003).

"I'm breaking up sensing to sight so computer vision, um to language you know to natural language processing, natural language understanding, natural language generation." (Interviewee 4)

"… the AI, a AI is, has a feature that is sort of, I don't know understanding, can understand language or match a pattern can lead to customer satisfaction." (Interviewee 10)

"… if you look inside machine learning our focus is typically um speech and, and more broadly NLP natural language processing so we spend a lot of time there." (Interviewee 12)

"this technology called chatbots, um where it's um using natural language processing, NLP to sort of um give that um human element towards solving your frequently asked questions and such." (Interviewee 13)

"… I would say a big portion of what we do um is in, well we, we focus a lot on natural language processing . . . I think the features will be, it will become pretty standard for computers to be able to, to translate between languages, and also to be able to transcribe um you know from um from voice and video and that sort of thing." (Interviewee 14)

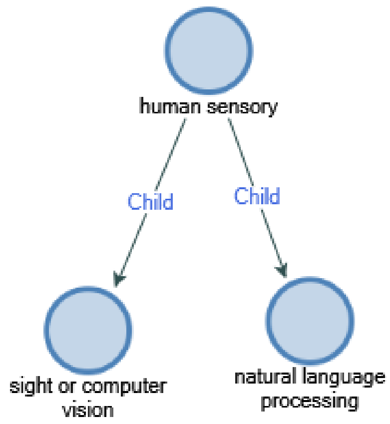


Figure 7. Human sensory theme and subthemes

AI Technology-Practitioner Affordances

To reiterate an excerpt from the literature review, AI affordances are "the possibilities for goal-oriented action [intended business outcomes] afforded to specified user groups [AI practitioners as organisational actors and representatives] by technical objects [AI technologies]" (Markus & Silver, 2008, p. 622). The AI affordances emerge "from the relation between an artifact [AI technology] and a goal-oriented actor or actors [AI practitioner representing the organisation]" (Strong et al., 2014, p. 69). These affordances are not simply AI features, but rather the possible organisational practices made available to the organisation by these relations (Fayard & Weeks, 2014). As shown in figure 8, the main themes related to AI affordance that emerged from this study were labelled using gerunds as suggested by Strong et al. (2014) and Fromm, Mirbabaie & Stieglitz (2020). The key themes that are discussed in the section that follows are: *Assessing efficiency and effectiveness*, *forecasting*, *analysing needs*, *analysing risk*, *tailoring information*, *translating information*, *providing prediction criteria* and *improving predictability*.

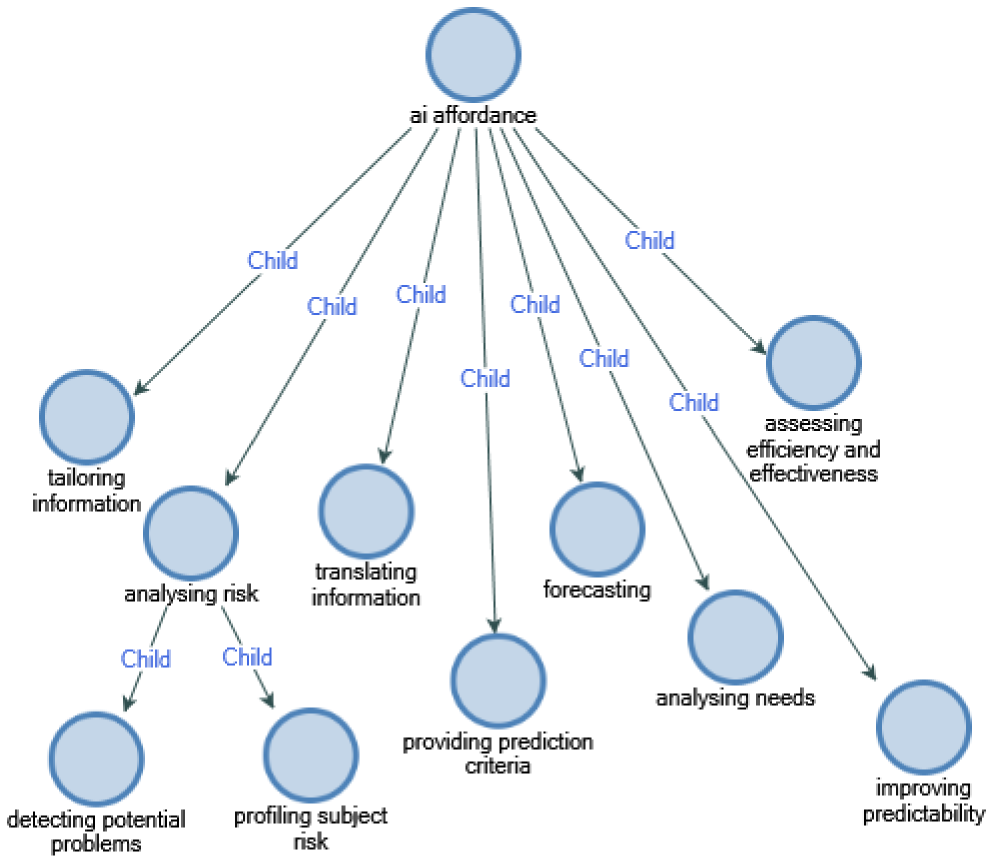


Figure 8. Themes and subthemes related to AI affordance

Assessing efficiency and effectiveness. The theme of *assessing efficiency and effectiveness* involve the assessment of a process to determine whether the process is optimised in terms of its efficiency and effectiveness.

"… our sales process you can restart with um, um, we look at all your data and then look at scenarios on that data. And then try to predict how, if we do something will it be more efficient and, and so forth with it." (Interviewee 1)

"For example if this person is good at solving FICA why don't we send all the FICA um, FICA um queries to this person. Or if, if um if a person, if another person is good at um resolving lets say um, change of number issues, why don't we um send most of the calls regarding resolve calling issue to this person. And the reason for this is um, you have, the customer would get a better satisfaction from having their call resolved to a support centre. And as well, it would prevent um people from jumping from one call to another. I don't know if you've experienced where you call and they just routing you to different people. So they wanted to prevent that from happening." (Interviewee 13)

"Then I think the AI affordance is the machine learning part that, that we are bringing in to say before you even do the three years can you actually get to complete in minimum time. So the whole concept there we, we had to, to design a model, create a model based on the previous historical data of students . . . Then based on that you'd actually create a model that would um that you would use to test now on the students that are starting right now, to see if they will be able to complete in record time." (Interviewee 9)

The first quote by interviewee 1 is an example of an AI-based assessment of a sales process. The information related to this sales process, including "scenarios" or outcomes of that specific process, is provided as input to the AI technology/model to determine whether the process can be improved. The second quote by interviewee 13 is an example of a contact centre process where the AI technology assesses whether the process can be improved in terms of efficiency (faster customer resolution) or effectiveness (answering the customer query correctly). In these cases, AI predicts how efficient/effective a "scenario" is based on the outcomes of such a "scenario". The third quote by interviewee 9 presents a similar scenario in that the AI technology uses historical student information (i.e. "scenario/s") to assess whether the student would be able to complete a course in the minimum timeframe; i.e. *assessing efficiency and effectiveness* using prediction.

Forecasting. The theme *forecasting* refers to planning based on insight. Insight is provided by the AI technology to allow the consumer of such information to improve planning. In some instances, this may refer to insight into personal spend, customer behaviour when it comes to spend, optimal rate of production of goods or inventory levels. The quoted term 'predict' in some of the following excerpts imply *forecasting* as an affordance.

"… the affordance that it gives us is the ability to better communicate with our customers, what their expenditure is on a monthly basis. Um so that gives us, that gives the customer insights into how they're spending their money um and it also gives them insights into how their peers for example are spending um their money um as well." (Interviewee 11)

"However the ones that do allow us to train a model that will allow us to categorize um expenditure in general. Um and in doing so through these artificial intelligence um we can then um accurately predict you know what's um peoples categorization of spend is based on a limited set of inputs" (Interviewee 11)

"We'll take some data and then start doing an experiment of how to develop um an AI model to actually help predict if they're about to run out of stock or not . . . last year I produced um 5000 items of um, 5000 items of item A. But this, this algorithm says rather than making 5000 make 3952." (Interviewee 15)

Analysing needs. The theme *analysing needs* involves obtaining insight into needs such as customer needs or training requirements. Using conversational data, the AI technology affords analysing the needs of the customer and thereby addresses these needs resulting in improved customer service. Similarly, training needs are analysed to suggest an optimal training method or relevant upskilling program.

"Some of which benefit from the aspect of machine learning and therefore are able to actually dig into what people are saying um pre-categorize it, perform analysis and understand what our customers concerns are. Um and that leads us to sort of recommendations and, and the like um and we can then use to optimize um not only that channel…" (Interviewee 12)

"… if I look at your specific personality profile, your strengths and weakness and the kind of job that you do. And I use models to, to, I can use models to determine the best way to train you. So some people are more visual, some are more auditory, some are more hands-on for instance." (Interviewee 7)

"The end goal was to actually come up with the framework of saying, cool here's a list of competencies, to fulfil those competencies what education does someone have to take, have to, have to have. What kind of qualifications do they need to fly, to be termed competent?" (Interviewee 15)

Analysing risk. *Analysing risk* is a theme that involves obtaining insight into risk exposure as part of a task or organisational process. This means that the AI technology performs a situational analysis that highlights potential risks. As shown in figure 9, one type of risk to analyse may be related to company equipment or tools where unplanned breakdowns cause greater risk exposure or unforeseen expenses as a result of such a breakdown. In this case, the AI technology enables the risk to be analysed so that imminent equipment failure can potentially be identified (*detecting potential problems*), prompting planned preventative maintenance. The other type of risk to analyse concerns the subject such as a person seeking a loan from a bank, the subtheme therefore named *profiling subject risk*.

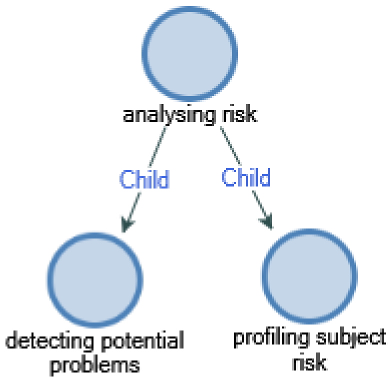


Figure 9. Analysing risk theme and subthemes

"… the one I was talking about of the geyser um I mean that was a particular use case where um they're wanting to pick up anomalies before the anomaly has happened to um prevent expenditure on the behalf of an insurance company." (Interviewee 3)

"I guess the easiest use case or example from that specifically was a predictive maintenance solution . . . we've built a, a model that's capable of detecting anomalies in real time and we can push actual ins, like insights to maintenance teams or operators…" (Interviewee 6)

Analysing risk may also mean *profiling subject risk*. By evaluating the profile of any individual or subject (be it organisation or natural person), the risk introduced to the organisation, as a result of the pending relationship between the two (or more) parties, may be better understood, thereby providing insight into the risk such as the degree of risk. This information would then support the organisation's decision making process/es.

"… the concept was to um maybe be to actually try leverage that transactional data to try and predict whether this individual will default on a loan or not . . . And then it would generate essentially a line of information and then submit it to this model. And then the model would give a yes or no decision back" (Interviewee 15)

Tailoring information. *Tailoring information* is a theme that involves customising information in a manner that is meaningful or specific to its intended recipient/s. The AI technology identifies patterns in the information (e.g. customer behavioural patterns, gender, age, etc.) and then uses this information to be able to provide customised/specific feedback to its intended consumers; e.g. market products intended for a specific customer demographic profile.

"One is to improve the customer offering in terms of the content we offer um you know the, the range of content and how we make it available. So that's personalization, recommendations, localization right." (Interviewee 5)

"So the actual training set or the outcome of the curriculum stays the same, but the way I, the training is delivered to me as an individual staff member is customised to my specific strengths and weaknesses and the role I'm being trained for." (Interviewee 7)

"so the salesperson would have OK, um they'd capture, let's say a new person they'd capture their detail. They'll say I'm a male at this age and I get this salary, and what it will do, it will, it will call a model once that salesman submit. And it will return a bunch of different policies to say, this person would mostly likely benefit from having this, this and that." (Interviewee 13)

Translating information. The theme *translating information* is an AI affordance that involves receiving information and *translating* that information for its intended recipient. The information that is received may be in one of several formats; e.g. speech, video (vision), text, etc. To elaborate using an example, the AI technology translates information from documents or images into a format of information that can be consumed by the intended recipient.

"So if you throw documents or images of places at the system it can I, automatically identify the brand and tell you that you know there's still a brand usage is this specific document . . . So I mean most of the types of AI's we use is um classification, um classifying of input, um or protection of input, predicting the class it belongs to" (Interviewee 10)

The data extracts reveal the notion of 'clustering' of affordances. For example, clustering translating information with tailoring information. In specific scenarios, information may need to be *translated* in order for *tailoring* to be effective. This may seem like a case for non-mutual exclusivity, but it may be presumptuous to argue that this is always the case since tailoring information does not need to be translated in all cases to make information specific to its intended recipient/s.

"And localization is about taking the same content and making it available in multi languages right. And we use AI for that. So we use um something called machine translation." (Interviewee 5)

“I think AI’s ability to translate it, to translate into your native into your native language or to your mother tongue language will open it up to more people and that’s, that’s your that’s your affordance. So the feature is um you know language trans-translation…” (Interviewee 14)

Providing prediction criteria. In some instances, the AI technology clusters the *providing prediction criteria* with other affordances in order to provide the recipient of the outcome with more information about the technology’s decision making process, and thereby supporting the decision-making process/es.

“somewhere in-between you’ve got a human machine interface um where typically like the AI would make a suggestion that says, this component is broken um, for this and this reason. The suggestion is that you need to replace this and go investigate or inspect that. And it's up to the operator to then look at it um, accept or deny or change or, you know it's up to them.” (Interviewee 6)

“… then the model would give a yes or no decision back and then it would give that decision back as well as more as a, as a short statement. Or at least the main issues on why it said um, on why it said yes or no . . . So the idea was to provide them with um with as much information as they could to actually make an informed decision . . . you can see why it's making those decisions um, you can kind of, it kind of gives a small list of why it's making those decisions.” (Interviewee 15)

Improving predictability. The theme *improving predictability* relates to better organisational predictability, which allows better organisational planning and improved customer relationships as a result. An example is the accurate capture of information which can be later used, with a high degree of confidence [predictability], for verification.

“What we do is we trying to focus into [AI-enabled] robotics process whereby we use OCR to analyse um an ID um document um so that we can capture a person’s information um more accurately. Um and this speaks to assisting say for example branches, if somebody comes into the branch we obviously have um our tellers who capture the information. Um scan through their ID’s for example and then what we do is we try and associate the um the, the OCR um to the um information that the teller captured and that just helps to better define um you know our data completeness and accuracy.”

Better organisational predictability also means better *forecasting*. Outcomes expected from AI are the ability to predict how much stock (inventory) an organisation needs to secure while maintaining an optimal inventory level, what stocks are likely to perform best on the stock market, or how likely a student would be successful in their course.

“And as well we have another client who does um, financial modelling. Stock markets predicting, um using machine learning to identify which stocks are going to be the best.” (Interviewee 13)

“… how much product should I make this month? . . . predict that um next month you should say, you should produce maybe X, Y and Z of product A and um and another amount of product B.” (Interviewee 15)

"… the university um strategy maybe that um focusses on the students success right. So the main goal is for us to see students succeeding." (Interviewee 9)

Constraining conditions facilitating affordance actualisation

This study found five conditions that facilitated affordance actualisation as shown in figure 10. These include the themes *trust*, *data management*, *change management*, *model maintenance* and *data availability*.

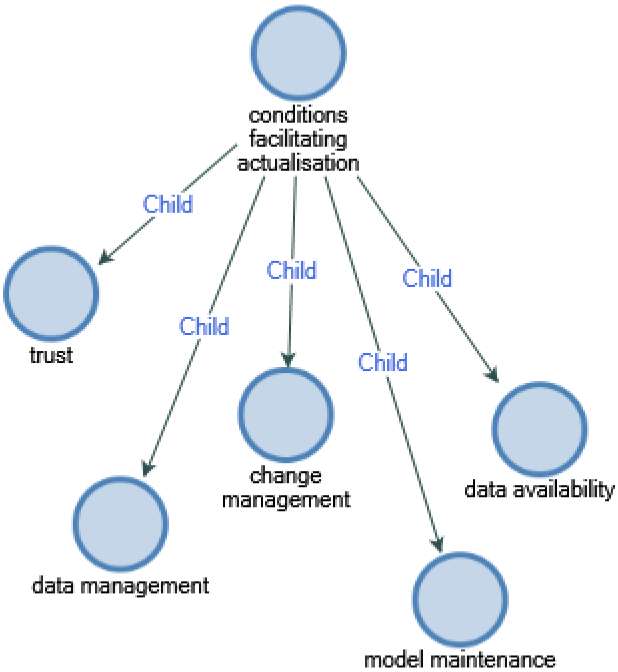


Figure 10. Themes related to constraining conditions facilitating affordance actualisation

Trust. The theme of *trust* is a constraining condition for affordance actualisation because an actualised affordance may not always result in what a human might expect. To use the forecasting (affordance) example, an actor in this context would not forecast (actualised affordance) or use the forecast information if trust was a constraint.

"We have to absolutely ensure that we protecting and are compliant with um appropriate data regulations and that the data that we actually are leveraging is data that enables us to develop an effective system and not . . . Unreliable in terms of the outputs um that it provides not that it's not going to provide an output but because of the data it took in the results are not maybe consistent which, what um a human might, might have done." (Interviewee 4)

"… if we build a solution, the computer can only be wrong once and then the person using it loses complete trust." (Interviewee 6)

"And you have to be willing to let the team go ahead and do that without ever having seen it before. Um and I think that, that is um an element of trust you know you have to trust that if these people execute it will go well." (Interviewee 12)

In the case of interview 9 (below), the AI model required information from advisors to improve the AI output, but the advisors voiced a concern around trust and whether this AI solution would provide an output they would typically expect. In addition, the AI technology would also be doing the analyses that the advisors would typically do, potentially creating a concern about job security.

"We're going to give you a machine learning component that's going to help you understand the, the student from the 360 degree angle and tell if they're going to succeed or not. And it will tell you as well the features that they need to work on, you understand. So it was, it was actually um we're actually taking a lot of strain from the advisors." (Interviewee 9)

The affordance *providing prediction criteria* also potentially influences the constraining conditions facilitating AI affordance actualisation.

"… if it just said yes or no you actually um, the, it's just the, it's essentially something saying a decision. So if you don't have reasons for it you might, you might be inclined even to not trust it or trust it blindly." (Interviewee 15)

Data availability and data management. The themes of *data availability* and *data management* are closely related. Affordance actualisation would be inhibited if access to data was constrained, there were inadequate data and/or if that data were not appropriately structured (managed) for the AI technology, in order to produce its intended outcome.

"… so if you um took the ability to store data easily in the cloud and then have your, the ease of spinning up a machine learning model . . . And because the data is now very close and very accessible you're able to actually really create this um feature of getting a particular outcome from that, from that model." (Interviewee 3)

Data must be therefore accessible and available to the AI technology. The same data would also need to be relevant for the purpose/s the AI technology is using it for. For example, to afford *translating information* (e.g. language), data would need to be accessible and available for the 'source' (original) language and the 'destination' (translated) language.

"The other problem is that some of these things require language data and the language data is not, like especially for South African languages and African languages the language data is not always available. So in some cases we have to create our own language data right." (Interviewee 5)

Affordances may also be constrained if data structures are not considered, particularly when data is being received from multiple sources or what outcome one expects to produce. An unintended outcome could be a skewed or incomplete result. This would likely have an impact on the *trust* constraining condition.

"So, so marketing would have one view of [person X] for instance and, and the sales guys who work with sales the force would have a totally different view of [person X]. So, so if you approach the company depending on who you spoke to they'd, they'd speak to you in a very different way. Um so the, so the biggest constraint was how, how do you aggregate all that data to produce one view of the customer?" (Interviewee 8) “the way that you constructed your data and the way you constructed your question led you to essentially only model on the one type of observation and um, and that’s why your model isn’t working.” (Interviewee 15)

Model maintenance. Environments and conditions in which AI technologies are implement do change. Such changes may mean new information or changes to existing information the AI technology receives. Therefore, affordance actualisation may require AI models to be maintained; this may mean the model would need to be regularly retrained. For instance, one interviewee referred to the Covid-19 pandemic and how data used prior to Covid would not serve as good a purpose within AI technologies.

“Covid has come along and that’s thrown a spanner in the works. So anybody who’s working on AI projects now um which is using linearity and . . . predictability based on those linear algorithms is screwed, because um what do we learn from the past twelve months? We learn that . . . it’s all new.” (Interviewee 3)

When there are changes in the environment, AI models may become outdated (or somewhat so), termed by interviewee 10 as ‘model drift’. These changes necessitate *model maintenance* (a constraining condition facilitating affordance actualisation).

“So one of the common challenges one faces is that the, the data can change and it causes what they term model drift. So or the, the conditions under which you operate change over time . . . company might introduce new products um with different business processes around it and all of a sudden . . . your model has not been trained to identify this intent. So now the model becomes outdated um which basically mean you have to renew the model and update it with new knowledge. So model drift or model, models becoming outdated for example is a challenge or a con, ya a constraint. Because models don’t update themselves.” (Interviewee 10)

“Taking into account that you know these environments and variables change continuously um and the model needs to be updated accordingly.” (Interviewee 11)

Change management. *Change management* refers to managing the expectations from AI and the organisational change that happens as a consequence of AI. For instance, AI brings with it concerns about the impact to the workforce (Kaplan & Haenlein, 2019; Rapanyane & Sethole, 2020) that needs to be managed or addressed by organisations. This view was echoed by several interviewees.

“… people don’t want to hear that they’re going to get fired. Um so it, that sales pitch just doesn’t work in a, in a business to say we’re just going to put in a machine.” (Interview 1)

“some of these systems are going into production, and they’re already in production right for, for some of the use cases. What it means is it impacts peoples job profiles right um it impacts what they do on a daily basis.” (Interviewee 5)

“The other one is, is organizational readiness. So do the people who work for you understand that you know the moment you, you use word like robotic process automation, especially in a highly um unionised area like a bank, and the realities of our country from an employment figures point of view, you open a lot of um, a can of worms really, internally.” (Interviewee 7)

Some interviewees also expressed suggestions such as organisational restructures, deliberate change management methods and reskilling to not only address the job security concern, but also the skills concern with regards to supporting an AI capability in the organisation.

"… one of the challenges is you have to reskill because if you don't you, you're also going to create lots of resistance right." (Interviewee 5)

"… one massive constraint is going to be the organizational resistance to that change. Um an, and even if that resistance is overcome then you need to overcome the training aspect and the knowledge aspect." (Interviewee 8)

"… like in the case of the email routing, you know free up a human from that sort of drudgery of reading an email and just clicking forward that can really improve your um staff morale or it can improve, and you can use that human for more intelligent you know creative type of work rather than that drudgery of just pointing a, sending emails around." (Interviewee 10)

"… it's the cultural change that needs to happen within an organization to make AI successful. Um you'll, you'll typically see a lot of push back if, if it's not well understood." (Interviewee 14)

Managing the change from an expectations perspective is also a constraining condition. What the recipients expect from AI is not always what happens in reality. Affordance actualisation depends on expectations being managed so that buy-in can be gained which in turn enables such affordance actualisation.

"I think the, the one challenge is um is to manage, is to manage expectations . . . Business expects something that can do this, you expected this um and there's just there's a bit of, a bit of disconnect between um you know, expectations." (Interviewee 14)

Goal-orientated outcomes

Goal-orientated outcomes refers to the "goal-oriented action [intended business outcomes] afforded to specified user groups [AI practitioners] by technical objects [AI technologies]" (Markus & Silver, 2008, p. 622). Main themes and subthemes that emerged related to goal-orientated outcomes are shown in figure 11, and expected as a result of an AI technology's influence. The key themes related to organisational outcomes are: *improve customer service*, *expand market reach*, *improve profitability*, *risk management*, *regulatory compliance*, and *automation and efficiency*.

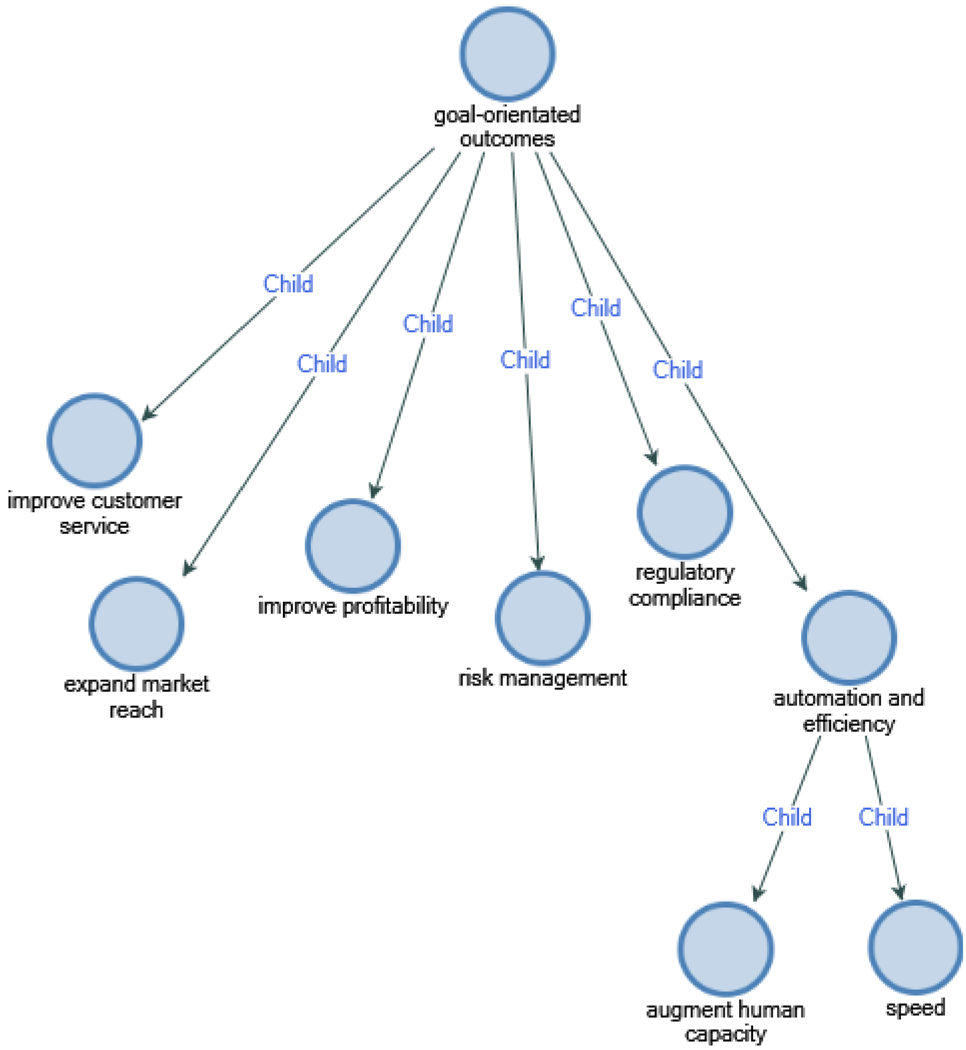


Figure 11. Themes and subthemes related to goal-oriented organisational change

Automation and efficiency. Figure 12 shows the number of codes referenced per goal-orientated AI [organisational] outcome. The theme *automation and efficiency* emerged as the theme with the highest reference count. As figure 13 shows, this theme refers to the expectation (by the AI practitioner representing the organisation) that AI will introduce or improve automation/efficiency (i) as an overall expectation, (ii) though the augmentation of human resource capacity, (iii) through speed, or (iv) through a combination of approaches.

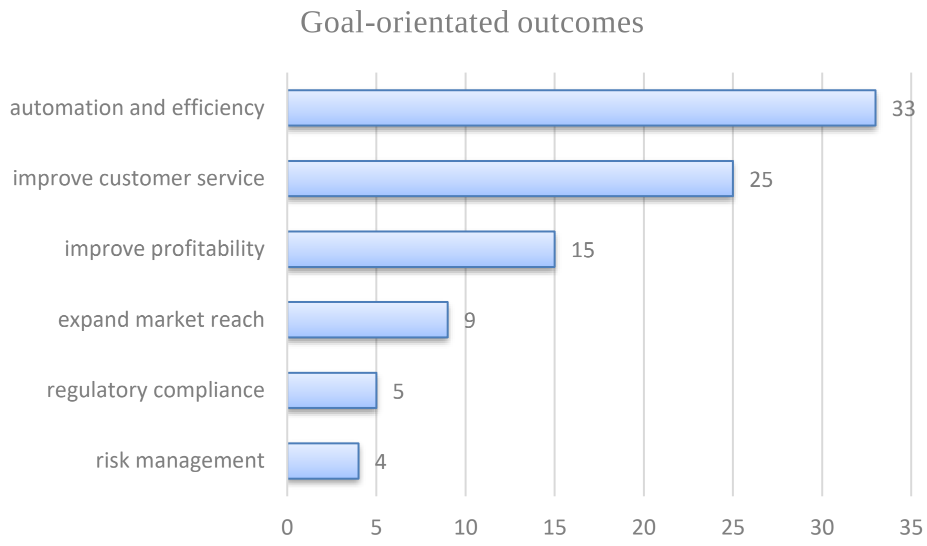


Figure 12. Number of references coded per goal-orientated AI outcome

Overall, *automation and efficiency* in organisational processes is typically expected from an AI technology. A few examples from the data are extracted below.

"… we don't sell our artificial intelligence as a product um but we sell it as a human machine assisted um technology to . . . provide optimization to clients . . . If you automate a call centre um and you add more um machine learning around it…" (Interviewee 1)

"So there's always a drive towards automating kind of routine based um capabilities. And part of that means that we employ quite a large amount of decision trees um business rules, engines um etcetera to be able to um to create those efficiencies operationally." (Interviewee 4)

"So reducing can um can be something like automating a process, a business process um instead of having humans um relying on it." (Interviewee 10)

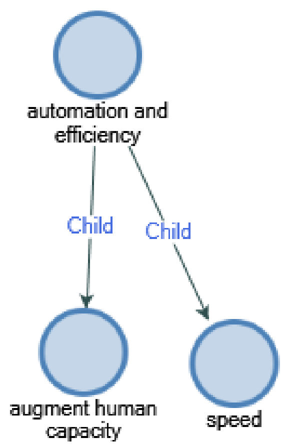


Figure 13. Automation and efficiency theme and subthemes related to goal-orientated business outcomes

The subtheme *augment human capacity* refers to the substitution of menial or repetitive human tasks with AI so that the freed up human capacity can be used to do more complex tasks. This augmentation ultimately results in improved organisational efficiency.

“the organization has multiple sort of decision trees and business rules engines um in multiple um of our processes. Um as a organization you always are trying to augment kind of human capacity um and assist them to kind of then focus on some of the items that are usually more complex.” (Interviewee 4)

“… we're talking about co-bottics. You know the bots are working with us. It's making me not have to focus on the mundane repetitive stuff. I can do more thought leadership stuff, whatever my talent is.” (Interviewee 7)

“so what actually happened is that this particular team which supports social media was being downsized. Um and so because they were being downsized they were already struggling to handle the volumes that were coming in, but because they were being downsized they were actually going to struggle a lot more, they’d been halved. Um so I would almost think about it like if we had introduced this bot and workload had reduced materially what would have probably seen as a reduction of the team size. But actually the team size reduction came first. And what happened is the introduction of the bot meant that they could now handle volumes.” (Interviewee 12)

The *speed* subtheme is an outcome that results in faster organisational processes. For example, the time it takes for a customer to apply for a loan or the time it takes to service a customer.

“… we’ve set up this chatbot which you know interacts um with customers um, ya that interacts with customers in a conversational way. And as a result we’ve been able to reduce our mean time to resolution by . . . some material percentage.” (Interviewee 12)

“So in other words um more efficient and effective so, you wanted somebody who’d be able to deal with the query quickly and, and appropriately or effectively.” (Interviewee 13)

“… the project entailed actually reducing the amount of time it took to actually apply for a loan…” (Interviewee 15)

The goal-orientated outcome of *automation and efficiency* is not only about improving internal business processes, but may also impact service. The theme *improve customer service* involves an AI technology that enables an enhanced customer experience and results in a higher degree of customer satisfaction. The following data extracts show some examples of the *improve customer service* outcome enabled by an AI technology (and *automation and efficiency* by implication).

“when you phone us when you use our WhatsApp channels or you know one of, one of our other social media cha-channels. How do we service you much better right. So AI helps to improve that customer service experience.” (Interviewee 5)

“… the business goal is often to service their customers better.” (Interviewee 7)

"… we try to read our twitter um replies and, and posts and comments um to determine you know what's the general sentiment is when we release a new product for example or when there's been an outage. Um and that gives us insights into how we've been performing which um gets attached to our NPS[7] score to um you know help better define the strategic decisions that the organization makes." (Interviewee 11)

Improve customer service. AI improves customer experience and satisfaction in several ways. For example, improved product or services offerings, or providing insight for customers.

"… to use the, the data you have on your clients, to better model around that, to, to better understands what your customers want, to give them better products and so forth." (Interviewee 7)

"… you continuously feedback the model um to be able to better predict um the categorization of spend. Um which would then benefit a customer by helping them to make the correct financial decisions based on um on their peers…" (Interviewee 11)

In addition to providing insight *for* the customer, another outcome is the insight provided *about* the customer to the organisation. Through the typical customer engagement process, the data processed by AI allows the organisation to reduce human error and provide more accurate statistics or information about the customer.

"I would say that the, the, the quality of the insights that we were able to derive from what's happening in the call centre are much, much higher. Because the bot doesn't have tea, it doesn't mislabel things" (Interviewee 12)

These customer insights also enable more meaningful customer engagement. The organisation would have more accurate information about their customer and able to provide customised, tailored advice based on that information.

"… the ability to better communicate with our customers, what their expenditure is on a monthly basis . . . Which means that we can have more meaningful conversations with those customers…" (Interviewee 11)

"… perform analysis and understand what our customers concerns are. Um and that leads us to sort of recommendations…" (Interviewee 12)

Expand market reach. The theme *expand market reach* refers to an AI outcome which allows the organisation to expand into new markets where it had not had the opportunity to do so in the past. AI would ultimately provide such an opportunity.

"So now we have you could almost say the ability to do that translation, do a very light validation of it right and then potentially sell that content to market where we don't necessarily originally have language um competency right. So that's one of the things that's, that's um as I said that's become an opportunity." (Interviewee 5)

[7] The Net Promoter Score (NPS) measures the likelihood of customers to recommend a business's products or services. It is intended to predict sales growth (Baehre, O'Dwyer, O'Malley Lee, 2022).

"… so that's the um primary outcome from a categorization view. It also give us insights into you know um how the market is doing for a specific segment um based on the categorization of their spend as well as their income bracket…" (Interviewee 11)

Improve profitability. The theme *improve profitability* involves the profitability of the organisation. It is expected that the AI technology will ultimately lead to additional revenue, better cost control, or improved margins.

"… so we do B to B into, into um into these businesses um drive change. Um deliver something and then on that measure the ROI . . . You know you do reduce cost and you make more, more profit." (Interviewee 1)

"Reduction of costs, operating costs. Businesses like making more money or making services cheaper so that they're more competitive in the market place. So reducing, reducing costs is also a big one. So reducing can um can be something like automating a process, a business process um instead of having humans um relying on it." (Interviewee 10)

"… we actually created a model that um break um, I mean achieved the sales of, increase in sales of about 6% for an insurance company." (Interviewee 13)

"We scored them and we picked the one with the, with the highest um sort of propensity towards AI. And ya, and the criteria was you know to show a return on investment. It was very important to be able to go back to business and save. You've given us money for this one project this is your return on investment." (Interviewee 14)

In one case, the interviewee discussed the lean fault detection and maintenance monitoring enabled by their AI technology. The technology assisted the organisation to detect imminent equipment failure and prompt for maintenance as a result. The organisational outcome was the avoidance of any unnecessary or unplanned breakdown costs by delivering preventative maintenance on such equipment.

"… if we had sensors connected to the engine of this mining truck and we are continuously measuring those sensors . . . algorithm would then predict whether the engine is normal, healthy or whether something abnormal is happening and it's about to fail." (Interviewee 6)

Regulatory compliance. There are organisations mentioned in this study that expect *regulatory compliance* as an outcome of AI. For example, organisations may need to screen their customers for fraud or money laundering. Organisations may use AI to scan legal documents or electronic mail in order to ensure compliance with privacy laws.

"We have to absolutely ensure that we protecting and are compliant with um appropriate data regulations." (Interviewee 4)

"… you look at flagging specific key words, or the combination of specific keywords in incoming and outgoing emails, it can flag the risk of confidential information is leaking the organization for instance." (Interviewee 7)

"… for example, companies need to um do screening of their customers for anti-modeling, um money laundering purposes, fraudulent purposes, fraud detection." (Interviewee 10)

Risk management. The last theme related to goal-orientated outcomes is *risk management*. Not to be confused with the affordance for *analysing risk*, some of the organisations in this study used AI to better manage their organisational risk. The affordance refers to analysing risk in a specific task or work function. This affordance is a result of the interaction between the AI practitioner and the AI technology, whereas the goal-orientated AI outcome refers to managing organisational risk as an organisational objective.

"Fundamentally ya, with this insurance company that we're working with now if we complete this project it will fundamentally change that, the way that they do business. You know um, um their risk assessment, all those things um with, with that." (Interviewee 1)

"increasing the likelihood that they would not grant a loan to a person who could not um, who could actually not afford it." (Interviewee 15)

Relationships Between Themes

Themes and subthemes of themes share common concepts and therefore implies an interdependent relationship exists between the two (Braun & Clarke, 2006). These relationships were identified and tabled in Appendix D, and illustrated in Appendix E using the 'Project Maps' feature in NVivo. A sample from the full list of relationships is shown in table 4 and illustrated in figure 14 using a NVivo project map.

Table 4. Relationships and associated data (sample)

Relationship	Data Extract
Data input enables identify and classify information	you can probably say it understands language or understands the image. (Interviewee 10)
Data input influences model maintenance	constantly improving the AI as well is, is an aspect of it. So um how often does the model need to be retrained? How often does it actually need to be um, um what are, what happens when there's more data that you find? So it's more the concept um, also it's the continuous improvement of the model as well. (Interviewee 15)
Identify and classify information enables tailoring information	So, so the salesperson would have OK, um they'd capture, let's say a new person they'd capture their detail. They'll say I'm a male at this age and I get this salary, and what it will do, it will, it will call a model once that salesman submit. And it will return a bunch of different policies to say, this person would mostly likely benefit from having this, this and that. (Interviewee 13)
Model maintenance improves prediction	predictability based on those linear algorithms is screwed, because um what do we learn from the past twelve months? We learn that . . . It's all new. (Interviewee 3)

Translating information enables tailoring information	And localization is about taking the same content and making it available in multi languages right. And we use AI for that. So we use um something called machine translation. I'm not sure if you’ve heard of it . . . so it's about taking a piece of text or a piece of speech right and automatically translating it to a different language and our use cases to give you subtitles right. (Interviewee 5)
Tailoring information improves customer service	the training is delivered to me as an individual staff member is customised to my specific strengths and weaknesses and the role I'm being trained for. (Interviewee 7)

The table 4 excerpt shows that the format and type of data used as input into an AI technology influences the maintenance of the AI model used. This *data input* feature, together with the features *identify and classify information* and *prediction*, affords an AI technology to tailor and/or translate information for a specific individual or group of individuals (e.g. that share a common social context such as a country, language etc.). This means that a lack of - or incorrect types or formats of - input data may result in an ineffective AI model. In turn, an AI model that is not maintained with the appropriate format and type of data may result in poor predictability and therefore poorly tailored information. Model maintenance is thus a constraining condition that facilitates [translating, tailoring] affordance actualisation. Conversely, a maintained AI model may enable the interaction between the AI practitioner and the technology (with features *data input*, *identify and classify information* and *prediction*) to give rise to clustered affordances *translating information* and *tailoring information*, and resulting in improved customer service as a business outcome. A sample from the NVivo project map that illustrates these relationships is shown in figure 14.

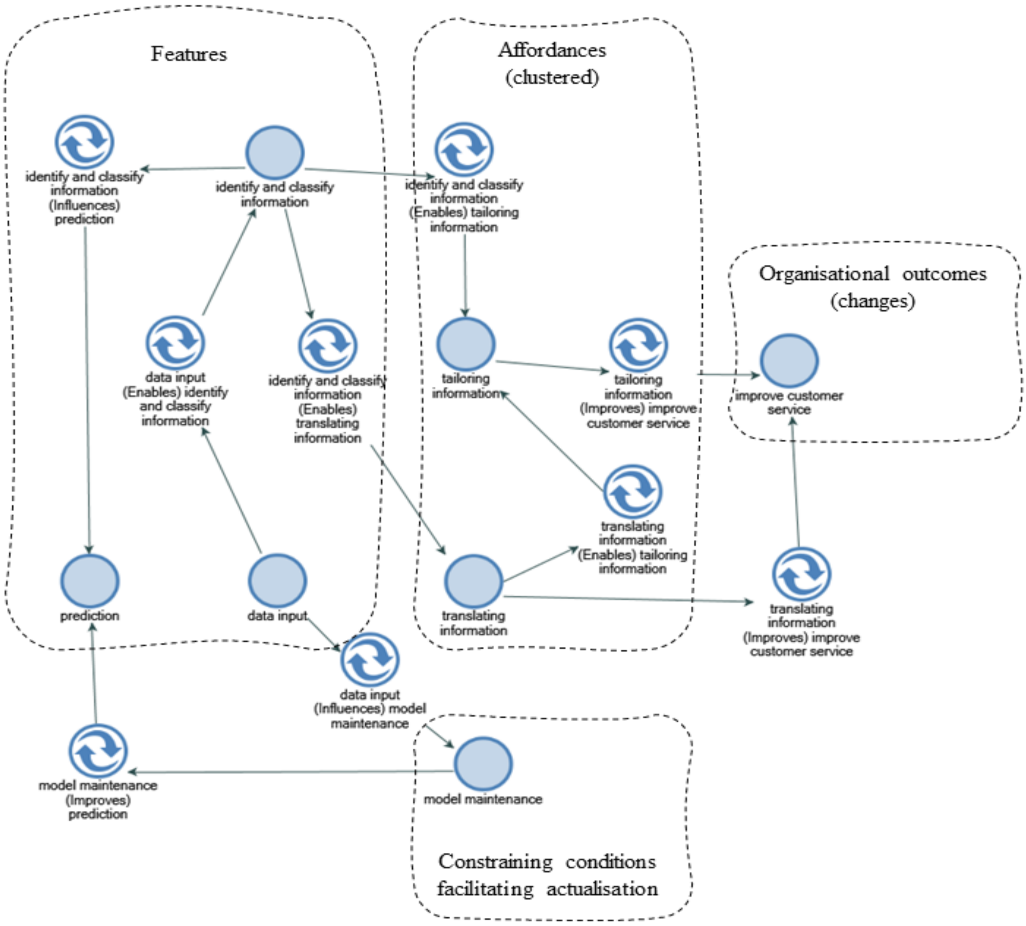


Figure 14. Relationships and associated data (sample)

The data analysis shows that there are several themes associated to AI features, the related affordances, constraining conditions facilitating actualisation of those affordances, and the organisational outcomes (changes). It also highlights the relationships between the themes and how this potentially influences the organisational outcome. The following chapter discusses these themes and the consequent relationships in order to describe of how AI affords organisational change through the lens of the Trajectory of Affordances.

6. Discussion

The concepts that have emerged in this study are related and begin to build a cohesive description of how AI affords organisational change. A new theory is proposed using Thapa & Sein's (2018) Trajectory of Affordances as a lens through which to describe how AI affords organisational change and achieve the objectives set out in this study.

6.1. Trajectory of Affordances

The AI Practitioner as an Actor

Figure 15 describes the relationships and affordances that arise as a result of the relations between the goal-oriented AI practitioner (representing the organisation) and the AI technology. The AI practitioner in this social context is considered the actor and is mandated by an organisation to achieve specific outcomes by the development and implementation of an AI technology (Lanamäki, Thapa & Stendal, 2016; Osmundsen, Meske & Thapa, 2022). The AI technology (IT artefact) is therefore implemented by the AI practitioner with the organisational outcomes in mind. Furthermore, the AI practitioner is not necessarily an employee of the organisation, but may also be a contractor who has been contracted to achieve specific organisational goals.

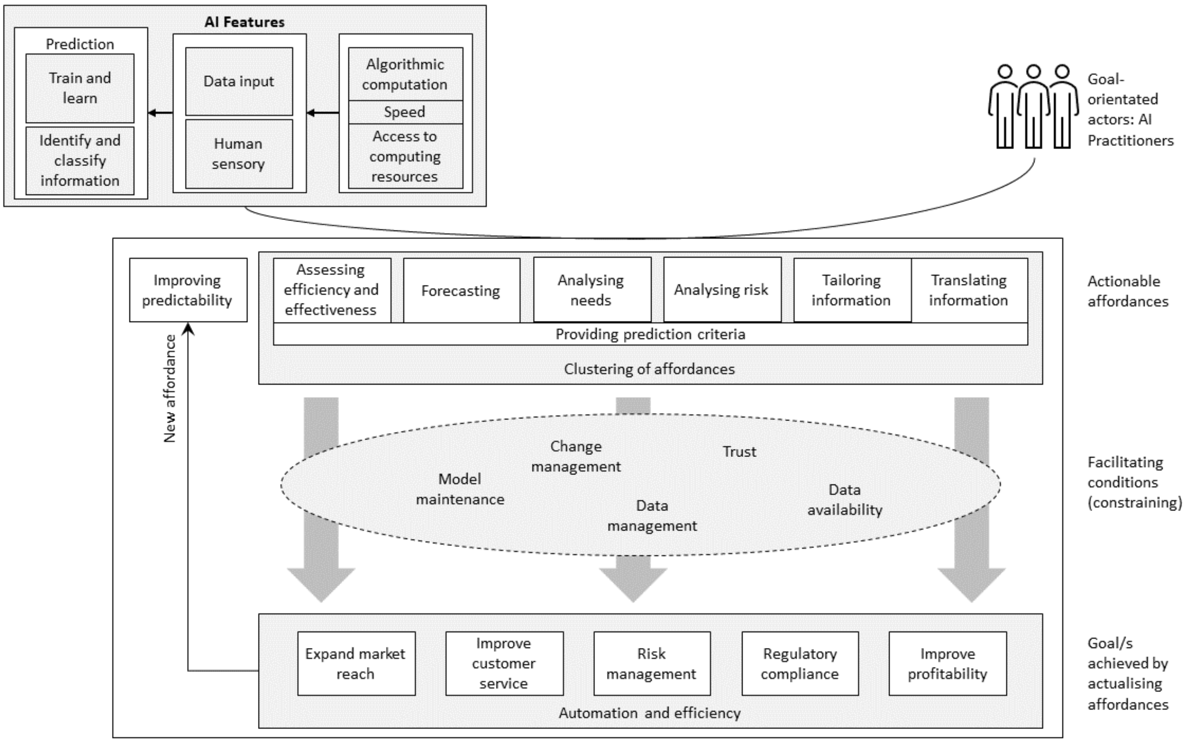


Figure 15. Adapted Trajectory of Affordances (Thapa & Sein, 2018)

Key AI Features

The IT artefact is represented by the AI technology features, answering the call to distinguish between AI features, emerging affordances and organisational outcomes (Fromm, Mirbabaie & Stieglitz, 2020). This also allows AI features to be mapped to affordances as a result of the relationship between the AI practitioner and the AI technology, thereby providing further insight into the relations between the AI practitioner, AI features and consequent affordances. It is assumed that *access to computing resources*, whether on-premises or remote/cloud, enables *computation* to be performed. *Computation* in turn enables exponentially condensed calculation timeframes; for example, solving a mathematical equation. In AI specifically, the subfield of algorithmic computation is used (Nadin, 2018). These three features are therefore considered inherently cojoined. The last decade's proliferation of cloud computing, with unlimited access to computing resources, enables organisations to not only optimise resource costs, but also stretch the boundaries of software design and deployment that was traditionally based on limited on-premises computing resources (Jamalodeen & Van Belle, 2022). Cloud computing has enabled AI practitioners to expand the experimentation and implementation of AI technologies, offering a considerable and innovative range of organisational opportunities (Gill et al., 2019; Valko, Goncharenko, Kushnir & Osadchyi, 2022).

The other five features (*data input*, *human sensory*, *train & learn*, *identify & classify information*, *prediction*) are not necessarily cojoined, but as mentioned earlier, *prediction* has a close relationship with *train & learn*, and *identify & classify information*. (Trocin et al., 2021). Through *training and learning*, the AI technology would be better able to predict outcomes. The AI technology would therefore be able to better [predict] *identify and classify information*. In turn, by being able to better *identify and classify information*, the technology's *prediction* feature improves (Davenport & Ronanki, 2018). The feature *data input* refers to the data formats and types of data the AI technology is able to receive. AI features include the mimicry of human senses, some examples being hearing (speech recognition), speaking (natural language generation/processing), reading (natural language processing) and writing (natural language processing) (Bawack, Wamba & Carillo, 2019; Eisenstein, 2019).

Figure 15 illustrates that through *data input* and *human sensory* features, an AI technology is able to *identify and classify information* (such as pattern recognition) and make *predictions* based on this information. For example, pattern recognition with prediction can assist with forecasting and other decision-making tasks in an organisation (Gill et al., 2019; Lindebaum, Vesa & Den Hond, 2020).

AI Technology-Practitioner Affordances

By entangling the AI practitioner and the AI technology (features), one or more of seven affordances may arise. Each affordance will potentially 'cluster' with the affordance of *providing prediction criteria*. For example, the affordance of *forecasting* refers to predicting an organisational process outcome. The clustered affordances of *forecasting* and *providing prediction criteria* not only predicts an organisational process outcome, but also provides the criteria which it used to predict this outcome. It is these criteria that explain why the AI technology predicted the specific outcome and this approach begins to answer the call in academia for "new AI techniques that are capable of making decisions explainable and understandable" (Adadi & Berrada, 2018, p. 52140). In the example of whether a banking customer should be granted a loan or not, the AI technology would also provide criteria why a loan would be approved or declined; in the case of a loan being declined, one criteria could be that the customer would not likely be able to pay the loan back based on the value of their assets, the environment and other data sets that an AI technology may use to create a credit rating (Biallas & O'Neill, 2020).

The affordance of *translating information* and *tailoring information* may also 'cluster' where *tailoring information* happens at the same time as *translating information*. One example is translating an English language media channel into a French language media channel. The affordance of *translating information* emerges, but at the same time so is the affordance of *tailoring information*; This is because French media channels may be tailored for French-speaking consumers of such media. It is important to highlight at this point that the affordance of *translating information* and *tailoring information* does not necessarily imply non-mutually exclusivity between the two affordance events; these affordance events do not necessarily happen at the same time and may also be independent from each other. For instance, the affordance of *translating information* may refer to text information that is translated into natural language (speech). Similarly, the affordance of *tailoring information* may also refer to the customisation of information intended for specific consumers based on their demographic profile, and therefore no translation of information may be necessary.

Assessing efficiency or effectiveness of an organisational process may include, for example, assessing information "to ensure that activities on the systems are consistent with the organizations policies, develops compliance reports and sends alerts when activities deviate from expected outcomes" (Pike & Pike, 2019, p. 2). *Analysing needs* may be seen, by way of example, as an AI-powered chatbot that is able to "analyze words, phrases and sentence constructions of customers so they can predict customer personality" in order to improve customer service (Nguyen & Sidorova, 2018, p. 2). *Analysing risks* may include, for example, analysing the risk of a patient developing a specific disease so that preventative measures can be taken to address the disease before the risk becomes insurmountable (Wilson & Daugherty, 2018). One or more of these affordances may be actualised to produce an organisational outcome which ultimately implies an organisational change. This is facilitated by several conditions.

Constraining Conditions Facilitating the Actualisation of AI Technology-Practitioner Affordances

This study identified five key constraining conditions facilitating affordance actualisation: *trust*, *data availability*, *data management*, *change management* and *model maintenance*. These conditions are referred to as constraining conditions because they refer to constraints that need to be managed or "released" in order to actualise the affordance/s (Volkoff, & Strong, 2013; Bygstad, Munkvold & Volkoff, 2016; Ostern, Rosemann & Moormann, 2020).

Data availability and data management. Data needs to be available in order to manage it and structure it in a way that the AI technology can use. In their AI adoption study, Hamm & Klesel (2021) found that data availability and the quality of data to be important prerequisites for AI's learning capability. This was echoed in the finding where, for example, the interviewee stated that while AI technology would be able to translate English language, it would be more of a challenge for African languages where limited data is available. The data quality is dependent on what data is received, the complexity of the data and the type of task AI is expected to execute; i.e. the management of such data (Kruse, Wunderlich & Beck, 2019).

Model maintenance. The study identified data availability and the way that data is managed play important roles in AI model maintenance, keeping the AI technology up to date with its environment so that its prediction feature remains relevant and accurate (Singh, N., 2020). In some cases such as medicine, autonomous transportation and security, model maintenance plays a critical role in AI technologies (Arrieta et al., 2020).

Trust. Data availability, data management and model maintenance also help gain or maintain trust so that the outcomes are ultimately delivered as a result of the AI technology (Carter, 2018). For instance, the profile of a banking customer may be out of date or irrelevant in order to analyse the risk (affordance: *analysing risk*) of providing the customer with a loan. An inaccurate analysis as a result of such data may be disparate from other information the [human] bank employee/user may have on record and thereby, according to the AI practitioner, creating distrust in the AI technology and inhibiting or constraining the affordance of *analysing risk*. In several industries the technique "explainable AI" is one approach that aids the facilitating condition *trust* so that actualised affordances may lead to intended organisational outcomes (Cui, Lee & Hsieh, 2019; Gunning, Stefik, Choi, Miller, Stumpf & Yang, 2019).

Change management. *Change management* is an organisational practice that ensures changes within organisations are successfully implemented (Rosenbaum, More & Steane, 2018). It involves managing resistance to change, which is evident in AI implementations because of any one of a number of factors (e.g. the fear of impact on job security). For example, human language translators that serve as employees of a media agency may be required to improve the way an AI technology translates information from one language into another language. Expectedly, these human translators may resist such a change and thereby impact the affordance actualisation of *translating information*. "Introducing change management will also reduce the organisational emotional divide between those that fear AI and those that embrace it" (Schoeman, Moore, Seedat & Chen, 2021, p. 17). Organisational change management programs therefore facilitate such scenarios through various means such as upskilling current employees (e.g. language translators) to perform more complex [human] tasks.

Intended organisational outcomes and new affordance

When the constraining conditions are eased, the organisational outcomes are likely to be realised. The intended outcomes are to (i) *expand market reach*, (ii) *manage risk*, (iii) *comply with regulations*, (iv) *improve customer service* and (v) *improve profitability*. The overarching outcome found in this study is the introduction or enhancement of *automation and efficiency* as a consequence of the affordances that emerge through the relationship between the AI technology (with specific features) and the AI practitioner. Through automation and efficiency, a new affordance emerges, *improving predictability*; this means that organisational predictability of the listed five outcomes is improved. In other words, an organisation would be able to better predict its market reach, exposure to risk, regulatory compliance, influence on customer service and influence on profitability.

7. Conclusions

This study sought to explore how AI technologies afford change in South African organisations from the perspective of the AI practitioner, by (i) identifying the key features of AI, (ii) identifying the affordances that arise as a result of AI in South African organisations, (iii) identifying the types of organisational change, and (iv) identifying the constraining conditions under which the AI affordances lead to these types of organisational change. It used an adaptation of Thapa & Sein's (2018) Trajectory of Affordances as a lens through which it describes how AI affords such organisational change. The research question is: How do artificial intelligence technologies afford change in South African organisations, from the perspective of the AI practitioner?

The study identifies and describes eight AI features: (i) access to computing resources (such as processing, storage and network), (ii) computation, (iii) speed (as a result of computation and resources), (iv) data input (type and format of data), (v) human sensory, (vi) train & learn, (vii) identify and classify information, and (viii) prediction. The AI practitioner represents the organisation as an internal human resource or contractor to the organisation.

Through the interaction between the AI practitioner representing the organisation and the AI technology (with features), seven affordances arise, some of which may be clustered in two or more affordances: (i) assessing efficiency and effectiveness, (ii) forecasting, (iii) analysing needs, (iv) analysing risk, (v) tailoring information, (vi) translating information, and (vii) providing prediction criteria.

One or more of these affordances lead to one of more of six organisational outcomes or types of changes: (i) expand market reach, (ii) improve customer service, (iii) manage organisational risk, (iv) regulatory compliance, (v) improve profitability, and (vi) automation and efficiency. These AI-driven organisational outcomes are based on the easing of specific conditions for affordance-actualisation, of which this study has identified five constraining conditions, namely (i) data availability, (ii) data management, (iii) AI model maintenance, (iv) trust and (v) change management. Where these conditions are eased, the types of organisational changes or outcomes are achieved, resulting in a new affordance of improving organisational predictability. This means that through the interaction between the goal-oriented AI practitioner (representing the organisation) and the AI technology, affordances arise. These affordances enable the organisation to better predict it's intended outcomes as long as the constraining conditions are eased.

7.1. Theoretical Contributions

Through abductive theorising, this qualitative study follows the affordance recommendations in IS literature (Fromm, Mirbabaie & Stieglitz, 2020) and demonstrates how affordance theory is used to explain the influence of AI on organisational change. This study therefore contributes to the growing body of knowledge on both information systems (AI in particular) and affordances (Wang, Wang & Tang, 2018; Fromm, Mirbabaie & Stieglitz, 2020) in the following ways. First, it answers the call for more studies to use the affordance lens in IS research (Volkoff & Strong 2017; Fromm, Mirbabaie & Stieglitz, 2020) and particularly addresses the paucity of AI-related affordance studies. Second, it explicitly identifies the affordances that emerge as a result of the relations between the AI technology and the AI practitioner representing the organisation. Third, it distinguishes between the technology features and organisational outcomes. Fourth, it demonstrates how multiple affordances may arise, either at the same time or as mutually exclusive events. Lastly, it explores the relationships between affordances and constraining conditions for affordance actualisation so that organisational outcomes may be achieved.

7.2. Practical Contributions

There has been much hype about AI over several decades, but the last decade has seen a significant adoption of AI in practice (Agrawal, Gans & Goldfarb, 2018; Burgess, 2018). However, organisations still grapple with the concept of AI and its contribution in organisational practice (Davenport & Ronanki, 2018; Enholm, Papagiannidis, Mikalef & Krogstie, 2021). This study explores AI in a broad sense without deep investigation into specific AI subfields or techniques such as machine learning or artificial neural networks where much of the organisational understanding may get lost in the terminologies used. This approach assists organisations to better understand the practical implications of AI technologies they may employ (Davenport & Ronanki, 2018). Such insight allows organisations to experiment and position AI for strategic organisational change (Collins, Dennehy, Conboy & Mikalef, 2021). This study further illustrates the concept of affordance as a useful tool to theorise how an information technology such as AI is involved in such strategic organisational change (Leonardi, 2011; Fayard & Weeks, 2014; Lehrer, Wieneke, vom Brocke, Jung & Seidel, 2018).

A practical perspective on how AI affords South African organisational change is offered, with the goal-oriented AI practitioner as the actor. The contribution of the AI practitioner's perspective is important because of the influential role the practitioner plays (compared to users) when actualising affordances (Osmundsen, Meske & Thapa, 2022). The interaction between the AI practitioner and the AI technology also depends on the AI features that are employed. This study therefore also answers the call to explore the relationship between human actors and the AI artefact (Bawack, Wamba & Carillo, 2019), as well as the key AI features that play a role in the AI technology-practitioner affordances (Wang, Wang & Tang, 2018; Leidner, Gonzalez & Koch, 2018; Karahanna, Xu, Xu & Zhang, 2018; Canhoto, 2021).

7.3. Limitations and Future Research

This study explores the affordances that emerge as a result of the relationship between the AI technology and AI practitioner representing the organisation. Using affordance theory as a lens, this study finds that an interpretive epistemology, while lending itself towards a constructivist ontology, is an appropriate socio-technical approach to understand the AI phenomenon from the perspective of the AI practitioner. Through this exploration, it begins to explain the phenomenon by identifying relationships between the constructs, but does not offer deep insight into such causal explanations. Using affordance theory to provide an in-depth explanation of why and how AI technologies afford change in organisations, future research should focus on case studies (Wynn & Williams, 2012) and adopt a critical realism paradigm that aims to understand the unexplained AI-related generative mechanisms that cause events and experiences (Bygstad, Munkvold & Volkoff, 2016; Volkoff & Strong, 2017; Fromm, Mirbabaie & Stieglitz, 2020).

The perspective of the AI practitioner involved in South African organisations is explored in this study. These AI practitioners may either be employed by the organisation as a full time employee or as a contractor to the organisation. There is a difference between IS workers as part of an organisation outside of the IS industry (such as a media organisation), and IS workers as part of an organisation inside of the IS industry (Gannon, 2013). This difference may offer different perspectives of the AI practitioner depending on whether the practitioner is employed by an organisation outside or inside the IS industry. Future research could look into distinguishing between the two scenarios. In addition, these AI practitioners are only involved in South African organisations, so future research outside of South Africa may offer alternative perspectives and findings.

Affordances refer to the actionable possibilities made available as a consequence of the relationship between the IT artefact and the goal-oriented actor in a social context (Markus & Silver, 2008; Bernhard et al., 2013; Volkoff & Strong, 2017). Gender and race are examples of social settings in South Africa where inequality continues to be prevalent; white males dominate the science and technology fields, while historically disadvantaged black individuals, and black women in particular, are not only underrepresented in the field, but also continue to face professional advancement challenges related to issues of racial and gender discrimination (Idahosa & Mkhize, 2021). Other considerations for future research may therefore focus on gender or race as part of the social context; note that none of the AI practitioners interviewed were female and the majority of interviewees were white.

Furthermore, the industry where the AI practitioners were mostly involved is the financial services industry. AI has become pervasive over the last decade and an interesting future research topic could focus on industries such as consumer goods or supply chain where the goods and services offered are more tangible in nature.

7.4. Concluding Remarks

Despite announcements by various technology corporations about AI deployments (Ernst & Young, 2019), the development of AI in South African organisations and lives has been somewhat quiet, but progressive. For instance, AI is already integrated into technologies in our pockets, homes, leisure and work. Organisations find themselves under much more pressure to compete in the digital world, especially considering the volatile state of the South African economy and the Covid-19 pandemic consequences imposed on the country. South Africans are seeking to better understand its future opportunities and exploit these opportunities through deliberate intervention such as skill-building. However, the desperate need to secure jobs related to routine or low-skilled tasks may hinder the country’s digital evolution and inhibit organisations from healthy competition by holding onto archaic vocational norms rather than reinventing jobs in line with the global digital economy (Downie, 2019; Burbidge, 2022).

This study begins to address these challenges. It raises organisational awareness of emerging technologies such as AI which has already encroached into everyday life. It also offers organisations some insight into AI and how they may strategically position themselves using AI in the digital economy. Furthermore, it outlines some of the skills (Appendix D) needed in such a digital economy and emphasises the need to prioritise upskilling of human resources. Perhaps AI as a technology is already well in play and deeply integrated into the interactions between human and technology.

8. References

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). *IEEE Access, 6*, 52138-52160.

Adams, C. (2015). Conducting semi-structured interviews. In J. S. Wholey, H. P. Hatry & K. E. Newcomer (Eds.), *Handbook of practical program evaluation* (3rd ed.) (pp. 365-377). San Francisco: Jossey-Bass.

Adisa, O. M., Botai, J. O., Adeola, A. M., Hassen, A., Botai, C. M., Darkey, D., & Tesfamariam, E. (2019). Application of artificial neural network for predicting maize production in South Africa. *Sustainability, 11*(4), 1145.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Alexander, A. J., Shi, L., & Solomon, B. (2017). How fintech is reaching the poor in Africa and Asia. *International Finance Corporation*. World Bank Group.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. In *Proceedings of the Twenty-Second Pacific Asia Conference on Information Systems (PACIS)* (p. 37). Japan.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82-115.

Baehre, S., O'Dwyer, M., O'Malley, L., & Lee, N. (2022). The use of Net Promoter Score (NPS) to predict sales growth: insights from an empirical investigation. *Journal of the Academy of Marketing Science, 50*(1), 67-84.

Bahari, S. F. (2010). Qualitative versus quantitative research strategies: contrasting epistemological and ontological assumptions. *Sains Humanika, 52*(1), 17-28.

Balmer, R. E., Levin, S. L., & Schmidt, S. (2020). Artificial intelligence applications in telecommunications and other network industries. *Telecommunications Policy, 44*(6).

Bankole, F. O., Osei-Bryson, K. M., & Brown, I. (2015). The impacts of telecommunications infrastructure and institutional quality on trade efficiency in Africa. *Information Technology for Development, 21*(1), 29-43.

Bauer, M., van Dinther, C., & Kiefer, D. (2020). Machine Learning in SME: An Empirical Study on Enablers and Success Factors. In *Proceedings of the Twenty-Fifth Americas Conference on Information Systems (AMCIS)*. Salt Lake City, United States of America.

Bawack, R. E., Wamba, S.F., & Carillo, K. D. (2019). Artificial intelligence in practice: Implications for IS research. In *Proceedings of the Twenty-Fifth Americas Conference on Information Systems (AMCIS)* (pp. 1-10). Cancun, Mexico.

Benbunan-Fich, R. (2019). An affordance lens for wearable information systems. *European Journal of Information Systems, 28*(3), 256-271.

Bernhard, E., Recker, J. C., & Burton-Jones, A. (2013). Understanding the actualization of affordances: A study in the process modeling context. In *Proceedings of the Thirty Fourth International Conference on Information Systems (ICIS)* (pp. 1-11). Milan, Italy.

Bhaskar, R. (2008). *A realist theory of science*. England: Routledge.

Bhatti, A., Akram, H., Basit, H. M., Khan, A. U., Raza, S. M., & Naqvi, M. B. (2020). E-commerce trends during COVID-19 pandemic. *International Journal of Future Generation Communication and Networking*, *13*(2), 1449-1452.

Biallas, M., & O'Neill, F. (2020). Artificial intelligence innovation in financial services. *International Finance Corporation: World Bank Group*.

Blaikie, N., & Priest, J. (2019). *Designing Social Research* (3rd ed.). Cambridge, United Kingdom: Polity Press.

Blanco, A. P. (2018). *Artificial intelligence and the consumer packaged goods supply chain*. Doctoral dissertation. Cambridge: Massachusetts Institute of Technology.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2020). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management, 57*.

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The acceptance of chatbots in an enterprise context–A survey study. *International Journal of Information Management, 60*.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101.

Bresnahan, T., & Yin, P. L. (2017). Adoption of new information and communications technologies in the workplace today. *Innovation Policy and the Economy, 17*(1), 95-124.

Bringsjord, S., & Schimanski, B. (2003). What is artificial intelligence? Psychometric AI as an answer. In *Proceedings of the 18th international joint conference on Artificial intelligence (IJCAI), August 09 - 15, 2003* (pp. 887-893). Acapulco, Mexico.

Bryman, A. (2004). *Social Research Methods* (2nd ed.). London: Oxford University Press.

Bryman, A., & Bell, E. (2007). *Business research methods* (2nd ed.). New York: Oxford University Press.

Brynjolfsson, E., & Mcafee, A. (2017). The business of artificial intelligence. *Harvard Business Review, 7*, 3-11.

Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *Proceedings of The Economics of Artificial Intelligence: An Agenda* (pp. 23-57). University of Chicago Press.

Buchanan, B. (2019). *Artificial intelligence in finance*. London: The Alan Turing Institute.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., Henke, N., & Trench, M. (2017). Artificial intelligence: The next digital frontier? *McKinsey Global Institute*.

Burbidge, M. (2022). The challenges of building AI in Africa. ITWeb. Retrieved March 9th, 2022, from https://www.itweb.co.za/content/Pero3qZxNoO7Qb6m

Burgess, A. (2018). *The Executive Guide to Artificial Intelligence: How to identify and implement applications for AI in your organization*. Cham: Springer.

Burrell, G., & Morgan, G. (2016). *Sociological paradigms and organisational analysis: Elements of the sociology of corporate life*. Abington, England: Routledge.

Bygstad, B., Munkvold, B. E., & Volkoff, O. (2016). Identifying generative mechanisms through affordances: a framework for critical realist data analysis. *Journal of Information Technology, 31*(1), 83-96.

Byrne, D. (2021). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity*, 1-22.

Calatayud, A., Mangan, J., & Christopher, M. (2019). The self-thinking supply chain. *Supply Chain Management: An International Journal*, *24*(1), 22-38.

Cambridge Dictionary. (n.d.). *dictionary.cambridge.org*. Retrieved February 4, 2022, from https://dictionary.cambridge.org/

Canhoto, A. I. (2021). Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. *Journal of Business Research, 131*, 441-452.

Capazario, M., & Venter, F. (2020). *The 2020 list of occupations in high demand: a technical report*. Department of Higher Education and Training, South Africa.

Carter, D. (2018). How real is the impact of artificial intelligence? The business information survey 2018. *Business Information Review, 35*(3), 99-115.

Cecez-Kecmanovic, D. (2011). Doing critical information systems research–arguments for a critical research methodology. *European Journal of Information Systems, 20*(4), 440-455.

Chemero, A. (2003). An outline of a theory of affordances. *Ecological Psychology, 15*(2), 181-195.

Chen, W., & Hirschheim, R. (2004). A paradigmatic and methodological examination of information systems research from 1991 to 2001. *Information Systems Journal, 14*(3), 197-235.

Chowdhury, G. G. (2003). Natural language processing. *Annual Review of Information Science and Technology, 37*(1), 51-89.

Coetzee, J. (2018). Strategic implications of Fintech on South African retail banks. *South African Journal of Economic and Management Sciences*, *21*(1), 1-11.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*(4).

Creswell, J., W. (2014). *Research design: Qualitative, quantitative and mixed methods approaches* (4th ed.). Thousand Oaks: Sage.

Crotty, M. (1998). *The foundations of social science research*. New South Wales: Allen & Unwin.

Cui, X., Lee, J. M., & Hsieh, J. (2019). An integrative 3c evaluation framework for explainable artificial intelligence. In *Proceedings of the Twenty-Fifth Americas Conference on Information Systems (ACIS)* (pp. 1-10). Cancun, Mexico.

Daramola, O., & Etim, E. (2022). Affordances of digital platforms in sub-Saharan Africa: An analytical review. *The Electronic Journal of Information Systems in Developing Countries*.

Daugherty, P. R., Wilson, H. J., & Chowdhury, R. (2019). Using artificial intelligence to promote diversity. *MIT Sloan Management Review, 60*(2), 9-12.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24-42.

Demlehner, Q., & Laumer, S. (2020). Shall we use it or not? Explaining the adoption of artificial intelligence for car manufacturing purposes. In *Proceedings of the Twenty-Eighth European Conference on Information Systems (ECIS)*. Marrakech, Morocco.

Dhir, K., & Chhabra, A. (2019). Automated employee evaluation using fuzzy and neural network synergism through IoT assistance. *Personal and Ubiquitous Computing, 23*(1), 43-52.

Dodd, A. Z. (2012). The essential guide to telecommunications (5th ed.). New Jersey, United States of America: Prentice Hall.

Downie, B. (2019). The president and the future. *Civil Engineering, 27*(5), 1-1.

Dremel, C., Herterich, M. M., Wulf, J., & Vom Brocke, J. (2020). Actualizing big data analytics affordances: A revelatory case study. *Information & Management, 57*(1).

Du, W. D., Pan, S. L., Leidner, D. E., & Ying, W. (2019). Affordances, experimentation and actualization of FinTech: A blockchain implementation study. *The Journal of Strategic Information Systems, 28*(1), 50-65.

Dubé, L., & Paré, G. (2003). Rigor in information systems positivist case research: current practices, trends, and recommendations. *MIS Quarterly, 27*(4), 597-636.

Easterby-Smith, M., Thorpe, R., & Lowe, A. (2002). *Management Research: An Introduction*. Thousand Oaks, California, United States of America: Sage.

Economist. (2016). Africa's port: The bottleneck. *The Economist*. Retrieved April 20, 2022, from https://www.economist.com/middle-east-and-africa/2016/03/19/the-bottleneck

Edwards, R., & Holland, J. (2013). *What is qualitative interviewing?*. London: Bloomsbury.

Eisenstein, J. (2019). *Introduction to natural language processing*. London: MIT press.

Eljasik-Swoboda, T., Rathgeber, C., & Hasenauer, R. (2019). Artificial intelligence for innovation readiness assessment. In *Proceedings of the 2019 IEEE International Symposium on Innovation and Entrepreneurship (TEMS-ISIE)* (pp. 1-6). IEEE.

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2021). Artificial intelligence and business value: a literature review. *Information Systems Frontiers*, 1-26.

Ernst & Young. (2019). *Artificial Intelligence in Middle East and Africa: South Africa Outlook for 2019 and Beyond*. A report commissioned by Microsoft and conducted by Ernst & Young. United Arab Emirates: EY Consulting LLC.

Ertel, W. (2018). *Introduction to artificial intelligence*. Cham: Springer.

Evans, M. (2020). *The digital consumer journey: Who is behind the crisis-inspired e-commerce surge?* [White paper]. Euromonitor International. Retrieved September 25, 2020, from https://go.euromonitor.com/white-paper-dc-200922-digital-consumer-journey.html?utm_source=blog&utm_medium=blog&utm_campaign=CT_WP_20_09_22_Digital%20Consumer%20Survey

Fayard, A. L., & Weeks, J. (2014). Affordances for practice. *Information and Organization*, *24*(4), 236-249.

fDiIntelligence. (2021). African tech ecosystems of the future 2021/22. *www.fDiIntelligence.com*. Retrieved April 20, 2022, from https://www.fdiintelligence.com/content/download/79718/2609471/file/African%20Tech%20Ecosystems%20of%20the%20Future%202021.pdf

Feldt, R., de Oliveira Neto, F. G., & Torkar, R. (2018). Ways of applying artificial intelligence in software engineering. In Proceedings of *2018 IEEE/ACM Sixth International Workshop on Realizing Artificial Intelligence Synergies in Software Engineering (RAISE)* (pp. 35-41). IEEE.

Francis, D., & Webster, E. (2019). Poverty and inequality in South Africa: critical reflections. *Development Southern Africa*, *36*(6), 788-802.

Fromm, J., Mirbabaie, M., & Stieglitz, S. (2020). A systematic review of empirical affordance studies: Recommendations for affordance research in information systems. In *Proceedings of the Twenty-Eighth European Conference on Information Systems (ECIS).* Marrakech, Morocco.

Gannon, B. (2013). Outsiders: An exploratory history of IS in corporations. *Journal of Information Technology*, *28*(1), 50-62.

Gibson, J. (1977). The theory of affordances. In R. Shaw & J. Bransford (Eds.), *Perceiving, acting, and knowing: Toward an ecological psychology* (pp. 67-82). Hillsdale, United States of America: Routledge.

Gill, S. S., Tuli, S., Xu, M., Singh, I., Singh, K. V., Lindsay, D., ... & Garraghan, P. (2019). Transformative effects of IoT, Blockchain and Artificial Intelligence on cloud computing: Evolution, vision, trends and open challenges. Internet of Things, 8, 1-30.

Girasa, R. (2020). International Initiatives in AI. In *Artificial Intelligence as a Disruptive Technology* (pp. 255-298). Cham: Palgrave Macmillan.

Giudici, P. (2018). Fintech risk management: A research challenge for artificial intelligence in finance. *Frontiers in Artificial Intelligence*, *1*, 1.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly, 30*(3) 611-642.

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI-Explainable artificial intelligence. *Science Robotics*, *4*(37).

Gurkaynak, G., Yilmaz, I., & Haksever, G. (2016). Stifling artificial intelligence: Human perils. *Computer Law & Security Review*, *32*(5), 749-758.

Hacker, J., vom Brocke, J., Handali, J., Otto, M., & Schneider, J. (2020). Virtually in this together–how web-conferencing systems enabled a new virtual togetherness during the COVID-19 crisis. *European Journal of Information Systems, 29*(5), 563-584.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 1-10.

Hamm, P., & Klesel, M. (2021). Success Factors for the Adoption of Artificial Intelligence in Organizations: A Literature Review. In *Proceedings of the Twenty-Seventh Americas Conference on Information Systems (AMCIS)*. Montreal, Canada.

Heft, H. (2001). *Ecological psychology in context: James Gibson, Roger Barker, and the legacy of William James's radical empiricism*. Mahwah, United States of America: Erlbaum.

Heinemann, T. (2019). Energy crisis in South Africa–a barrier to higher economic growth. *KfW Research Economics in Brief, 178*.

Hutchby, I. (2001). Technologies, texts and affordances. *Sociology, 35*(2), 441-456.

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of AI: strategy and leadership when algorithms and networks run the world*. Harvard Business Press.

Idahosa, G. E., & Mkhize, Z. (2021). Intersectional experiences of black South African female doctoral students in STEM: Participation, success and retention. *Agenda, 35*(2), 110-122.

International Monetary Fund. (2022). World Economic Outlook Database. *International Monetary Fund*. Retrieved June 26, 2022, from https://www.imf.org/external/pubs/ft/weo/2022/01/weodata/groups.htm#oem

Jamalodeen, S., & Van Belle, J. P. (2022). The adoption of cloud computing in South Africa's oil and gas industry. In *Proceedings of the Eighteenth European, Mediterranean, and Middle Eastern Conference on Information Systems* (pp. 215-228). Cham: Springer.

Jarrahi, M. H. (2019). In the age of the smart artificial intelligence: AI's dual capacities for automating and informating work. *Business Information Review, 36*(4), 178-187.

Jones, K. S. (2003). What is an affordance?. *Ecological Psychology, 15*(2), 107-114.

Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1996). Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, *4*, 237-285.

Kallio, H., Pietilä, A. M., Johnson, M., & Kangasniemi, M. (2016). Systematic methodological review: developing a framework for a qualitative semi-structured interview guide. *Journal of Advanced Nursing, 72*(12), 2954-2965.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15-25.

Karacay, G. (2018). Talent development for industry 4.0. In *Industry 4.0: Managing The Digital Transformation* (pp. 123-136). Cham: Springer.

Karahanna, E., Xu, S. X., Xu, Y., & Zhang, N. A. (2018). The needs–affordances–features perspective for the use of social media. *MIS Quarterly, 42*(3), 737-756.

Keller, R., Stohr, A., Fridgen, G., Lockl, J., & Rieger, A. (2019). Affordance-Experimentation-Actualization Theory in Artificial Intelligence Research: a Predictive Maintenance Story. In *Proceedings of the Fortieth International Conference on Information Systems (ICIS)*. Munich, Germany.

Kim, T. K. (2020). Short research on voice control system based on artificial intelligence assistant. In *Proceedings of the International Conference on Electronics, Information, and Communication (ICEIC)* (pp. 1-2). Busan, Republic of Korea.

Klein, C. (2021). Government ICT policy is harming consumers. *Free Market Foundation*. Retrieved August 29, 2021, from https://www.freemarketfoundation.com/article-view/media-release-fmf-launches-socio-economic-impact-assessment-seia-government-ict-policy-is-harming-consumers

Klein, H. K., & Myers, M. D. (1999). A set of principles for conducting and evaluating interpretive field studies in information systems. *MIS Quarterly, 23*(1), 67-93.

Kohavi, R., & Longbotham, R. (2017). Online controlled experiments and A/B testing. *Encyclopedia of machine learning and data mining, 7*(8), 922-929.

Köhler, T., Bhorat, H., Hill, R., & Stanwix, B. (2021). COVID-19 and the labour market: Estimating the employment effects of South Africa's national lockdown. *Development Policy Research Unit Working Paper 202107*. DPRU, University of Cape Town.

Kordon, A. (2020). Applied artificial intelligence-based systems as competitive advantage. In *Proceedings of the 2020 IEEE Tenth International Conference on Intelligent Systems (IS)* (pp. 6-18). IEEE.

Kruse, L., Wunderlich, N., & Beck, R. (2019). Artificial intelligence for the financial services industry: What challenges organizations to succeed. In *Proceedings of the Fifty-Second Hawaii International Conference on System Sciences* (pp. 6408-6417). Hawaii, United States of America.

Kshetri, N. (2020). Artificial intelligence in developing countries. *IEEE Annals of the History of Computing, 22*(04), 63-68.

L'heureux, A., Grolinger, K., Elyamany, H. F., & Capretz, M. A. (2017). Machine learning with big data: Challenges and approaches. *IEEE Access, 5*, 7776-7797.

Lam, K. C., Oshodi, O. S., & Lee, E. W. M. (2016). Forecasting construction demand: A comparison of Box-Jenkins and Support Vector machine model. In *Proceedings of the 9th Construction Industry Development Board (CIDB) Postgraduate Conference, 2-4 February 2016* (pp. 14-23). Cape Town, South Africa: Department of Construction Economics and Management.

Lanamäki, A., Thapa, D., & Stendal, K. (2016). When is an affordance? Outlining four stances. In *Proceedings of the Working Conference on Information Systems and Organizations* (pp. 125-139). Cham: Springer.

Leaper, C., & Starr, C. R. (2019). Helping and hindering undergraduate women's STEM motivation: Experiences with STEM encouragement, STEM-related gender bias, and sexual harassment. *Psychology of Women Quarterly*, *43*(2), 165-183.

Lee, A. S., & Baskerville, R. L. (2003). Generalizing generalizability in information systems research. *Information Systems Research, 14*(3), 221-243.

Leedy, P. D., & Ormrod, J. E. (2010). *Practical research: Planning and design* (9th ed.). New Jersey: Merrill.

Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How big data analytics enables service innovation: materiality, affordance, and the individualization of service. *Journal of Management Information Systems*, *35*(2), 424-460.

Leidner, D. E., Gonzalez, E., & Koch, H. (2018). An affordance perspective of enterprise social media and organizational socialization. *The Journal of Strategic Information Systems, 27*(2), 117-138.

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS quarterly*, *35*(1), 147-167.

Leyer, M., Schneider, S. (2019). Me, You or AI? How do we feel about delegation. In *Proceedings of the Twenty-Seventh European Conference on Information Systems (ECIS)* (pp. 1-17). Stockholm-Uppsala, Sweden.

Lindebaum, D., Vesa, M., & Den Hond, F. (2020). Insights from "the machine stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations. *Academy of Management Review*, *45*(1), 247-263.

Liu, F., & Myers, M. D. (2011). An analysis of the AIS basket of top journals. *Journal of Systems and Information Technology*, *13*(1), 5-24.

Luke, D. (2019). Making the case for the African Continental Free Trade Area. In D. Luke & J. MacLeod (Eds.), *Inclusive Trade in Africa: The African Continental Free Trade Area in Comparative Perspective*. New York: Routledge.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., ... & Söllner, M. (2019). AI-based digital assistants. *Business & Information Systems Engineering, 61*(4), 535-544.

Mahomed, S. (2018). Healthcare, artificial intelligence and the Fourth Industrial Revolution: Ethical, social and legal considerations. *South African Journal of Bioethics and Law*, *11*(2), 93-95.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, 120, 262-273.

Malinga, S. (2021). Spectrum policy flaws 'will alienate millions of South Africans'. *ITWeb*. Retrieved August 29, 2021, from https://www.itweb.co.za/content/lwrKxv3KadXvmg1o

Malinga, S. (2022). Female engineers unpack persistent barriers to STEM fields. *ITWeb*. Retrieved July 15, 2022, from https://www.itweb.co.za/content/KBpdg7pmalGMLEew

Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. (2017). A future that works: Automation, employment, and productivity. *McKinsey Global Institute*, 1-28.

Markus, M. L., & Silver, M. S. (2008). A foundation for the study of IT effects: A new look at DeSanctis and Poole's concepts of structural features and spirit. *Journal of the Association for Information systems*, *9*(10), 609-632.

Mashamba-Thompson, T. P., & Crayton, E. D. (2020). Blockchain and artificial intelligence technology for novel coronavirus disease-19 self-testing. *Diagnostics, 10* (4).

Masondo, H. (2022). Energy crisis and the economy. *Without Prejudice, 22*(1), 44-45.

May, A., Sagodi, A., Dremel, C., & van Giffen, B. (2020). Realizing digital innovation from artificial intelligence. In *Proceedings of the Forty-First International Conference on Information Systems (ICIS)*. India.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12-14.

McCorduck, P., & Cfe, C. (2004). *Machines who think: A personal inquiry into the history and prospects of artificial intelligence*. CRC Press.

Mesgari, M., & Okoli, C. (2019). Critical review of organisation-technology sensemaking: towards technology materiality, discovery, and action. *European Journal of Information Systems, 28*(2), 205-232.

Michaels, C. F. (2003). Affordances: Four points of debate. *Ecological Psychology, 15*(2), 135-148.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3).

Mikalef, P., Fjørtoft, S. O., & Torvatn, H. Y. (2019). Developing an artificial intelligence capability: A theoretical framework for business value. In *Proceedings of The International Conference on Business Information Systems* (pp. 409-416). Cham: Springer.

Mingers, J., Mutch, A., & Willcocks, L. (2013). Critical realism in information systems research. *MIS Quarterly, 37*(3), 795-802.

Mitchell, A. (2018). A review of mixed methods, pragmatism and abduction techniques. *The Electronic Journal of Business Research Methods, 16*(3), 103-116.

Morgan, G., & Smircich, L. (1980). The case for qualitative research. *Academy of Management Review*, *5*(4), 491-500.

Moss-Racusin, C. A., Sanzari, C., Caluori, N., & Rabasco, H. (2018). Gender bias produces gender gaps in STEM engagement. *Sex Roles, 79*(11), 651-670.

Mtembu, X. (2022). 2022 breaks the record with over 192 720 minutes of load shedding. *IOL*. Retrieved March 04, 2023, from https://www.iol.co.za/business-report/careers/2022-breaks-the-record-with-over-192-720-minutes-of-load-shedding-80c72d9e-4337-4cc8-8eee-b359299ed575

Murray, A., Rhymer, J., & Sirmon, D. G. (2020). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552-571.

Myers, M. D. (2019). *Qualitative research in business and management* (3rd ed.). London: Sage.

Myers, M. D., & Klein, H. K. (2011). A set of principles for conducting critical research in information systems. *MIS Quarterly, 35*(1), 17-36.

Mzekandaba, S. (2018). Gartner lists top 10 tech trends for 2019. *ITWeb*. Retrieved September 16, 2020, from https://www.itweb.co.za/content/5yONPvEEG84vXWrb

Nadin, M. (2018). Machine intelligence: a chimera. *AI & Society, 34*(2), 215-242.

Naidoo, P. (2021). South Africa Unemployment Rate Rises to Highest in the World. *Bloomberg*. Retrieved August 29, 2021, from https://www.bloomberg.com/news/articles/2021-08-24/south-african-unemployment-rate-rises-to-highest-in-the-world

Nascimento, A. M., da Cunha, M. A. V. C., de Souza Meirelles, F., Scornavacca, E., & de Melo, V. V. (2018). A literature analysis of research on artificial intelligence in management information system (MIS). In *Proceedings of the Twenty-Fourth Americas Conference on Information Systems (AMCIS)* (pp. 1-10). New Orleans, United States of America.

National Planning Commission. (2011). *National development plan: vision for 2030*. Pretoria: Republic of South Africa.

Nguyen, Q. N., & Sidorova, A. (2017). AI capabilities and user experiences: a comparative study of user reviews for assistant and non-assistant mobile apps. In *Proceedings of the Twenty-Third Americas Conference on Information Systems (AMCIS)* (pp. 1-10). Boston, United States of America.

Nguyen, Q. N., & Sidorova, A. (2018). Understanding user interactions with a chatbot: a self-determination theory approach. In *Proceedings of the Twenty-Fourth Americas Conference on Information Systems (AMCIS)* (pp. 1-5). New Orleans, United States of America.

Norman, D. A. (1988). *The psychology of everyday things*. Basic books.

O'Dea, S. (2021). iPhones installed base in the United States, China and ROW 2017. *Statista*. Retrieved August 28, 2021, from https://www.statista.com/statistics/755625/iphones-in-use-in-us-china-and-rest-of-the-world/

Okoli, C. (2021). *Inductive, abductive and deductive theorizing*. SKEMA Business School, Paris, France.

Oosthuizen, K., Botha, E., Robertson, J., & Montecchi, M. (2021). Artificial intelligence in retail: The AI-enabled value chain. *Australasian Marketing Journal, 29*(3), 264–273.

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information Systems Research, 2*(1), 1-28.

Osmundsen, K. S., Meske, C., & Thapa, D. (2022). Familiarity with digital twin totality: Exploring the relation and perception of affordances through a Heideggerian perspective. *Information Systems Journal*, 1-28.

Ostern, N., Rosemann, M., & Moormann, J. (2020). Determining the idiosyncrasy of blockchain: An affordances perspective. In *Proceedings of the Forty-First International Conference on Information Systems (ICIS)*. Hyderabad, India.

O'Sullivan, A., & Sheffrin, S. M. (2003). *Economics: Principles in action*. New Jersey, United States of America: Pearson Prentice Hall.

Owoyemi, A., Owoyemi, J., Osiyemi, A., & Boyd, A. (2020). *Artificial intelligence for healthcare in Africa. Frontiers in Digital Health, 2*, 6.

Öztürk, D. (2021). What does artificial intelligence mean for organizations? A systematic review of organization studies research and a way forward. *The Impact of Artificial Intelligence on Governance, Economics and Finance, Volume I*, 265-289.

Papagiannidis, E., Enholm, I. M., Mikalef, P., & Krogstie, J. (2021). Structuring AI resources to build an AI capability: A conceptual framework. In *Proceedings of the Twenty-Ninth European Conference on Information Systems (ECIS)*. Marrakesh, Morocco.

Paré, G. (2004). Investigating information systems with positivist case research. *Communications of the Association for Information Systems, 13*(1), 233-264.

Paterson, M., & Higgs, J. (2005). Using hermeneutics as a qualitative research approach in professional practice. *The Qualitative Report, 10*(2), 339-357.

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. United States of America: Sage.

Pike, N., & Pike, R. (2019). Progressing from the SOC to the EOC. In *Proceedings of the Twenty-fifth Americas Conference on Information Systems (AMCIS)* (pp. 1-5). Cancun, Mexico.

Plastino, E., & Purdy, M. (2018). Game changing value from artificial intelligence: eight strategies. *Strategy & Leadership*, *46*(1), 16-22.

Pozzi, G., Pigni, F., & Vitari, C. (2014). Affordance theory in the IS discipline: A review and synthesis of the literature. In *Proceedings of the Twentieth Americas Conference on Information Systems (AMCIS)* (pp. 1-12). Savannah, United States of America.

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In *Proceedings of the Twenty-Seventh European Conference on Information Systems (ECIS)* (pp. 1-15). Stockholm-Uppsala, Sweden: Darmstadt Technical University, Department of Business Administration, Economics and Law, Institute for Business Studies (BWL).

Purcărea, T., Ioan-Franc, V., Ionescu, Ş. A., & Purcărea, I. M. (2021). The profound nature of the connection between the impact of using artificial intelligence in retail on buying and the consumers' perceptions of artificial intelligence on the path to the next normal. *Amfiteatru Economic*, *23*(56), 9-32.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192-210.

Ramaphosa, C. (2018). *President Cyril Ramaphosa: 2018 State of the Nation Address*. Retrieved August 29, 2021, from https://www.gov.za/speeches/president-cyril-ramaphosa-2018-state-nation-address-16-feb-2018-0000

Rao, A. S. S., & Verweij, G. (2017). Sizing the prize: What's the real value of AI for your business and how can you capitalise? *PriceWaterhouseCoopers*.

Rapanyane, M. B., & Sethole, F. R. (2020). The rise of artificial intelligence and robots in the 4th Industrial Revolution: implications for future South African job creation. *Contemporary Social Science*, 1-13.

Republic of South Africa. (2003). Broad-Based Black Economic Empowerment Amendment Act, No. 46 of 2013. Retrieved April 16, 2022, from http://www.thedtic.gov.za/financial-and-non-financial-support/b-bbee/

Rietveld, E., & Kiverstein, J. (2014). A rich landscape of affordances. *Ecological Psychology, 26*(4), 325-352.

Rosenbaum, D., More, E., & Steane, P. (2018). Planned organisational change management: Forward to the past? An exploratory literature review. *Journal of Organizational Change Management*, 31(2), 286-303.

Rzepka, C., & Berger, B. (2018). User interaction with AI-enabled systems: a systematic review of IS research. In *Proceedings of the Thirty Ninth International Conference on Information Systems (ICIS)* (pp. 1-17). San Francisco, United States of America.

Salam, M. A., & Khan, S. A. (2018). Achieving supply chain excellence through supplier management: a case study of fast moving consumer goods. *Benchmarking: An International Journal*, *25*(9), 4084-4102.

Sallstrom, L., Morris, O., & Mehta, H. (2019). Artificial Intelligence in Africa's Healthcare: Ethical Considerations. *Observer Research Foundation Issue Brief, 4*.

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). England: Pearson Education Limited.

Sayer, R. A. (1992). *Method in social science: A realist approach* (2nd ed.). England: Psychology Press.

Schaefer, C., Lemmer, K., Samy Kret, K., Ylinen, M., Mikalef, P., & Niehaves, B. (2021). Truth or dare?–How can we influence the adoption of artificial intelligence in municipalities?. In *Proceedings of the Fifty-Fourth Hawaii International Conference on System Sciences* (pp. 2347-2356). Hawaii, United States of America.

Schmidt, R., Zimmermann, A., Möhring, M., & Keller, B. (2020). Value creation in connectionist artificial intelligence–a research agenda. In *Proceedings of the Twenty-Fifth Americas Conference on Information Systems (AMCIS)*. Salt Lake City, United States of America.

Schoeman, W., Moore, R., Seedat, Y., & Chen, J. Y. (2021). Artificial intelligence: Is South Africa ready? *Gordon Institute of Business Science*.

Scholvin, S., & Draper, P. (2012). The gateway to Africa? Geography and South Africa's role as an economic hinge joint between Africa and the world. *South African Journal of International Affairs*, *19*(3), 381-400.

Schrage, M. (2020). Data, not digitalization, transforms the post-pandemic supply chain. *MIT Sloan Management Review,* 29th July.

Searle, J. R. (1990). Is the brain a digital computer?. In *Proceedings and addresses of the American Philosophical Association* (Vol. 64, No. 3, pp. 21-37). Newark, United States of America: American Philosophical Association.

Seidel, S., Recker, J., & Vom Brocke, J. (2013). Sensemaking and sustainable practicing: functional affordances of information systems in green transformations. *MIS quarterly*, 1275-1299.

Shoham, Y., Perrault, R., Brynjolfsson, E., Clark, J., Manyika, J., Niebles, J. C., ... & Bauer, Z. (2018). The AI index 2018 annual report. *AI Index Steering Committee, Human-Centered AI Initiative*.

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, *31*(2), 47-53.

Siau, K., & Yang, Y. (2017). Impact of artificial intelligence, robotics, and machine learning on sales and marketing. In *Proceedings of the Twelve Annual Midwest Association for Information Systems Conference (MWAIS)*. Springfield, United States of America.

Sicular, S., & Brant, K. (2018). Hype cycle for artificial intelligence. *Gartner.* Retrieved July 16 2019, from *https://www.gartner.com/doc/3883863/hype-cycle-artificial-intelligence*

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, D. (2017). Mastering the game of go without human knowledge. *Nature*, *550*(7676), 354-359.

Singh, N. (2020). Artificial intelligence and human thinking. *International Journal of Computer Science and Technology*, *11*(1), 9-11.

Singh, V. (2020). AI and data in South Africa's health sector. *Policy Action Network*. Retrieved August 29, 2021, from https://policyaction.org.za/sites/default/files/PAN_TopicalGuide_AIData6_Health_Elec.pdf

Sloman, A. (1986). Did Searle attack strong or weak strong AI. *Artificial Intelligence and Its Applications*. Brighton, United Kingdom: John Wiley and Sons.

Smith, E. (2019). Facing slowing growth and credit downgrades, South Africa's economy is stuck in the mire. *CNBC*. Retrieved September 25, 2020, from https://www.cnbc.com/2019/10/10/south-africas-economy-struggles-as-world-bank-downgrades-forecast.html

Stöckli, E., Dremel, C., Uebernickel, F., & Brenner, W. (2019). How affordances of chatbots cross the chasm between social and traditional enterprise systems. *Electronic Markets*, 1-35.

Stoffregen, T. A. (2003). Affordances as properties of the animal-environment system. *Ecological Psychology, 15*(2), 115-134.

Strong, D. M., Volkoff, O., Johnson, S. A., Pelletier, L. R., Tulu, B., Bar-On, I., Trudel, J., & Garber, L. (2014). A theory of organization-EHR affordance actualization. *Journal of the Association for Information Systems*, *15*(2), 2.

Sutherland, E. (2020). The fourth industrial revolution–the case of South Africa. *Politikon, 47*(2), 233-252.

Tavory, I., & Timmermans, S. (2014). *Abductive analysis: Theorizing qualitative research*. United States of America: University of Chicago Press.

Thapa, D., & Sein, M. K. (2018). Trajectory of affordances: Insights from a case of telemedicine in Nepal. *Information Systems Journal, 28*(5), 796-817.

Theodoridis, P. K., & Gkikas, D. C. (2019). How artificial intelligence affects digital marketing. In *Strategic Innovative Marketing and Tourism* (pp. 1319-1327). Cham: Springer.

Traumer, F., Oeste-Reiß, S., & Leimeister, J. M. (2017). Towards a future reallocation of work between humans and machines–taxonomy of tasks and interaction types in the context of machine learning. In *Proceedings of the Thirty Eighth International Conference on Information Systems (ICIS)* (pp. 1-11). South Korea.

Trocin, C., Hovland, I. V., Mikalef, P., & Dremel, C. (2021). How Artificial Intelligence affords digital innovation: A cross-case analysis of Scandinavian companies. *Technological Forecasting and Social Change, 173*.

Turvey, M. T. (1992). Affordances and prospective control: An outline of the ontology. *Ecological Psychology, 4*(3), 173-187.

Ungerer, C., Portugal, A., Molinuevo, M., & Rovo, N. (2020). Recommendations to leverage e-commerce during the COVID-19 crisis. *World Bank Group*.

United Nations. (n.d.). Standard country or area codes for statistical use (M49). *United Nations Statistics Division*. Retrieved June 26, 2022, from https://unstats.un.org/unsd/methodology/m49/

Urban, T. (2015). The AI Revolution: The Road to Superintelligence. *Wait But Why*. Retrieved May 11, 2019, from https://waitbutwhy.com/2015/01/artificial-intelligence-revolution-1.html

Valko, N. V., Goncharenko, T. L., Kushnir, N. O., & Osadchyi, V. V. (2022). Cloud technologies for basics of artificial intelligence study in school. In *Proceedings of the Nineth Workshop on Cloud Technologies in Education* (pp. 170-183). Ukraine.

van Rijmenam, M., & Logue, D. (2021). Revising the 'science of the organisation': theorising AI agency and actorhood. *Innovation*, *23*(1), 127-144.

Varian, H. (2019). Artificial Intelligence, Economics, and Industrial Organization. In *The Economics of Artificial Intelligence: An Agenda* (pp. 399-419). Chicago: University of Chicago Press.

Veeragandham, M., Patnaik, N., Tiruvaipati, R., & Guruprasad, M. (2020). Consumer buying behaviour towards e-commerce during COVID-19. *International Journal of Research in Engineering, Science and Management, 3*(9), 78-82.

Volkoff, O., & Strong, D. M. (2013). Critical realism and affordances: Theorizing IT-associated organizational change processes. *MIS Quarterly, 37*(3) 819-834.

Volkoff, O., & Strong, D. M. (2017). Affordance theory and how to use it in IS research. In *The routledge companion to management information systems* (pp. 232-245). Routledge.

von Wolff, M. R., Masuch, K., Hobert, S., & Schumann, M. (2019). What Do You Need Today?-An Empirical Systematization of Application Areas for Chatbots at Digital Workplaces. In *Proceedings of the Twenty-fifth Americas Conference on Information Systems (AMCIS)* (pp. 1-10). Cancun, Mexico.

Walsham, G. (2006). Doing interpretive research. *European Journal of Information Systems*, *15*(3), 320-330.

Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal, 26*(7).

Wang, H., Wang, J., & Tang, Q. (2018). A review of application of affordance theory in information systems. *Journal of Service Science and Management, 11*(01), 56.

Wasserman, H. (2019). Africa’s new free trade deal: Here's how it will affect SA businesses. *Business Insider SA*. Retrieved July 16, 2019, from https://www.businessinsider.co.za/africa-free-trade-deal-2019-7

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: humans and AI are joining forces. *Harvard Business Review, 96*(4), 114-123.

World Health Organisation. (2020). *Coronavirus disease (COVID-19) pandemic*. Retrieved September 16, 2020, from https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/novel-coronavirus-2019-ncov

Wright, S. A., & Schultz, A. E. (2018). The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, *61*(6), 823-832.

Wynn Jr, D., & Williams, C. K. (2012). Principles for conducting critical realist case study research in information systems. *MIS Quarterly*, *36*(3), 787-810.

Xu, M., David, J. M., & Kim, S. H. (2018). The fourth industrial revolution: opportunities and challenges. *International Journal of Financial Research*, *9*(2), 1-6.

Zeng, D., Tim, Y., Yu, J., & Liu, W. (2020). Actualizing big data analytics for smart cities: A cascading affordance study. *International Journal of Information Management*, *54*.

Zhang, D., Maslej, N., Brynjolfsson, E., Etchemendy, J., Lyons, T., Manyika, J., … & Perrault, R. (2022). The AI index 2022 annual report. *AI Index Steering Committee, Stanford Institute for Human Centered AI*. Stanford University.

9. Appendix A – Interview Questions

This appendix contains a list of interview questions developed from the conceptual framework.

1. Background (all participants)

a) What is your position/title within your organisation?

b) What is the primary business of your organisation?

c) What are your responsibilities within your organisation?

d) What are the key skills you need to fulfil your responsibilities?

e) What industries do you serve?

f) What is your understanding of the term "artificial intelligence" (AI)?

To ensure a common understanding of AI, we would like to introduce the following definition: a system that makes decisions based on external information (rather than an explicit set of rules) and uses this data to learn about the environment in which it operates, and adapts itself to achieve specific [human] goals.

1.1. Based on this understanding, are you or your organisation delivering any AI projects?

2. AI explained

2.1. How would you describe the components of AI; e.g. subfields, techniques, etc.? And how are they used in your AI journey?

2.2. What type of learning is used: Supervised learning, unsupervised learning or reinforcement learning?

3. AI for organisational change

Think about a customer/project or two where you recently implemented (or currently implementing) AI.

3.1. Identify the affordances of AI and organisational change

a) What were/are you wanting to achieve by using AI?

b) How does the AI technology **afford** those goals?

c) What is your customer wanting to achieve by using AI if not the same?

d) How does the AI technology **afford** those goals?

3.2. Identify the AI key features and techniques

Please describe in detail the current technology infrastructure for the use of AI.

a) What would you consider to be features of AI that result in these affordances? And which features of AI you are implementing?

b) Are there any other features that we have not discussed?

c) How do these features relate to enabling what you and/or your customer/s are trying to achieve?

4. AI constraints and challenges

a) Were there any constraints leading up to the implementation of the AI technology? Why?

b) Were there any constraints/drawbacks as a result of the implementation of the AI technology? Why?

5. Repeat, recap and conclusion

5.1. How is the business or customer affected by the introduction of the AI technology?

5.2. How are possible actions for organisational change at your customer/s made available by the AI technologies you deliver; e.g. describe how AI transforms information into possible actions?

5.3. Is there anything else that you'd like to mention that would be affected by the introduction of this AI technology?

5.4. Did we forget anything? Is there anything else you would like to discuss?

5.5. Could we get back to you in case we have further questions from our data analysis?

6. Demographic questions may be coded without asking (Adams, 2015)

6.1. Age group: 18-30, 31-39, 40-49, 50-59, 60+

6.2. Nationality

6.3. Gender

6.4. Race

6.5. Education: High school, College/Technical Diploma, University undergraduate degree, University postgraduate degree, Doctoral, Other

10. Appendix B – Word Frequency Query

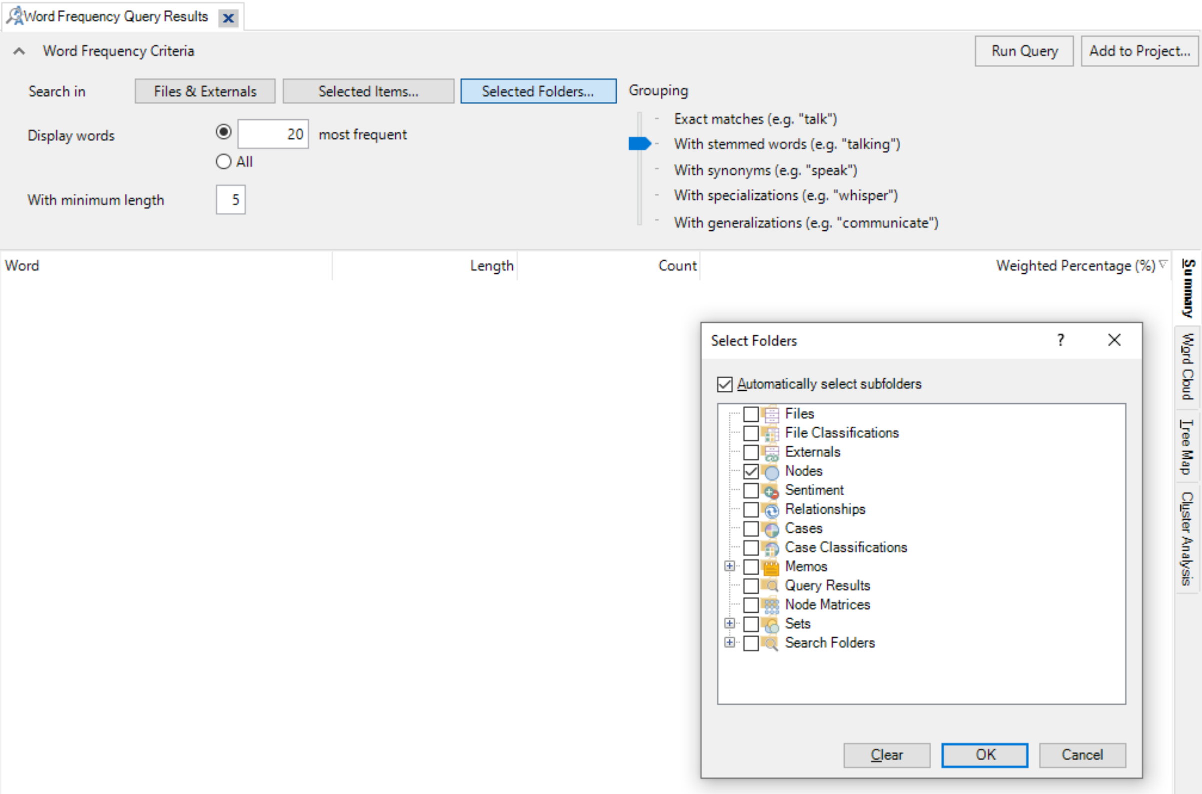
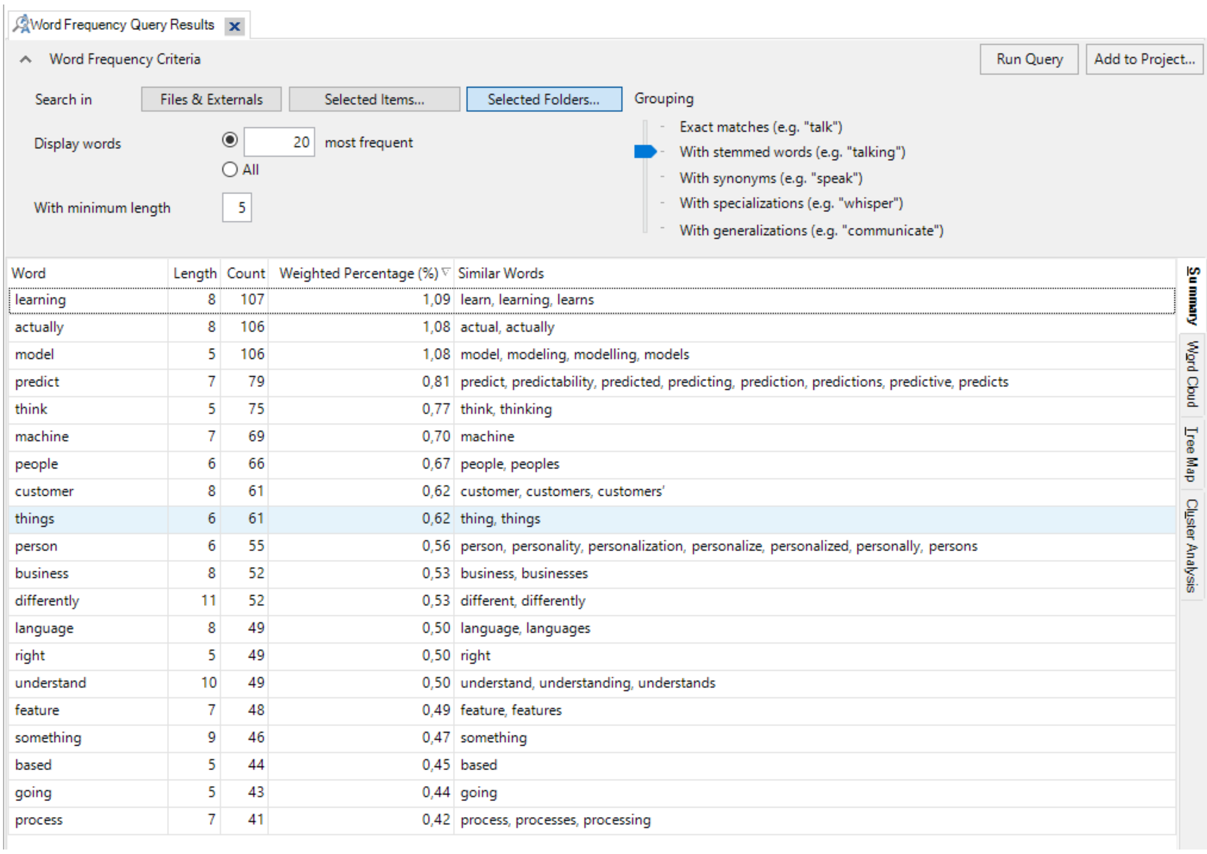


Figure 16. Word frequency query configuration and selection



Word	Length	Count	Weighted Percentage (%)	Similar Words
learning	8	107	1,09	learn, learning, learns
actually	8	106	1,08	actual, actually
model	5	106	1,08	model, modeling, modelling, models
predict	7	79	0,81	predict, predictability, predicted, predicting, prediction, predictions, predictive, predicts
think	5	75	0,77	think, thinking
machine	7	69	0,70	machine
people	6	66	0,67	people, peoples
customer	8	61	0,62	customer, customers, customers'
things	6	61	0,62	thing, things
person	6	55	0,56	person, personality, personalization, personalize, personalized, personally, persons
business	8	52	0,53	business, businesses
differently	11	52	0,53	different, differently
language	8	49	0,50	language, languages
right	5	49	0,50	right
understand	10	49	0,50	understand, understanding, understands
feature	7	48	0,49	feature, features
something	9	46	0,47	something
based	5	44	0,45	based
going	5	43	0,44	going
process	7	41	0,42	process, processes, processing

Figure 17. Word frequency query results

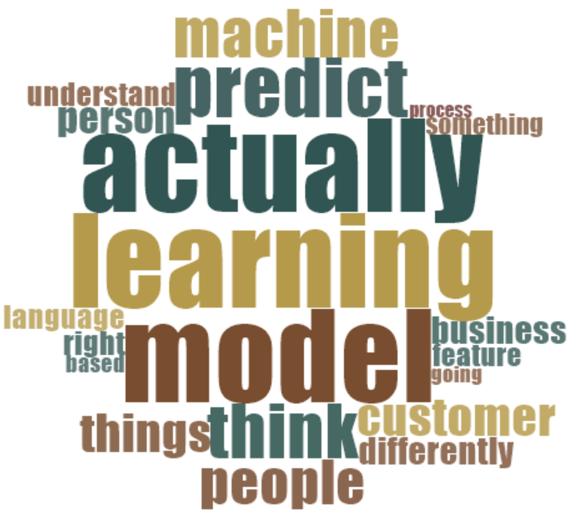


Figure 18. Word frequency query on the 'nodes' folder (with stemmed words, at minimum length of 5 letters)

11. Appendix C – Interviewee Perspective of AI Skills Required

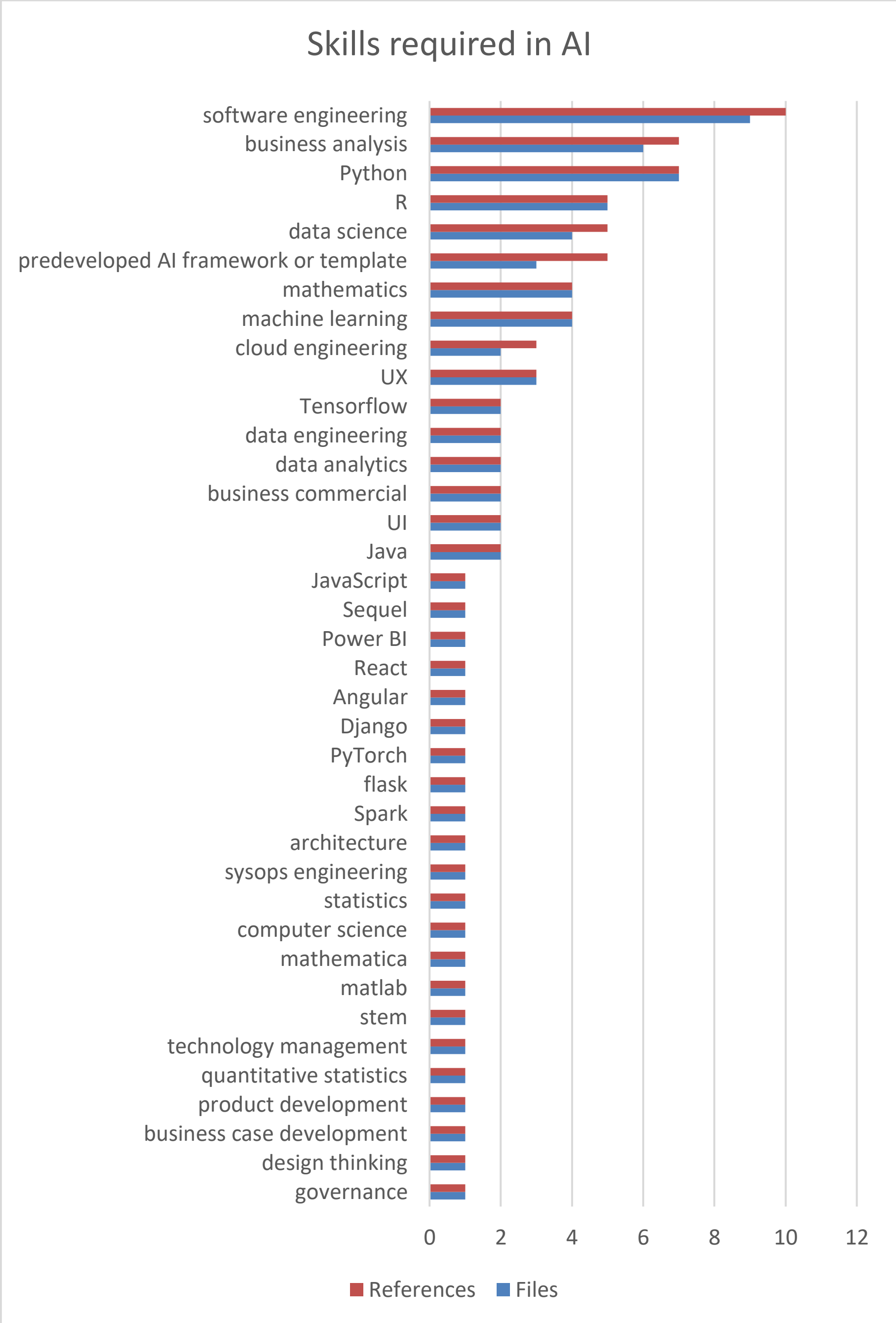


Figure 19. AI practitioner skills

12. Appendix D – Theme Relationships and Related Data

Table 5. Relationships between themes and related data

#	From Theme	Relationship Type	Relationship Direction	To Theme	Data Extract
1	ai affordance\analysing needs	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	So the, the goal, the business goal is often to service their customers better. So in other words, to use the, the data you have on your clients, to better model around that, to, to better understands what your customers want, to give them better products and so forth. (Interviewee 7)
2	ai affordance\analysing risk	Improves	→	ai outcome\goal-orientated outcomes\risk management	I was talking about of the geyser um I mean that was a particular use case where um they're wanting to pick up anomalies before the anomaly has happened to um prevent expenditure on the behalf of a an insurance company. (Interviewee 3)
3	ai affordance\analysing risk	Improves	→	ai outcome\goal-orientated outcomes\improve profitability	We scored them and we picked the one with the, with the highest um sort of propensity towards AI. And ya, and the criteria was you know to show a return on investment. It was very important to be able to go back to business and save. You've given us money for this one project this is your return on investment. (Interview 14)

4	ai affordance\analysing risk	Enables	→	ai outcome\goal-orientated outcomes\regulatory compliance	And you know, I think we, we need a serious lawsuit in our country for people to take POPIA serious you know. But so you can for instance by looking, if you, if you monitor the communication of your staff for instance and you look at flagging specific key words, or the combination of specific keywords in incoming and outgoing emails, it can flag the risk of confidential information is leaking the organization for instance. (Interviewee 7)
5	ai affordance\assessing efficiency and effectiveness	Improves	→	ai outcome\goal-orientated outcomes\automation and efficiency	90% of the students, they were actually predicted correctly. To say you know what actually they were, they were completing in minimum time or they were not completing in minimum time. So that, itself actually showed that um we're actually doing a great job. (Interviewee 9)
6	ai affordance\forecasting	Enables	→	ai outcome\goal-orientated outcomes\improve predictability	Um so the main one that I'm looking at here, so the organizational change is really the um the inful – you know um what answering, you know what education / qualifications one would need to fill a specific list of competencies. (Interviewee 15)
7	ai affordance\forecasting	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	We'll take some data and then start doing an experiment of how to develop um an AI model to actually help predict if they're about to run out of stock or not. (Interviewee 15)

8	ai affordance\providing prediction criteria	Improves	→	ai constraints\constraining conditions facilitating actualisation\trust	if it just said yes or no you actually um, the, it's just the, it's essentially something saying a decision. So if you don't have reasons for it you might, you might be inclined even to not trust it or trust it blindly. (Interviewee 15)
9	ai affordance\providing prediction criteria	Improves	→	ai constraints\constraining conditions facilitating actualisation\change management	if it just said yes or no you actually um, the, it's just the, it's essentially something saying a decision. So if you don't have reasons for it you might, you might be inclined even to not trust it or trust it blindly. (Interviewee 15)
10	ai affordance\tailoring information	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	the training is delivered to me as an individual staff member is customised to my specific strengths and weaknesses and the role I'm being trained for. (Interviewee 7)
11	ai affordance\tailoring information	Enables	→	ai outcome\goal-orientated outcomes\expand market reach	would interact with our website and then our um other electronic channels at a certain time he would prefer a certain channel to another one, um you'd preferred a different product and all of that information is kind of aggregated so that, so that we can personalize marketing to you, if that makes sense. (Interviewee 8)
12	ai affordance\translating information	Enables	→	ai affordance\tailoring information	And localization is about taking the same content and making it available in multi languages right. And we use AI for that. So we use um something called machine translation. I'm not sure if you've heard of it . . . so it's about taking a piece of text or a piece of speech right and automatically

					translating it to a different language and our use cases to give you subtitles right. (Interviewee 5)
13	ai affordance\translating information	Enables	→	ai outcome\goal-orientated outcomes\expand market reach	Because there's now capability to do machine dubbing right. So previously you'd had a, a voice artist who would, who would say take a basic Korean content and dub it to English right. But now there are um capabilities were you, you don't have to use a voice actor. Basically you use um the machine to do a synthetic voice. (Interviewee 5)
14	ai affordance\translating information	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	One is to improve the customer offering in terms of the content we offer um you know the, the range of content and how we make it available. So that's personalization, recommendations, localization right. (Interviewee 5)
15	ai affordance\translating information	Enables	→	ai outcome\goal-orientated outcomes\automation and efficiency	automated audit of where the brands are used. So if you throw documents or images of places at the system it can I, automatically identify the brand and tell you that you know there's still a brand usage is this specific document. (Interviewee 10)

16	ai constraints\constraining conditions facilitating actualisation\change management	Influences	↔	ai constraints\constraining conditions facilitating actualisation\trust	after you’ve done it for a while you learn it’s one of the, absolutely the first things that you set down in a, when you start discussing an AI project is, you know what is the, what is the metric for success. And what is the, what does success looks like in an AI project? Um because that’s the one thing that I’ve, that I’ve picked up implementing AI projects is, is, it's just there’s different expectations. Business expects something that can do this, you expected this um and there’s just there’s a bit of, a bit of disconnect between um you know, expectations. (Interviewee 14)
17	ai constraints\constraining conditions facilitating actualisation\data availability	Improves	→	ai constraints\constraining conditions facilitating actualisation\data management	The other problem is that some of these things require language data and the language data is not, like especially for South African languages and African languages the language data is not always available. So in some cases we have to create our own language data right. (Interviewee 5)
18	ai constraints\constraining conditions facilitating actualisation\data management	Improves	→	ai constraints\constraining conditions facilitating actualisation\trust	that the way that you constructed your data and the way you constructed your question led you to essentially only model on the one type of observation and um, and that’s why your model isn’t working. (Interviewee 15)

19	ai constraints\constraining conditions facilitating actualisation\data management	Improves	→	ai constraints\constraining conditions facilitating actualisation\model maintenance	obtaining a label set can prove challenging. Um sometimes it's, it's easy but in other times it's, it's not as easy and you might have to design a system where there’s a human in the loop that can do this um labelling and then only can you take the data that’s been generated in that fashion and create a model to automate that process. (Interviewee 10)
20	ai constraints\constraining conditions facilitating actualisation\model maintenance	Improves	→	ai features\prediction	predictability based on those linear algorithms is screwed, because um what do we learn from the past twelve months? We learn that . . . It's all new. (Interviewee 3)
21	ai features\accessibility to resources	Enables	→	ai features\computation	what tends to happen is that you then um sort of um constrained from a resource perspective of physical CPU’s / memory perspective. Um this is obviously alleviated now days by the access to the cloud especially now we’ve got cloud providers in South Africa. (Interviewee 11)
22	ai features\computation	Enables	→	ai features\identify and classify information	if you’re going to undertake some kind of um machine learning task where you want to build either a regress or a classifier. (Interviewee 15)
23	ai features\computation	Enables	→	ai features\speed	if you had humans doing the same audit um they would literally either you know open it if it's electronic copy in word and scan through every page, page by page and look for the pattern OK. And you might need a team of ten people to, to, to do that within a reasonable amount of time because you know they didn’t have a lot of

					time to do this. But computer vision and automatic pattern matching enabled them to um automate a task to a higher degree. (Interviewee 10)
24	ai features\computation	Enables	→	ai features\prediction	I can then correct the system based on what I think is accurate. Um and in doing so you continuously feedback the model um to be able to better predict um the categorization of spend. (Interviewee 11)
25	ai features\data input	Associated	—	ai features\human sensory	this new technol, well not new technology but this technology called chatbots, um where it's um using natural language processing, NLP to sort of um give that um human element towards solving your frequently asked questions and such. (Interviewee 13)
26	ai features\data input	Enables	→	ai features\identify and classify information	you can probably say it understands language or understands the image. (Interviewee 10)
27	ai features\data input	Associated	—	ai constraints\constraining conditions facilitating actualisation\data availability	especially for South African languages and African languages the language data is not always available. (Interviewee 5)

28	ai features\data input	Influences	↔	ai constraints\constraining conditions facilitating actualisation\model maintenance	constantly improving the AI as well is, is an aspect of it. So um how often does the model need to be retrained? How often does it actually need to be um, um what are, what happens when there's more data that you find? So it's more the concept um, also it's the continuous improvement of the model as well. (Interviewee 15)
29	ai features\human sensory	Influences	↔	ai affordance\translating information	So it's about taking a piece of text or a piece of speech right and automatically translating it to a different language (Interviewee 5)
30	ai features\identify and classify information	Enables	→	ai affordance\translating information	I think AI's ability to translate it, to translate into your native into your native language or to your mother tongue language will open it up to more people. (Interviewee 14)
31	ai features\identify and classify information	Enables	→	ai affordance\tailoring information	So, so the salesperson would have OK, um they'd capture, let's say a new person they'd capture their detail. They'll say I'm a male at this age and I get this salary, and what it will do, it will, it will call a model once that salesman submit. And it will return a bunch of different policies to say, this person would mostly likely benefit from having this, this and that. (Interviewee 13)
32	ai features\identify and classify information	Enables	→	ai affordance\providing prediction criteria	you've got a human machine interface um where typically like the AI would make a suggestion that says, this component is broken um, for this and this reason. (Interviewee 6)

33	ai features\identify and classify information	Enables	→	ai affordance\analysing risk	look at the patterns in the time series data and connect it to the real world events in that transactional data. So we could see that as the temperature increased in the engine, it probably meant the oil was running low and something was wearing out. (Interviewee 6)
34	ai features\identify and classify information	Enables	→	ai affordance\analysing needs	dig into what people are saying um pre-categorize it, perform analysis and understand what our customers concerns are. (Interviewee 12)
35	ai features\identify and classify information	Enables	→	ai affordance\forecasting	last year I produced um 5000 items of um, 5000 items of item A. But this, this algorithm says rather than making 5000 make 3952. (Interviewee 15)
36	ai features\identify and classify information	Enables	→	ai affordance\assessing efficiency and effectiveness	our sales process you can restart with um, um, we look at all your data and then look at scenarios on that data. And then try to predict how, if we do something will it be more efficient. (Interviewee 1)
37	ai features\identify and classify information	Influences	↔	ai features\prediction	So I mean most of the types of AI's we use is um classification, um classifying of input, um or protection of input, predicting the class it belongs to, named. Whether it's you know computer vision and the example there where we're predicting it belongs to a cat or a dog. (Interviewee 10)
38	ai features\prediction	Enables	→	ai affordance\forecasting	All put together to say we ass, um we predict that um next month you should say, you should produce maybe X, Y and Z of product A and um and another amount of product B. (Interviewee 15)

39	ai features\speed	Influences	↔	ai features\prediction	So every minute if you want to know what's up, you just check your model and it should be able to provide you those insights in real time. Um so it's definitely computational capability, you can process a hell of a lot of data in a really quick amount of time. (Interviewee 6)
40	ai features\speed	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	So if you can understand the intent of the email from the customer you can automate that process. And um you can reduce your reliance on humans and basically I mean I don't think it's a very exciting job in any case to be doing. So having a human doing something as tedious as that, reading 500 emails a day and just sending it to the relevant per-it might be a bit tedious. (Interviewee 10)
41	ai features\speed	Enables	→	ai outcome\goal-orientated outcomes\automation and efficiency	here's um something that was driven I suppose both cost reduction and speed of um doing a specific thing . . . So if you throw documents or images of places at the system it can I, automatically identify the brand and tell you that you know there's still a brand usage is this specific document. Go and change or update the source document to remove the branding etcetera. And they had thousands of documents and it would have taken thousands of human hours basically to review all the document and photo's. (Interviewee 10)

42	ai features\train & learn	Influences	↔	ai features\data input	it's learning from customer responses based on specific input from card data. (Interviewee 11)
43	ai features\train & learn	Improves	→	ai features\prediction	This is where my expenses existed um and I can then correct the system based on what I think is accurate. Um and in doing so you continuously feedback the model um to be able to better predict um the categorization of spend. (Interviewee 11)
44	ai features\train & learn	Improves	→	ai affordance\assessing efficiency and effectiveness	But when you add more features to the student, let's say we're saying [PersonY] stays in Khayelitsha. And [PersonA] doesn't have electricity at home or can't read at night. Those features, yes we might assume that these ones they're going to pull, pull him back but actually the model can actually predict and say this one is going to complete in minimum time. (Interviewee 9)
45	ai features\train & learn	Improves	→	ai affordance\analysing needs	But if I look at your specific personality profile, your strengths and weakness and the kind of job that you do. And I use models to, to, I can use models to determine the best way to train you. So some people are more visual, some are more auditory, some are more hands-on for instance. (Interviewee 7)
46	ai features\train & learn	Improves	→	ai affordance\forecasting	the ones that do allow us to train a model that will allow us to categorize um expenditure in general. Um and in doing so through these artificial intelligence um we can then um accurately predict you know

					what’s um peoples categorization of spend is… (Interviewee 11)
47	ai features\train & learn	Improves	→	ai affordance\analysing risk	Where we’ve built a, a model that’s capable of detecting anomalies in real time and we can push actual ins, like insights to maintenance teams or operators and, and it's focused…. the AI would make a suggestion that says, this component is broken um, for this and this reason. (Interviewee 6)
48	ai features\train & learn	Improves	→	ai affordance\tailoring information	So, so the salesperson would have OK, um they’d capture, let’s say a new person they’d capture their detail. They’ll say I’m a male at this age and I get this salary, and what it will do, it will, it will call a model once that salesman submit. And it will return a bunch of different policies to say, this person would mostly likely benefit from having this, this and that. (Interviewee 13)
49	ai features\train & learn	Improves	→	ai affordance\translating information	And localization is about taking the same content and making it available in multi languages right. And we use AI for that. So we use um something called machine translation. (Interviewee 5)

50	ai outcome\goal-orientated outcomes\automation and efficiency	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	the customer would get a better satisfaction from having their call resolved to a support centre. And as well, it would prevent um people from jumping from one call to another. I don't know if you've experienced where you call and they just routing you to different people. (Interviewee 13)
51	ai outcome\goal-orientated outcomes\automation and efficiency	Improves	→	ai outcome\goal-orientated outcomes\improve profitability	Automate more than 60% of our incoming um social media support and service volumes. (Interviewee 12)
52	ai outcome\goal-orientated outcomes\expand market reach	Improves	→	ai outcome\goal-orientated outcomes\improve profitability	So now we have you could almost say the ability to do that translation, do a very light validation of it right and then potentially sell that content to market where we don't necessarily originally have language um competency right. So that's one of the things that's, that's um as I said that's become an opportunity. (Interviewee 5)
53	ai outcome\goal-orientated outcomes\improve predictability	Improves	→	ai outcome\goal-orientated outcomes\improve customer service	So if we've for example working with somebody giving them a view of um, um predictability in their business and um so we're working on forecasting lets, let's take that as an example. Um the customer's impact after that is we're working with the production person in that environment and um they are trying to get a better handle on um their ordering process. (Interviewee 3)

13. Appendix E – Theme Relationships Diagram

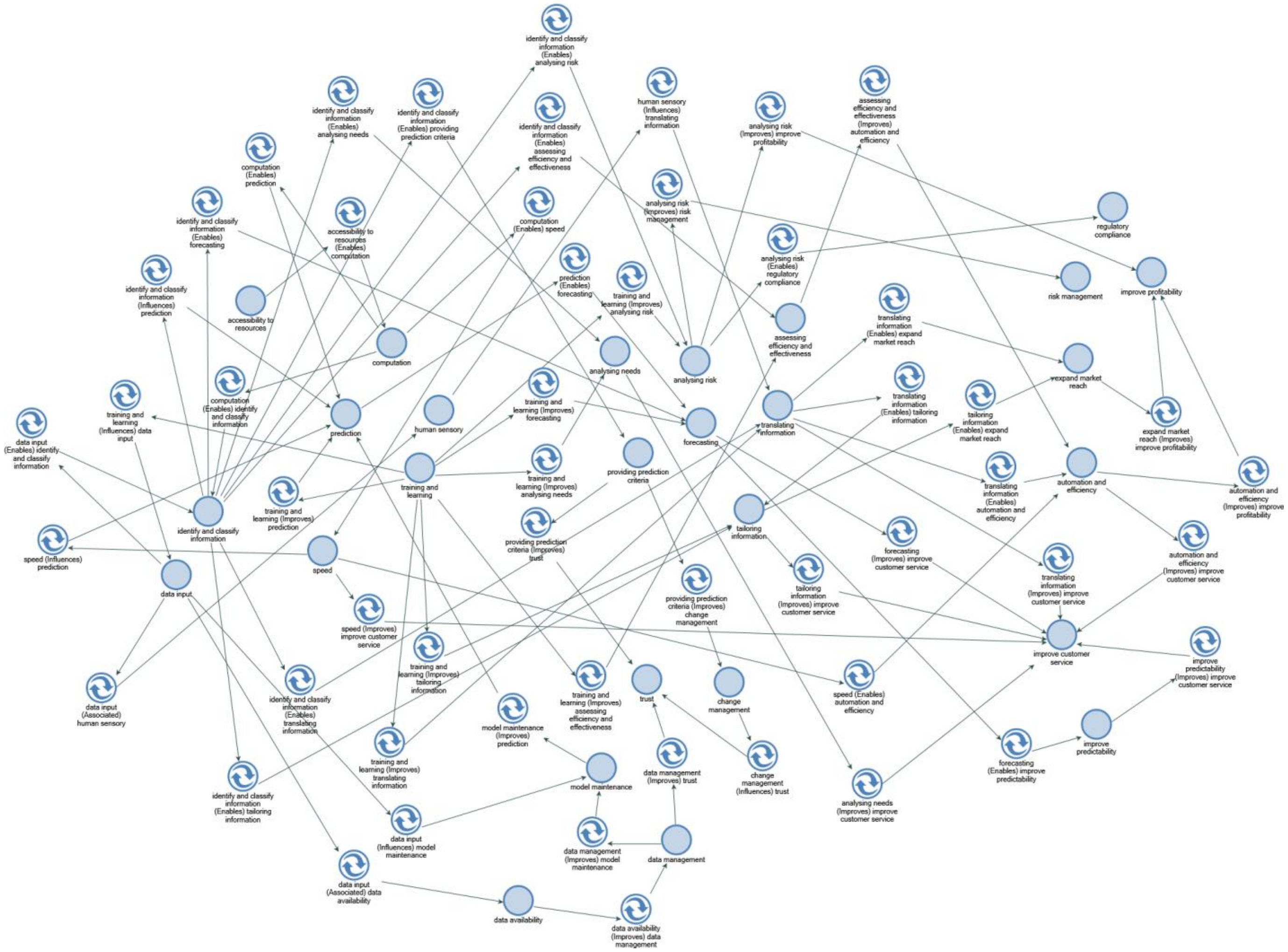


Figure 20. Relationships between themes illustrated using NVivo Project Maps

14. Appendix F – Systematic Review Method

Review Method of AI Affordance Literature

This methodology employs the six generic steps involved in conducting a systematic review, as proposed by Paré, Tate, Johnstone & Kitsiou (2016). The first step is to define the review plan, followed by a literature search as the second step. Thirdly, papers are selected for appropriateness in the study of AI affordances and business innovation. Fourthly, the quality of the studies is evaluated, followed by the fifth step of data extraction. The final step includes the analysis and synthesis of information with the aim of identifying the affordances for business innovation offered by AI. Gaps in the literature are also identified in this process.

Step 1: Review Plan

As Paré et al. (2016) suggest review planning involves (i) developing a review question, (ii) selecting the type and method of review, and (iii) formulating a review protocol. These are outlined further in this section.

Review Question. This review intends to explain the affordances of AI that result in business innovation in organisations, leading to the following research question: How do artificial intelligence technologies afford business innovation in organisations? The objectives are the following: Identify the key features of AI; Explain what is considered business innovation; Explain how AI features afford business innovation; Identify the types of business innovation afforded.

Type and Method of Review. A developmental or theory-building review type (Templier & Pare, 2015) is adopted as the aim is to develop a typology of affordances for business innovation that arise from AI features. Such an outcome can be described as a descriptive theoretical contribution (Berger et al., 2018).

Review Protocol. The review strategy chosen was more iterative than sequential, thereby allowing the study to start with initial ideas, guided by the research question (Pare et al., 2016). As learning on the topic of AI developed, search strategies were adjusted and searching continued based on this new information. This approach was particularly useful in this review considering the exploratory and explanatory nature of developmental reviews (Rowe, 2014) and because the definitions of AI are very broad (Gurkaynak et al., 2016; Berger et al., 2018; Ertel, 2018).

Step 2: Literature Search

An initial search was carried out, followed by sorting, selecting, acquiring and reading publications (Boell & Cecez-Kecmanovic, 2014). Through reading, additional terms were identified and searching continued. This iterative process also began to highlight gaps in the literature.

The objective of the initial search was to consolidate a set of recent and relevant publications that help achieve the research objectives. To do so, the top seven journals from the Association for Information Systems (AIS) were searched (Lowry et al., 2013), i.e.: MIS Quarterly, Information Systems Research, Journal of Management Information Systems, Journal of the Association for Information Systems, Information Systems Journal, European Journal of Information Systems, and Journal of Strategic Information Systems. The following leading information systems conference papers were also searched: International Conference on Information Systems (ICIS), European Conference on Information Systems (ECIS), Pacific Asia Conference on Information Systems (PACIS), and Americas Conference on Information Systems (AMCIS).

To help to identify the key features of AI and explain how these AI features afford business innovation, the following search string was used to search the title, abstract and keywords: (“artificial intelligence” AND (feature* OR characteristic*)) OR (“artificial intelligence” AND afford*). The search was limited to full-text, peer-reviewed journals and conference papers only, and within a ten-year period (2009 to 2019) as is commonly practiced for systematic reviews (Rowe, 2014). The period of ten years was also selected due to the recent introduction of commercially available AI-powered services; one example being Tesla’s autonomous vehicle. Databases such as Ebsco, Web of Science, Taylor & Francis Online and ScienceDirect were initially trialed for the journal search. The Association for Information Systems (AIS) library was used for the search of conference proceedings.

The results of the initial search across the journals and conference papers yielded a total of 15 articles. This was considered too few and the search was reconducted using the ‘broader’ search string of “artificial intelligence” in all article’s dimensions, as suggested by Bandara et al. (2015) for emerging topics like AI. The journal search produced 95 results, while the conference search produced 978 articles in total. To refine the search, the same search string was limited to the title, abstract and keywords. In addition, the Financial Times Top 50 journals (Ormans, 2016) were also included to cover the scope of management outside of the domain of information systems. AI affordances for business innovation is of direct interest to management, and so it was expected that there would be research on this phenomenon there too. This search resulted in 86 journal articles (Web of Science – all databases) and 153 conference papers. The Journal of Management Information Systems and MIS Quarterly contained 14 and 12 articles respectively, with the remaining articles spread across the remaining 23 journals, indicating that the topic of AI is still primarily discussed in information systems literature rather than management literature, as shown in the figure 21 below.

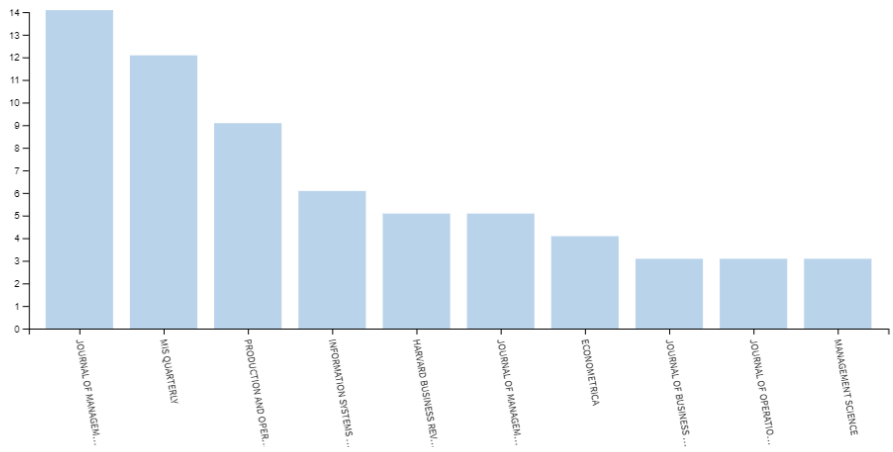


Figure 21. Journal search results

The 153 conference papers were well distributed across the four conferences as shown in figure 22.

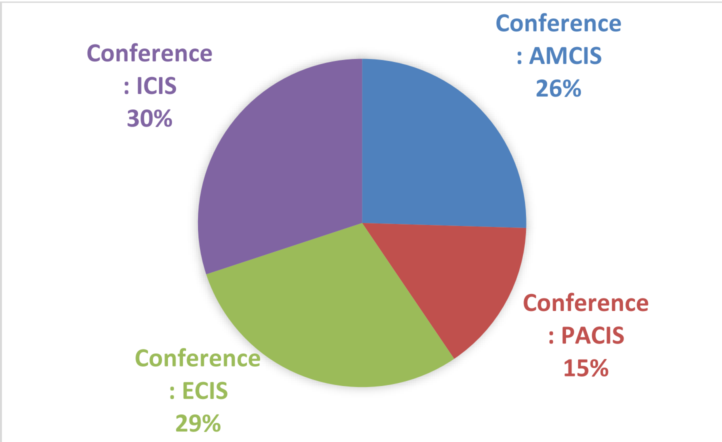


Figure 22. Conference search results

Step 3: Selection

Each of the 86 journal articles and 153 conference papers' titles and abstracts were read. Articles were selected based on whether it was related to, or provided information about: (i) Affordances of artificial intelligence, (ii) business innovation where artificial intelligence is involved, (iii) features of artificial intelligence, or (iv) a combination of the first three. Where abstracts were not available, the article introduction was read. Articles not related to these four focal points of the research were excluded from further review. This resulted in a total of 34 articles being included for full text review. Most articles were conference papers.

Step 4: Quality

The full text of the 34 articles were then reviewed. First the introduction and conclusion were read to screen for further relevance and paper credibility (Mikalef et al., 2018). It was found that several articles did not address any of the four criteria listed in the selection step. These were thus also excluded from the review, leaving the total at 19 articles.

Step 5: Extraction

The plan to extract data is based on the core broad topic of artificial intelligence affordances for business innovation, while recognising relevant data in the text related to (i) definitions and key features of AI, (ii) explanations of business innovation, (iii) explanations of affordance in the context of AI, (iv) explanations about how AI or its features afford business innovation, and (v) identification of the types of business innovation afforded by AI.

Step 6: Analysis and Synthesis

The qualitative analysis software application NVivo Pro (version 12) was used to extract and prepare the data for thematic analysis using Braun & Clarke's (2006) six recursive phases, namely (i) data familiarisation (see step 3 to step 5), (ii) creation of codes (iii) arranging themes from the codes, (iv) reviewing themes for consistency with the data, (v) refining and naming of themes, and (vi) writing the report. The codes were further refined into themes and data analysed within each theme as discussed next.

15. Appendix G – Ethics Approvals

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29/11/2019

Luqman Achmat
Department of Information Systems
University of Cape Town
REF: REC 2019/011/038

Artificial Intelligence Affordances for Business Innovation in South African Supply Chain Companies

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid until 30 November 2020

Your clearance may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Signed by candidate 2019.11.29 15:45:41 +02'00'

Jacques Rousseau
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Internet: www.uct.ac.za
@Commerce UCT UCT Commerce Faculty Office

17/03/2020

Luqman Achmat

Department of Information Systems

University of Cape Town

REF: REC 2020/03/010

Artificial Intelligence Affordances for Business Innovation in South Africa: Perspectives from Information Technology Professionals

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid until 31-Mar-2021 .

Your clearance may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Signed by candidate

2020.03.17
14:55:18 +02'00'

Jacques Rousseau
Commerce Research Ethics Chair
University of Cape Town
Commerce Faculty Office
Room 2.26 | Leslie Commerce Building

Office Telephone: +27 (0)21 650 2695 / 4375
Office Fax: +27 (0)21 650 4369
E mail: jacques.rousseau@uct.ac.za
Website: https://www.commerce.uct.ac.za/Pages/Ethics-in-Research

"Our Mission is to be an outstanding teaching and research university, educating for life and addressing the challenges facing our society."

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@Commerce UCT **UCT Commerce Faculty Office**

24th February 2021

Mr Luqman Achmat
Department of Information Systems
University of Cape Town

Dear Luqman Achmat,

REF: REC 2020/03/010

ARTIFICIAL INTELLIGENCE AFFORDANCES FOR ORGANISATIONAL CHANGE: PERSPECTIVES FROM SOUTH AFRICAN INFORMATION TECHNOLOGY PROFESSIONALS

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid for 1 year and may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Shandre Swain
Administrative Assistant
University of Cape Town
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17th January 2022

Luqman Achmat
Department of Information Systems
University of Cape Town

Dear Luqman Achmat

REF: REC 2020/03/010

ARTIFICIAL INTELLIGENCE AFFORDANCES FOR ORGANISATIONAL CHANGE: PERSPECTIVES FROM SOUTH AFRICAN ARTIFICIAL INTELLIGENCE PRACTITIONERS

We are pleased to inform you that your ethics extension has been approved. Unless otherwise specified this ethical extension is valid until 31 December 2022 and may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

Shandre Swain
Administrative Assistant
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16. Appendix H – Invitation for Research Participation

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Internet: http://www.commerce.uct.ac.za/informationsystems/

25 November 2019

Request to conduct research and interview participation consent form

Dear Sir/Madam,

In terms of the requirements for completing a Masters Degree in Information Systems at the University of Cape Town a research study is required.

The researcher, in this case Luqman Achmat, has chosen to conduct a case study entitled Artificial Intelligence Affordances for Business Innovation in South African Supply Chain Companies. The objectives of the research is to (i) Identify the affordances of AI in a South African supply chain organisation, (ii) Identify the key AI features that play a role in its affordance for business innovation in a supply chain organisation, (iii) Identify the types of innovation in supply chain organisations that are afforded by AI, and (iv) Explain how AI affords business innovation in a South African supply chain organisation; How does the organisation translate the affordances into business innovation; What are the challenges of AI affordances?

Your participation in this research is voluntary. All information will be treated in a confidential manner and used exclusively for the purpose of this study. No individual names will be recorded or published. You will not be requested to supply any identifiable information, ensuring anonymity of your responses. You can choose to withdraw from the research at any time for whatever reason, in accordance with ethical research requirements.

The data collection method will be based on observations and one-on-one interviews, both of which I prefer to be recorded by audio or video, and only if permitted to do so. The interviews will be conducted at the organisation's premises and will last approximately 2 to 3 hours. If you are willing to participate in this study, kindly sign the attached form and return to me at your earliest convenience.

Should you have any questions regarding this research, please feel free to contact me on 0844560077 or email: luqman.achmat@gmail.com.

Your participation in this study would be greatly appreciated, but is entirely voluntary.

Sincerely,

Signed by candidate

Luqman Achmat
Researcher \ M.Com Student, (UCT)
Department of Information Systems
University of Cape Town
Email: luqman.achmat@gmail.com

Irwin Brown
Research Supervisor
Department of Information Systems
University of Cape Town
Email: irwin.brown@uct.ac.za

ur Mission is to be an outstanding teaching and research university, educating for life and addressing the challenges facing our society."

Research Participant Consent Form

I, ______________________________, consent to participate in the research on Artificial Intelligence Affordances for Business Innovation in South African Supply Chain Companies.

I am aware that participation is voluntary and that I may choose to withdraw from this study at any time, should I choose to do so.

______________________ ______________________

Signature Date