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The Role of Artificial Intelligence in Shaping the Future of Agile Fashion Industry

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Abstract

Artificial intelligence (AI) has become an integral part of every industry. With the emergence of big data, the industries, and more especially textile and apparel (T&A) industry, are on the brink of relationships with consumers, suppliers, and competitors. They need to handle different scenarios with a multitude of complex correlations and dependencies between them and uncertainties arising from human interaction. It has become imperative for them to manage huge amounts of data for the optimisation of decision-making processes. In such circumstances, AI techniques have shown promise in every segment of the T&A value chain, from product discovery to robotic manufacturing. The potential wide-ranging applications of AI in T&A industry have found their ways into design support systems to T&A recommendation systems, intelligent tracking systems, quality control, T&A forecasting, predictive analytics in supply chain management or social networks and T&A e-commerce. The research recourses to the qualitative method in the form of systematic literature review and in-depth interviews from senior management people and industry experts. Findings identify the dimensions of AI to develop dynamic capability along with its potential impact and probable challenges. As such, the findings contribute to relevant literature and offer useful insights for academia and practitioners.

Key words: Artificial intelligence, dynamic capability, big data analytics, apparel, textile and fashion industry, agile manufacturing,

1. Introduction

Although there are a number of key technological innovations, industry 4.0, in particular, has transformed how firms plan and manufacture goods, develop logistics networks irrespective of the industry sector (Bibby and Dehe 2018; Gölzer and Fritzsche 2017). This has led to contemporary operations and supply chain management (OSCM) being significantly influenced by Artificial Intelligence (AI) (Helo & Hao 2021). Artificial Intelligence has also revolutionised the Textile & Apparel (T&A) industry since it incorporates a wide range of activities, such as, design support systems, fashion recommendation systems through sensory evaluation, intelligent tracking systems, textile quality control, fashion forecasting, decision making in supply chain management or social networks and fashion e-marketing (Thomassey and Zeng 2018). However, the application of AI within the OSCM context of the fashion industry presents considerable managerial and organisational challenges. Little is known about the contribution of AI for productivity and performance improvements, particularly how AI creates value in the T&A industry in the current digital age when it is combined with other Industry 4.0 cutting-edge technologies. On the other hand, agile manufacturing refers to the development of the processes, tools, and training to enable it to respond quickly to customer needs and market changes while still controlling costs and quality.

Agility of the system is, therefore, the firm's ability to envision change correctly, reconfigure operations seamlessly and offer transparent value additions to its products (Dubey and Gunasekaran 2015). Since the 1960s, the strategic manufacturing approaches have evolved significantly from mass production, lean production, time-based competition to mass customisation, leading up to agile manufacturing in this millennium, which is regarded as an emergent model for coping with sporadic and turbulent change (Gunasekaran et al. 2017). While emphasising the role of agile manufacturing, Christopher, Lowson and Peck (2004) argued that conventional organisational structures and forecast-driven supply chains are not adequate to meet the challenges of volatile and turbulent demand of the competitive and ever-changing apparel industry. In the context of manufacturing and operational procedure, agile manufacturing paradigm has direct influence over the firm's operational, financial and marketing performance (Cao and Dowlatshahi 2005; Inman et al. 2011; Iqbal et al. 2018). The extant literature has recognised the importance of contemporary information system-based technologies such as Big Data and Business Analytics (BDBA) in achieving an enhanced level of agile manufacturing practices (Gunasekaran et al. 2017). However, there is limited research knowledge about the impact of AI in agile production and operations management, particularly for the textile and apparel industry.

In the context of clothing exporting, Bangladesh is regarded as one of the top three exporters of Ready-Made Garments (RMG) products in the world market in 2020 (Statista 2021a). However, in 2020, the export value of RMG in Bangladesh was 27.95 billion U.S. dollars which was a decrease from the previous year (34 billion U.S. dollars) (Statista 2021b). In RMG supply chain management, several studies have addressed the issue of increasing performance using IT and collaborative relationships, focusing on integrated relationship management, and so forth. However, the impact of AI in the agile manufacturing process has yet to be explored. Therefore, this study aims to develop a framework for building AI capabilities/competencies for the organisation. In pursuing this objective, the primary research question of this study is: What resources can be identified to develop AI as the organisation's dynamic capability in order to enhance the overall competitive advantage in the manufacturing sector? To establish the relationship between AI capabilities, agility and competitive advantage, we use Dynamic Capability Theory (DCT). This enables us to provide a conceptual lens for explaining firms' competitive advantage and the processes through which firms can develop and configure their AI capabilities to respond effectively to changes in the marketplace (Eisenhardt and Martin 2000). In this study, dynamic capabilities (DCs) are considered a combination and reconfiguration of management processes, adaptability and resource capabilities, support the analysis of organisational agility and growth. A basic assumption of DCT is that inter-firm performance variance over time is explained by firms' dynamic capabilities to acquire and to deploy resources in ways that match the marketplace.

2. Literature review

Artificial Intelligence (AI) has a strong influence on an organisation's economic and cognitive developmental outcomes and remains critical for leading modern corporations. About 80% of top executives consider AI as the most impactful and disruptive technology that they invest in (Forbes 2019). Many large organisations directly or indirectly accelerate investment in AI. However, the area is currently dominated by an oligopoly of centralised mega-corporations with a primary focus on the interests of their stakeholders (Montes and Goertzel 2019). Despite such popularity, AI provides a multifaceted conceptualisation to many academics and practitioners. Few experts suggest that due to the convergence of several computational, machine-learning, technological, statistical, analytics and research trends, we are standing on the threshold of an era of ubiquitous AI (Davenport 2018; Paschen et al. 2019). We acknowledge Poole and Mackworth's (2010, p. 3) view that AI is "computational agents that act intelligently". Paschen et al. (2019) have, however, moved away from the thought that AI is all about machines that can display human-like intelligence. The conceptualisation of AI focuses on acting intelligently, which refers to performing the above-outlined processes towards achieving any goal-directed behaviour. This view is consistent with Russell and Norvig's (2016) perspective which measured the performance of AI in terms of an ideal performance called rationality. Another element of the conceptualisation of Paschen et al. (2019) is the "computational agent" which perceives its environment and acts upon this environment. These authors suggested that the AI systems should encapsulate six building blocks: structured data, unstructured data, pre-processes, main processes (i.e. problem-solving, reasoning and machine learning), knowledge base and information. Considering AI as a natural evolutionary outgrowth of analytics, Davenport (2018) described the evolution of AI in four stages. Stage 1, referred to as Analytics 1.0, is the era of artisanal descriptive analytics, data management, and the advent of analysis and reporting tools. Analytics 2.0 encompasses the era of big data analytics and the emergence of data scientists who dealt with powerful new data management platforms (e.g., Hadoop) and tremendous innovation around information-based offerings and social media. The era of data economy analytics, termed Analytics 3.0, saw the inclination of other organisations in traditional industries to embrace big data and analytics. Analytics 4.0 announces the strong presence of AI which delineates analytical sophistication and cognitive technologies for organisations (Davenport 2018).

Current industry 4.0 manufacturing operations are converted into smart factories, which integrate various advanced technologies, e.g. Industrial Internet of Things (IIoT) and Big Data. This is with the view to optimise performance, quality, controllability and transparency of manufacturing processes (Nguyen et al. 2019). To become a smart manufacturing unit, a factory undergoes a long-term and complex process, which requires a deep understanding of advanced technologies. IIoT, Big data and AI are integrated to engender smart manufacturing. IIoT is used in industrial manufacturing processes where large-scale data are collected and analysed through sensors and other modern technologies such as cyber-physical systems, cloud computing, mobile technologies, and radio frequency identification (RFID). These are embedded in all the components of a manufacturing process. AI provides advanced computing technologies such as machine learning, neural networking, and cognitive technology to process massive, complex and heterogeneous Big Data and eventually revolutionise the industrial manufacturing process.

IIoT, AI and Big data in intelligent manufacturing and smart factories help maximise operational efficiency, improved productivity, predictive maintenance or just-in-time, maintenance exploiting analytics for innovation, optimising business operations, protecting systems and enhancing overall organisational performance. Another significant influence of AI, IIoT and Big Data in manufacturing operations include product lifecycle management (PLM) (Nguyen et al. 2019). PLM strategy discusses continuous integration of product information and knowledge such as design, production, support and disposal, throughout all the stages of a product lifecycle (Cao et al. 2011).

2.1 Dynamic Capability Theory

The literature on Resource-Based View (RBV) framework has examined how organisations develop distinctive tangible and intangible resources over time and sustain competitive advantage by leveraging their resources (Prahalad and Hamel 1990, Amit and Schoemacher 1993, Barney et al. 2001). Extending the RBV, *Dynamic Capabilities Theory* (DCT) suggests that organisations need to determine the best course of action in the face of rapid changes and complex settings. This will help them build, develop, integrate and reconfigure their internal and external resources and capabilities (Teece, Pisano, and Shuen 1997). Dynamic capabilities Theory emphasises the achievement of internal fit between strategy and structure and external fit between resources and the environment (Raman and Bharadwaj 2017).

The modern business environment is changing rapidly owing to various reasons such as complexity and innovation in product development, geographic, technological, political, and economic situations. To cope up with the turbulent environment, DCT provides the firm with required capabilities and skill (Kindström et al. 2013). DCT enables the firm to create a competitive position for itself in the market by creating capabilities to perform better during environmental uncertainties (Mandal, Roy and Raju 2017). We aspire to extend that understanding.

The firm's dynamic capability and agility are integrally related to achieving desired organisational outcomes (Côrte-Real, Oliveira, and Ruivo 2017; Ghasemaghaei et al. 2017). In the organisational context, agility refers to the ability to respond flexibly to environmental changes, making quick adjustments to product developments while redirecting resources, in an efficient and effective way. Chen et al. (2014) argued that the firm's analytics based business value essentially depends on the complementary relationship of the firm's agility with regard to its management of business processes. Achieving agility within the organisation generally requires acquiring and processing a large and varied amount of data, which eventually results into the operational flexibility of organisational processes and IT systems to support change (Chen et al. 2014). In the current age of BDA and AI, DCT will help the organisation to develop capabilities to capitalise digital and analytics-based intelligence. Teece (2007) argued that organisations not only need deep and internalised knowledge of its product portfolio, but also need hard-to-imitate capabilities to leverage intellectual assets –see also Khin and Ho (2019).

There is still limited understanding of how firms align these capabilities with the changing environment (technological, competitor, and market conditions), while utilising the dynamic capability to facilitate this capability alignment (Wilden and Gudergan 2015). For the textile and apparel industry, previous research has emphasised the marketing capability, moving capability, knowledge development technology, as dynamic capability. However, there is limited research regarding the impact of data-driven decision-making, artificial intelligence in predicting customer demand and operationalising the agile manufacturing process through the lens of DCT.

2.2 AI Capability Dimensions

AI offers strong resources for any organisation and leads to development of dynamic capabilities to enhance overall competitive advantage. In order to develop the AI capability, the organisation needs to consider several dimensions, which comprise tangible, human and intangible resources (Davenport 2018; Mikalef et al. 2019; Ransbotham et al. 2018). Davenport (2018) first visualised AI in terms of business capabilities as technologies for AI overlap with each other in most cases and lead to ambiguity. He argued that three main business capabilities of AI included process automation, cognitive insight and cognitive engagement. Process automation could be defined as automation of structured and repetitive work processes, carried out by either robotics or robotic process automation. Cognitive insight could be acquired mostly by machine learning, through extensive analysis of structured data. In his opinion, the insights differed from traditional analytics in three different ways. They allowed maximum use of data so that the models became much more comprehensive. However, the models were required to be trained with available data in most cases. Therefore, they developed their ability to learn and improve their capacity to use new data to confer predictions or arrange items into categories. Cognitive insights were generally applied to improve the performance of machine- only jobs, such as to perform numerical calculations or conduct extensive manipulations of numerical data at higher speed in automated fashion beyond human ability. Lastly, he stated cognitive engagement which allowed engagement of customers and employees by means of natural language processing chatbots, intelligent agents, and machine learning.

2.3 Trends and Patterns of AI in Agile Manufacturing in Apparel and Textile Industry

The textile manufacturing industry is one of the largest contributors in the global economy, which represents 38%, 26% and 22% in the Asia Pacific, Europe and North America, respectively. However, these existing industries needed to maximise resource utilisation. Emerging AI techniques could be adopted to create a sustainable digital supply chain (Shang et al. 2013) and were successfully utilised at various stages such as apparel design, pattern making, forecasting sales production, supply chain management (Guo et at. 2011). Due to the volatile nature of this industry, it was important that the industry quickly responded to changes in trends and continuously evolved to meet the customer needs.

AI capabilities have played instrumental roles in transforming and shaping up the textile manufacturing industry. Current industrial approaches have been substantially improved with the provision of advanced machines and processes. Therefore, the overall efficiency of the industrial processes has improved significantly. At the managerial level, application of AI is well understood and at the same time its utility has been recognised at various operating processes. However, there is still room for further improvement for the applied AI in the textile manufacturing supply chain (Guo et al. 2011). Based on AI capabilities, both classification and clustering techniques were employed in textile manufacturing (Yildirim, Birant and Alpyildiz 2018). At present, AI capabilities, such as machine learning, decision support systems, expert systems, optimisation, image recognition and vision, are generally employed.

Machine Learning

Machine Learning is a technical process in which the computers are trained to perform the assigned task without human intervention and learn from the patterns of the data itself (Bishop 2006). Machine learning can be classified into supervised or unsupervised learning. In brief, Machine learning has been adopted for prediction of sales, analysis of trends, prediction of colours (Hsiao et al. 2017), forecasting of demand (Thomassey and Zeng 2018), detection of fabric defects (Ghosh et al. 2011) and prediction of fabric behaviours based on mechanical properties.

Decision Support Systems

As one of the promising AI capabilities, the decision support system (DSS) is employed at the commercial scale for carrying out mid-level or high-level managerial decisions in an organisation. It can be manipulated in an automatic fashion or controlled by humans or a mixture of both. In the textile manufacturing industry, it has found widespread application to modify numerous tasks through enabling optimisation of decision-making process in the supply chain (Tu and Yeung 1997). DSS assists actors in apparel manufacturing and production to determine appropriate processes and resources to reduce the overall cost of the supply chain (Wong and Leung 2008).

Expert Systems

Expert systems employ reasoning approaches to draw solutions for complex problems, which are attributed by ‘‘if-then’’ rules (Jackson 1990). Expert systems are classified into two categories: inference engine and knowledge base. ‘Knowledge base’ is guided by the principle of facts and rules, while ‘inference engine’ considers the rules to learn from the facts and subsequently derive new facts. The expert systems are extensively used in apparel manufacturing and production to determine appropriate processes and equipment for controlling environmental pollution (Metaxiotis 2004). In addition, they are utilised for developing a recommendation engine in fashion retail which is used to improve the overall satisfaction of customers (Wong Zeng and Au 2009).

Optimisation

AI possesses the ability to solve complex problems and provide numerous solutions by intelligent searching. Classical search algorithms begin with random guesses and is then improved using the iterative process. For example, 'Hill climbing', 'Beam search' and 'Random optimisation' are notable methods. Machine learning algorithms utilise 'search algorithms', based on optimisation techniques. Simple exhaustive searches are found to be very slow in operation and therefore 'Heuristics' approach is preferred (Nilsson 1998). However, the utility of the heuristics search approach is limited with larger datasets (Tecuci 2012). An evolutionary algorithm has been found in literature, which is another form of optimisation search. Other popular evolutionary algorithms are genetic algorithms (GA), gene expression programming and genetic programming. GA has been extensively used in the textile manufacturing industry to eliminate the problems of scheduling and design layout and accommodate quick changes (Lu et al. 2015; Hui et al. 2007).

Image Recognition and Vision

In AI, computer vision is regarded as a scientific area, which provides training to a machine to accomplish high-level interpretation of the images or videos. Computer vision algorithms perform several tasks which include extraction, pre-processing, exploration of the high dimensional data and generation of supervised or unsupervised models. For proper understanding of images and extraction of useful information, models utilise the concept and knowledge of geometry, statistics, physics, and machine learning theory (Forsyth and Ponce 2003). Computer vision also includes object recognition, video tracking, motion estimation etc. Machine vision is used in textile manufacturing to conduct automation of many industrial applications, such as inspection and process control (Steger, Ulrich and Wiedemann 2018). Other popular applications of image recognition and vision are content-based image retrieval systems, virtual try-on and augmented reality, which are now frequently used in this industry (Yuan et al. 2013; Cushen and Nixon 2011).

2.4 AI Applications in Textile Manufacturing Industry

Various processes of textile production such as fibre grading, prediction of yarn properties, fabric fault analysis, and dye recipe prediction are performed regularly utilising different AI capabilities. Similarly, AI can be applied in all the stages (pre-production, production, and post-production) of textile manufacturing. It involves processes such as conceptualisation, design development, production planning and control (PPC), spreading, cutting, bundling, sewing, pressing, and packaging.

2.5 Challenges of AI integration in Textile manufacturing Industry

Due to their dynamic nature, AI capabilities have revolutionised textile production approaches and processes. However, there are several areas that require further developments as they limit the uses of AI capabilities in textile manufacturing and restrict them to reach full potential. For example, the accuracy of classification in fibre selection could be improved by adopting more powerful learning strategies. Simulation could be substantially improved by AI to predict the decreased number of ends in yarn manufacturing in accurate fashion and less occurrence of small knot of entangled fibres (e.g., NEPS). In addition, further research is required to determine and predict yarn properties accurately at higher spinning speeds. Accuracy of predicting fabric properties is influenced by the quantity and quality of data, which are subsequently used for AI training. Therefore, different ANN configurations along with adequate qualitative training data need to be explored for accurate prediction of fabric properties, determination of quality parameters of yarns and overall fabric quality.

Research and development (R&D) helps to monitor fabric faults online at higher speeds. Thus, the application of AI could be explored into 3D space from its current application in 2D space and the results of AI prediction in higher speeds require validation. In addition, the application of AI in 3D pattern prediction requires standardisation and further developments. More research is required to investigate different aspects of sizing and the virtual fit pattern. Limited research with AI application is available on issues related to clothing comfort due to complex parameters in the fabric properties. Other challenges include long computational time for handling a large amount of data, determination of adequate model inputs, choice of suitable network architecture, and validation of the predicted results.

3. Methodology

We used multiple methods comprising of systematic literature review and semi-structured interview. This enabled the researchers to triangulate the findings of literature review with the interviews. A mix of multiple methods ensures rigour in such a research process by establishing reliability (Fusch et al. 2018). Specifically, the interviews enable such research to investigate in details how people interact with AI dynamics through various process, structure and context (Silverman 2011).

Using this review approach was critical to organise evidence pertinent to the research question in a systematic and rational manner. To capture AI capabilities, challenges and applications in the textile industry, the study embraced the following research protocol in search strategy and publication selection. First, search strings were carefully selected to identify relevant publications containing the keywords ‘Artificial Intelligence*’ with several other terms such as, ‘Artificial Intelligence* AND Textile Industry’, ‘Artificial Intelligence* AND Fashion Industry’ and ‘Artificial Intelligence* AND Capabilities’, ‘Artificial Intelligence* AND Challenges’ ‘Artificial Intelligence* AND Applications’. Second, based on the search strings, we identified relevant databases such as Business Source Complete (EBSCOhost), ABI/Inform Complete (ProQuest), Web of Science (Thomson Reuters), ScienceDirect (Elsevier) and Scopus (Elsevier) and industry sites (e.g., McKinsey & Company, Deloitte and IBM) to capture all relevant journals, periodicals and industry reports. Following a stringent search process using inclusion and exclusion criteria on the title, abstract and keywords, we excluded disciplines that were not directly relevant. The search of the abovementioned databases returned 9381 hits. 107 publications were downloaded and reviewed after the exclusion of duplicates. Finally, 38 publications were selected based on the quality criteria of the Chartered Association of Business Schools (ABS), Academic Journal Guide (AJG) and Australian Business Deans Council (ABDC).

The primary reason for choosing Bangladesh for collecting the interview data is the country’s current leading position in clothing export worldwide (Rahman et al. 2020) and its approach to incorporating industry 4.0 technology in the T&A industry (Noor 2020). Both private and public sectors have recognised the importance of the fourth industrial revolution and AI technologies in shaping up the overall performance of the industry, and therefore relevant measures are taken. The data provided insights about the adoption, challenges, possible outcomes and industry perspectives of industry 4.0; thus, considering Bangladesh for the current study’s contexts as appropriate and timely.

The interviews were conducted with AI experts, including academics, researchers and professionals from Bangladesh (as detailed in Table 1). One of the key reasons to interview the academics is their expertise and knowledge in this field. Understandably the practitioners have first-hand experience about the operation of their business and may not have the updated theoretical knowledge. Moreover, the management people in the RMG sector of the country have learned the trade and operations through experience. The academics are aware of the latest developments around the world in relevant area and an industry—academia alliance will be always fruitful. Therefore, to shed light on these issues, we have interviewed the academics. To collect the primary data, we conducted 28 in-depth interviews. The respondents were selected based on purposive sampling because of their current position of key decision makers and managerial positions the relevant experiences, representation of a wide range of sectorial areas. We stop interviewing after twenty-eight participants, as it reached theoretical saturation and due to continuous repetition of themes (Glaser and Strauss 2017; Taylor and Bogdan 1998). To ensure the right criteria of our respondents, the interviewees were communicated through the researchers' professional and personal connections. The respondents were made aware of the details of the research following a two-way, open communication atmosphere. We ensured ethical issues and confidentiality and anonymity of interviewees during the interview data collection process.

The interviews lasted 45 minutes to 1 hour. To ensure convenience and optimise the response rate, the interviews were carried out through a combination of face-to-face, telephone and online communication. Most of the interviews were recorded if not the respondents opted for non-recording of the interviews for professional reason. Interview protocol plays a key role in the studies where the experiential investigation is subjective as it works as an action plan, helps in operationalising the research, and establishes protocols for data gathering. In the present study, the interview guide was initially developed based on the themes identified in the literature (Table 2).

Insert TABLE 1 Here

Insert TABLE 2 Here

The interview data were analysed using QSR NVivo 11 software, one of the leading software package for thematic analysis, to identify richer insights from interview excerpts in the form of meaningful themes backed by solid evidence (Bazeley and Jackson 2013). After the interviews were transcribed, template analysis was applied to identify and organise the recurrent themes in meaningful category. In this research, we identified several broad themes such as AI as a dynamic capability, trends, patterns, challenges and applications of AI in Agile manufacturing. The themes, subsequently broken down in codes, were identified based on the research objectives and key themes in the literature review (Table 3). Some of the codes and themes were driven by data, while some were driven by theory (Fereday and Muir-Cochrane 2006). In order to embrace further rigour in the thematic analysis, the study used Krippendorff's alpha (or, Kalpha) as a reliability measure, which is 0.84 exceeding the threshold value of 0.70 (Hayes and Krippendorff 2007).)

Insert TABLE 3 Here

4. Findings

In this paper, it has been endeavoured to identify the resources to develop AI as the organisation's dynamic capability in order to enhance the overall competitive advantage. The detailed findings offer deep insight into the conceptualisation of AI as dynamic capability for an agile manufacturing context in Bangladesh. As such, this paper offers the following empirical and conceptual findings with regard the following major constructs:

4.1 AI Capability Dimensions

The theoretical framework of RBV and DCT underscores the importance of creating and combining various strategic resources to create organisational capabilities, which generate competitive advantage. For the organisations, the resources can be physical, human, technological, reputational and intangible. The amalgamation of various resources resulted into an organisation's capability development, which is non-transferable and aim to enhance the application of other resources. Therefore, the capabilities are a compulsory strategic tool for any organisation. However, they depend on the environmental conditions in which an organisation operates (Gunasekaran et al. 2017). Our findings suggest that to develop an AI capability the organisation should enhance its dynamic capabilities such as the infrastructure, database, people and relevant technology. However, the significance of intangible factors cannot be understated such as the organisational culture for technology orientation, people skill and knowledge sharing. One of the participants suggests that:

> *As an application-based concept AI's been around for few decades; however, in this decade of 21st century industrial landscape, AI's gaining momentum in manufacturing ecosystems along with the service sectors. Manufacturers are now keen to develop AI capability because of its operational efficiency, cost effectiveness and data management and processing technology.* [Participant 12]

To operationalise both a large amount of data and run the complicated and iterative algorithms, AI framework must comprise of the dynamic capability to collect, cleanse, share and process large amount of data in the quickest possible timeframe. There exists a strong two-way relationship between AI capability and smart manufacturing factory, which is a networked production unit that adopts digital information technology, big data processing capabilities, advanced robotics, analytics-integrated manufacturing, highly adaptive and rapid design changes. Generally, in a smart factory AI is enabled with the help of Industrial internet of things (IIoT) which is an advanced ecosystem of devices and database management systems. The machines and touchpoints of IIoT generally generate significant relevant data to be fed in for the machine learning, neural networking and cognitive technology. Therefore, to develop AI capability organisations should focus on developing smart manufacturing enabled through IIoT, as suggested by several participants.

In a smart manufacturing, the management must install and maintain right machinery and devices coupled with computer-aided technology, which can process large-scale data. For smart factories, data is the fundamental output to use as the primary input to optimise the operations. Increasingly, factories are equipped with industrial internet of things (IIoT)—analytics-based eco-system comprising of cutting-edge technology, data processing algorithms and integrated devices. The smart factory collects large volumes of data from various sensors and processes them to feed into the artificial intelligence-based decision making. [Participant 15]

AI works on real-time data generated from various onsite and offsite sensors, through smart manufacturing operations, to identify any issue in the factory while forecasting demands, accelerating new product development by feeding operations and environmental data back which eventually significantly improves the organisation's dynamic capability and affecting the favourable performance. Smart manufacturing or IIoT has a transformative impact on the industry's daily operations—particularly for an agile manufacturing unit. [Participant 5]

The AI infrastructure must have the capability to compute and analyse millions of data fields to store outputs, retrieve outcomes, and develop networked decisions in real time while ensuring a secured atmosphere. Therefore, to develop AI capability, organisations must ensure the availability of appropriate technological infrastructure such as, enterprise networks system, cloud-based technology, CPU with updated computational power, graphical processing unit (GPU) and AI accelerators such as artificial neural networks, machine vision and machine learning. AI technology and infrastructure requires large-scale investment for which the management needs to be inclined to. The management readiness and their visionary plan is significantly influenced by the predictable production efficiency and favorable return on investment. Therefore, to set up and manage an AI infrastructure, not only the management's readiness is important but also there should be organization-wide AI orientation and culture. One of the interviewees suggested that:

To develop organisational AI capability, I believe the hardware infrastructure is the most important aspect, which incorporates data and skills. AI technology is still at emerging stage and is expensive; therefore, it requires heavy investment to develop a fully functioning infrastructure. In agile textile manufacturing, factories rely on several technologies such as fabric pattern inspector, defect spotters, colour tolerant etc. to *ensure the consistency in outputs.* [Participant 10]

An important factor for developing AI capability dimension is the management readiness and AI culture. This finding supports the organisation's RBV, capability-based view and knowledge-based view which emphasises the resources, capability and technological know-how are key to the development of dynamic capability. Management's readiness is an important factor for the adoption of new technology since it can be lingered and, in many instances been dropped, due to lack of management support, enterprise's non readiness and cultural resistance. It is the management's responsibility to establish and maintain enterprise-wide analytics driven culture to ensure production efficiency and facilitate effective decision-making. In several manufacturing organisations, managers would like to stick to antiquated leadership style, lack knowledge of analytics and are sceptical about adopting any new ideas or technology. Management's leadership views about AI would establish the culture for rest of the team; therefore, management should initiate to establish a data driven culture in various stages of decision-making process. Our participants suggest that barriers should be removed to instil AI culture throughout the organisation. Manufacturers should make formal arrangements to promote shared organisational learning. In the organisation, there should be a strong practice to search, acquire, assimilate and exploit new and emerging knowledge, since they play an important role in enhancing AI capability. While emphasising the role of management readiness of AI, several participants suggested that:

> *Top management's interest and encouragement for new technologies will set up the organisation-wide foundation for AI orientation. If senior managers are indifferent about adopting new technologies as they only see the cost of it and failed to envision the benefit, it becomes difficult to deploy most advanced ideas or technology. Therefore, implementing cutting-edge technology like AI requires support from the top.* [Participant 13]
>
> *In the market economy, most technical support and services can be outsourced from other independent vendors; however, in case of manufacturing sector, where the adoption of AI needs to be present on-site, the management need to set up it within the factory premises for which it needs a culture of data-based decision making. In manufacturing organisations, allocation of resources has a long-lasting impact and has huge sunk cost; therefore, it needs a great deal of discretion, which should overlook political negotiation and so on.* [Participant 20]

Another important factor in developing AI capability is the people capability, which is a combination of intangible and tangible resources and important element for the organisation's dynamic capability (Mikalef et al. 2019; Ransbotham et al. 2015; Sousa and Rocha 2019). Our finding underscores the organisation's RBV, capability and knowledge-based views by highlighting the importance of people as an important resource to develop AI capability. The people skill consists of technical skills, capability to manage technology, business know-how and relational knowledge which are key to initiate and implement AI projects. The significance of people or talent capability, as an underlying dynamic capability for building AI capability, revolves around the fact that the organisations require skilled people who not only can foresee the requirement of tangible resources of hardware and infrastructure for AI but also possess the capacity to operate various AI-enabled programmes to generate outputs for the manufacturing plants. In manufacturing sector, there is dearth of skilled people from every stage of the manufacturing cycle. In many instances, it is difficult to upgrade the skillset of existing people through training since, to enhance capability in advanced technology such as big data or AI. Several interviewees suggested their opinions.

> *Human skill is critical enterprise success whether it is a manufacturing or service organisation. The significance of skilled people is more realised when the organisation gets involved in advanced tech-based projects such as big data, AI and automated operations. In textile and fashion manufacturing, there's always a shortage of efficient people at every level of the operational process.* [Participant 7]

> *The employees are always a vital resource to the organisation because they bring in required capability, skill, technical knowhow and experience which are key for organisational AI-based operations.* [Participant 15]

> *AI's been making an important contribution to design of fabric and final fashion/apparel products. The designers are fed in with the customers' preferences and develop probable design outputs using large volumes of data. The hardware part of the AI is fed with data inputs; however, from a creative perspective, it's the human skill, expertise and creativity which are important role in analysing the outputs, understand customers' fashion preference to create novel design from AI.* [Participant 28]

In agile manufacturing plants, whether textile or other goods, a big task remains about upgrading the skillset of the existing employees with a view to fully capitalise the AI as dynamic capability. However, for the existing employees occasionally it becomes quite difficult to train them in advanced technology (e.g., big data analytics, AI, cognitive technology), if they are not familiarised with its background and related technologies. Generally, manufacturing plants are run by experienced technicians who have achieved their skill through first-hand experience of several years practice rather than through theoretical knowledge. Although transferring the skill of most advanced technology in AI amongst is difficult, the adoption of capability-based view and knowledge-based view would play an instrumental role to position AI as a potent dynamic capability.

4.2 Trends, Patterns, and Applications of AI in Agile Manufacturing in Textile

AI is engrossing in many sectors of the global business. Its presence is more prevalent within service industry compared to manufacturing sector, according to McKinsey Global Survey report (2018). However, AI has strong growth potential in manufacturing although it is in automotive manufacturing (Forbes Insight report 2018). The advent of AI techniques has made significant impact in most areas of management, marketing and production of T&A products. In case of garments and textile manufacturing sector, several AI techniques are being used such as expert system, neural network (NN), fuzzy logic (FL), genetic algorithm (GA), evolution strategy (ES), artificial immune system (AIS), deep learning, optimisation, computer aided design and multiagent system (MAS) which can provide superior solutions over classical systems due to their heuristic and intelligent nature. While emphasising the revolutionary changes that AI has made on the traditional garments and textile manufacturing process and fashion retailing, our interviewees have shared their expert opinions.

> *The application of AI has become omnipresent in the manufacturing and retailing of any commodity—and textile and garments are no exclusion to this. It has infiltrated in consumers' lifestyle gradually. Presently the firms use machine learning, predictive modelling, image recognition and other AI technologies. Currently, various start-up companies have evolved to provide supports such as trend analysis, material handling, product curation, customised and tailored fashion.* [Participant 25]

> *Now garment manufacturers rely mostly on human expertise and experience, and in many cases apply computer aided design, simulation and automation process. Therefore, while dealing with so many variables manually, in several cases, there exists*

of high probability of errors in almost every stage of the manufacturing and marketing process (whether it is management, production, finishing etc.). I believe there comes the effectiveness and efficiency of AI based decision-making which depends on big databases to integrate and coordinate the variables and end results. [Participant 16]

The textile and apparel industry is still lagging behind the real world in terms of applying AI technology. Apart from adopting automation in its production process such as, weaving, cutting, sewing, colouring, washing and grading, manufacturers can adopt AI-supported tools in spotting defects, inspecting textile density, pattern inspection, colour matching. AI tools can be applied to do predictive modelling the customers' buying pattern, preference and changes in apparel sense. [Participant 1]

AI has a significant implication for the textile and garment production. With regard to the fibre and yarn production for the fabric, several AI techniques can be used for virtual modeling of yarn, analysing yarn and fibre tensile properties, assessing their roughness and overall yarn engineering. AI tools such as machine learning, fuzzy logic, ANN have been applied to predict functional and aesthetic properties, comfort (both sensorial and thermophysiological), performance, sewability and durability of any fabric. Regarding the colour pigmentation and dye of the fabric and finished garments, expert systems as an AI tool can do the colour matching and reduce the deviation of the final garment from permitted standard of dyeing. In textile and apparel industry, the defect and rejection of goods cause a significant damage to the manufacturing output. A participant suggested that:

In textile manufacturing, rejects and defects are a common factor, which certainly negatively affect or reduce the value of the outputs. To manage this issue and inspecting the fabric, textile manufacturers apply various AI-based advanced techniques such as machine learning, Artificial Neural Network and image analysis. [Participant 21]

In garment manufacturing, AI integrated CAD (combining apparel CAD and graphic algorithm) can be used to explore apparel designs. For example, fashion brand Tommy Hilfiger developed a project named Reimagine Retail, where they have made a strategic collaboration with IBM and The Fashion Institute of Technology (FIT) Infor Design. The primary objective of this collaboration is to develop more customer-focused and modern design by capitalising the power of AI technologies such as computer vision, natural language understanding, and deep learning techniques. The tools were various images which include, 15000 product images of the fashion retailer, 0.6 million publicly available images and 0.1 million fabric patterns.

There has been a significant impact made by AI-enabled technologies in predicting customers' preference and behavior for apparel products. The fashion retailers are applying AI (e.g., machine learning, intelligent automation and predictive analysis) to maximise the brand's sales revenue while enhancing the customers' shopping experience. It has been a rising trend amongst apparel retailers to leverage various conversational assistants such as chatbots and voice assistant devices (e.g., Google Home, Apple Siri, Amazon Alexa) to collect customer data. The application of AI has enhanced the dynamic capabilities of the organisations in predicting the customers' buyer behaviour. AI is encompassing e-commerce and shopping apps on mobile platform to offer customers their preferred design. One of the experts suggested that:

> *In predicting customers' behavioral pattern, fashion/apparel retailers can use intelligent conversational agent (e.g., Cortana, Apple Siri, Google Home, Alexa from Amazon) with a view to gather data through interactions with the customers.* [Participant 19]

> *The application of AI tools in the fashion/apparel merchandising operations is limited because as merchandisers we receive instructions from the fashion retailers for procurement, execution, management, supervision and delivery of any consignment. Buying houses or merchandising units requires various software applications where we feed in lots of data to enable seamless planning and execution. However, we understand that big label fashion brands apply various predictive analysis tool, machine learning to predict the customers' future preferences, reduce inventory and minimise manufacturing errors.* [Participant 27]

An important trend in manufacturing sector is the emphasis on human resources and technology as key resources. Textile manufacturers adopt RBV and capability view to implement AI technology to boost their dynamic capability.

4.3 Challenges of Implementing Artificial Intelligence

The implementation of AI is also facing some challenges particularly for the quality and availability of data, organisational capability to manage AI, requirement of huge investment and lack of resources to establish and maintain AI within an organisation despite the organisation's approach to RBV, knowledge-based view and capability-based view. AI is one of the most updated technology which, unfortunately requires serious investment in several areas of the organisation such as hardware, infrastructure, software, technology, management and in people. Organising these many issues in the context of any manufacturing unit certainly challenges its existing operating procedure and, in many instances, may require to overhaul the core procedure of the business operations. Arranging resources, whether it is tangible or intangible, is one of the most pivotal factors while implementing AI in case of fashion and textile manufacturing sector. Moreover, there is a perception among general people that AI and robots will replace human jobs (Morgan 2018). Experts have provided their opinions in this regard.

> *The application of AI-enabled technology is expensive for the fabric and manufacturers fashion, which certainly affects the organisation's cost effectiveness. AI could be still a luxury for many brands and may hamper its performance seriously, if it's not addressed. Since the technology is in its nascent stage, key resources such as hardware, infrastructure, skilled people and large volume of data are scarce, thus costly to implement. [Participant 13]*

> *There is a widespread discussion that people will lose jobs due to the companies adopting AI technology. There is debate which provides stronger argument for both sides (i.e., replace the job or not). I understand many factory level routine works can be replaced with AI technology or robots. But my point is, how many companies can afford this or is it really cost effective or not. [Participant 9]*

Another challenging matter for setting up AI is its lack of explainability of model or outcome. As we know, based on the huge dataset, AI makes a decision, and in most cases, does supplement the model with an explanation. Therefore, if the decision-makers disagree with the model outcome and want to understand the underlying phenomena, it will be difficult in case of AI-enabled decision-making process. In the service industry, particularly in medical science where not only the outcome but also the process is important, sometimes the underlying explanation bears more significance than the outcome. However, in manufacturing sector, it will be of little problematic particularly for a routine-based repetitive jobs. One of the experts opined that:

> *The application of AI is fraught with some limitations. The most important one is the lack of explainability of the outcome or prediction. Analysing the data and trend, the*

> *model will be suggested; however, it does not come with any underlying explanation, which discusses the process. So, as a decision-maker, if I don't agree with the outcome there is no way I can continue and look for further information. This problem won't be that much be prevalent in case of error detection, pattern matching or colours sensing.* [Participant 17]

There is strong academic and practitioner literature which augment the positive implication for adopting AI in the industry although the implementation plan for AI varies from industry to industry. As other advanced technologies, AI is facing several challenges associated with its implementation. In agile the manufacturing sector, where there is significant potential, AI needs to manage the aforementioned technical, technological, financial and management related issues.

5. Discussion and Contribution

In this study, we have explored AI as a dynamic capability in the context of an agile manufacturing sector. In the current age of the data-driven business world, AI is gradually encroaching almost every industry. Although AI has higher scope of implementation in the manufacturing sector, service sector is ahead of the manufacturing sector in adopting AI, as suggested by a McKinsey Global Survey report (2018). However, AI has a strong growth potential in the manufacturing sector although it is in automotive manufacturing (Forbes Insight report 2018). The garments, textile and apparel manufacturing sector is lagging behind in implementing AI although it bears significant potential to embrace the technology. Research related to the implication of AI in manufacturing is in the nascent stage, despite an increasing interest in this area from both academia and practitioners (Mikalef et al. 2019).

Mikalef et al. (2019) emphasised on the roles of tangible, intangible and human intelligence and skills in developing AI capabilities in light of the RBV. Furthermore, they underscored the significance of data to implement AI and its supported technology since data management systems and decentralised databases were strong prerequisites for AI capability development (Ransbotham et al. 2018). However, an appropriate technological infrastructure, such as computational power by state-of-the-art CPUs and GPUs, were required for preparation and processing of large amounts of data to support advanced AI capability (Lemley et al. 2017). With regard to intangible components, an organisation requires a human element to utilise AI capability. Human skills and intelligence were one of the most important factors to develop and implement an organisation's AI initiatives to develop and train AI applications, in particular, and develop foresight and managerial capacity to apply such methods to address business problems (Sousa and Rocha 2019). Another important category of intangible resources was dependent on organisations' AI orientation culture, organisation-wide learning and knowledge sharing (Ransbotham et al. 2018).

Contribution of the study

While the novelty of this paper remains in explaining the role of AI in developing dynamic capability in the manufacturing sector, it also addresses key research questions as outlined in the beginning. Therefore, the theoretical contribution of the paper incorporates, explaining the dynamics and dimensions of AI under the prominence of RBV and dynamic capability theory, and exploring the trend and application of AI implementation and its challenges. The entire process and theoretical contribution of this paper has been delineated in figure 1.

Insert FIGURE 1 Here

Our findings suggest that organisations cannot rely only on the tangible resources and therefore need to emphasise technical know-how, knowledge and intelligence about implementing and managing AI-related operations for achieving a competitive advantage and enhance overall performance. For an organisation AI transforms into dynamic capability provided that it can integrate its tangible and intangible resources to build the platform which is in line with the theoretical context of DCT and RBV. The DCT has extended RBV to develop, integrate and reconfigure the organisation's internal and external resources and capabilities to prepare them to survive and sustain in the turbulent business environment (Teece, Pisano, & Shuen 1997). The DCT helps the organisations to conceptualise analytics-based information processing as a unique capability to generate competitive advantage for the organisations (Chen, Preston and Swink 2015; Côrte-Real, Oliveira, and Ruivo 2017).

Our findings extend this thought by arguing that RBV locates the essential tangible and intangible resources for implementing AI while DCT suggests how to integrate, reconfigure and convert those resources into dynamic capabilities for organisations. Moreover, we extended the understanding of DCT since, it enhances the organisation's capability to sustain in turbulent environment while incorporating agility. AI not only enhances the firm's intangible and human knowledge but also helps the firm to identify and seize the opportunities and transform them. AI and its relevant technologies such as machine learning equip the firm with the dynamic capability to predict customers behavior, generate more confirmed sales lead, maximise customer lifetime value and increase customer retention. The findings contribute theoretically by emphasising that both RBV and DCT hold the ability to integrate and develop an attractive approach to explain business value stemming from IT investments which are important for developing AI capabilities (Mikalef et al. 2019; Sirmon et al. 2011). The findings will also reinforce the past research in the broader IS domain which has applied the RBV and DCT quite extensively with a view to establish the significance of data analytics, artificial intelligence in achieving organisational objectives (Braganza et al. 2017; Chen et al. 2015; Côrte-Real et al. 2017; Ghasemaghaei, Hassanein and Turel 2017; Wamba et al. 2017).

The findings suggest that for the Textile and Apparel industry, Artificial Intelligence brings opportunities whose implementation can, however, present challenges. To address those challenges the manufacturers need to develop appropriate resources, capabilities, generate intelligence and manage knowledge. Our findings suggest that organisations should not understate the importance of intangible resources in developing AI capability dimensions. Large, resourceful and cash-rich organisations can procure the tangible resources (e.g., hardware and infrastructure) with ease; however, they face unmountable challenges when they try to hire skilled people for implementing and running the AI based projects. The organisations should focus on developing talent resources, which can be acquired with easily considering the nature and complexity of the technology. Although the study has been contextualised in with the theoretical framework of RBV and DCT, the findings suggest that the complexity of implementing AI in T&A manufacturing requires intelligence orientation and knowledge management to theoretically underpin and extend RBV and DCT. As such, the findings will advocate that a theoretical integration of RBV, DCT, knowledge-based view is essential to tackle the challenges of implementing AI.

Furthermore, the study findings suggest about the employees' negative perception of AI as it will replace human skills. With regard to the implementation of AI, there is a widespread perception among the existing people in manufacturing industry that AI will replace the human and a good number of people will lose job. Our findings suggest that while the manufacturers appreciate the advent and application of AI, they are concerned that it may affect the unemployment rate. Organisations and the government could work on this macroeconomic issue to upgrade or diversify people's skills to reduce to impact of technologies on job security and employment levels. Therefore, the findings reinforce the idea that DCT enables the organisation to be able to transform over time as organisations reconfigure new capabilities to achieve results (Braganza et al. 2017).

Another important contribution of our study is that it suggests developing AI capability in the context of agile manufacturing. DCT is more important in the context of the agile T&A industry since the manufacturers need to be more adaptive and responsive to the turbulent environment particularly the changes in the customer demands, short lifecycle of the products and designing new products. Agile manufacturing process is implementable with advanced analytics-based procedures (e.g., Big data analytics or AI). In agile industry, firms develop a higher-order dynamic capability through the development of their work routines and leveraging information technology to align, enhance, and reconfigure other capabilities and resources (Ghasemaghaei et al. 2017; Teece 2007). Dynamic capabilities play a crucial role to promote organisational agility to facilitate the integration and organisation of resources and knowledge and to operate in a turbulent environment.

Practical Implications

The study findings also have some practical implications. There is no doubt that AI possess significant potential to influence the production (for textile, yarn, garments and other fashion items), marketing, retailing and predicting customers' behavior and preference. Our study findings suggest several challenges for implementing AI such as data-related issues, lack of intangible resources, explainability of the outcome model, shortage of skilled people management AI orientation and culture. Of these challenges, we found that data-related issue and shortage of skilled human resources have more challenging impact since there is dearth of reliable sources and volume of data as well as lack of skilled people. Moreover, there is dearth of appropriate training facilities which is restricting the capitalise its full potential. Furthermore, biasedness of any outcome model is significantly related to data quality. Another challenge is to ensure explainability of the model outcome. After feeding the big data, the AI tool generates an outcome model; however, it is not clear if the users disagree with the model since there is no scope of explanation to amend one's understanding and position. This is acceptable in case of routine work in manufacturing sector; however, with regard to creative designing, the users/adopter of the technology may disagree which may result in a bottleneck, particularly while predicting customer preference.

1. Conclusion

Presently the manufacturing world is in the era of ubiquitous AI due to the convergence of several computational, machine-learning, technological, statistical, analytics and research trends. As evident, AI has been considered to the most impactful disruptive technology and has exerted significant implication for the manufacturers' economic and cognitive developmental outcomes.

In this study we have explored how AI can be regarded as dynamic capability for T&A industry recognising the importance of modern information system-based technologies such as Big Data and Business Analytics (BDBA) in achieving an enhanced level of agile manufacturing practices. The study findings would enhance our research knowledge about the impact of AI in agile production and operations management, particularly for T&A industry. Fashion is unique in a way that it provides functional purpose and defines a crucial aspect of human existence. It reveals and explores emotion and creativity. As the industry is very dynamic and constantly evolving, it needs to adopt and adapt new emerging technologies. Being no exception, AI has found its way into T&A industry with its diverse capabilities and started to revolutionising the way we say see this industry. However, different application areas, techniques, and tools have specific strengths and weaknesses while performing the similar tasks for different purposes. Now, we see that AI capabilities are often targeted at addressing specific needs, such as , image- vs. language-related problems are addressed using computer vision and natural language processing respectively. Therefore, it is important that we understand the techniques and tool properly before applying AI. However, AI, and especially machine learning and deep learning have the ability to manipulate data and models to understand and make predictions about issues which we have no answers and even, we can ever imagine. Increase in computing power, open source machine and deep learning models, specialised hardware, system architecture and cloud technology for the AI capabilities targeted toward T&A industry offer limitless opportunities and growth in near future. However, the manufacturers also need to extend their conceptualisation of resources to recognise the significance of skilled and knowledgeable people as intangible resources and capabilities. Therefore, a integration of RBV, capability view and knowledge based view would provide a more comprehensive approach to the implementation of AI as dynamic capability which is an important theoretical and practical contribution. Future studies can be conducted, adopting a quantitative approach to examine the conceptual model suggested in this study and delve into the impact of other disruptive information technologies in Textile & Apparel industry.

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Tables and Figures

Table 1: Details of the respondents/interviewees

Participants	Sector	Position	Age	Experience	Education
Participant No. 1	Textile	Senior level management	46	18	Postgraduate
Participant No. 2	Ready-made garments	Senior level management	53	19	Postgraduate
Participant No. 3	Textile	Mid-level management	40	10	Postgraduate
Participant No. 4	Textile	Senior level management	45	19	Postgraduate
Participant No. 5	Textile	Senior level management	49	14	Postgraduate
Participant No. 6	Ready-made garments	Mid-level management	39	11	Postgraduate
Participant No. 7	Ready-made garments	Senior level management	44	13	Postgraduate
Participant No. 8	Ready-made garments	Senior level management	47	15	Postgraduate
Participant No. 9	Information technology	Consultant & Researcher	43	10	Doctorate
Participant No. 10	Textile	Mid-level management	40	11	Postgraduate
Participant No. 11	Textile	Senior level management	49	16	Postgraduate
Participant No. 12	Industry expert	Researcher	52	9	Doctorate
Participant No. 13	Industry expert	Academician	39	7	Doctorate
Participant No. 14	Industry expert	Researcher	46	10	Doctorate
Participant No. 15	Information technology	Consultant	37	9	Postgraduate
Participant No. 16	Textile	Mid-level management and Engineer	42	12	Graduate
Participant No. 17	Apparel	Designer	36	8	Graduate
Participant No. 18	Textile	Academician	41	11	Doctorate
Participant No. 19	Apparel	Entrepreneur	55	21	Graduate
Participant No. 20	Ready-made garments	Senior level management and Director	52	18	CA
Participant No. 21	Ready-made garments	Mid-level management	48	20	Graduate
Participant No. 22	Ready-made garments	Senior level management and Director	55	23	Postgraduate
Participant No. 23	Ready-made garments	Senior level management	52	20	Postgraduate
Participant No. 24	Garments buying house	Merchandiser	32	6	Postgraduate
Participant No. 25	Garments buying house	Senior Merchandiser	38	11	Postgraduate
Participant No. 26	Garments buying house	Senior Merchandiser	40	12	Postgraduate
Participant No. 27	Garments buying house	Merchandising manager	34	7	Postgraduate
Participant No. 27	Ready-made garments	Designer	42	11	Postgraduate
Participant No. 28	Textile and Ready-made garments	Textile designer	39	9	Postgraduate

Table 2: Interview guide

1. Discussion about demographic background: Age, educational background, experience in the current position, experience in the current industry.
2. Please discuss how much you are aware of big data, artificial intelligence and the internet of things.
3. Please discuss your idea about *artificial intelligence (AI)* and its application in T&A industry.
4. To what extent are you applying AI in your current organisation (e.g., process automation, cognitive insight, and cognitive engagement)? Please discuss some of the instances where you have achieved success by applying this technology.
5. Please discuss the impact of AI on productivity and performance improvements in production planning and control.
6. How can managers use AI applications to capture benefits, efficiency, productivity and value using customer product feedback?
7. Discuss the importance of artificial intelligence for the resilience and agility of T&A industry.
8. What are the primary constraints that you have faced while adopting *artificial intelligence* in your current organisation/industry? How do you think these constraints can be overcome?
9. Please discuss the Frameworks to explain AI implementation in your organisational/industry context.
10. How do you apply AI and BDA to analyse and predict consumers' behavior, which affect the overall product portfolio and strategy?
11. How would you explain the importance of artificial intelligence in T&A industry in future?

Table 3: Relevant themes and codes for data analysis

Research themes	Theory driven	Data driven
AI Capability Dimensions	Tangible, intangible, knowledge and human, RBV, DCT	Human, Capital, Data, People, Management, Technology, AI as dynamic capability, AI culture. Build, develop, integrate & reconfigure internal and external resources,
Trends and Patterns of AI in agile manufacturing	Complex network of Supply chain, industry 4.0, sustainability	AI-enabled technologies in manufacturing, Smart manufacturing, IIoT
Challenges and outcome of AI integration and implementation	Infrastructural, Management and Resources	Resources, Management, Policy level, lack of explainability of model or outcome, Integration of organisation's view, Automation, Operational Efficiency, Organizational Performance

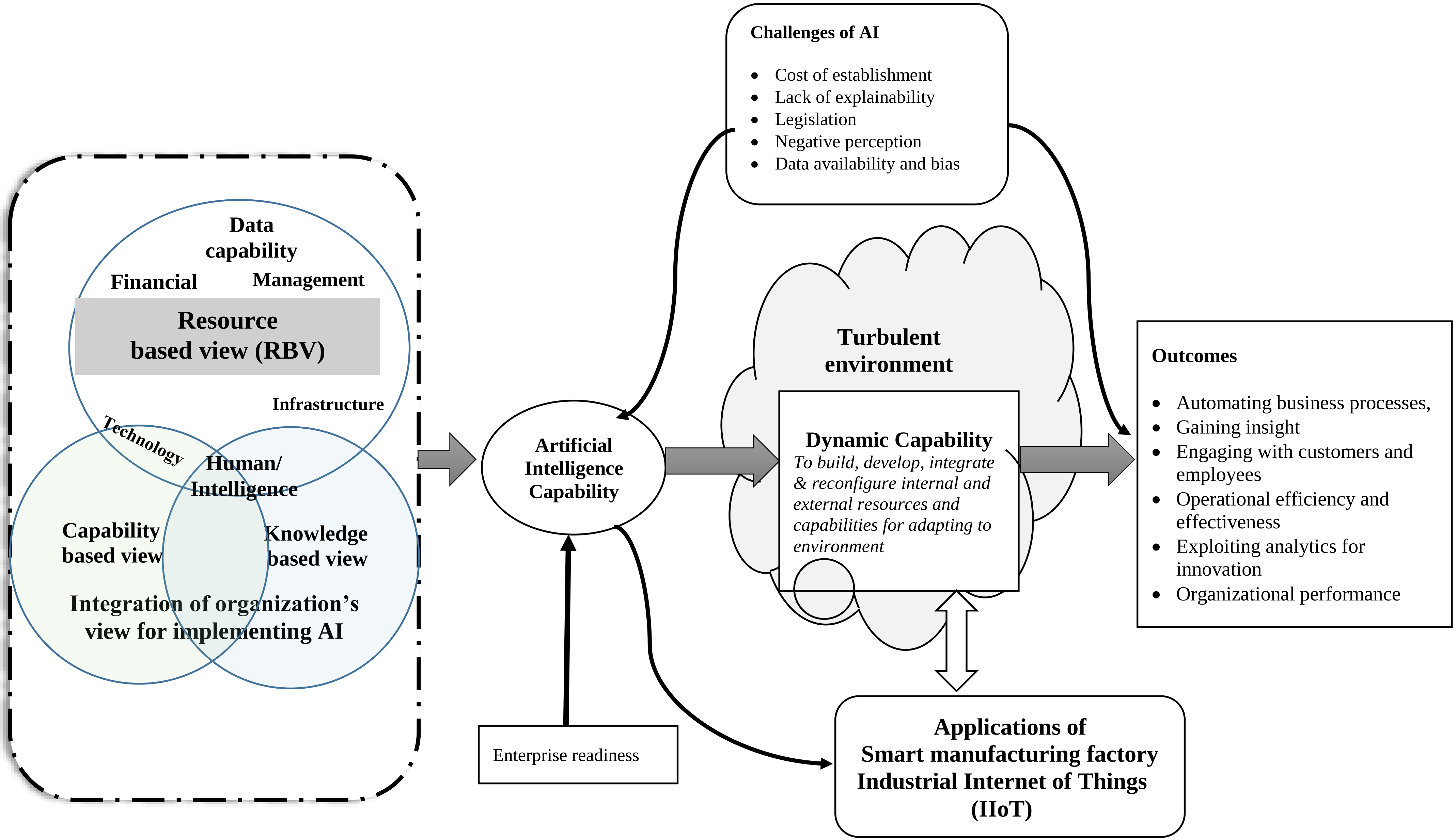

Figure 1: Artificial intelligence enhances the organizations dynamic capability to improve overall performance