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Artificial Intelligence in E-Commerce Fulfillment: A Case Study of Resource Orchestration at Alibaba's Smart Warehouse

Abstract

Despite heightened interest, it remains challenging to integrate artificial intelligence (AI) into businesses. Recent surveys show that up to 85 percent of AI initiatives ultimately fail to deliver on their promises. There is still a lack of studies on successful applications of AI, which would provide invaluable lessons for organizations embarking on their AI journey. This study is therefore motivated to understand how AI technology, people, and processes should be managed to create value successfully. Building on the resource orchestration perspective, this study analyzed the successful applications of AI at Alibaba's e-commerce fulfillment center. Findings indicate that the key AI resources include data, AI algorithms, and robots. These resources must be orchestrated (e.g., coordinated, leveraged, deployed) to work with other related resources such as warehouse facilities and existing information systems, in order to generate strong AI capabilities. The key AI capabilities generated include forecasting, planning, and learning. More importantly, AI capabilities are not independent – they interact and co-evolve with human capabilities to create business value in terms of efficiency (e.g., space optimization, labor productivity) and effectiveness (e.g., error reduction). The implications of understanding these social informatics of AI for research and practice are discussed.

Keywords: Artificial intelligence; E-Commerce, Fulfillment center, Smart warehouse; Resource orchestration

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1. Introduction

Applications of artificial intelligence (AI) have developed rapidly over the past few decades. In the early days, AI was used to provide recommendations in expert systems (e.g., Lu & Mooney, 1989) and knowledge-based systems (e.g., Ingwersen, 1984). More recently, with technological breakthroughs in big data, supercomputing, and machine learning, AI has become more human-like and more capable of problem solving, learning, manipulating objects, and navigating physical space (Duan, Edwards, & Dwivedi, 2019).

Investment in AI applications is expected to grow exponentially. It is projected that about 70 percent of businesses will use AI by the year 2030 (Bughin, Seong, Manyika, Chui, & Joshi, 2018). The technology is anticipated to drive business transformations (Dwivedi, et al., 2019; Pan, Pan, & Devadoss, 2008), with three quarters of executives believing that "AI will substantially transform their companies within three years" (Davenport & Ronanki, 2018, p. 110). Various industries have explored AI applications, including finance, healthcare (Gupta & Kumari, 2017; Pee, Pan, & Cui, 2019), education (Nye, 2015; Yoon & Baek, 2016), manufacturing (Ying, Pee, & Jia, 2018), retailing (Paolanti, Liciotti, Pietrini, Mancini, & Frontoni, 2018), and supply chain management (Mahroof, 2019). The adoption of AI has also been boosted by government support worldwide. For example, China invested about $12 billion in 2017 and is expected to spend up to $20 billion in 2020. At least 20% of China's Gross Domestic Product (GDP) is forecasted to be due to AI by 2030 (Dwivedi, et al., 2019).

Despite heightened interest, it remains challenging to integrate AI into businesses. A recent survey indicated that 85 percent of AI initiatives ultimately fail to deliver on their promises (Rayome, 2019). Many businesses continue to take a wait-and-see approach, postponing adoption until more information about appropriate AI strategies is known (Panetta, 2018). Integrating AI is more than a technical challenge. In an industry survey of 152 AI projects, Deloitte (2017) reported that 47 percent of senior managers found it difficult to integrate AI with existing people and processes. Similarly, research studies have observed issues around upskilling employees to work with AI, fitting AI with existing processes, and coordinating the AI augmented workforce (Davenport & Ronanki, 2018; Jarrahi, 2018; Miller, 2018). Indeed, "organizations are entering a landscape characterized by unprecedented collaboration among managers and intelligent machines. There are no maps available yet for navigating through this challenging and unknown terrain" (Kolbjørnsrud, Amico, & Thomas Robert, 2017, p. 6). There is still a lack of research analyzing successful applications of AI, which would provide invaluable lessons for organizations embarking on their AI journey (Duan, et al., 2019; Pettey, 2018).

This study is therefore motivated to understand how AI technology, people, and processes should be managed to create value successfully. To this end, the resource orchestration perspective (Sirmon, Hitt, Ireland, & Gilbert, 2011) offers useful theoretical concepts for analyzing how technological, human, and organizational resources can be arranged to generate AI-enabled capabilities that lead to enhanced efficiency and effectiveness. The resource orchestration perspective suggests that resource management, including the structuring of resource portfolio (e.g., acquiring resources), bundling of resources to build capabilities, and leveraging of capabilities, constitute the key to creating business value. These concepts are useful for identifying AI-related resources and describing how they combine into strong capabilities in AI applications.

In sum, the research question addressed in this study is: ***How can AI-related resources, capabilities, and their interactions be managed to achieve valuable outcomes in AI applications?*** Considering that successful applications of AI in businesses are still rare, we conducted an in-depth case study of Alibaba's Smart Warehouse, a leading e-commerce fulfillment center in China (Mahroof, 2019). Fulfillment center is a type of warehouse where e-commerce orders are received, processed, and filled. Warehouse management has been a critical component of logistics and supply chain management owing to its significant influence on overall time and labor costs (Mahroof, 2019). Key challenges in warehouse management include space constraints, workforce shortages, poor layouts, and outdated IS (Faber, De Koster, & Smidts, 2013). These issues are exacerbated in fulfillment centers, which tend to process a large number of small packages and a wide assortment of items, while facing tight delivery schedules (e.g., next-day or even same-day) and highly volatile demands (e.g., due to seasonal sales; Boysen, de Koster, & Weidinger, 2019). Various AI applications are being developed to address these issues, including Automated Guided Vehicle (AGV) assisted picking, shelf-moving robots, and mixed-shelf storage (Boysen, et al., 2019). This study examines how these and other AI applications had been successfully managed along with other related human and organizational resources to improve operational efficiency and order accuracy at Alibaba's Smart Warehouse. The findings provide insights into the specific AI-related resources that should be orchestrated to generate AI-related capabilities.

The resource orchestration perspective is appropriate and valuable for this case study for three reasons. First, resources are commonly regarded as a core component of warehouse management (Karagiannaki, Papakiriakopoulos, & Bardaki, 2011). The theoretical perspective allows us to not just identify significant resources for the application of AI in warehouse management, but also how they should be orchestrated (Chirico, Sirmon, Sciascia, & Mazzola, 2011). Second, AI's diverse capabilities to undertake complex tasks have been of much interest to researchers and practitioners (Duan, et al., 2019; Min, 2010). The theoretical perspective helps direct our attention to process-related questions, such as the capability development process (Baert, Meuleman, Debruyne, & Wright, 2016; Cui, Pan, & Cui, 2019). Third, the theoretical perspective also orientates us towards understanding the impact of resource orchestration on organizational outcomes, such as performance (Ndofor, Sirmon, & He, 2011; Wales, Patel, Parida, & Kreiser, 2013), innovation (Carnes, Chirico, Hitt, Huh, & Pisano, 2017; Cui, Pan, Newell, & Cui, 2017), and value creation (Wang, Liang, Zhong, Xue, & Xiao, 2012). This allows us to identify AI-enabled outcomes in warehouse applications.

This article is structured as follows. The next section reviews the theoretical concepts underlying the study. This is followed by a description of the case study research method (section 3) and case description (section 4). The case analyses are then presented in section 5 and their implications for research and practice are discussed in section 6. The study is concluded in section 7.

2. Conceptual Background

2.1 Artificial Intelligence Applications in Warehouse Management

The focus of AI is to "understand the phenomenon of human intelligence and to design computer systems that can mimic human behavioral patterns and create knowledge relevant to problem-solving" (Min, 2010, p.14). AI also has the potential to overcome intellectual and physical limits of humans (Daugherty & Wilson, 2018), opening up a variety of application opportunities with significant impacts on productivity and performance (Dwivedi, et al., 2019).

The expected business benefits of AI include optimizing internal business operations, making better decisions, improving existing products, freeing up workers for more creative work, creating new products, and pursuing new markets (Davenport & Ronanki, 2018). More generally, AI generates business value in three main ways: automating processes, creating innovative insights, and engaging with stakeholders in the business processes (Dwivedi, et al., 2019). Although AI has great potential, there are still many challenges around its application in practice. It has been argued that for many companies, AI applications have fallen short of achieving the expected productivity because managers do not know how to effectively integrate AI with existing processes and systems (Brynjolfsson, Rock, & Syverson, 2017; Davenport & Ronanki, 2018).

AI applications are widely expected to improve the management of warehouses, including e-commerce fulfillment centers (Min, 2010). As a key component of logistics and supply chain management (Aziz, Razak, Yaacob, Hussin, & Razmin, 2016), warehouse management is “a combination of the planning and control systems and the decision rules used for inbound, storage, and outbound flows”(Faber, et al., 2013, p. 1232), to support “process-oriented businesses centered on managing the flow of material and abstract resources, between a point of origin and point of destination” (Mahroof, 2019, p. 177). With a focus on coordinating the activities related to goods and orders, warehouse management is inherently an information-intensive process (Davarzani & Norrman, 2015) and human-centered process that demands a skilled human workforce (Faber, De Koster, & Van de Velde, 2002).

Various AI applications for warehousing have been proposed (Mahroof, 2019). For example, AI can be used to understand and predict sales trends for storage planning and replenishment management (Mahroof, 2019; Min, 2010). JuniperResearch (2018) predicts that demand forecasting based on AI is expected to more than triple by 2023. AI also has the potential to transform various manual tasks and processes in which human workers are constrained by their physical capacity (Dwivedi, et al., 2019). Thus, integrating AI with human employees in work processes is considered an effective solution for overcoming limitations related to the labor force and workload (Miller, 2018; Risse, 2019).

Although it is well recognized that AI has much potential to significantly improve warehouse management, there has been a lack of understanding of how AI applications should be managed along with other existing organizational elements (Mahroof, 2019). Most prior studies tend to focus on the technical elements and offer limited insights into how AI applications interact with other elements such as employees and work processes (Davarzani & Norrman, 2015). There have also been calls for more research that can provide richer understanding of actual AI applications using empirical research methods (Duan, et al., 2019).

2.2 Resource Orchestration Perspective

The resource-based view (RBV) is commonly used to identify a firm’s valuable, rare, inimitable and non-substitutable resources that can generate competitive advantage, such as physical, human, and organization capital (Barney, 1991; Rai, Patnayakuni, & Seth, 2006). Based on RBV, the resource orchestration perspective was proposed by Sirmon, et al. (2011) to understand how a firm gains competitive advantage through dynamically organizing resources. There are three types of resource orchestration actions: structuring, bundling, and leveraging (Sirmon, et al., 2011). Structuring involves developing a resource portfolio through acquiring, accumulating, and divesting resources; Bundling refers to the use of resources to build capabilities (i.e., stabilizing, enriching, and pioneering); Leveraging focuses on creating value through mobilizing, coordinating, and deploying resources.

There are two main streams of research on resource orchestration. One focuses on the impact of resource orchestration on outcomes, such as performance (e.g., Ndofor, et al., 2011; Wales, et al., 2013), innovation (e.g., Carnes, et al., 2017; Cui, et al., 2017), and value creation (e.g., Wang, et al., 2012). The other stream seeks to identify resource-focused actions in different contexts (e.g., Baert, et al., 2016; Cui, et al., 2017). For example, Cui, et al. (2019) analyzed e-commerce development in rural China and observed that the resources of product knowledge and technology platform were orchestrated to develop individual as well as community capabilities in e-commerce.

Contributing to both streams of research, this study identifies the key resources related to AI applications in warehousing, as well as their orchestration actions and the resultant AI-enabled outcomes. This is in line with the suggestions of AI management researchers, that organizations should make use of a collection of resources and develop fitting capabilities when integrating AI (Davenport & Ronanki, 2018). The resource orchestration perspective is also appropriate for studying e-commerce fulfillment centers in that warehouses have been considered as a combination of processes and resources (Karagiannaki, et al., 2011). It has been argued that the performance of warehouse management depends on whether resources are orchestrated in a timely, complete, and reliable fashion (Faber, et al., 2013).

3. Research Method

This study adopts the case study method for three reasons. First, the method is particularly useful for exploratory studies addressing “how” questions (Pan & Tan, 2011; Walsham, 1995), such as our research question. Second, the method provides an opportunity to develop novel theoretical arguments (Eisenhardt, 1989), and the use of AI is currently under theorized (Duan, et al., 2019). Third, this study focuses on the process of how AI-related resources are orchestrated to generate value, and the case study method is particularly appropriate for understanding processes (Pan & Tan, 2011).

This case study focuses on Alibaba’s Smart Warehouse located in Tianjin, China. The warehouse served as an e-commerce fulfillment center for Alibaba’s Tmall Supermarket, an online platform selling food, beverages, household products, and beauty products by local as well as international brands. The mega-sized fulfillment center occupied more than 400,000 square meters. AI applications at the fulfillment center had significantly reduced labor by 70 percent and helped to realize next- and same-day deliveries to residents in the Beijing-Tianjin-Hebei megalopolis.

A single-case study is appropriate for the following reasons. First, sampling of a single case is typically due to their revelatory nature or because they are exemplars of a phenomenon or provide unusual research access (Yin, 1994). Alibaba's case offers valuable insights into highly successful AI applications in a real-world business setting, which are still rare in practice (85% of AI initiatives fail; Rayome, 2019) and understudied in information management research. Alibaba's fulfillment warehouse is also exemplary in that it was operating in China, the largest e-commerce market in the world (Allison, 2018). Second, single-case studies are also useful when theoretical knowledge concerning a particular phenomenon is still limited and the case offers inspiration for new ideas (Siggelkow, 2007). Theories for managing AI in businesses are still being established and Alibaba's case sheds light on the nature and role of resource orchestration. This is expected to contribute towards a nomological framework theorizing the application and management of AI in businesses.

3.1 Data Collection

Data for the case study were collected in two phases. The first phase began in early 2018 and focused on data from secondary sources ranging from traditional media, company website, to articles on the Internet. This data allowed us to prepare for primary data collection by obtaining "a rich set of data surrounding the specific research issue, as well as data capturing the contextual complexity" (Benbasat, Goldstein, & Mead, 1987, p. 374).

In the second phase, we interviewed employees and managers at Alibaba's e-commerce fulfillment center (operated by ALOG, a newly acquired logistics service provider) as well as the online supermarket unit, Tmall. We also observed the AI applications at work in the fulfillment center. To better understand the design of the AI applications, we interviewed Alibaba's AI technology solution developer, MEGVII. In total, we collected data from 25 informants (see Appendix A).

The interviews focused on the following key questions, which sought to understand resources and capabilities related to AI applications, as well as the valuable outcomes of AI applications:

- What are the current applications of AI in the fulfillment center?
- What is the role of each application?
- How were the AI applications selected? Why not others?
- To what extent does each application influence performance or create value?
- How do AI applications work with one another?
- What are the roles of human employees in relation to the AI applications?
- What affects the performance of AI applications?
- How has the organization/structure/processes/practices changed with the integration of AI applications?
- What resources and capabilities affect or have been affected by AI applications?

Each interview lasted 60 to 90 minutes and was digitally recorded and transcribed for data analysis. During the on-site interviews, we also took field notes, photographs, and short videos to supplement the data. The archival data, transcripts, field notes, photographs, and videos allowed us to maintain an adequate level of data triangulation (Klein & Myers, 1999).

3.2 Data Analysis

Data analysis and data collection were carried out concurrently to allow for the emergence of empirical data and theoretical concepts in capturing a novel phenomenon (Eisenhardt, 1989). We conducted three iterative rounds of data analysis, following the approach commonly undertaken by case studies (e.g., Andriopoulos & Lewis, 2009; Du, Pan, Leidner, & Ying, 2019; Kotlarsky, Scarbrough, & Oshri, 2014).

In the first round, we read and coded all the available data, including interview transcripts and secondary data, based on the resource orchestration perspective. Specifically, we identified information related to resources, capabilities, their interrelationships and management with respect to AI applications, as well as valuable outcomes. To ensure consistency in coding, regular meetings were conducted to review emergent first-order concepts (Klein & Myers, 1999; Pan & Tan, 2011). Examples of the coding are illustrated in Appendix B.

In the second round, we merged related first-order concepts into second-order themes and compared the emerging themes with the resource orchestration perspective (Pan & Tan, 2011). For example, the first-order concepts related to how different types of data were synthesized using AI systems to improve order-packing performance or reduce errors were grouped under the second-order theme of "leveraging data and system resources", in which "leveraging" is a resource orchestration action identified in previous research.

More importantly, concepts that did not fit into the existing resource orchestration perspective prompted the development of new themes. For example, in order packing, we observed that human workers' ability to avoid errors was greatly augmented by AI applications, while the capabilities of AI applications were constantly strengthened based on feedback from human workers. This suggests that capabilities are not independent and led to a new theme of "AI-Human capability co-evolution".

In the third round, we organized the second-order themes logically to develop a coherent framework for managing AI applications in businesses (Montealegre, 2002). The framework highlights the AI-related resources and capabilities contributing to successful applications of AI in businesses, as well as interactions and co-evolution among AI and human capabilities in creating business value. We then iterated back to the data and coding to refine the framework until theoretical saturation was attained (Pan & Tan, 2011). The case and its analyses are detailed in the following sections.

4. Case Background

The e-commerce fulfillment center was constructed in 2014 to support Alibaba in capturing the market of millions of consumers embracing online shopping in the Beijing-Tianjin-Hebei megalopolis. As consumers began to use online shopping for everyday items, the demand for reliable next-day or even same-day home delivery emerged and became a critical differentiator that set competing e-commerce platforms apart. The manager of the fulfillment center highlighted the key challenges in offering rapid delivery:

> *The number of orders received has increased sharply, peaking at 150 thousand orders daily. To meet the growing need for diversified goods, we had to constantly increase the number of SKUs [stock-keeping unit] in our Smart Warehouse. At the beginning, we had roughly 10 thousand SKUs, and the number has increased to more than 30 thousand now. This growth trend as well as the dynamic market brought great complexity to demand forecasting, inventory planning, and warehousing. For instance, as the number of SKUs increased, the space for storing and picking orders must be used more efficiently…The workload of workers also increased…We had to recruit more workers, which added to the difficulty and cost of human resources management…Moreover, it was not easy to recruit workers given the harsh work conditions and high work intensity.*

To address these challenges, Alibaba decided to explore AI applications by working with ALOG, a logistics service provider experienced in advanced technologies and MEGVII, an AI solution developer well known for its visual recognition technology. Through a four-year progressive transformation, the fulfillment center embraced AI applications extensively to improve the efficiency and effectiveness of key business processes, as explained by the director of operations:

> *We now have more than 500 robots working collectively in the Smart Warehouse. AI applications have helped to reduce manpower by more than 70% and dramatically increased the accuracy of order picking. As a result, we can now complete an order picking process within three minutes and deliver most orders to consumers accurately within twelve hours.*

At the time of the study, AI applications were used for the business processes of goods storing, order picking, and order packing. Given the focus of our research question, this study analyzed the three processes and excluded others that did not apply AI, such as goods receiving, outbound shipping, and inventory auditing.

4.1 Goods storing

The main AI application for storing inventoried goods from grocery suppliers is the Automatization Tridimensional Storehouse (ATS). The fulfillment center manager explained how it differed from traditional structures:

> *Unlike traditional structures that have spacious aisles for manual handling of goods by human workers and forklifts, the ATS uses both land and vertical space more fully, automatically accesses goods without human intervention, and organizes goods rationally to maximize access efficiency.*

More specifically, goods received at the fulfillment warehouse are placed in a pallet and sent to the ATS via a conveyer belt. With weight sensors, visual recognition sensors, and barcode scanners installed at the entry of the conveyer, the pallet's total weight, three-dimensional size, and identity are instantly identified and updated as stock-in data in the warehouse management system (WMS). The most efficient position to store the pallet is then calculated based on historical data and the pallet is forwarded accordingly.

By predicting the demand for goods, WMS can determine the need for replenishment and provide instructions to the Warehouse Control System (WCS). Together, WMS and WCS work to guide ATS in goods storing and replenishment to ensure a smooth order-picking process.

4.2 Order picking

The key AI applications in order picking are "Order to Man" (O2M) automated guided vehicles (AGVs), "Goods to Man" (G2M) AGVs, and Forklift AGVs. As soon as an order is received, WMS determines the suitable packing box based on stock-in data (e.g., 3D dimensions) and the packing algorithm. Choosing the right box helps to reduce costs while preserving natural resources. The box is then picked manually by a worker, who attaches a barcode and places it on the shelving rack held by an O2M AGV. A robotics engineer at MEGVII explained:

> *It looks like a large robotic vacuum cleaner, equipped with Wi-Fi and self-charging functions. It is able to haul goods weighing up to 500 kilograms and move at a speed of 1.5 meters per second. Each shelving rack can carry up to 12 order boxes at a time…when the robot completes order picking for all the orders, they are moved to the packing zone.*

O2M AGV works in the first zone, where order boxes approach workers who would pick up goods from specific shelves organized adjacently, as instructed by their personal digital assistant. The goods are shelved such that those frequently purchased together are stored close to one another. This greatly reduces the distances human workers have to travel.

The order boxes are then moved to the second zone, where G2M AGVs are used. Goods in this zone are stored in boxes that would be brought to workers at fixed workstations for picking. A robotics engineer from MEGVII explained how this type of robot works:

It looks similar to O2M robots. A key difference is that an O2M robot handles a fixed set of order boxes while a G2M robot handles different boxes at the same time. When an O2M robot requires an item in the second zone, a G2M robot would retrieve the storage box containing the item and move it to a worker, who would then pick the item and place it in the order box.

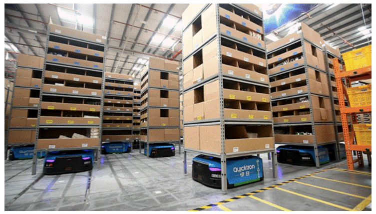
The third zone contains larger items that are handled by forklift AGVs. Like G2M AGVs, these robots move required goods to workstations so that they can be picked and placed into relevant order boxes by human workers.

All robots in the order-picking process use real-time data collected by laser sensors. These data are analyzed by WCS using a robotic motion control algorithm to get around physical obstacles and coordinate different robots to avoid clashes and congestion.

4.3 Order packing

In this process, the order boxes with picked items are checked and packed. Human workers would scan the barcodes of each order box and all items inside for automatic comparison and checking by WMS. The system would alert the human worker of a potential error when a mismatch is detected, so that any error can be corrected manually.

Table 1. AI Applications in Alibaba’s E-Commerce Fulfillment Center

Process	Goods storing	Order picking			Order packing
Description	Collect stock-in data; Optimize storage location	Retrieve ordered goods from storage accurately and rapidly			Check goods picked for each order and pack safely
Data	Historical sales, real-time stock-in data, real-time order data	Historical sales, real-time order data, stock-in data, real-time operations			Order data, stock-in data
Algorithms*	Sales forecasting, location recommendation	Sales forecasting, location recommendation, 3D packing, order wave combination, route planning, robot scheduling, robotic motion control			3D packing
Systems	WMS, WCS	Warehouse Management System (WMS), Warehouse Control System (WCS)			WMS
Robots/ Facilities/ Equipment	ATS, sensors and scanners 	Automated Guided Vehicle (AGV)			Scanners 
		“Order to Man” AGV 	“Goods to Man” AGV 	Forklift AGV 	

* See Appendix C for a brief overview of the algorithms

After confirming that the picked order is correct, the human worker would pack the order box following the instructions of a 3D packing algorithm. This helps to ensure that items are safely packed and the box space is optimally utilized. For example, the algorithm ensures that potentially leaky items are placed at the bottom while fragile items are positioned on top. Packed boxes are then placed on a conveyer belt for outbound delivery. Table 1 summarizes the AI applications in the processes of goods storing, order picking, and order packing.

5. Case Analyses

The resource orchestration perspective was used as a theoretical basis for analyzing the case to identify important and novel insights. Overall, Alibaba's successful application of AI indicates that *various resources are orchestrated* in different ways in the business processes to develop different *AI capabilities*. More importantly, AI capabilities interact with *human capabilities* in different ways, generating valuable *AI-enabled outcomes* (see Figure 1). Our case analyses focused on the three business processes of goods storing, order picking, and order packing in Alibaba's e-commerce fulfillment center, as the center manager highlighted:

> *We structured the Smart Warehouse into three processes and allocated a distinctive zone for each process. As each process has a different set of requirements and tasks, we adopted different AI applications which called for unique ways of organizing workers to achieve a multitude of beneficial outcomes.*

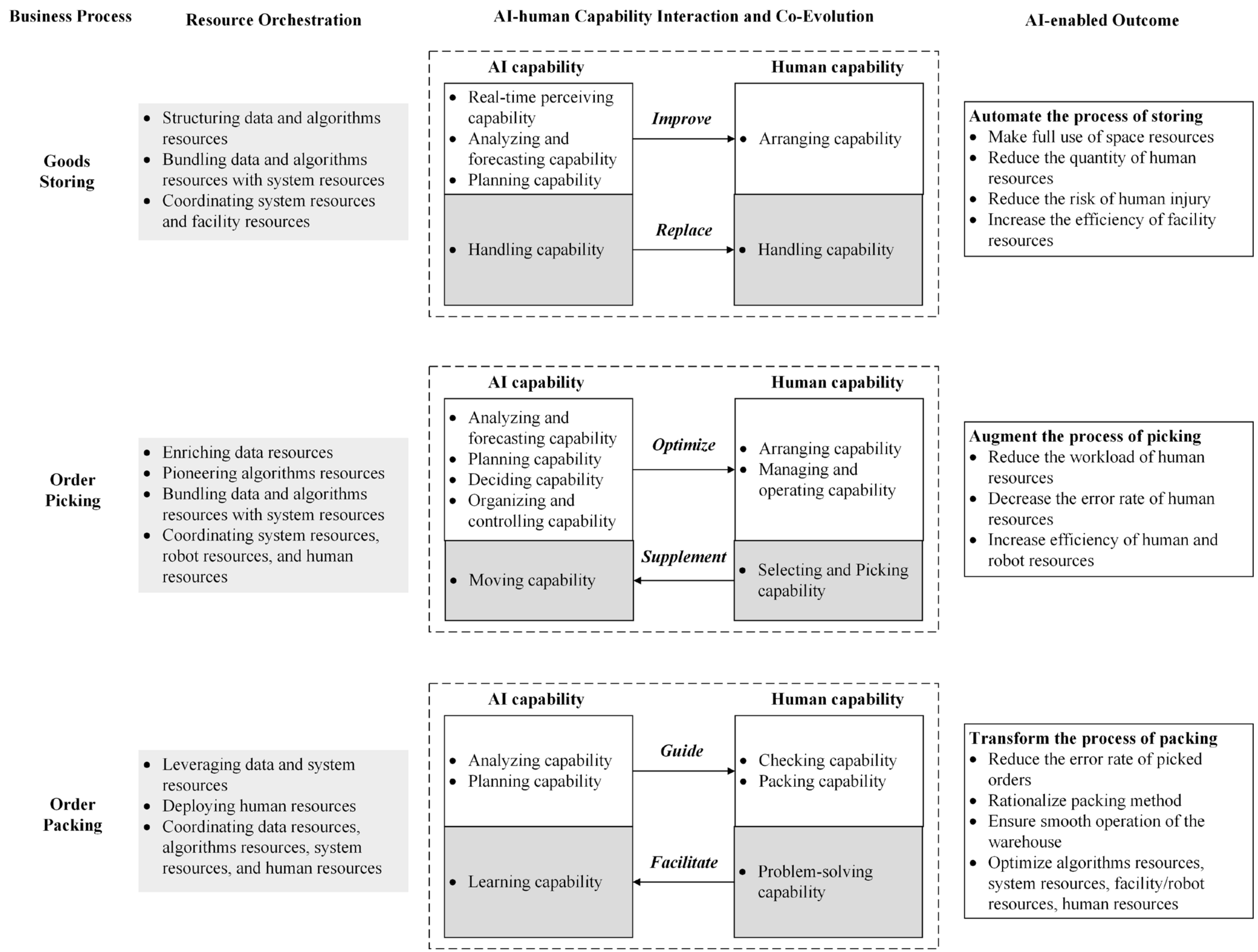


Figure 1. Framework of Orchestrating Resources in AI Applications

5.1 Developing AI capability through resource orchestration

Our case analysis indicated that AI capability, as the key capability in the smart fulfillment center, was generated through orchestrating relevant resources. Given the focus of our research question, this study highlights the role of AI capability and identifies the resources and resource-focused actions for developing the capability.

In the process of goods storing, the ATS was introduced to replace the manual storehouse for automating the storing process. To effectively operate the ATS, the real-time stock-in data of packed goods must be automatically collected through sensors and scanners and synchronized with the WMS for follow-up analyses. An operator explained:

> *Before (introducing the ATS), workers had to manually record the information of incoming goods for further storing, which was time consuming and error prone. Now, AI technologies are able to collect the information effortlessly and instantaneously when the goods enter the ATS... It automatically determines the kinds of goods being stored and the quantity. The additional data captured through sensors, such as volume and weight, can also be used for further planning of storage.*

This suggests that a *real-time perceiving capability* is gained as an AI capability through *structuring relevant data* to automatically record all the goods received by the fulfillment center. Furthermore, docking with the sales database of Alibaba, other *data resources* (i.e., historical sales data and real-time order data) were also acquired, which further fueled the development and optimization of *algorithm resources* such as sales forecasting algorithms and location recommendation algorithms. An AI engineer described the role of big data and algorithms in the fulfillment center:

> *Supported by AI technologies, we have a so-called 'intelligent brain' in our smart fulfillment center, which is mainly supported by big data and algorithms. The algorithms are developed and trained using historical big data. Through analyzing real-time big data, different algorithms are responsible for supporting the performance of the 'intelligent brain' functions, including planning of tasks, optimizing the operating efficiency of machines, coordinating machines and humans, making autonomous decisions about overall operations, and adjusting operating strategies based on real-time feedback.*

Accordingly, after *structuring data and algorithm resources*, these resources *are bundled with system resources* (i.e., the WMS and the WCS). The systems run with big data as the input, and algorithms as the processing tools. The analysis results are provided to human coworkers for collaboration or for directing other systems. Focusing on ATS, an IT engineer detailed how the results are produced in the systems based on big data and algorithms:

We used the big data on historical sales and machine learning to develop and constantly optimize the algorithms for sales forecasting. The WMS is connected to the real-time order database, which helps to identify goods with a high sales trend and high replenishment frequency. Such goods are stored near the exit of ATS to minimize the retrieval time…

…The weight and size of goods on a pallet also influence the location of its storage. For instance, the total weight of goods on a rack must not exceed its maximum capacity…

…Synthesizing the sales forecasting algorithms, the allocation rules, and the related data, the location recommendation algorithms can allocate an optimal storage location as soon as barcodes are scanned. The locations of the goods are dynamically adjusted to the changing sales trend.

Accordingly, through bundling data and algorithm resources with system resources, the *analyzing and forecasting capability* to predict the sales trend and the consequent *planning capability* for the layout of goods in the ATS were developed. Furthermore, according to the real-time location recommendation results, the WMS provides instructions to the WCS on moving goods; the WCS then guides the ATS to execute the instructions. Therefore, through *coordinating system resources* (i.e., the WMS and the WCS) *and facility resources* (i.e., the ATS), the *handling capability* is developed to automatically handle goods in the process of goods storing.

In the process of order picking, robots are embedded into the process to manage workload and improve efficiency. In addition to the data on goods and orders, the *data resources are enriched* as the real-time operation data are acquired by the sensors equipped on the robots. Based on the integration of these data, several new *algorithm resources* (i.e., 3D packing algorithms, order wave combination algorithms, route planning algorithms, robot scheduling algorithms, and robotic motion control algorithms) are *pioneered* to assist the operation of robots as well as the collaboration between robots and human workers. Furthermore, *bundling data and algorithm resources with system resources* (i.e., the WMS and the WCS) and then *coordinating system resources, robot resources, and human resources* enable the development of new AI capabilities in this process.

Specifically, through bundling data and algorithm resources with system resources, the *analyzing and forecasting capability* is developed to classify goods into three types based on their sales trend and to identify consumption correlations. An AI engineer explained the mechanism of classifying goods for picking:

The classification is based on historical sales data and the algorithms for sales forecasting. Type-A goods are the prospective best sellers, containing about 2000 SKU, with a high probability of being picked for orders in the fulfillment center.

Type-B goods have a relatively lower probability of order picking compared to type-A, covering roughly 6000 SKUs. Type-C goods are those with the lowest anticipated sales, constituting about 27,000 SKUs. The classification results in the WMS system guides goods layout for picking.

Thus, a *planning capability* for the layout of the types of goods is developed. Meanwhile, through bundling the order data and the goods data on its volume as well as 3D packing algorithms with the WMS system, the *deciding capability* to choose the suitable size of box for an order is developed. Further, through bundling data and the order wave combination algorithms and the route planning algorithms with the WMS system, the *planning capability* to select orders into a wave for minimizing distance and time for picking and to set an optimal route for picking through the three subzones is also created. For instance, a robotics engineer from MEGVII described:

With the order wave combination algorithms and the real-time order data, in WMS, orders that could optimize picking efficiency and shorten the O2M robot's traveling time are planned into a wave on the same robot. Further, in WMS, combining order data and goods data with route planning algorithms, the route of each robot to pick items located in different places is also planned in advance for further shortening the order picking time.

Finally, the real-time operating data returned by robots enrich the existing data. Thus, bundling them and the related algorithms (i.e., robot scheduling algorithms and robotic motion control algorithms) with both WMS and WCS systems enables the development of the *organizing and controlling capability* to arrange the collective collaboration of robots and manipulate the robots in real time as well as the *moving capability* to transport either the orders or the goods by the robots.

In the process of order packing, the picked order is further reviewed and is then packed for outbound delivery. In this process, *data resources* (i.e., the data on orders and picked items) a*nd system resources* (i.e., the WMS) *are leveraged* to develop the *analyzing capability*, with which the related data are compared to check the accuracy of the picked order. If it is correct, the *planning capability* is further generated by the WMS based on the data on orders and goods to suggest the optimal packing methods for the order. If errors are reported on the picked order, *human resources* (e.g., fulfillment center operatives) *are deployed* to check the errors. Furthermore, *data resources, algorithm resources, system resources, and human resources are coordinated* to generate the *learning capability* to not only identify the erroneous links and resolve the errors but also advance the acquisition, processing, and analysis of data, optimize algorithms, modify systems, and further enhance human-AI collaboration.

Synthesizing the resource orchestration for the creation of AI capability across the three processes shows that data resources and algorithm resources are structured as the foundation for developing AI capability. Big data with multiple sources feed the algorithms to enable them to provide excellent functions for analyzing, forecasting, planning, deciding, organizing and controlling. Furthermore, by bundling the enriching data resources and optimizing algorithm resources with system resources, these specific functions can be implemented to practically operate and manage the fulfillment center. For the systems, the WMS plays roles as the analyzer, planners and decision makers to provide commands to the WCS, which is as the conductor and controller to send real-time instructions to robots, which are the executors. Ultimately, all the related resources are coordinated to generate the AI capability for the smooth operation of the smart fulfillment center.

5.2 Interaction and co-evolution of AI capabilities and human capabilities

The case analysis reveals that the developed AI capability interacts with the human capability in each process to effectively utilize AI in the process of fulfillment. Previous AI studies have discussed the relationship between AI and the human workforce, supporting that AI can affect the nature of work and has a potential influence on human workers' status in the working process (Dwivedi, et al., 2019; Risse, 2019). Some research has raised the concern that AI may pose occupational threats to human workers (Davenport & Ronanki, 2018) while some research argues that AI should be used to augment, rather than replace, human contributions (Jarrahi, 2018; Miller, 2018). This study unearths the mutual influences of AI and the human workforce, focusing on the interactions and co-evolution of their respective capabilities. A fulfillment center manager from Tmall explained their view on the AI-human relationship in the fulfillment center:

> *From our perspective, humans and AI are complementary in the completion of both cognitive and physical tasks. In our fulfillment center, they work symbiotically to supplement and enhance each other's capabilities.*

In the process of goods storing, the ATS supported by AI is used to replace the traditional storehouse for storing goods to manage the dramatically increasing number of SKUs. The process in a traditional storehouse was human intensive, as human workers were solely responsible for arranging the received goods in the storehouse as well as for handling them to store and withdraw for further order picking. In the conventional process, the arrangement of goods was roughly based on the workers' previous experience and routines. However, in the smart fulfillment center, with the help of AI, the newly developed AI capability, including *real-time perceiving capability, analyzing and forecasting capability,* and *planning capability*, collectively ***improves*** human workers' original *arranging capability*. An IT engineer explained the improvement:

Previously, storing workers arrange the received goods based on their estimation about the size and weight of the goods, locating them randomly or based on their previous experience. Now, although AI refers to some rules and experience of the storing workers, it is more efficient as it is based on more aggregated data and more rigorous and dynamic analysis. Surpassing human workers' arrangement, AI can also predict the probability of goods retrieval and accordingly plan the layout of goods and the future actions for retrieving to increase efficiency and save time.

Furthermore, following the instructions created by the AI capability mentioned above, the facility in the ATS utilizes its *handling capability* to completely ***replace*** the human workers' *handling capability* to achieve automation in this process. A fulfillment center manager from Tmall stated that

Due to the consideration for labor safety, human workers are all excluded from the storing zone. In the ATS, machines, directed by the 'intelligent brain' supported by AI, totally replace workers in handling goods.

In the process of order picking, AI-based systems and more than 500 robots are used to augment the original picking process in the fulfillment center. Previously, human workers pulled the portable shelves with order boxes on them to find the ordered items and pick them into the boxes. They walked back and forth in the order-picking zone to fulfill all the orders on their shelves, and repeated this workflow during their work hours. With the help of AI, a new working mode was developed and implemented in this process, focused on human-robot symbiosis. First, the generated AI capability (i.e., *analyzing and forecasting capability* and *planning capability*) ***optimizes*** humans' *arranging capability* to achieve a rational and highly efficient layout in the three subzones based on the classification of goods. The operation manager described that:

Workers previously put some goods together for layout, which they thought were more likely to be in an order. This was based on their experience and sometimes helpful. However, buying trends are dynamically changing but their experience is relatively fixed. However, the AI-enabled functions on analyzing and forecasting trends of the WMS are able to automatically identify the changing trends, based on which the layout can be planned in a better way.

Second, for ordering picking, the AI capability developed through resource orchestration includes the *deciding capability* to choose a suitable box size for further picking an order and the *organizing and controlling capability* to execute the picking activities, containing the operation of robots and the collaboration between robots and human workers. This AI capability also ***optimizes*** the *humans' original managing and operating capability*, enabling a smoother management and operation of the smart fulfillment center.

Third, although the adoption of robots has dramatically shortened the walking distances of human workers, the robots can only achieve the transportation of either the goods or the order boxes. Thus, human workers' *selecting and picking capability* to choose and place particular items into order boxes also ***supplements*** the robots' *moving capability* to collectively complete the task of order picking. A robotics engineer from MEGVII stated:

> *Robots still have some limitations. Although they can automatically move order boxes or items of goods, it is quite harder and more expensive for them to achieve the precise actions of selecting and picking. However, human workers can make these actions easily. When the items of goods are moved by the robots to the workers, they can even double check the correctness of the items before picking them into the order box…We consider this as a perfect collaboration that robots are responsible for the simple moving action that requires a lot of workload while humans are responsible for the complicated selecting and picking action that requires fine movements.*

In the process of order packing, the picked orders are reviewed and packed. First, AI's *analyzing capability* compares data on orders and picked items to ***guide*** the packing workers' *checking capability* and ensure the accuracy of orders. Meanwhile, the *planning capability* based on 3D packing algorithms and related data also ***guides*** the workers' *packing capability* to rationally pack the items into the order boxes. A worker for packing in the fulfillment center described that

> *When I check a picked order, I only need to scan the items in it and the computer (AI-enabled system) automatically helps me to verify whether it matches the order. If it is wrong, there is warning on the screen. Then, I report it and hand the box to my colleagues for further processing. If it is correct, a 3D picture showing the simulated positions of all items in a box is on the screen, following which I can finish packing the items into the order box in a very short time.*

Second, if errors are found during the checking process, fulfillment center operators are sent to check the errored links and address the issues. Thus, human *problem-solving capability* further ***facilitates*** AI's *learning capability* to modify the process involving data, algorithms, systems, and human-robot collaboration. The operation manager stated that:

> *In the last process, the operators also play a vital role in keeping the smooth operation of the fulfillment center. Problems in any links of the fulfillment process may cause serious consequences on operating efficiency and order accuracy. Timely discovering and addressing the issues is especially significant. The operatives' capability is more flexible and agile for solving these unexpected problems, which would enable the use of AI in a virtuous cycle.*

By synthesizing the AI-human capability interaction in the three processes, AI capability interacts with human capability in different ways under different considerations. For instance, in the storing process, the limited human capability of arranging and handling actually constrains space utilization and increases the risk of human injury in the storehouse. Thus, the AI capability both improves humans' arranging capability and replaces humans' handling capability to make full use of space and ensure work safety. Accordingly, in this process, AI mainly plays a role as a replacement for human workers. In the picking process, the major issue is the intensive workload of human workers. In that case, on the one hand, AI capability optimizes human arranging capability and the capability of managing and operating the fulfillment center; on the other hand, human selecting and picking capability works in conjunction with AI's moving capability to complete the practical tasks of order picking. Therefore, in this process, AI and human workers are collaborators. Finally, order reviewing is the most significant task in the packing process, to not only check the picked orders but also identify any problematic links in the AI-enabled process. While the AI capability guides human checking and packing capability, its learning is in turn facilitated by the human problem-solving capability. Thus, in this process, AI is used as the assistant to human workers, while humans play a role as examiners and problem solvers for AI.

5.3 Achieving AI-enabled outcomes for fulfillment processes

Based on the data analysis, it is found that through resource orchestration and AI-human capability interaction, AI enables a change in the fulfillment process to address the existing issues faced by warehouses and make them smarter. According to previous literature, although AI has been considered a promising technology for fulfillment (Davarzani & Norrman, 2015; Min, 2010), there has been little exploration of the potential of AI technology and its specific influences in the fulfillment context (Mahroof, 2019). The findings in this study specify the AI-enabled outcome for each of the three processes in the fulfillment center.

In the process of goods storing, AI automates the process of storing. As the fulfillment center is considered a place to store goods and pick items for orders (De Koster, Le-Duc, & Roodbergen, 2007), space resources always play a key role in fulfillment and constrain the fulfillment center scale. An operator in the fulfillment center explained the main reason regarding space for using AI to automate the process in this process:

> *For the traditional storehouse, considering the safety of handling workers and limitations on the working range of forklifts, the number of layers of goods racks was constrained to five. As the number of SKU in the fulfillment center was increasing rapidly, the space as well as the labor for storing goods became*

insufficient. However, the new one (ATS) has dramatically addressed this issue. The process of putting on and pulling off goods is totally automated, without any human workers working inside it. Thus, the dimensional space of the fulfillment center can be fully utilized for storing, as the layer number of racks can reach to more than ten, being filled below the ceiling height, and the previous aisles for the activities of workers and forklifts can be also omitted.

Furthermore, fulfillment has been acknowledged as a human-centered process in which human resources are one of the determinants that either promote or limit fulfillment center efficiency (Mahroof, 2019; Myers, Griffith, Daugherty, & Lusch, 2004). In the smart fulfillment center, by orchestrating related resources, AI capability improves human arranging capability and replaces human handling capability. The introduced ATS successfully replaces the traditional storehouse and its storage modes by automating the process and removing human workers from the storehouse. Thus, the ATS assists in significantly *reducing the quantity of human resources* by automatization, and the fulfillment center only retains a small number of workers to handle the received goods into the ATS. Correspondingly, the ATS also *reduces the risk of human injury* and can ultimately *make full use of space resources* by adding layers of goods racks and deleting the previously necessary aisles. Furthermore, AI enables real-time layout planning, which is derived from data-based analysis and forecasting, thereby i*ncreasing the efficiency of facility resources* (i.e., ATS) when handling goods for further order picking.

In the process of order picking, AI augments the process of picking. Traditional order picking has long been regarded as highly labor intensive, requiring a large amount of human resources and intensive workload (De Koster, et al., 2007; Wäscher, 2004). An operator in the fulfillment center explained that:

Previously, the order-picking workers always complained about their heavy workload as they needed to drag the shelf with order boxes running all over the picking zone to pick different items for the orders in the whole working shift. This is one of the major reasons for the high turnover rate in the fulfillment center.

AI robots take over the majority of moving work previously conducted by human workers. The walking distances of human workers have been shortened to the greatest extent, which *reduces the workload of human resources*. Meanwhile, instead of assigning the picking workers overall responsibility for order picking, AI greatly narrows the range of selection for the workers and guides them to select and pick specific items for the orders, which also *decreases the error rate of human resources*. The cooperation between humans and robots allows each to enhance the other's capability, which *increases the efficiency of human and robot resources*.

In the process of order packing, AI transforms the process of packing. The AI-enabled WMS has transformed the checking step such that human workers focus on error correction rather than checking. WMS helps the fulfillment center operators to identify the erroneous links and they can address the issues to *ensure the smooth operation of the fulfillment center*. Furthermore, the reported error data in turn help to *optimize the algorithm resources, system resources, facility/robot resources, and human resources* to make the fulfillment center smarter. The director of operations explained:

> *The smart fulfillment center has its own 'evolution mechanism': the system automatically collects and stores the reported error data, based on which periodic analysis is made to evaluate all the links and resources and provide some improvement suggestions. Thus, we can continuously optimize all the relevant resources and ultimately, the process to make the fulfillment center smarter.*

AI applications have also transformed packing to allow any worker, not just those experienced, to *pack properly and safely following a rationalized method*. A worker from the fulfillment center, who is responsible for packing, described that

> *Before (applying AI), I had to consider how to pack all the picked items into the box based on my own experience. The box size was estimated and selected by the order pickers based on their experience. Sometimes I found the box was too big that too much room was left while sometimes it was too small that I needed to repack the items in a bigger one. Now, with AI, I only need to follow the instructions shown on the screen. The box size is selected by AI before order picking, and its room can be fully used for packing. AI also suggests the positions for some particular items, for instance, the ones that are fragile or easy to leak.*

Synthesizing the AI-enabled outcome across the processes reveals that the orchestration of AI-related resources and the interaction between the developed AI capability and human capability help to break the restrictions of the original resources—space resources and human resources—which are the critical resources for the conventional process of fulfillment (Faber, et al., 2013; Mahroof, 2019). On the one hand, existing space resources are fully utilized through AI-enabled automatization and augmentation, allowing the storage of an increasing amount of goods. On the other hand, the process revolution of human-AI collaboration successfully releases human resources to focus more on specific tasks, thereby increasing their working efficiency. Furthermore, emerging resources for the use of AI (e.g., data resources, algorithm resources, robot resources) are also being optimized as the checking step is introduced into the iterative fulfillment process.

6. Discussion

This study set out to address the research question: How can AI-related resources, capabilities, and their interactions be managed to achieve valuable outcomes in AI applications? By analyzing successful AI applications at Alibaba's e-commerce fulfillment center, we have identified several key insights and developed propositions that can be tested in further research.

Our findings indicate that data, AI algorithms, and robots are the key AI resources contributing to the development of AI capability. In the case study, other than traditional warehousing resources (e.g., space and human resources) (Faber, et al., 2013), data from various sources played a vital role in analyzing and forecasting capability, planning capability, and deciding capability. AI consumes vast quantities of data to discern patterns, make predictions and obtain insights (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2020; Sipior, 2020). This is in line with the expectations of prior studies that the value of AI is being realized and explored with the availability and reliability of data (Coombs, 2020; Duan, et al., 2019; Dwivedi, et al., 2019; López-Robles, Otegi-Olaso, Porto Gómez, & Cobo, 2019; Ranjan & Foropon, 2021). Algorithms are also important – we found that various algorithms have been developed to rapidly process and leverage the data for real-time optimization and decision making in Alibaba's Smart Warehouse. The case illustrates how algorithms serve as "the building blocks" that make up AI (Dwivedi, Ismagilova, et al., 2020; Eldrandaly, Abdel-Basset, & Abdel-Fatah, 2019). Robots are also instrumental in actualizing the affordances of data and AI algorithms. Our case study details how robots perform repetitive, mundane, and even dangerous tasks and improve the work conditions for human workers, as widely touted as a benefit of AI robots (Sinha, Singh, Gupta, & Singh, 2020). The significance of these resources is captured in the following proposition:

Proposition1. Data, AI algorithms, and robots are significant resources in the development of AI capability

This case study also suggests that the orchestration of AI resources along with other resources led to the development of strong AI capabilities. We have identified the key orchestration actions to be structuring, bundling, coordinating, enriching, pioneering, leveraging, and deploying. Many of them involve the orchestration of non-AI resources such as warehousing facilities and human resources. For instance, in the goods storing process, data, algorithms, and warehousing facilities must be coordinated such that goods can be stored in the optimal location (i.e., handling capability). These findings concur with existing research that simply owing resources (e.g., data, algorithms, robots, and systems) generates little value (Foster, McLeod, Nolin, & Greifeneder, 2018; Mahroof, 2019; Sinha, et al., 2020). More importantly, they extend the resource orchestration perspective by identifying new orchestration actions (Badrinarayanan, Ramachandran, & Madhavaram, 2019; Cui, et al., 2019; Sirmon, et al., 2011), while contributing to theoretical development of AI applications in businesses by offering insights into how investment in AI resources can lead to the development of strong AI capabilities such as forecasting, planning, and learning. Accordingly, we put forth the following:

Proposition 2. The orchestration of AI resources and other related resources lead to the development of strong AI capabilities.

Further, we found that AI capabilities interact and co-evolve with human capabilities to influence business performance. The relationship between human workers and AI applications has been a major topic of debate in research and practice (Chen & Lin, 2020; Duan, et al., 2019; Dwivedi, et al., 2019; Fan, Zhang, Yahja, & Mostafavi, 2019; Hu, Lu, Pan, Gong, & Yang, 2021). On the one hand, acknowledging AI's capabilities to think and act like human (Gursoy, Chi, Lus, & Nunkoo, 2019), some studies have warned about the large scale displacement of human workers through intelligent automation (Muhuri, Shukla, & Abraham, 2019; Parveen, 2018). On the other hand, other studies have noted how AI can help to overcome physical and cognitive limitations of humans, thereby enhance human workers through a human-in-the-loop arrangement (Kumar, 2017). Researchers like Duan, et al. (2019) have called for further investigation into the co-existence between human beings and AI.

This case study finds that the AI-human relationship at work can be one of co-evolution. Specifically, in order packing, while AI enhanced human workers' checking and packing capabilities, human workers provided constant feedback about false negative errors that helped to improve the AI system's accuracy more orders are handled. Over time, both the human workers improve in terms of their capabilities in problem solving and learning. This co-evolution in turn improve work efficiency and effectiveness. Instead of competing, they complement and strengthen each other at work and develop stronger capabilities as they gain experience working with one another.

This finding contributes to research adopting the task-based perspective that seeks to provide a more granular understanding of human-AI interdependence (e.g., Autor, 2015; Rai, Constantinides, & Sarker, 2019; von Krogh, 2018), by extending the understanding with the perspective of capability interactions and co-evolution. In particular, the finding about the co-evolution of AI and human capabilities is consistent with and extends Miller (2018)'s argument that human and AI enhance each other's capabilities. The finding about interactions highlights that the implementation and application of AI should be designed such that they are aligned with task types (Coombs, 2020; López-Robles, et al., 2019). Existing research has suggested that AI should be used to automate repetitive, time-consuming, and hazardous tasks, while human workers should focus on higher-value tasks that require human ingenuity and creativity (Dwivedi, et al., 2019; Nishant, Kennedy, & Corbett, 2020). Based on prior research and our findings, we state that:

Proposition 3. AI capabilities interact and co-evolve with human capabilities to create value.

Proposition 4. The interaction and co-evolution involving AI and human workers depend on task type.

This case study shows that AI resources and capabilities in AI applications contribute to business performance in terms of both efficiency and effectiveness, by automating, augmenting, and transforming important business processes. In the case of Alibaba's Smart Warehouse, the AI capabilities develop through orchestrating AI and other related resources led to the automation of the process of goods storing. This had improved efficiency in terms of space utilization, human labor, risks of accidents and injuries, and warehousing facility optimization. Those involving human labor is especially valuable as the warehousing industry tends to experience high turnover and attracts more scrutiny from the perspective of labor rights (Mahroof, 2019). The AI capabilities such as forecasting and deciding also resulted in augmentation of the process of goods picking, which increased efficiency by reducing workload, minimizing errors, maximizing the utility of robots. More generally, automation and augmentation frees human workers from simple and repetitive tasks and move them up in the value chain to focus on more sophisticated and creative tasks (Borges, et al., 2020; Dwivedi, et al., 2019). Further, the co-evolution of AI capabilities and human capabilities had transformed the process of goods packing, by enhancing the packing method such that even less experienced workers are able to pack items optimally. The concepts of automation, augmentation, and transformation enriches the existing literature on the value of AI, which is the key driver of investment (Dwivedi, Hughes, et al., 2020; Dwivedi, Ismagilova, et al., 2020; López-Robles, et al., 2019), with a resource-specific perspective. These are captured in the following proposition:

Proposition 5. AI applications create business value in terms of efficiency (e.g., space optimization, labor productivity) and effectiveness (e.g., error reduction), by automating, augmenting, and transforming key business processes.

6.1 Theoretical Contributions and Implications

This study contributes to research in several ways. First, for the management of AI applications in businesses, the resource orchestration perspective offers a useful lens for identifying significant AI resources and related resources and understanding how they should be orchestrated to develop strong AI capabilities. The resource orchestration perspective helped to ensure that our analysis looked beyond AI technology and examined how they must work along other existing systems, processes, and people to succeed in businesses. More importantly, we found that AI capabilities can be strengthened continuously in a positive feedback loop if they are managed such that they co-evolve with human capabilities. Without the resource orchestration perspective, the interactions of AI technology with other resources and non-IT capabilities would have been less noticeable and the long-term growth potential for AI capabilities could be easily overlooked.

Second, this study is one of the earliest empirical research on successful AI applications in businesses and the findings provide a useful basis for further empirical research (Dwivedi, et al., 2019). Based on data collected from Alibaba's extensive experience with AI applications in a very demanding context, we identified the key AI-related resources to be data, AI algorithms and robots. Data resources should be bundled and coordinated with algorithms and robots as well as human resources to develop AI capabilities. The key AI capabilities include forecasting, planning, and learning. Further, these AI capabilities can be leveraged to generate business value in terms of automating, augmenting, and transforming business processes such that they are more efficient, effective, and safe. This set of resources, capabilities, and valuable outcomes serves as a useful starting point for further research seeking to evaluate their contribution towards business value. For example, as AI applications become more common, future studies can survey the influence of different resources and capabilities to assess their relative influence on business outcomes.

Third, for the theoretical development of the resource orchestration perspective, we found that different capabilities can co-evolve such that they each become stronger over time. In the case of Alibaba's fulfillment center, AI capabilities enhanced human workers' ability to avoid errors, while human workers drew upon their experience to improve AI systems' ability to recognize or predict errors more accurately. This learning allowed both human and AI capabilities to improve as they interact, generating a symbiotic capability that is greater than the sum of its parts. This indicates an opportunity to extend the resource orchestration perspective to account for not just interactions among resources and capabilities, but also the longitudinal co-evolution of capabilities in value creation.

Fourth, the co-evolution of human and AI capabilities also has implications for information systems research on AI, which recognizes that AI helps to overcome certain limitations of human workers or even replace them (Jarrahi, 2018; Miller, 2018; Muhuri, et al., 2019; Parveen, 2018; Pee, et al., 2019; Rai, et al., 2019). Our findings suggest that human and AI can go beyond collaboration or competition to engage in co-evolution when human workers are provided with the opportunity to take part in the continuous learning of AI systems. This contributes novel understanding to research adopting a task-based perspective that seeks to provide a more granular understanding of human-AI interdependence (e.g., Autor, 2015; Rai, et al., 2019; von Krogh, 2018).

6.2 Implications for Practice

The findings of this case study offer several practical insights for managing AI applications in businesses. First, Alibaba's case indicate that despite the high failure rate observed (Rayome, 2019), AI applications can generate substantial business value and significantly improve performance when AI resources and capabilities are orchestrated along with other resources and capabilities through a systemic perspective. In addition to AI technology, managers need to recognize the roles and contributions of other AI-related resources including data, existing IS, and human resources. These resources should be organized such that they work together to generate strong AI and symbiotic capabilities. As shown in this study, AI technology is necessary, but not sufficient to fully realize the business potential offered by the technology. Existing resources are often adapted, and new resources need to be acquired to ensure that AI applications are fruitful. The AI-related resources and capabilities identified in this study provides a pragmatic starting point for planning and managing AI applications for successful integration into businesses.

Second, our framework suggests a realistic divide-and-conquer approach for tackling the seemingly complex endeavor of integrating AI applications into a business. The approach involves first identifying key business processes that could be automated, augmented, or transformed by AI. The AI-related resources and capabilities constituting each process can then be identified and their interactions analyzed. This approach helps businesses focus on the most value-adding processes and narrow down to appropriate AI applications based on business needs rather than technological capabilities. Avoiding the technology-led, "shiny object syndrome" is a key to minimize failures due to incompatibilities and lack of integration. In Alibaba's case, the fulfillment center chose to focus on the business processes of goods storing, order picking, and order packing considering that these were the most costly and labor intensive. The managerial effort was concentrated on optimizing these processes rather than scattered across all processes that could possibly be enhanced by AI. As a result, initial success was achieved more rapidly and prominently, lending confidence and enthusiasm among employees for further integration of AI applications into other businesses processes.

Third, the success of Alibaba shows that a key to integrating AI applications into businesses is to manage the interactions and co-evolution of AI capabilities and human capabilities. As AI applications proliferate, the collaboration between humans and machines becomes inevitable. Given that such collaborations may be resource intensive and time consuming to develop, managers must recognize the existence and understand the nature of the dynamic relationships for planning. The design of AI applications should go beyond the technological artifact to account for the work practices and organizational structure influenced by the technology. The design should also ensure that the long-term growth potential of AI and human as complex adaptive systems is not overlooked. This will require a greater respect for human agency and AI-human interfaces that promote mutual learning for a more resilient collaboration instead of overindulgence in short-term efficiency addiction and economic return.

6.3 Limitations and Future Research Directions

The findings of this study should be interpreted in light of several limitations, which also present opportunities for further research. First, being a case study, the results have limited statistical generalizability compared to other methods such as survey (Yin, 1994). To generalize the findings to a population, future research could collect data from more businesses and more industries as AI applications grow in practice. The AI-related resources and capabilities identified in this study provide a useful empirical basis for determining the factors to focus on in future survey studies. Together, studies using different methods would contribute to both statistical and theoretical generalizability for advancing conceptual development of the phenomenon of AI applications in businesses.

Second, our analysis of the e-commerce fulfillment center focused on the business processes of goods storing, order picking, and order packing but not other common warehousing processes such as goods receiving, outbound logistics, and inventory auditing. At the time of the study, Alibaba had not integrated AI applications in other processes and it was therefore impossible to include them. Despite being a rare case of success that offers early and valuable insight, this study is limited in that not all the warehousing processes are covered. More studies of other warehousing processes are needed to fully understand all the AI applications in e-commerce fulfillment centers.

Third, the scope of this study is limited to resources and capabilities within an organization, owing to the resource orchestration perspective adopted. Although external influences such as technological advancement were reflected in our analyses to the extent that they affected the availability of resources and level of capabilities, they were not explicitly accounted for in the framework developed. This indicates a potentially fruitful opportunity for further research to expand our framework by directly analyzing the impacts of external factors such as government policies, societal beliefs, and economic conditions on the integration of AI applications into businesses. Such macro-level studies would complement micro-level studies as discussed in this article to offer a more comprehensive understanding of the topic.

7. Conclusion

It is widely accepted that AI creates unprecedented possibilities that will transform businesses across many industries (Davenport & Ronanki, 2018). To unlock its potential, it is necessary to understand the technology and align it with the other organizational elements that AI has to work along with. Through a case study of successful AI applications, we have identified the specific resources and capabilities related to AI, as well as their interactions and co-evolution. Based on the resource orchestration perspective, they are organized into a framework that represents a systemic approach to integrate AI applications into businesses. This holistic approach helps organizations stay focused and avoid wasting limited time and energy on pursuing the wrong applications or spreading thin across too many different business processes at the same time. It also reminds managers to leverage existing resources and capabilities, for example, unleash the learning power of AI with the ingenuity of human employees. Instead of throwing AI at the business, managers should recognize the malleability of the technology and the organization and ask how they can be shaped to develop the X factor that will increase productivity through automating and augmenting business processes and create stronger relationships with customers through transforming processes.

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Appendix A: List of Interviewees

Organization	Description	Interviewee Role	Interviewee Count
Tmall	Alibaba's online supermarket unit that processes orders through the e-commerce fulfillment center studied	Fulfillment center manager	1
		Worker	7
ALOG	A newly acquired logistics service provider operating the e-commerce fulfillment center studied	Director of operations	1
		Operation manager	1
		Operator	3
		IT manager	1
		IT engineer	3
		AI engineer	2
MEGVII	An AI solution provider developing AI applications for the e-commerce fulfillment center studied	Vice president	1
		Product manager	1
		Robotics engineer	4

Appendix B: Coding of Data related to AI Applications in Order Packing

1st Order Concepts	2nd Order Themes	Aggregate Dimension
• Comparing order data with picked items data via using the AI-enabled system to check the picking accuracy • Synthesizing order data and operation data via using the AI-enabled system to trace back and check the whole process	Leveraging data and system resources	**Resource Orchestration**
• Deploying human to collect the picked items data by scanning items • Deploying human to pack the order following the guidance from AI • Deploying human to solve problems	Deploying human resources	
• Coordinating the 3D packing algorithms with the data on goods and orders to show packing suggestion via the AI-enabled system • Coordinating all available resources to identify errors in the picked orders and correct the error orders • Coordinating all available resources to identify problems in the whole process and address the problems	Coordinating data resources, algorithms resources, system resources, and human resources	
• AI-enabled system (WMS) comparatively analyze the matching between order data and picked items data • WMS analyze the operation data to trace back the process to identify problems	Analyzing capability	**AI Capability**
• The packing method for fully using box space is planned by AI-enabled 3D packing function of the WMS • The packing method for protecting items is planned by AI-enabled 3D packing function of the WMS	Planning capability	
• AI algorithms are iteratively optimized based on accumulated training data • Functions of AI-enabled systems are advanced based on error message • AI-human collaboration modes are adjusted based on feedback	Learning capability	
• The AI-enabled comparative analysis guides workers to check and find error order • The AI-enabled back-tracing analysis guides operatives to check and find problems in the process • The AI-enabled 3D packing planning guides workers to pack the order	AI capability **guides** human capability	**AI-human Capability Interaction and Co-Evolution**
• Operatives solve the discovered problems on systems to facilitate AI learning the development and operation of the systems • Operatives solve the discovered problems on AI-enabled machines and workers to facilitate AI learning the AI-human cooperation	Human capability **facilitates** AI capability	
• Retain the primary process of packing • Add the step of checking supported by AI • Use AI-based 3D packing function to guide packing • Identify errors through the function of AI-based backtracking • Send operatives to address the discovered AI issues	**Process** Transform	**AI-enabled Outcome**
• Reduce the error rate of picked order • Rationalize packing method • Ensure smooth operation of the warehouse • Optimize algorithms resources, system resources, facility/robot resources, human resources	Final Effects	

Appendix C: Introduction of the Algorithms

Algorithms	Brief Introduction
Sales forecasting algorithms	The sales forecasting algorithms are developed based on historical sales data to accurately forecast the sales in the future. The algorithms are mainly for the preparation of the arrangement of tasks in the next few days, for instance, replenishing goods in both the storing and picking zones, dynamically adjusting the location of goods, and alleviating the traffic congestion of robots.
Location recommendation algorithms	The location recommendation algorithms are based on the data about the sales, volume, and other goods attributes with the analysis results on the sales correlation between different goods. By using the algorithms, the types of goods with higher correlation regarding sales are recommended to be displayed adjacently to shorten the moving path of robots. Thus, the algorithms are developed for rationalizing the location of each item of goods and minimizing the order processing time.
3D packing algorithms	The 3D packing algorithms are developed mainly based on the data about the shape, volume, and other relevant goods attributes. The algorithms are responsible for addressing two issues. One is recommending a suitable size of the order boxes to contain all the ordered items of goods. The other is recommending the reasonable way to pack all the picked items into the box for fully using the room of the box and protecting the items during transportation.
Order wave combination algorithms	The order wave combination algorithms are based on the real-time order data and the correlation between orders. The algorithms are used to select orders from thousands of real-time orders into a wave to increase the picking concentration. In other words, the combined wave includes the orders having a higher probability to contain same goods or the goods located adjacently, and thus it can avoid the issue of robots moving all over the picking zone with the order boxes. The algorithms can minimize the moving time of a robot to finish picking items for all the orders carried by it.
Route planning algorithms	The route planning algorithms are based on both the data about the goods locations in the picking zone and the real-time orders. The algorithms are responsible for shortening the routes of the robots to a maximum extent, which is expected to optimize the picking efficiency.
Robot scheduling algorithms	The main purpose of the robot scheduling algorithms is minimizing the order processing time by coordinating all the robots. To achieve this, the algorithms need to consider a substantial amount of factors, including the order for processing the orders and the allocation of the most suitable robot at the particular position to process the order as well as the overall traffic situation of the robots' network.
Robotic motion control algorithms	The robotic motion control algorithms are responsible for the real-time movement of the machines themselves. The algorithms are closely related to the data captured by the sensors on robots for identifying the surroundings and avoiding the unexpected obstacles in real time.