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Government with Algorithm: Strategy to Improve Synchronous Public Service Using Artificial Intelligence (AI) in Indonesia

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Abstract

This study reviews how government by algorithm uses AI in the public sector. Artificial intelligence has been heralded as the next source of business value in the public and private sectors. Building on organizational resource-based theory and recent work on AI in organizational contexts, this study (1) identifies AI-specific resources that together create AI capabilities, (2) develops models to capture AI capabilities in public services, and (3) looks at public trust capabilities, and (3) examines the relationship between AI capabilities and creativity and organizational performance. The research method uses a qualitative approach with a case study strategy. This type of case study is explanatory. Empirical findings show that Artificial Intelligence (AI) changes how government agencies carry out their functions and roles to improve performance, compliance, and security activities in public service and public goods. Rapid developments in AI can reduce essential governance costs and improve quality and power-based administrative data so that government performance is more efficient and effective. The implications prove that AI capabilities result in increased creativity and organizational performance.

Keywords
artificial intelligence; public trust; capability; resource-based theory; public service

I. Introduction

Artificial intelligence (AI) has emerged as an organization's top technology priority over the past few years, primarily driven by big data and the emergence of sophisticated techniques and infrastructure field. A recent report by Gartner shows that the number of organizations implementing AI grew 270% in the last four years and tripled in the last year. While there are many benefits to the potential business value that AI can provide, organizations starting to adopt AI solutions face many challenges that prevent them from realizing improved performance. In a 2019 global executive study published in the MIT Sloan Management Review, seven out of 10 organizations reported that AI has had minimal or no business impact. Despite the enormous potential that AI technology holds, highlights that we are dealing with a modern productivity paradox. One of the main reasons AI has not delivered the expected results is delays in implementation and restructuring. Therefore, organizations need to invest in complementary resources to leverage their AI investments. Understanding what complementary resources need to be developed and deployed is critical to realizing the performance gains from AI. In other words, it is time to examine how organizations build AI capabilities. Organization must have a goal to be achieved by the organizational members (Niati et al., 2021).

This study draws on the resource-based theory of organizations and seeks to examine the resources required to build AI capabilities. Previous studies have shown that resource theory is an appropriate theoretical lens for dynamic and turbulent environments, especially when resource complementarity is fostered and organizations develop specific

capabilities around their respective resources; this study, therefore, defines "AI capability as the ability of an organization to select, manage, and utilize its AI-specific resources."

In developing the notion of AI capabilities, we draw on the IT capability literature and recent studies on AI in organizational contexts. This study understands the enablers and effects of various types of IT capabilities, such as social media capabilities, social trading capabilities, and business analytics capabilities. However, as with any new technology, such as AI, organizations need to develop unique resources to leverage their investments to generate business value effectively. Building on previous studies and recent research on AI in organizational contexts, we identified several key resource types and then categorized them into tangible, human skills, and intangible resources. In addition, this study develops a survey instrument to measure resources and measure an organization's AI capabilities. We also examined the nomological validity of the AI capability scale by examining its relationship to organizational creativity and organizational performance. This study then discusses this research's theoretical and practical implications and some other essential limitations.

II. Review of Literature

2.1 Resources

Organizational resources have become one of the most widely applied theoretical perspectives in explaining how the resources owned or owned by an organization under its control can cause differences in performance in the same function. Based on the strategic management literature, resource states that organizations compete based on the resources they have under their control, which are valuable, rare, and difficult to imitate. Non-replaceable performance gains. Subsequent research in resources distinguished resource selection and capacity building, two main aspects of different theories. defines resources as tradable and non-specific organizational assets and non-tradable organizational-specific capabilities to integrate, deploy, and utilize resources. Thus, resources represent inputs from the production process, while capabilities are the potential to deploy these resources to increase productivity and produce services. Adopting this perspective gives an inherent assumption that organizational capabilities depend on and are developed based on the available set of corporate resources. Therefore, the strength of organizational capabilities is determined by the resources formed by.

2.2 Artificial Intelligence

Although AI has been a topic of interest for decades, there is still a lack of universally accepted definitions throughout the literature. The lack of an explanation for basic empirical studies on AI has led to fundamental problems in understanding AI as a whole Building knowledge of AI; it is first necessary to explore the notion of "intelligence" before assuming this concept to machines and defining the combined term "artificial intelligence." To measure the intelligence of various technologies, such as those covered under the umbrella term AI, we must step back from system specifications and establish the underlying basis for what we are trying to capture through the term "intelligence." Field developed an integrated description of intelligence based on the previous definitions, describing it as "the ability to interact, learn, adapt, and use information from experience, and deal with uncertainty." In combination with the above, the notion of "artificial" relates to the idea of something made by humans, an imitation or replica of something natural. Based on the meaning of these two core ideas, we need to develop a more sophisticated understanding of the term AI.

2.3 Contextual AI Capability

Although published research on the business value and use of AI in organizational settings is minimal, few studies have identified obstacles in the successful implementation of projects. Most of these studies come from the practice-based press, which continues to sample leading organizations in terms of AI adoption and use. For example, a survey by Ransbotham found that a lack of technical competence is one of the most significant barriers to gaining value from AI. In particular, their findings highlight that nearly one in five organizations do not understand the data requirements of AI and the associated technology infrastructure required to store and transport it. Another recent study by Davenport and Ronanki noted that difficulties in integrating AI projects with existing processes and systems are a significant problem for thwarting AI initiatives. In the public sector context, Mikalef & Gupta find that the main problem is the inability to integrate systems and data and ensure that quality data is used to train AI. New technological solutions are needed to address the unique challenges posed by the data characteristics required for AI. Nevertheless, there have been significant advances in AI-related technological advancements.

2.4 Public Trust

Trust can be defined as "belief in others, through actions or not taking steps that can contribute to our lives and trying to control ourselves, which can collapse relationships between one person and another. The definition of trust has two main elements of trust: a hope for something benevolent (benevolent) and a willingness to accept input or criticism. The level of change tendency if there trust in the organization it will be able to foster an increase in the character of the organization, which includes several factors, including other; organizational structure, supervisory mechanism, job design, communication, job satisfaction, commitment, and organizational behavior citizens Changes in public organizations require trust between subordinates and their leaders so that they can successfully achieve organizational goals. Much attention in the literature and public policy articles is about the declining trend of public trust in public sector organizations. The case in Indonesia where the use of AI in public services is declining. Therefore, there needs to be a comprehensive and integrated effort to increase public trust. Public trust can realize through the form of trust given by groups or individuals in social institutions or systems. In general, public trust is related to behavior. Public trust can be influenced by a person's experience concerning a representative institution or design and can also be affected by the media's image.

III. Research Method

Research with a qualitative approach with a case study strategy. The type of case study is explanatory. This study presents the results of qualitative methods carried out in South Sulawesi Province (Makassar City), Central Java Province (Yogyakarta), and West Java Province (Bandung City). Collected data was through interviews with informants using the snowball technique and direct observation at the research site and the media. Key informants are the Heads of Service Offices that provide public services at government offices, IT technicians and administrative staff, and other necessary informants. Observations were carried out directly at the research site and using the media. The topic of the interview is AI in government organizations. Primary data includes interviews and results of discussions with informants. Secondary data comes from documents, data available on the website, and other data that support the analysis. Data analysis was carried

out by conceptualizing the results of interviews, empirical facts, and data collected for data reduction. Data analysis is focused on 3 (three) things: AI capability, Public Trust, and AI resources (tangible, human, and intangible).

IV. Results and Discussion

This study highlights some of the resources that organizations need to develop to derive value from public services from AI investments in government organizations in Indonesia. This research also tries to find gaps in how organizations can create AI capabilities in the delivery of public services; this is important because it can show the core areas that must be directed by public organizations when implementing AI initiatives and provide ideas for measuring the achievement of good governance.

4.1 Public Trust Artificial Intelligence Capability in Public Sector

Artificial intelligence or artificial intelligence can accelerate public services organized by the Government. The implementation of artificial intelligence is a form of service transformation that includes e-services, strengthening community supervision, and strengthening the innovation ecosystem. Artificial intelligence in public services can be applied to the help desk in the service unit, analysis of service complaints, directing complaints to the intended agency, and even answering objections. Implementation of artificial intelligence is one of the Government's priorities to support the activities and work carried out by the state civil apparatus (ASN). The work is technical in nature. The nature of administration and data processing sly manual can be switched by utilizing technology, making it more efficient and shortening the time.

a. Public Trust Performance

The performance of machines or automated devices or systems is a trust field facilitator. The placement of AI at the forefront of public services makes public service interactions no longer person to person but person to machine. AI demonstrates confidence in performance when it is technically competent to deliver the information seekers need in the form of seamless responses. But AI is not fully capable in this regard, considering that AI works based on rigid algorithm commands. So, when the order cannot detect things, the community can be unserved. The placement of AI as a solution to public service bureaucratic problems is also a generalization.

AI user feedback on the frontline revealed that many users did not get most of the information they wanted or only received half of it. In the absence of information about AI's reputation on the front, some public members may be initially sceptical of AI's ability to answer their questions effectively. Society may expect AI to show high performance.

While previous studies of trust in machines focused on technical competencies, this study proposes that other types of competencies, listed in Table 1, are crucial for AI at the frontline to provide reliable responses. One of these competencies is the ability to demonstrate empathy, or "the ability to recognize, understand, and respond to" the feelings of others'". Empathy is arguably an essential quality of public administrators, whose job it is to serve citizens in need of services, some of which are not provided by or are unreachable. Therefore, trustworthiness not only consists in the precise and smooth delivery of the information required by the user but also involves some display of empathy towards the user to facilitate socially appropriate interactions. This criterion can also apply to Frontline's AI response, as humans can respond socially to technology.

b. Public Trust in Proces

In the public sector context, the basic trust process relates to making the logic behind decision-making transparent and understandable to the public. It ultimately boils down to the issue of making government decisions accountable to the people. Accountability in the public sector has a special place in state democracies, where the government is based on the consent of the governed. Without accountability, administrators may exercise discretion without democratic consciousness.

In a public context, abuse of administrative authority and lack of accountability can be a source of concern, notably in the Street-Level Bureaucracy. These frontline administrators can significantly influence people's lives for good or for bad. Their job is to provide public services directly to citizens, allocate funds and rights among them, and even make decisions that can affect their human rights.

Digitization has been seen to limit the Street-Level Bureaucracy's discretion by shifting the locus of preference from the street-level bureaucracy to the system-level bureaucracy. Digitization, thus, can prevent errors and abuse of choice in the Street-Level Bureaucracy but creates a need for democratic control at the system level, which necessitates the creation of publicly accessible programming algorithms. Calls for system-level accountability amid the increasing use of AI-enabled decision systems in society have led to recent regulatory initiatives, such as Indonesia's General Data Protection Law, which requires explanations of the logic involved in AI-assisted decisions to be provided upon request. The resulting system-level accountability can increase the source of trust processes in AI-enabled decision systems. However, the effect can be limited when multiple algorithms are combined in very complex modern governance. System-level algorithmic accountability and transparency can improve their basic trust processes.

c. Public Trust in Purpose

When humans cannot judge the ability of machines to be greater than human abilities, humans must rely on devices. Humans' sense of responsibility in service turns into a design-based intention or purpose. Since machines are not programmed to explain their intent or purpose, the designer's intent becomes essential. However, in the public sector, what is vital for public trust is not the intention or purpose stated by the designer but the government to introduce and use AI frontline. If the public perceives that the government uses AI with good intentions and benevolence, they will trust the planned technology. Government to be introduced without asking much. Furthermore, such positive perceptions might also help increase their confidence in the "data science trail" behind machines and alleviate widespread concerns over the misuse of confidential data collected through interactions with devices.

Table 1. Public Trust Responses in AI in the public sector

Sources	Description
Public Trust in Process	User's understanding of AI frontline technology and the algorithms behind it
Public Trust in Performance	• AI Frontline capability to show technical competency • AI Frontline capability to show empathy • AI Frontline capability to make a situational judgment
Public Trust in Purpose	The intention of a government to introduce or use AI Frontline

The setting of service standards and the business processes that follow are the key to the length and length of the government bureaucracy. Through the bureaucracy, the government must be present to provide the best service by placing the community as a subject, not an object of service. "With this perspective, it is hoped that the level of public trust in the government bureaucracy will be built and strengthened."

4.2 Human Artificial Intelligence Capability

An organization's human capital is often measured by assessing its employees' knowledge, skills, experience, leadership qualities, vision, communication and collaboration competencies, and problem-solving abilities. Previous research on digital capabilities has identified technical and business skills as essential pillars of the human resources. Following this line of thinking, this research demonstrates that AI-specific technical and business skills are two critical components of an organization's AI human capital.

a. Technical Skills

When we refer to technical AI skills, we mean the skills needed to handle the implementation and realization of AI algorithms, manage the infrastructure to support these initiatives, and introduce and ensure AI applications meet objectives. More specifically, algorithm developers must take advantage of the latest AI research and turn it into an iterative process through mathematical formulas that can be implemented through hardware and software. It has been suggested that most careers in the technical aspects of AI will require individuals with a solid background in statistics, probability, prediction, calculus, algebra, Bayesian algorithms, and logic. In addition, a good experience in programming, logic, data structures, language processing, and cognitive learning theory has been highlighted as an essential technical AI skill. A recent article in the MIT Sloan Management Review presents three key roles that will emerge as technical profiles in the AI era: coach, explorer, and supporter. Trainers are concerned with teaching AI systems how they should work, and includes the task of helping service chatbots, for example, identify the complexities and subtleties of human communication. The explainer bridges the gap between technologists and business managers by providing a non-technical audience with clarity on how the inside of AI systems works. Lastly, proponents ensure that AI systems operate as expected and that unforeseen consequences are handled appropriately. These three roles include a more detailed list of job functions that have become important to contemporary organizations. While these skills are currently scarce in the market, it is argued that they will gradually become more common as higher education and online training courses appear, making these resources a commodity across companies overtime, field field.

b. Business Skills

One of the most frequently cited barriers to adopting and utilizing AI technologies in organizational settings is managers' lack of knowledge on how and where to apply the technology. In fact, in a recent survey published in the MIT Sloan Management Review, lack of leadership support for AI initiatives was ranked as one of the main barriers to the AI adoption field fi. Realizing business value for AI investments requires accurate understanding and commitment from leaders to drive large-scale change. In addition, managers need to understand the potential application areas of AI and how to handle the transition to AI-enabled activities. A surprising finding by Davenport and R. Ronanki notes that one in three managers do not understand how AI technology works. Therefore,

managers must be familiar with AI technologies and their potential use in various organizational functions. Another important aspect is the ability of managers to initiate and plan AI deployments. AI is essential when considering the vital forces within organizations against change and the threat that AI could replace many of the jobs currently held by employees. Thus, managers must develop good working relationships between technical employees and line function staff to minimize friction and potential inertial forces, delaying AI adoption and hindering the business value field. Being able to seize opportunities from multiple AI technologies and manage organizational change associated with AI deployments is likely a problematic resource for other companies to emulate**.**

4.3 Intangible Artificial Capability

The three main types of organizational resources identified in the RBT, intangible resources are considered resources that are more difficult to imitate by other firms and are particularly important in an uncertain and volatile market. In contrast to the two different categories of resources, intangibles are much more challenging to understand and identify in organizations'. Nevertheless, although difficult to measure, they are also a resource that needs to be catered to. AI means that no two resources are the same across companies because they are very heterogeneous and unique. The heterogeneity and non-replicability of intangible resources owe their debt because they were developed through the unique mix of organizational history, people, processes, and conditions that characterized the organization. Early reports on the drivers of AI success and the long history of empirical IS research highlight the importance of intangible resources in reaping business benefits from adopted technologies. In the context of AI, the resources we identified were interdepartmental coordination, organizational change capacity, and risk propensity.

a. Coordination between Departments

The ability to coordinate tasks and share a shared vision among various organizational departments is considered a cornerstone of success in cross-disciplinary projects. Inter-departmental coordination has long been a critical driver of innovation and creativity in organizations. Inter-departmental coordination has been defined as “a state of high shared values, commitment to shared goals, and collaborative behavior”. Based on this perspective, what is essential is continuous inter-departmental relationships rather than simple interdepartmental transactions. On the same line, recent studies in AI and business values argue that to unleash AI technology's worth, organizations must cultivate a culture of teamwork, collective goals, and shared resources field.

AI has the most significant impact when developed by a cross-functional team with various skills. As a result, organizations will ensure that AI initiatives address broad organizational priorities and not just isolated business issues. By fostering interdisciplinary teams, organizations are also advised to be able to think about the operational challenges that new applications may require, thereby improving the overall performance of the implemented AI solutions. Finally, improving inter-departmental coordination will likely make organizations more agile and adaptable in deploying AI applications. A shared language and shared understanding of employees across different departments will reduce the time it takes to deploy new AI applications or adapt existing ones when the need arises. Which highlighted that functional silos are one of the most critical barriers to obtaining business value from AI investments. It limits the end-to-end solutions being developed.

b. Organizational Change Capacity

The ability of organizations to initiate and follow up on the implementation of plans has long been considered a critical success factor in the digital transformation. Organizational change capacity focuses on potential problems arising from a failed transition from the old to the new process. In the management literature and Information Systems studies, developing abilities that minimize the friction and inertia associated with change is an essential resource for digital transformation capability and overall business value. Grover et al. note that organizational change capacity requires breaking the administrative status quo and introducing new practices, deals, and structures. AI applications introduce significant changes to how organizations perform their primary activities by replacing traditional human tasks or augmenting existing processes. Planning and managing these changes at various levels within the organization is critical in realizing value from AI investments.

In an article recently published in the Harvard Business Review, one of the critical findings of making AI provide businesses includes the ability to overcome unique barriers to change.

Every organization will present a unique set of inhibiting factors that delay or hinder change. Therefore, managers need to develop the capacity to anticipate, plan, and implement change at the organizational level. An organization that is unable to overcome these forces of resistance is unlikely to be able to derive value from AI investments. Even with large amounts of data, highly skilled technical personnel AI infrastructure, an organization that cannot leverage it and changes existing ways of doing business to incorporate AI advances will not be able to realize the performance gains. Tendency to risk

c. Risk Tendency

Organizations that adopt a more risk-oriented approach to new ventures like AI reap the benefits long before their competitors or new entrants do. This strategic orientation toward risk-taking has been highlighted in management under different terms (e.g., risk propensity, entrepreneurial orientation, proactive attitude). It is associated with typologies reflecting bold and aggressive initiatives to change the competitive scene (e.g., prospectors). In terms of adoption, this research highlights that organizations that embrace risk tendencies deepen their commitment to AI and establish their position, making it harder for others to catch up. One of the most attractive, value-added, and competitive parts of the business in the future shows that risk-takers perceive AI as an opportunity they must seize before competitors do. The orientation shift required to derive value from AI reveals that risk-takers perceive AI as an opportunity they must capture before competitors do. The orientation shift is necessary to derive value from AI.

Organizations must depart from a risk-averse strategic orientation and become agile, experimental, and adaptable. The main idea is that companies that are willing to move away from standard practices and adopt new and more ambitious targets are also more likely to see the establishment of strong AI capabilities than those that adopt a more conservative approach. Based on the above, it is safe to suggest that organizations with a high propensity towards risky projects are likely to be the first to embrace AI and gain the first-mover advantage. Organizations can consolidate their position long after and join the group of pioneers who enjoy a competitive advantage by leveraging their AI resources towards strategic goals.

V. Conclusion

This research is motivated by the surge of interest in AI phenomena by practitioners and academics, especially during the last five years. Despite considerable contributions in the literature from practitioners within the academic community of public administration, it is only in recent years that the topic has gained some traction. As a result, there is much discussion about the potential of shared services using AI without clearly defining what AI means and without a concrete definition of an organization's AI capabilities. In this study, we draw insights from RBT. We developed and validated a conceptualization of AI capabilities with public trust in mind through this approach and input from a group of experts and a survey-based large-scale survey. We argue that eight types of complementary resources should include a set that contributes to the emergence of AI capabilities. Specifically, tangible resources consist of data, technology, and primary resources; human skills consist of technical and business skills. In contrast, critical intangible resources include coordination between departments, organizational change capacity, and risk tendencies. Finally, this study develops a survey instrument to measure the AI capabilities of organizations, which are empirically validated, showing that by developing AI capabilities, public organizations can realize service excellence in terms of creativity and organizational performance.

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