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Building Technological Capability in Indonesia's Defense Industry: The Mediating Roles of Organizational Innovation and Technology Management Capability

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ABSTRACT

Indonesia's National Defense Industry (INHAN) faces intensifying Industry 4.0 pressures while operating under security constraints, long research and development (R&D) cycles, and policy-driven demand. This study examines how Absorptive Capacity (AC) strengthens Technological Capability (TC) and tests the mediating roles of Organizational Innovation (OI) and Technology Management Capability (TMC). Using purposive sampling, survey data were collected from 116 senior personnel (supervisors, managers, and directors) across 54 firms. The model was estimated using variance-based PLS-SEM (SmartPLS 4.0) after convergent validity, discriminant validity, and reliability checks. The results show that AC strongly increases OI ($\beta = 0.818$) and TMC ($\beta = 0.832$). Both OI ($\beta = 0.287$) and TMC ($\beta = 0.297$) positively affected TC, while AC also had a direct effect on TC ($\beta = 0.334$). Mediation tests confirmed significant indirect effects via OI ($\beta = 0.235$) and TMC ($\beta = 0.247$). The model explains 75.5% of the variance in TC ($R^2 = 0.755$), indicating that capability upgrading depends on a combined learning–innovation–governance system rather than technology acquisition. Practically, INHAN firms should institutionalize external knowledge scanning, strengthen innovation-supporting structures, and professionalize technology governance to translate partnerships and technology transfers into sustainable technological capabilities and competitiveness. The findings extend resource-based and dynamic capability arguments by specifying internal translation mechanisms for knowledge absorption in sensitive sectors. They also inform policymakers that capability programs should couple technology procurement with incentives for learning systems, cross-functional process redesign, and the development of managerial talent.

1. INTRODUCTION

The defense industry is widely recognized as a strategic arena underpinning deterrence, sovereignty, and national security. Within this sector, technological superiority has historically generated not only military advantages but also substantial spillovers into civilian industries, as innovations developed for defense applications have diffused into commercial products, production systems, and broader technological ecosystems. Contemporary defense operations increasingly integrate cyber-physical systems, artificial intelligence, and robotics to enhance efficiency, precision, and operational resilience, reinforcing the view that competitiveness in defense manufacturing and services is closely associated with advanced technology development and deployment [1, 2].

Simultaneously, the defense industry is structurally distinct from many other industrial sectors. National defense industries typically exhibit high capital intensity, long research and development (R&D) cycles, and strong economies of scale. These characteristics can make defense production commercially challenging, particularly in developing countries, where comparative advantage may lie in less capital-intensive sectors. However, the strategic imperative of defense autonomy often leads states to preserve or expand domestic defense industrial capacity through policy protection, subsidies, and procurement arrangements that stabilize demand. Consequently, defense industries operate within a hybrid governance environment shaped by security objectives, industrial development strategies, and market constraints, creating a complex institutional setting in which capability development is often as important as cost efficiency.

This context is directly relevant to Indonesia's National Defense Industry (INHAN), which is being reshaped by rapid technological changes and intensifying capability requirements. Digital transformation and Industry 4.0 technologies are altering competitive and institutional conditions, creating opportunities for market expansion, broader stakeholder engagement, and improved operational efficiency, while simultaneously raising the performance thresholds that firms must meet to remain competitive. In increasingly dynamic competition, technology-based advantages can be disrupted quickly when capability renewal does not keep up. Consequently, transformation in INHAN should be understood as a strategic process of capability building and organizational renewal, rather than a narrow agenda focused on adopting tools, implementing automation, or adding isolated digital features.

Within this transformation trajectory, three internal capability domains become particularly salient: Absorptive Capacity (AC), Organizational Innovation (OI), and Technology Management Capability (TMC). Firms must develop AC to leverage external knowledge and translate it into productive internal routines; strengthen OI to reconfigure structures, processes, and decision rights so that learning can be converted into innovation outcomes; and build TMC to govern technology choices, align technological investments with strategy, and ensure that technology generates measurable organizational value [2-4]. Together, these capabilities form a practical basis for understanding why some firms respond to technological turbulence with upgrading and competitiveness, while others experience stagnation or disruption in their operations.

Industry 4.0 technologies are frequently positioned in the literature as levers for sustained competitive advantage, particularly in technology-intensive industries, where the speed of technological change and the importance of system integration shape competitive outcomes. Technological Capability (TC) can be conceptualized as the integration of technology across production and service operations, where cyber-physical systems and intelligent applications enable new production configurations and expand the feasibility of production data analytics [2]. Under this conceptualization, TC is not limited to owning machinery or software; it is expressed through the organization's ability to integrate digital and physical systems, redesign work processes, collect and interpret data for operational improvement, and sustain continuous technological upgrading throughout the value chain.

However, transformation is rarely linear in the defense industry. Defense firms often delay capability development, particularly in digital systems and data-driven production, owing to concerns about data integrity, cybersecurity, and strategic confidentiality, as well as continued reliance on traditional managerial tools and legacy production routines. This hesitation is costly because TC increasingly functions as a foundational condition for efficiency, revenue growth, and innovation performance. Where TC is underdeveloped, firms may struggle to achieve stable quality, meet delivery targets, or respond quickly to evolving operational requirements. Therefore, readiness assessment, which evaluates whether an organization possesses baseline technological and organizational prerequisites, is critical before selecting transformation roadmaps and business models that can translate technology investments into measurable performance improvements.

In practice, INHAN firms face a set of operational and strategic paradoxes that complicate their capability-building efforts. They are expected to reduce costs while investing in AC, even though AC development is resource-intensive and often requires sustained spending on learning systems, training, knowledge governance, and collaboration mechanisms. They are expected to accelerate production while being constrained by limited OI, including rigid structures, conservative decision-making processes, and weak cross-functional coordination. They are expected to pursue efficiency and modernization while lacking sufficient TMC to design and implement technology strategies and business models that capture value from technology adoption [5-7]. These paradoxes imply that technology-related challenges in INHAN cannot be treated as isolated engineering problems; they are closely linked to knowledge governance, organizational design and managerial decision architectures.

Because the business model mediates how firms transform technology and knowledge into value, it becomes a central lens through which capability-building challenges can be diagnosed. Research highlights that business models help firms recalibrate their processes, practices, and operations to capture emerging opportunities and survive fast-moving and unpredictable competition [8]. In a defense setting, this mediation role can be even more pronounced: firms may have access to technology or external partners but still fail to translate such inputs into performance improvements if they do not have the internal managerial and organizational capabilities to integrate and exploit technology. In this sense, TC depends on an enabling configuration that links external knowledge acquisition, internal learning, organizational redesign, and technology governance into a coherent system.

Within Indonesia, INHAN is positioned as a cornerstone of defense self-reliance, supplying multi-domain capabilities and electronic systems while functioning as a strategic partner of the government [9]. Although domestic production capacity supports key Indonesian Armed Forces requirements, the sector's TC is often assessed as mid-level [10]. This assessment reflects both achievements and constraints: domestic firms have developed significant production experience but remain challenged by limits in advanced system integration, high-end component mastery, and sustained innovation cycles. Frequently cited examples include PT Pindad's support for land-based defense systems, PT Dirgantara Indonesia's collaboration in aircraft and helicopter production and development, and PT PAL's role in constructing maritime platforms, including large-scale warships, with private firms contributing to fast patrol craft [11]. Strengthening INHAN's fundamentals is also associated with improvements in technology and manufacturing readiness, including testing capacity, from components to fully integrated systems. Key pathways include licensing, co-production, production modernization, joint development, and the enhancement of R&D facilities, supported by universities and research institutes to reinforce basic-to-applied research linkages [12].

A useful theoretical foundation for understanding capability differences across firms is the Resource-Based Theory (RBT), which argues that resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable underpin sustained competitive advantage [13]. This perspective shifts the strategic focus from external market pressures toward the inventory, development, and renewal of internal capabilities. This suggests that firms should begin strategic planning by identifying and strengthening the resources and capabilities that generate durable advantages rather than relying solely on environmental positioning. This is particularly relevant in the defense industries, where the market structure is often characterized by monopsony procurement and policy-driven demand, making internal capability differences a primary driver of performance and competitiveness. According to this logic, firms that systematically invest in learning, technology governance, and organizational renewal are more likely to achieve sustainable advantages, even when market conditions are constrained.

The Value, Rarity, Imitability and Organization (VRIO) framework operationalizes RBT by providing an internal analytic tool to evaluate whether resources meet the Valuable, Rare, Inimitable, and Organized criteria, helping to identify which capabilities can generate a durable advantage [14]. In the INHAN setting, VRIO provides a structured way to evaluate whether TC, AC, OI, and TMC can function as sources of sustained advantage. For example, TC may be valuable in improving efficiency and meeting performance requirements; it may be difficult to imitate when embedded in firm-specific processes; and it may generate a sustained advantage when the firm is organized to exploit it through effective governance and talent systems.

However, RBT alone can be insufficient when the environment is characterized by rapid technological changes, shifting operational requirements, and evolving threats. In such dynamic contexts, resource-based rents can erode as technologies diffuse, standards change, or new entrants disrupt traditional advantages. This is why a dynamic capabilities lens is frequently used alongside RBT to explain continuous adaptation and renewal in technology- and manufacturing-oriented organizations [15-17]. Dynamic capabilities emphasize an organization's ability to sense opportunities and threats, seize opportunities through investment and strategic choice, and reconfigure resources and processes to maintain relevance in changing environments. In the defense industry, where technology trajectories can change quickly and procurement expectations can shift, dynamic capability is often a necessary complement to the resource-based perspective.

This theoretical framework clarifies why managerial capability related to technology governance is strategically significant. TMC is increasingly viewed as central because maintaining advantage cannot rely solely on operational efficiency and cost minimization. Countries and firms that lead technological progress are often those that can manage technological assets effectively, align technology investments with their strategy, and convert technical options into organizational value [18]. In this view, technology development is valuable insofar as it produces realizable organizational outcomes; therefore, the capability to evaluate, select, integrate, and exploit technology becomes critical, particularly in a sector where technology choices are expensive, path-dependent, and frequently subject to security constraints [19]. In this sense, TMC is not simply an administrative function; it is a strategic managerial capability that shapes TC development over time.

AC provides another foundational pillar for capability development. It is defined as the ability to recognize, assimilate, and apply external knowledge [20]. In defense contexts, foreign technology transfer is often a critical input; absorbing and re-innovating external knowledge can accelerate the modernization of weapons capabilities, and foreign inputs can constitute a substantial share of capability development in some settings [1]. The key implication is that technology acquisition alone is insufficient: without strong AC, technology transfer risks producing dependence rather than capability upgrading. Conversely, when AC is strong, external knowledge can be recombined with internal knowledge, creating conditions for domestic capability accumulation.

The literature links AC to dynamic capabilities and R&D investment, showing that AC expands knowledge and skill bases, improves future information assimilation, and ultimately supports innovation development and TC [5, 21-23]. This linkage is particularly relevant for INHAN because firms are often required to integrate external knowledge from technology partners, universities, research institutions, suppliers, and government agencies. Where AC is weak, learning remains fragmented and difficult to institutionalize. When it is strong, firms can create routines for scanning and acquiring knowledge, building internal competence, and converting knowledge into applied innovation and production improvement.

OI provides the internal mechanism that often determines whether knowledge absorption yields sustained upgrading. OI, supported by leadership, human resource management, knowledge management, creativity, and innovation management, is argued to strengthen innovation performance and contribute to higher TC [24, 25]. OI can take many forms, including redesigning work processes, changes in decision authority, new collaboration arrangements, and revised incentive structures that encourage experimentation and learning. In defense firms, OI can be particularly difficult because of hierarchical structures, confidentiality constraints, and conservative risk cultures. However, it can be decisive in enabling cross-functional integration, accelerating learning cycles, and supporting the adoption of advanced manufacturing and digital technologies.

Importantly, despite the rapid growth of AC research, definitional ambiguity, construct validation challenges, and inconsistent empirical findings persist, motivating more structured empirical testing, particularly to clarify mediation mechanisms [5, 26]. These inconsistencies matter because they suggest that AC does not automatically translate into TC; rather, the translation likely depends on internal mechanisms that shape how knowledge is integrated and exploited. OI and TMC can serve as mediators. OI can explain how absorbed knowledge is converted into renewed processes and structures, whereas TMC can explain how technology choices, governance routines, and strategic alignment shape the conversion of knowledge and technology into operational and competitive outcomes.

In response to these theoretical and empirical gaps, the present study examines the effect of AC on TC in Indonesian defense industry firms, specifying OI and TMC as mediators. This approach tests both direct and indirect pathways to explain prior inconsistencies and illuminate the internal mechanisms through which INHAN can strengthen TC. The conceptual contribution lies in treating TC as a product not only of technology investment but also of a broader capability system in which knowledge absorption, organizational renewal, and technology governance jointly determine whether firms can sustain competitiveness under rapid technological change.

2. LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Literature review

TC in the global defense industry is widely viewed as a strategic prerequisite for safeguarding national security while also strengthening competitiveness with spillovers to civilian sectors, because defense firms are major sites for developing and deploying advanced technologies with cross-sectoral impacts [1]. Recent advances in cyber-physical systems, artificial intelligence, and robotics illustrate how defense technologies are increasingly embedded in operations to improve efficiency, precision, and resilience [2]. In this sense, TC is not merely equipment ownership; it is an organizational capacity to integrate technologies, create value and respond to rapid environmental change.

The defense industries are structurally characterized by high capital intensity, long R&D cycles, and economies of scale [27]. These features often do not align neatly with the comparative advantages of developing economies such as China. Nevertheless, defense production is typically treated as indispensable, so state support through protection and subsidies is frequently used to sustain domestic capabilities. Consequently, the defense industries operate at an institutional intersection where market pressures, security mandates, and technology-led industrialization agendas interact. This is directly relevant to INHAN, where rapid technological changes are reshaping competitive conditions. Digital transformation is increasingly unavoidable because it promises market expansion, improved stakeholder engagement and cost efficiency. Therefore, firms with stronger technological advantages may become pivotal in technology-driven competition [2-4]. However, outcomes depend strongly on internal capabilities, particularly AC, OI, and TMC, which determine whether technological turbulence produces upgrading or disruption.

INHAN firms face managerial paradoxes that complicate capability development. They are pressured to reduce costs while investing in AC, despite the fact that AC development is resource-intensive [5]. They are expected to accelerate production, even though OI can remain constrained by legacy routines and rigid structures [7]. They are also required to modernize, while TMC may be insufficient to design coherent technology strategies and business models that reliably convert technology adoption into performance gains [6]. These tensions elevate the business model as a coordination mechanism that aligns process redesign, operational practices, and resource allocation to capture opportunities in volatile environments [8].

Industry 4.0 technologies intensify both the pressure and opportunities. They are often framed as levers for sustained competitive advantage; without continuous investment, firms risk falling behind [28]. Under this framing, TC involves integrating technology across production and service operations, with cyber-physical systems and smart applications reshaping value chains and enabling data-driven production and analytics [2, 28]. However, defense firms often postpone upgrading due to concerns over data integrity and security and continued reliance on traditional management tools. Such delays can be costly because TC increasingly functions as a baseline condition for operational efficiency, revenue generation, and innovation outcomes [29]. This implies that firms should assess their readiness and capability maturity before launching transformation initiatives, and that strategy and business models should be designed to ensure that technology investments generate organizational value.

At the national level, INHAN is positioned as a pillar of self-reliant defense development: domestic firms supply multi-domain capabilities and collaborate with the government as strategic partners, while the technological complexity and contract scale of defense programs require strong managerial capacity [9]. Empirically, Indonesia's defense industry is often described as operating at an intermediate technological level, with state-owned enterprises and private actors producing and supplying equipment and platforms, including PT Pindad, PT Dirgantara Indonesia, PT PAL, and private shipyards such as Palindo and Lundin for fast patrol vessels [10, 11]. This suggests a meaningful industrial base but also a substantial scope for upgrading quality, autonomy, and system integration capability.

Upgrading efforts are frequently assessed through technology and manufacturing readiness because readiness determines the capacity for change, innovation, and testing from components to integrated systems. Common pathways include licensing, co-production, engineering modernization, joint development, and strengthening research facilities such as laboratories and prototyping centers, supported by universities and R&D institutions that reinforce basic-to-applied research linkages [12]. The broader "catching-up" logic, which combines foreign technology access with domestic capability accumulation, remains influential. At the firm level, the ability to acquire, assimilate, transform, and exploit external knowledge supports both exploitative and explorative innovation and can enable business model redesign for efficiency and novelty [22]. This reinforces the centrality of AC, not only as an internal learning asset but also as an institutionalized system of knowledge exchange and capability building across networks.

Theoretical grounding for these capability dynamics is often provided by RBT, which argues that resources and capabilities that are valuable, rare, difficult to imitate, and non-substitutable can generate sustained competitive advantage [13]. RBT emphasizes an inside-out logic: strategic planning should begin with the identification and development of internal resources and capabilities [30, 31], including continuous renewal and reconfiguration [32]. The VRIO framework operationalizes RBT by assessing whether resources are Valuable, Rare, Inimitable, and Organized to yield a sustained advantage [13]. However, when environments are dynamic, resource-based advantages can erode, motivating the use of a dynamic capabilities lens that emphasizes adaptation and reconfiguration in the face of technological change [17, 33]. In technology- and manufacturing-intensive organizations, the boundary between dynamic capabilities and TMC can be blurred because effective technology and innovation management is a primary channel through which firms capture opportunities and sustain competitiveness [15, 16].

Therefore, TMC is positioned as strategically decisive. Maintaining an advantage cannot depend solely on operational efficiency and cost minimization; rather, it depends on the ability to manage technological assets, evaluate and select technologies, and align technology investments with strategy [18]. Because technological development generates value only when it produces realizable organizational outcomes, TMC is essential in the defense industry, where technology choices are costly, security-sensitive, and path-dependent [19]. Within this framework, TMC functions as an organizational mechanism for selecting, integrating, and exploiting technology in ways that strengthen TC.

AC is equally foundational. It is classically defined as the ability to recognize, assimilate, and exploit external knowledge [20]. In defense settings, foreign technology transfer is often a critical input, and modernization programs may depend heavily on external knowledge and technology [1]. The key implication is that technology acquisition alone is insufficient: without adequate AC, technology transfer can deepen dependence rather than generate upgrading; conversely, strong AC enables the recombination of external and internal knowledge and supports domestic capability accumulation. Empirical work links AC with innovation and TC across multiple sectors, suggesting that it expands knowledge bases, improves the assimilation of future information, and supports technological innovation and capability development [5, 21-23].

TC, however, is multi-dimensional rather than a single attribute. Beyond innovative capacity, it includes broader efforts to absorb and build production-relevant knowledge, effectively use resources, and internalize foreign technology [34]. It is also conceptualized as integrative: firms must combine different technology streams and mobilize technological resources across organizational and national elements [35]. As a body of practical and theoretical knowledge, procedures, experience, methods, tools, and equipment, TC reflects heterogeneous technical resources linked to design technology, product technology, information technology, and the integration of external knowledge [36]. Its determinants include internal factors such as technical experts, engineers, and R&D capacity, and external factors such as government policy and intellectual property regimes [37]. Innovation stimuli, leadership, human resource management, knowledge management, creativity, and innovation management are frequently argued to be necessary for strong innovation performance and capability upgrading [24].

The literature also supports OI as a mechanism linking learning and technology outcomes. Empirical findings indicate that product, process, management, and administrative innovation can strengthen performance dimensions associated with TC, positioning OI as a mediator that converts absorbed knowledge into renewed processes, structures, and practices that enable capability upgrading [26, 38]. This is particularly relevant in developing-country defense industries, where organizational rigidities and policy discontinuities can impede the conversion of technology acquisition into durable capability building.

Finally, persistent research gaps justify the need for integrated modelling. Despite the rapid growth in AC scholarship, definitional ambiguity, construct validation challenges, and inconsistent findings remain [5, 39]. TC is path-dependent and cannot be replicated exactly because firms follow distinct trajectories, although learning can occur through experience and partner collaboration [40]. New knowledge creation also depends on existing capabilities and evolves through replication and recombination, making AC alone an incomplete explanation [5]. These arguments motivate models that test how AC translates into TC through internal mechanisms, particularly OI and TMC, rather than assuming a direct and automatic relationship.

2.2 Conceptual framework

Defense science and technology investment is widely framed as a strategic instrument for deterring threats, expanding policy options beyond direct warfare, and preserving stability by preventing escalations. It is also seen as strengthening responses to non-conventional threats, such as terrorism, and improving intelligence functions for national risk assessment. Accordingly, contemporary military capability is structurally dependent on scientific and technological progress, particularly in developing sophisticated weapons systems. Historically, since the 1940s, advanced economies have expanded R&D spending and built large-scale high-technology defense-industrial bases, treating technological superiority as central to defense effectiveness and R&D as a principal channel for accessing advanced technologies.

Therefore, the defense industry should be understood as embedded in the national economic system rather than as a stand-alone sector. Its production and exchange dynamics are intertwined with broader macroeconomic development, which means that defense industries must adapt to economic transformation agendas, including transitions from centralized and planned systems to more market-based arrangements. Such shifts are strategically consequential because they shape defense firms' ability to compete and stimulate innovation through evolving government–private sector relations [41]. Simultaneously, defense science, technology, and industry have distinctive strategic interests and development patterns, making strengthened management essential so that governance arrangements reflect national and military priorities while remaining grounded in domestic economic and technological realities through collective judgment and scientific evidence [29].

Changes in international relations and intensifying competition in high-technology domains have further pushed states to reassess their defense strategies and treat advanced technology as a key pathway for strengthening comprehensive national power and securing strategic initiatives. Historical experience suggests that states that can absorb and adapt to change are more likely to gain defense advantages, especially when they master high technologies relevant to defense systems [41]. However, a persistent paradox remains: although defense industries are often portrayed as engines of innovation that elevate national TC, many defense-originated innovations remain "locked" within defense ecosystems and are not widely recognized in civilian markets. For this reason, the literature emphasizes more deliberate communication about the defense industry's role in generating and disseminating new technologies [29].

Beyond applied development, defense industrial bases also invest in basic science research that can shape future capability trajectories. This includes materials and component innovations with potentially transformative effects, even without immediate commercial applications; commonly cited examples include gallium nitride for radar systems and advanced energy research expected to influence future strategic systems [42]. Therefore, sustained innovation is indispensable for national security and technological superiority. Because no stable "handbook" exists for future innovation, TMC is framed as an accumulated stock of knowledge and experience developed through decades of innovation practice, enabling organizations to navigate uncertainty and convert technological options into strategic outcomes [38, 43].

In this framework, TC extends well beyond technical mastery. It includes the ability to extend and diffuse core competencies, combine different technology streams, and mobilize technological resources across organizational and national elements [35]. It also encompasses practical and theoretical knowledge, procedures, experience, methods, tools, and equipment, as well as heterogeneous resources associated with design technology, product technology, information technology, and the integration of external knowledge [36]. These components are consistently linked to performance differences between organizations. Related work further connects higher science and technology levels to the importance of technology transfer and argues that valuation methodologies in defense contexts can strengthen bargaining positions and support more forward-looking budgeting for technology development [29].

Building on this literature, as shown in Figure 1, the conceptual framework positions AC as the central driver of OI, TMC, and ultimately TC. AC is defined as the ability to recognize the value of external information, acquire it, assimilate it, and apply it commercially; it is treated as cumulative and dynamic, such that a broader knowledge base enables the faster acquisition of additional knowledge [20, 25]. Therefore, empirical and conceptual studies treat AC as a foundational learning mechanism that shapes innovation and capability development [23].

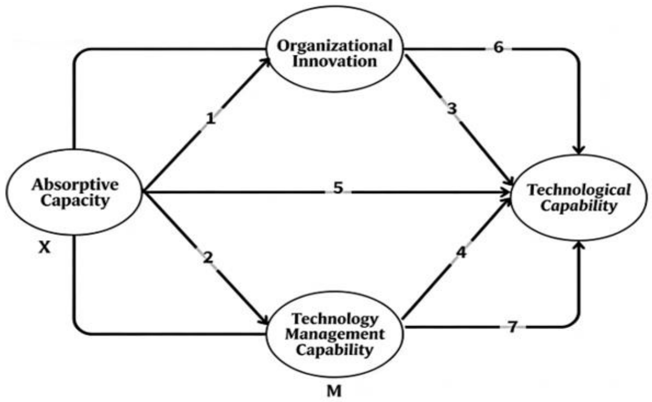

Figure 1. Conceptual framework

Following this logic, AC is expected to strengthen OI because organizations that can absorb new knowledge should be better able to translate it into renewed practices, processes, and structures [20]. Evidence also supports a positive relationship between knowledge-based capabilities and innovation outcomes, including product and process innovations [23]. AC is also expected to enhance TMC because the assimilation and application of external knowledge require organizational mechanisms, communication structures, and effective skill management [6]. In defense settings, where external inputs through technology transfer are often salient, effective absorption becomes even more critical for recognizing and leveraging external knowledge [1]. OI and TMC are expected to increase TC by accelerating organizational renewal, improving technology selection and deployment, and aligning technology use with performance objectives [29]. In addition, AC is expected to exert a direct effect on TC because capability upgrading involves recognizing opportunities, integrating new knowledge into the firm's knowledge base, and transforming stored knowledge into technological outcomes [20, 25]. Therefore, the model tests both direct and mediated pathways while acknowledging the growing overlap between innovation management and technology management, including the evolution of R&D laboratories and open innovation practices [44, 45].

3. RESEARCH METHOD

The study covered 54 firms classified within INHAN. Firm selection was not based solely on the Wikipedia list [46]; it also considered representation, resource constraints, operational diversity, accessibility, and data availability to maintain methodological rigor and capture variation in TC and innovation across different firm types and scales. Primary data were collected through a structured questionnaire and supplemented by interviews with a subsample of respondents. Secondary data were used to support the assessment of TC, drawing on internal company documents and relevant literature and peer-reviewed sources aligned with the study variables.

The study population comprised leaders, managers, and senior employees within 54 defense firms. In line with the definition of population as the full set of units whose characteristics are estimated [47], the population was operationalized as supervisor-, manager-, and director-level personnel, totaling 162 potential respondents in the sample. These groups were targeted because they are assumed to have the most informed perspective on firm strategy, resource allocation, technology adoption, innovation practices, and performance, and are more likely to have access to sensitive organizational information than other employees.

Purposive sampling, a non-probability approach that selects respondents based on criteria aligned with the research objective [48], was used. The eligibility criteria emphasized leadership position (supervisor/manager/director), responsibility for operational oversight or strategic decision-making, and at least five years of work experience. Although the initial design targeted 162 respondents, data screening was applied to improve the precision. After filtering by position, the dataset was reduced to 153 responses. Responses completed in less than two minutes were removed because pre-test evidence suggested that typical completion required 7–15 minutes, leaving 128 responses. Further screening excluded questionnaires with identical answers across all items, resulting in a final sample of 116 respondents. Data collection was conducted primarily via Google Forms to improve efficiency, allowing both online and offline completion to support objectivity.

The research instrument was a questionnaire using a five-point semantic differential scale, which was treated as interval data. Consistent with survey research practices, the questionnaire was administered in a standardized order; this approach also aligns with the broader definition of questionnaires that can include structured interviews and online formats [49]. Constructs were operationalized through indicators measured by multiple items, but the analysis was conducted at the indicator level rather than at the individual-item level. Following Hair et al. [50], indicators were considered closer representations of the underlying constructs; therefore, this study used indicator mean scores to represent each indicator, consistent with recommendations for instruments with many items [47]. This approach was intended to simplify the analysis, improve measurement stability, reduce measurement error, mitigate item-level bias via aggregation, support interpretation within a first-order model, and present results more clearly.

Instrument quality was assessed through validity and reliability tests. Validity is defined as the extent to which an instrument measures what it is intended to measure [51]. Because the model used reflective indicators, convergent validity was evaluated through outer loadings, applying a threshold of 0.70 for the item-to-construct correlations [52]. The Average Variance Extracted (AVE) was also used, with 0.50 as the minimum threshold for adequate convergent validity [52], and indicators with loadings below 0.70 were treated as failing validity–reliability requirements. Reliability was defined as the consistency of measurement across conditions [49]. Reliability assessment relied on composite reliability and internal consistency reliability (Cronbach's alpha), with alpha ideally above 0.70, while acknowledging that some perspectives treat values above 0.50 as minimally acceptable, albeit indicating low reliability [49].

Data analysis proceeded by treating measurement evaluation as a prerequisite for hypothesis testing, followed by structural model estimation using path analysis. The study adopted a first-order construct specification rather than a higher-order model to improve interpretability, align with the theoretical framing, reduce complexity, and lower the risks of overfitting and estimation error given the sample-size constraints. Hypothesis testing was conducted using Structural Equation Modeling (SEM) to support prediction and model testing, allowing the estimation of direct, indirect, and total effects among exogenous and endogenous variables [49]. SEM was positioned as an integrating factor analysis, regression, and path analysis, and was suitable for handling interactions, non-linearity, measurement error, correlated errors, and correlated latent variables measured with multiple indicators [53]. Mediation analysis was applied to clarify the mechanisms through which mediators explain the relationships between independent and dependent variables [47]. In PLS-SEM, SmartPLS algorithm and bootstrapping procedures provide direct effects, total and specific indirect effects, and total effects, enabling both single- and multiple-mediation tests [53].

The study employed variance-based, non-parametric PLS-SEM using SmartPLS because it does not require normality assumptions, supports models with many constructs and indicators, and is suitable for relatively small samples, such as the 116 respondents in this study. SmartPLS also relies on bootstrapping and is primarily prediction-oriented compared to covariance-based SEM, which is more confirmatory and typically assumes multivariate normality. The explanatory power of the inner model was assessed using R^2 values. As an initial step, a pre-test with 38 respondents was conducted to assess the instrument strength. Given the limited pre-test sample, SPSS 26 was used for validity testing via Pearson correlations and reliability testing via Cronbach's alpha [47]. The pre-test indicated that all indicators were significant at $p < 0.05$, and therefore valid. For the main sample size of 116, the critical r value at the 0.05 level was 0.183, and all the indicator correlations exceeded this threshold. Reliability was also supported, with Cronbach's alpha values above 0.70 for all variables, as reported in the SPSS output.

4. RESULT AND DISCUSSION

4.1 Results

This section reports the results of model testing in Indonesian defense industry firms to identify the determinants of TC. The analysis proceeds from respondent and indicator descriptive statistics to the assessment of the measurement model (convergent validity, discriminant validity, and reliability), evaluation of structural model adequacy, and finally path analysis for hypothesis decisions using SMART-PLS 4.0.

A total of 116 respondents were included in the final analyses. The respondent profile (Table 1) indicates a strong predominance of male respondents (107 respondents; 92.24%). In terms of organizational level, most respondents were supervisors (86 respondents; 74.14%), followed by managers (27 respondents; 23.28%), suggesting that the dataset largely reflects perspectives from the operational and middle management. The experience distribution reinforces this interpretation: the majority reported more than seven years of experience in the defense industry (101 respondents; 87.07%), pointing to relatively senior and contextually informed respondents. The age composition further indicates a mature workforce, with the largest group aged 41–50 years (45 respondents; 38.79%), followed by those over 50 (31 respondents; 26.72%), 31–40 (26 respondents; 22.41%), and 20-30 (14 respondents; 12.07%). Overall, these characteristics suggest that the responses primarily capture assessments from experienced personnel who are likely to be directly engaged in technology-related operations and decision-making processes in the defense industry.

Table 1. Respondent characteristic

Category	Sub-Category	Frequency	Percentage (%)
Gender	Male	107	92.24
	Female	9	7.76
Job level	Director	3	2.59
	Manager	27	23.28
	Supervisor	86	74.14
Industry experience	1-3 years	5	4.31
	4-7 years	10	8.62
	> 7 years	101	87.07
Age	20-30	14	12.07
	31-40	26	22.41
	41-50	45	38.79
	> 50	31	26.72

Source: Primary data processed (2024).

Descriptive statistics for the primary constructs show that respondents tended to provide high evaluations, with most responses concentrated on scale points 4 and 5. For AC, the indicator with the highest mean score was X1.9 (mean 4.319), while the lowest mean was X1.3 (mean 3.556). For OI, the highest mean was observed for X2.4 (mean 4.043) and the lowest for X2.1 (mean 3.836). For TMC, the highest mean was X3.17 (mean 4.216), whereas X3.15 had the lowest mean (mean 3.681). For TC, the highest mean was Y.1 (mean 4.263) and the lowest was Y.3 (mean 3.728). Taken together, these patterns indicate that respondents generally perceived their organizations as performing positively in knowledge absorption, innovation-related practices, technology management, and technology-related capability, although some indicators were assessed less strongly than others, suggesting non-trivial variability across dimensions, even within an overall positive perception trend.

The measurement model evaluation indicated that convergent validity was achieved through both AVE and outer loadings (Figure 2). AC achieved an AVE of 0.720, with all outer loadings exceeding 0.7. OI demonstrated an AVE of 0.837, with outer loadings above 0.7. TMC reached an AVE of 0.797 after model modification, which involved removing two indicators whose outer loadings did not meet the required criteria (X3.14 and X3.17). TC achieved an AVE of 0.801, with outer loadings greater than 0.7. These results suggest that the constructs adequately explain the variance in their indicators and that the reflective measurement specification provides sufficient convergent validity for subsequent structural testing.

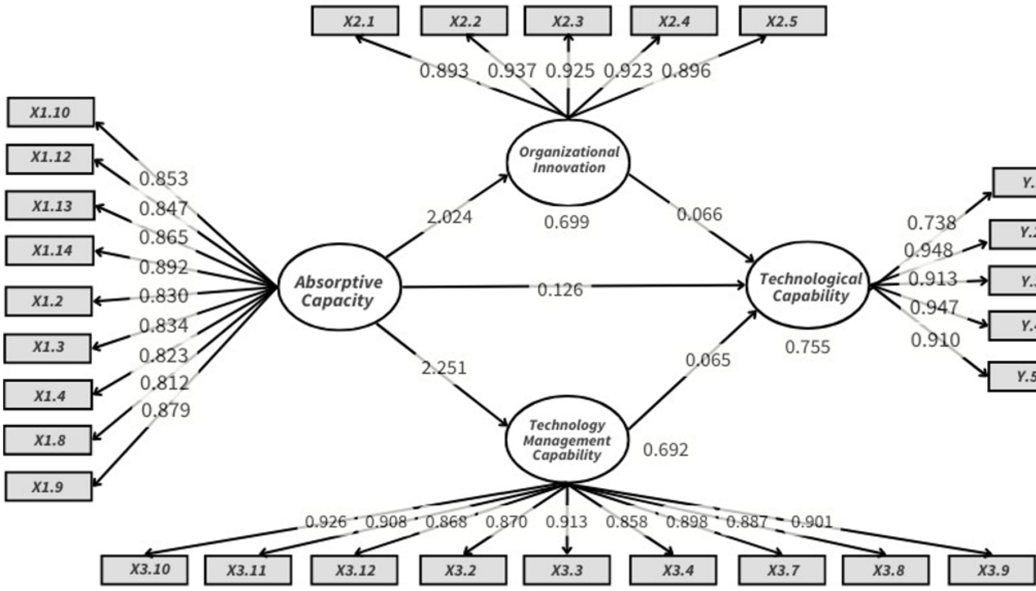

Figure 2. Outer loadings

Table 2. Reliability test result

Variable	Cronbach's Alpha	Composite Reliability (ρA)	Composite Reliability (ρC)
AC	0.965	0.966	0.969
OI	0.951	0.954	0.962
TMC	0.973	0.975	0.976
TC	0.936	0.944	0.952

Source: SmartPLS 4.0 (2024).
Note: AC = Absorptive Capacity, OI = Organizational Innovation, TMC = Technology Management Capability, TC = Technological Capability.

Construct reliability was found to be very strong across the model, as shown in Table 2. Cronbach's alpha and composite reliability values were well above the conventional threshold of 0.70 for all constructs: AC (α = 0.965; CR = 0.968), OI (α = 0.952; CR = 0.963), TMC (α = 0.963; CR = 0.967), and TC (α = 0.961; CR = 0.965). Such consistently high internal consistency indicates that the measurement instrument exhibits robust reliability in this context and provides a stable basis for inferences about the relationships among constructs.

Table 3. Fornell-Larcker criterion

	AC	OI	TC	TMC
AC	0.846			
OI	0.805	0.915		
TC	0.82	0.823	0.895	
TMC	0.832	0.885	0.829	0.892

Source: SmartPLS 4.0 (2024).
Note: AC = Absorptive Capacity, OI = Organizational Innovation, TMC = Technology Management Capability, TC = Technological Capability.

Discriminant validity was assessed using the Fornell–Larcker criterion (Table 3) and cross-loading. During this process, the model required adjustment because some indicators initially failed to meet the discriminant validity criteria, implying that they did not sufficiently distinguish one construct from another. To strengthen the empirical separability among constructs, several indicators were removed so that each construct could be demonstrated as more "unique" relative to its correlation with other constructs. Following these modifications, discriminant validity was considered satisfactory, supporting the interpretation that AC, OI, TMC, and TC represent empirically distinct constructs rather than overlapping measures of the same underlying dimension.

The structural model results indicate a strong explanatory power (Table 4). The R-squared value for OI was 0.669 (adjusted 0.666), and for Technology Management, it was 0.692 (adjusted 0.690). These values suggest that both constructs are strongly explained by AC in this model. TC demonstrated an R-squared of 0.755 (adjusted 0.749), indicating that a substantial proportion of variance in TC can be explained jointly by AC, OI, and TMC. The effect size evaluation (f-square) provides additional nuance. AC exhibited a very large effect on OI (2.024) and TMC (2.251), while its effect on TC was small-to-moderate (0.126). The effects of OI and TMC on TC were comparatively small (0.066 and 0.065, respectively). This pattern implies that AC is the dominant driver for the two mediating constructs and that TC is shaped by both direct and mediated pathways, although each mediated pathway contributes a modest incremental explanatory influence.

Table 4. Structural model strength

Variable	R-Square	R-Square Adjusted
OI	0.669	0.666
TMC	0.692	0.69
TC	0.755	0.749

Source: SmartPLS 4.0 (2024).
Note: AC = Absorptive Capacity, OI = Organizational Innovation, TMC = Technology Management Capability, TC = Technological Capability.

Model fit indices were also reported to indicate whether the estimated model achieved an acceptable level of fit within the PLS-SEM context. The standardized root mean square residual (SRMR) was 0.060 for the saturated model and 0.083 for the estimated model. The normed fit index (NFI) declined slightly from 0.656 (saturated) to 0.649 (estimated) in the revised model. These values indicate that the model remains within an acceptable range for PLS-SEM applications, where fit indices are typically interpreted more cautiously than in covariance-based SEM and where predictive and explanatory performance is often the primary objective.

Table 5. Path coefficients

Relationship	Original Sample (O)	Sample Mean (M)	Std. Dev. (STDEV)	T-Statistics (|O/STDEV|)	P-Values
AC -> OI	0.818	0.819	0.03	27.295	0
AC -> TMC	0.832	0.833	0.027	30.55	0
OI -> TC	0.287	0.284	0.111	2.594	0.005
TMC -> TC	0.297	0.304	0.118	2.524	0.006
AC -> TC	0.334	0.33	0.093	3.59	0
AC -> OI -> TC	0.235	0.233	0.091	2.581	0.005
AC -> TMC -> TC	0.247	0.254	0.1	2.47	0.007

Source: SmartPLS 4.0 (2024).

Note: AC = Absorptive Capacity, OI = Organizational Innovation, TMC = Technology Management Capability, TC = Technological Capability.

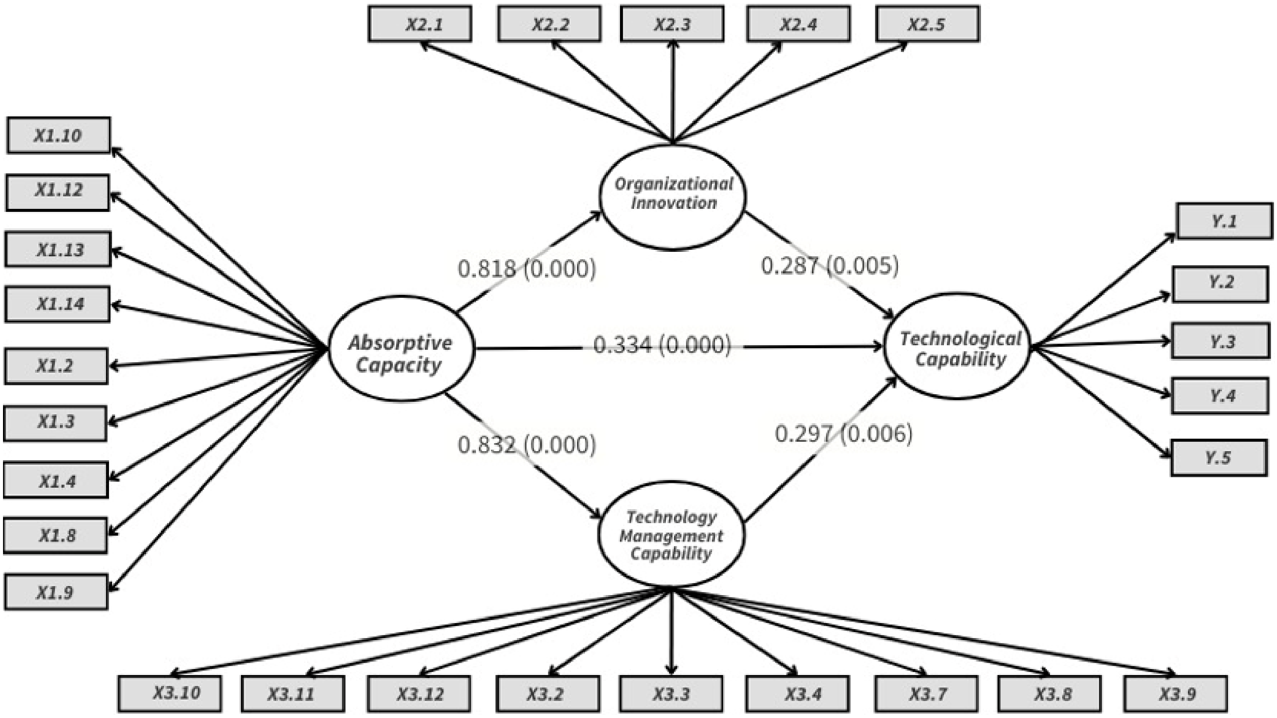

Figure 3. Path coefficient

The path analysis results show that all tested relationships were statistically significant and that all hypotheses were supported (Table 5). AC had a positive and significant effect on OI (β 0.818; T 27.295; p 0.000) and on TMC (β 0.832; T 30.550; p 0.000). OI had a positive effect on TC (β 0.287; T 2.594; p 0.005), and TMC also positively influenced TC (β 0.297; T 2.524; p 0.006). Additionally, AC had a direct positive effect on TC (β 0.334; T 3.590; p 0.000). Mediation tests confirmed that the indirect effect of AC on TC through OI was significant (β 0.235; T 2.581; p 0.005), and the indirect effect through TMC was also significant (β 0.247; T 2.470; p 0.007). Collectively, these findings indicate that AC strengthens TC both directly and indirectly by fostering OI and TMC as internal mechanisms of capability translation. This result is also illustrated in Figure 3.

4.2 Discussion

The hypothesis discussion emphasizes the centrality of AC in defense industry capability development. The significant effect of AC on OI supports the argument that organizations that can identify, assimilate, and apply external knowledge are more likely to innovate in internal processes and decision-making. This interpretation aligns with the foundational view of AC as a determinant of the ability to convert knowledge into innovative outcomes [20, 23]. The significant effect of AC on TMC further indicates that higher levels of absorption are associated with a stronger capacity to plan, coordinate, control, and exploit technology, which is consistent with the need for dynamic capability in managing technology in the defense sector, where sensitivity to technological advances is exceptionally high [6].

The effect of OI on TC is interpreted as evidence that innovation functions as an internal renewal mechanism that updates processes, working methods, and strategies, enabling organizations to respond more quickly to technological change. In the context of defense, the implication is that firms capable of generating and implementing OI are more likely to build an adaptive and competitive technological base, consistent with the view that innovation provides leverage for technology mastery and technological development [54]. The mediation results provide a crucial process-level interpretation. Even though AC exerts a meaningful direct influence on TC, both OI and TMC remain significant mediating pathways, clarifying how absorption is translated into technological outcomes. The discussion also notes that the mediated pathway via OI appears weaker than the direct effect of AC, suggesting that the role of OI in converting absorption into TC may still require strengthening in the Indonesian defense industry setting.

Beyond hypothesis testing, the results were used to motivate a theoretical proposition described as "Defense Technology

Integrative Capability Theory (DTICT)." DTICT is framed as an integrative approach that combines AC, OI, and TMC to explain improvements in TC in technology-intensive and highly competitive defense environments. The core premise is holistic: internal resource strengthening and strategic integration with external capabilities are required to produce sustainable innovation and effective technology management, enabling organizations to treat rapid change as an opportunity through strategic adaptation. The practical implications follow directly from this capability theory. Defense firms are encouraged to invest in continuous training and learning to remain aligned with global technological developments while ensuring that the adopted technologies are systematically managed and integrated into day-to-day operations. The discussion also highlights the importance of local–international strategic partnerships to access knowledge and technology, the need to strengthen innovation culture, the management and retention of talent, more agile business model adjustment, intellectual property protection, and systematic evaluation of technology management performance.

Finally, the study acknowledges the limitations that constrain generalization and points to directions for future research. Limitations include time and resource constraints, restricted data access due to defense industry confidentiality policies, and limited participation from senior executives. The study also did not cover the full spectrum of potential determinants of TC, such as market dynamics, long-term human capital sustainability, and broader external conditions, including national defense policy, regulatory regimes, bilateral relations, and global geopolitical change. These constraints imply that future work could extend the model by incorporating multilevel determinants and external contingencies while also strengthening data access strategies and sampling coverage to enable more comprehensive inferences about capability building in the defense industry.

5. CONCLUSION

This study concludes that AC makes a substantive contribution to strengthening OI and TMC within INHAN. Organizations with stronger AC are more capable of integrating novel ideas into their existing knowledge base, thereby reinforcing innovation in an industrial sector characterized by technological complexity and high coordination demands. Moreover, AC enables firms to assimilate and apply externally sourced knowledge and technologies more efficiently, which in turn improves the effectiveness of technology-related decision-making and optimizes TMC. Future research should strengthen collaboration with public institutions and industry associations with wider authority and access, such as the Ministry of Defense, state-owned enterprises, and relevant industry associations, to obtain more comprehensive datasets. Future studies should also employ in-depth case studies of defense firms that have successfully improved OI and TC to derive actionable lessons while exploring how international partnerships can be leveraged to strengthen AC, OI, and TC. A comparative analysis with countries facing similar constraints or those that have successfully upgraded their defense capabilities would be valuable for identifying strategies that can be adapted to Indonesia. Finally, assessing the socio-economic impacts of innovation and TC upgrading, including contributions to economic growth, employment creation, and infrastructure development, is important to capture the broader returns on investment in INHAN's TC.

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