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**Diffusion Requirements of Military AI:
How the United States are meeting
the Ecosystem Challenge**

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I. Introduction

"We have perhaps driven men into the service of the machine, instead of building machinery for the service of man."
- Antoine de Saint-Exupéry

Artificial intelligence (AI) is widely recognised as a general-purpose technology (GPT) with the potential to impact various aspects of human activity, driving innovation and reshaping the economic and security landscape. This global recognition of AI's strategic importance has initiated a race for supremacy in economic and military realms as states strive to harness its potential for power and influence in the international arena (Friedman 2022, 2). Besides ongoing research, the integration of this novel technology into the military domain is already underway. As with previous transformative technologies, strategic studies have sparked a debate on the potential strategic implications of AI, with discussions centring around its prospect to drive the next Revolution in Military Affairs (RMA) (Raska 2021, 456).

The ability for technological innovation has always been closely tied to international influence and national power, encompassing economic competitiveness, political legitimacy, military strength, and internal security (Raska and Bitzinger 2023, 2). Military innovation is, therefore, a key topic in International Relations research. Scholars interested in the distribution of military power have focused on how states seek to gain advantages over competitors by developing new methods of generating military superiority (Johnson 2022, 478). Finding new ways to inflict violence and exert power materialises in military innovations, which was driven by the traditional defence sector (Bitzinger and Raska 2015, 129; Horowitz 2010, 18).

But the diffusion of AI technology is fundamentally different from past experiences (Raska and Bitzinger 2023, 1). This is due to two reasons. First, Western countries in general, and the U.S. in particular, were leading in the development of cutting-edge military technologies between the 1970s and 2010s. Following diverse paths and patterns, these advancements were then disseminated to allies and strategic partners, including smaller and middle powers in Europe and East Asia (Raska 2020). But after decades of its military-technological supremacy, the U.S. now finds itself confronted by China as a strategic peer competitor with its own rapidly advancing military capabilities and novel technologies, with AI being at the forefront (Johnson 2021; Mahnken 2012). Second, the current wave of AI-enabled technologies represents a significant shift in military innovation itself, with the prominence of commercial-technological advancements playing a substantial role in shaping the development of weapons platforms and systems (Raska 2016). This allows small states and middle powers to develop niche AI technologies that enhance their defence capabilities and bolster their economic competitiveness, political influence, and standing on the global stage (Barsade and Horowitz 2018). As a consequence, military forces worldwide are actively pursuing the integration of AI into their system portfolio, aiming to gain a distinct competitive edge over their adversaries (Raska and Bitzinger 2023, 3).

It is commonly assumed that AI will lead the next RMA (Raska and Bitzinger 2023a) but a theoretically informed analysis of the military AI innovation process is yet missing. On the one side, research on how militaries innovate and innovations diffuse has yielded several distinct theories but solely focused on innovation within the traditional industrial defence sector. On the other, scholars focusing on innovation trajectories regarding military AI have not made use of existing theorisation and treated AI not as a GPT like electricity but as a relatively narrow technological advance similar to nuclear weapons or aircraft carriers (Ding and Dafoe 2023, 1).[1] This finding is rather puzzling given its importance and broad impact described above. Therefore, the thesis aims to address those shortfalls by bringing these research streams together. It employs a theory-driven analysis and seeks to address the following question:

How does a state successfully develop and integrate military AI?

This study proceeds as follows. First, the literature on military innovation, innovation diffusion, and military AI will be summarised to carve out shortfalls. Second, the theoretical framework is explained. This part entails an introduction to the concept of GPTs, a summary of the used theory, its transformation into a causal mechanism, and the theoretically informed definition of scope conditions. Third, it is explained how far AI qualifies as GPT and what is meant by military AI. Fourth, the research design, the methodology (theory-testing process tracing) and the data selection are outlined. Fifth, a population of cases will be created, out of which a case will be selected. This will be followed by the empirical analysis. Finally, this study concludes by discussing the findings and its limitations.

II. Literature Review

The following literature review summarises the military innovation, innovation diffusion, and military AI research landscape to shed light on the current state of research and its flaws. The

[1] A more detailed literature review will be conducted in Chapter II.

review of military innovation research demonstrates that scholars often lacked both a clear picture of what military innovation actually is and that important factors for a state's ability to innovate were disregarded. Newer research in the field of innovation diffusion yielded promising theoretical frameworks which capture innovation as a process but were not designed for nor tested on GPTs such as AI. In the field of military AI, scholars mainly focused on questions related to the distribution of power, governance, international law, and ethics. Novel studies indeed examined military AI innovation trajectories but were merely descriptive.

A. Innovating in the Military Realm

Research on how militaries innovate has yielded several distinct theories. Four main schools of thought can be identified: civil-military relations, interservice politics, intraservice politics, and organisational culture (Grissom 2006, 908). Each school offers its explanatory model of military innovation, identifying key factors that determine whether a military organisation will innovate. The first school argues that innovation requires statesmen to intervene in the development of military doctrines from within the service (Posen 1984). The interservice model focuses on the relationship between different military services within a state. It posits that resource scarcity catalyses innovation since it yields competition (Armacost 1969; Sapolsky 1972). The third school emphasises that military innovation often involves competition between established and new branches that adopt new military capabilities (Rosen 1991). Supporters of the cultural model argue that culture sets the context for military innovation by inherently shaping an organisation's reactions to technological and strategic opportunities (Farrell 2005).

Those theories were individually applied to cases of technological innovation (Beard 1976; Campbell 2003; Davis 1967) but entail two major flaws. First, they only focus on innovation within the traditional defence sector in a closed technological innovation system (Cronin 2020, 19). They are not designed to include commercially developed GPTs like AI in today's era of open technological innovation (Cronin 2020, 73). Second, they only describe the drivers for innovation but do not treat innovation as a process with multiple steps like development and integration (Horowitz and Pindyck 2023). The process of innovation was rather taken as given.

Newer theoretical work in the field of military innovation diffusion sheds light on the process of military innovation by refining traditional approaches. The main schools of thought, namely the neorealist, the sociological institutionalist, and the cultural approach, can only answer when states decide to innovate and assume that a state's decision to do so will automatically lead to success (Goldman and Eliason 2003; Horowitz 2010; Waltz 1979; Wendt and Barnett 1993). In contrast, the Adoption Capacity Theory (ACT) and the Ecosystem Challenge (EC) integrate innovation requirements and therefore attempt to explain diffusion dynamics. The ACT developed by Horowitz focuses on two key factors, namely financial intensity (costs for innovation) and organisational capital (bureaucratic changes necessary for adopting an innovation). The EC was established by Gilli & Gilli and draws upon management literature. They argue that the effective integration and use of military innovations hinge upon meeting the platform and the adoption challenge (Gilli and Gilli 2016, 56). The ACT and the EC represent matured theoretical frameworks which are useful not only in the research stream of innovation diffusion but for innovation research itself.

B. Military AI in the International Relations Literature

Research on military AI is young and steadily growing. In the field of military AI politics, the majority of scholars tend to reflect realist and traditional strategic studies perspectives, with a focus on the impact of AI on military capabilities and the global balance of power (Ayoub and Payne 2016; Haas and Fischer 2017; Horowitz 2019; Jensen, Whyte, and Cuomo 2019). Existing approaches typically view military AI as tools that enhance or alter capabilities and as potential game-changers in terms of states' military power. In the case of governance research, the literature body is rather narrow (Fischer and Wenger 2021). Here, scholars mostly concentrated on AI-enabled autonomy in weapons systems and its regulation (Kralingen 2016). Further focus has been put on the intersection between military AI and international law, raising questions about the applicability of current norms (Bode and Huelss 2018; Garcia 2016). A more popular research stream engages in the discussion about ethics and the use of military AI (Clancy, Bode, and Zhu 2023; De Swarte, Boufous, and Escalle 2019; Hagendorff 2020).

Few works have concisely addressed military AI innovation trajectories. The book *The AI Wave in Defence Innovation: Assessing Military Artificial Intelligence Strategies, Capabilities, and Trajectories* offers an international and interdisciplinary viewpoint on the adoption and governance of AI in military innovation, focusing on the perspectives of major and middle powers (Raska and Bitzinger 2023b). In a similar vein, individual state-focused case studies have been conducted. The Defense AI Observatory (DAIO), a project of the Helmut Schmidt University, systematically analyses policy, development, organisation, funding and implementation of military AI of various states within their papers (Schaal 2023). Those studies always followed a case-centric approach. No cross-case analysis has been conducted. Yet, no study systematically examined the development and integration of military AI based on theories but were merely of descriptive nature.

This literature review concisely depicts the current state of research in military innovation, innovation diffusion, and military AI, along with their weaknesses and shortfalls. Military innovation scholars have mainly focused on technologies which were developed in a closed innovation system and failed to see innovation as a process. Newer theories of the diffusion of military innovation were able to refine former approaches but were not tested on commercially developed and software-based GPTs. Finally, research focusing on innovation trajectories regarding military AI has not made use of existing theorisation. This study attempts to do precisely this. In the upcoming chapter, a theoretically informed process will be established which aims at shedding light on how a state develops and integrates military AI.

III. Theoretical Framework

To systematically analyse military AI innovation, a theory which can incorporate GPT characteristics is needed. The ACT is deemed insufficient here since its factor of financial intensity rests on the assumption that merely devoting financial resources will translate into innovation (Horowitz et al. 2019, 191). Therefore, the Ecosystem Challenge will serve as the theoretical foundation. Gilli & Gilli developed the EC to account for technological complexities involved in developing military technology and additional financial and organisational obstacles posed by the essential material support these technologies require, factors that have been disregarded in previous research (Fischer, Gilli, and Gilli 2021, 225; Gilli and Gilli 2016, 55, 58). It is designed to account for all military technological innovations and will be adjusted to GPTs to allow for developing a consistent causal theory and mechanism. In what follows, the concept of GPTs will be introduced. Then, the EC will be discussed in more detail in order to derive a causal theory and mechanism along with the necessary scope conditions.

A. The Concept of General-Purpose Technologies

Before the theory is discussed in more detail, clarification on the concept of GPTs is needed for the EC to be adjusted. Economists and historians generally concur on three defining criteria (Ding and Dafoe 2023, 4). First, GPTs possess significant potential for continuous improvement, surpassing other technologies in their capacity for adaptations and modifications. As agents learn and develop technologies, it is common for widely used technologies to undergo a process of improvement and evolution in various forms (Lipsey, Carlaw, and Bekar 2005, 97). Second, GPTs are characterised by the potential for pervasive use, encompassing a diverse range of applications (Bresnahan and Trajtenberg 1995, 84; Lipsey, Carlaw, and Bekar 2005, 97). Lastly, GPTs display strong technological complementarities, implying that their maximum benefits are realised through adjustments in related technologies (Ding and Dafoe 2023, 4). Accordingly, a GPT's adoption can be understood as a "[…] trajectory of incremental technical improvements, the gradual and protracted process of diffusion into widespread use, and the confluence with other streams of technological innovation" (David 1990, 356).

B. The Ecosystem Challenge

Gilli & Gilli developed the EC as a theoretical framework to explore the conditions under which the diffusion of military technology occurs quickly and widely and when it does not. As noted in the previous section, the EC is composed of two key factors, the platform and the adoption challenge (Gilli and Gilli 2016, 56). They will be further discussed in subsequent subsections to provide a more comprehensive understanding.

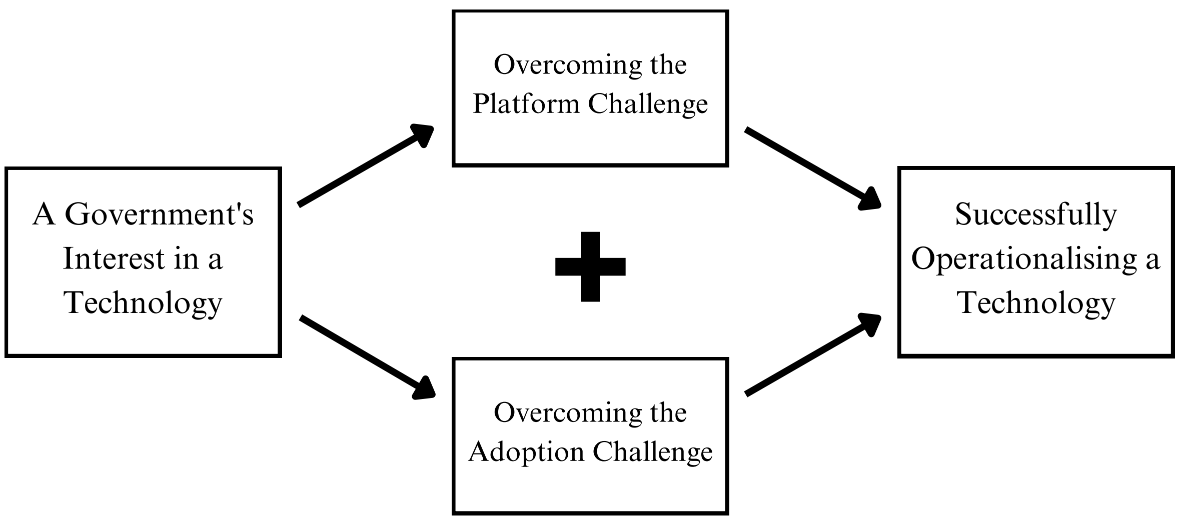
The platform challenge implies that designing, developing, and manufacturing military technology entails technological and industrial challenges (Gilli and Gilli 2016, 56). The level of difficulty in introducing a new technology depends on two factors. First, it is influenced by the capabilities of the technology itself, encompassing their technological advancements. Developing a technology becomes more challenging when it possesses specific features. Second, a state's potential for technological innovation relies on its technological capacity. Simply put, the more demanding the technology, the more unique and challenging the required capacity becomes (Gilli and Gilli 2016, 58).

Through the adoption challenge, Gilli & Gilli capture existing research identifying organisational constraints and add infrastructural challenges which were previously disregarded (Gilli and Gilli 2016, 58). To fully capitalise on a technology requires the development of appropriate codes, practices, doctrines, and a competent workforce organised in suitable formats (organisational challenge) (Gilli and Gilli 2016, 59). The salience of the organisational challenge depends on whether a state already possesses the organisational structure necessary for adopting a specific innovation, has to undertake bureaucratic reforms, or has to start from scratch (Gilli and Gilli 2016, 59). Additionally, innovations require infrastructure support (infrastructural challenge). Similar to the organisational challenge, the degree of difficulty for a state to adopt a technology depends on whether a state already has the necessary infrastructure or needs to acquire capabilities or develop everything from scratch. The greater the need for adaptation, the bigger the challenge is.

C. Building a Causal Theory

While the EC has been tested on individual military systems, the formulation and the derived hypothesis of this theory are not describing a concrete process but are probabilistic in nature.[2] This study is aiming at understanding the process of developing and integrating military AI. It is, therefore, necessary to reformulate the EC into a causal theory in a first step (Beach and Pedersen 2013, 108). The independent variable is a state's interest in adding a technology to its military portfolio since a process to develop and integrate technology logically departs from this point. The intervening variables are overcoming both the platform challenge and the adoption challenge, which, according to the EC, leads to the successful development and integration, i.e. operationalisation of the technology (Gilli and Gilli 2016, 56).[3] The causal theory is illustrated in Figure 1.

Figure 1: A Causal Theory derived from the Ecosystem Challenge



Own visualisation, modified and adapted from Beach and Pedersen (2013)

D. Building a Causal Mechanism

To analyse the process in question, it is necessary to reconceptualise the causal theory as a causal mechanism (Beach and Pedersen 2013, 110). This approach allows for studying "[…] the dynamic transmission of causal forces through the mechanism to produce the outcome"

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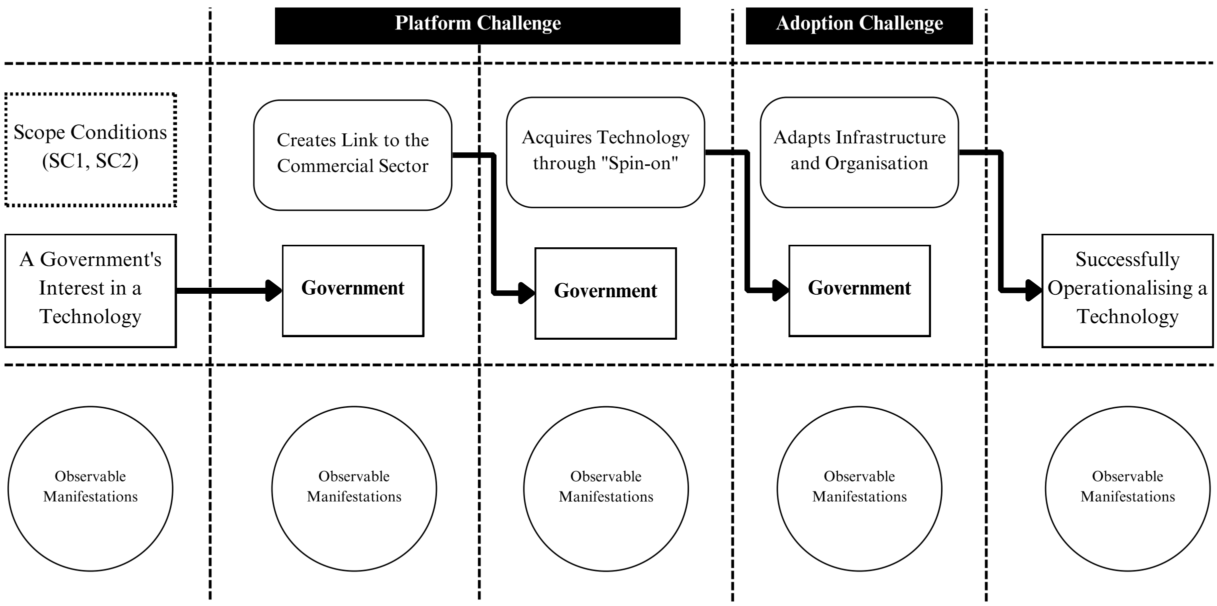
[2] It is noteworthy that the authors label both the platform and the adoption challenge as causal mechanisms (Gilli and Gilli 2016, 1), which differs from the definition used in proper process-tracing (Beach and Pedersen 2013, 57).

[3] The outcome cannot be defined in strict set-theoretic terms due to the nature of GPTs and the comparatively young age of the AI, which will be discussed in more detail in Chapter VI.

(Beach and Pedersen 2013, 110). Gilli & Gilli have not conceptualised the process by which a state overcomes the individual challenges. What's more, Gilli & Gilli, in line with previous scholars, only briefly mentioned commercially driven technological inventions and their distinct characteristics but failed to systematically include them in their work. To be able to deduce a causal mechanism, additional theoretical research will be included to flesh out each individual step along with the necessary scope conditions in an inductive fashion (Beach and Pedersen 2013, 56).

In this study, the causal theory is reconceptualised as a three-step mechanism, taking into account GPT characteristics. To start, a government is interested in adding a GPT to its military portfolio. It then establishes a link to the commercial sector of interest. Next, it solves the platform challenge by "spin-on", i.e. the flow of technology from the civilian to the military sphere. In a third step, a government then meets the adoption challenge by establishing the necessary infrastructure for a GPT, and a government adapts its military organisation to capitalise on the potential of the technology. Those steps are distinct but can take place simultaneously as "[o]rganizational and infrastructural requirements are […] two sides of the same coin" (Gilli and Gilli 2016, 59). In sum, this should lead to the outcome. The complete mechanism is depicted in Figure 2. In the following, the theorised mechanism is discussed in more detail.

Figure 2: A Causal Mechanism derived from the Ecosystem Challenge



Own visualisation, modified and adapted from Beach and Pedersen (2013)

1. The Independent Variable: A Government's Interest in a GPT

As discussed in previous chapters, a government's wish to introduce a GPT into its military represents a logical starting point for the process in question. As noted in the introduction, states compete to develop the most advanced military technologies possible (Brodie and Brodie 1973, 6; Dupuy 1984, 199). Returning to Gilli & Gilli, the technological capacity needed for the development of a technology depends on whether a state possesses the necessary qualified workforce as well as an advanced technological and industrial base with appropriate laboratories, testing and production facilities, and accumulated experience and know-how (2016, 57). According to Ding & Dafoe, the momentum for GPT's development lies in the civilian realm, not within the traditional defence sector (2023, 2). The wide-ranging applicability of GPTs across various sectors, coupled with the greater number of potential application scenarios in the civilian economy compared to the military domain, accounts for this characteristic (Ding and Dafoe 2023, 7). Hence, militaries "[…] must draw on talent, industry, and infrastructure in the civilian realm" (Ding and Dafoe 2023, 2).

2. Meeting the Platform Challenge

a) Establishing a Link to the Commercial Sector

To be able to draw from the technological capacity which is to be found in the civilian realm and to introduce a GPT into its military sphere, a government must create a link to the commercial sector (Ding and Dafoe 2023, 7). This link should serve two purposes. First, it should foster mutual information exchange between commercial developers, governments, and military end-users. This is due to the fact that possible military application scenarios for GPTs are hard to predict (Ding and Dafoe 2023, 5). Use cases potentially differ between the military and the civilian sphere, and commercial developers do not precisely know what military end-users need, as the GPT is developed for civilian applications. In a similar vein, the governmental side lacks the technological knowledge concentrated in the commercial sector and should therefore have no clear image of how the GPT could be used concretely. In order to get a better understanding of how a GPT can actually help improve military capabilities, a platform for information exchange is needed. This mutual exchange of information between developers and end-users lays the foundation for project initiation being the second purpose, thus leading to the next step.

b) Technology "Spin-On"

Governments were able to better understand a GPT by creating links to commercial players. With the gained knowledge, it is now possible to initiate projects together with commercial companies, leading to the actual development of military technology. Besides traditional ways of developing military capabilities within a closed innovation system, this way of pursuing innovation in an open system allows for a so-called "spin-on", being the techno-military paradigm referring to the process of adapting technologies initially designed for civilian or commercial purposes for military or defence-related use (Samuels 1994, 18, 26; Stanley-Lockman 2021, 487). This solves the platform challenge, which, according to the EC, leads to the adoption challenge, comprising both infrastructural and organisational challenges (Gilli and Gilli 2016, 58).

3. Meeting the Adoption Challenge

a) Infrastructure Development

According to Gilli & Gilli, "[a]ny innovation needs some sort of infrastructural support" (Gilli and Gilli 2016, 60). It is therefore theorised that a government needs to create appropriate infrastructure, or a "platform ecosystem" (Stanley-Lockman 2021, 488), to be able to introduce a GPT into its military. This allows for continual development, which is a characteristic of GPTs as enabling technologies (Ding and Dafoe 2023 4; Stanley-Lockman 2021, 488).

b) Organisational Adaptation

In addition to creating the necessary infrastructure, a government is required to develop appropriate codes, practices, doctrines, and a competent workforce organised in suitable formats (Gilli and Gilli 2016, 59). To make a case for GPTs, successful organisational adaptation should require the government and the military to accommodate civilian-guided GPT development practices (Ding and Dafoe 2023, 7). Further, GPTs will have various applications within the entire military (Ding and Dafoe 2023, 5). Implementing such a technology therefore happens throughout the whole military organisation, and the decision to do so is inherently top-down (Horowitz and Pindyck 2023, 101-102).

E. Scope Conditions

Next, the boundaries of applicability of the causal mechanism will be theorised by defining the specific context in which the mechanism is expected to operate (Falleti and Lynch 2009; Walker and Cohen 1985). This is crucial since the same causal mechanism can potentially yield different outcomes when applied in distinct contexts (Falleti and Lynch 2009, 1160). In order for the depicted causal mechanism to function, two interconnected scope conditions are theorised to be necessary. First and rather self-explanatory, a GPT must have been developed by the commercial sector (SC1). Just if that is the case, a government can actually create interest in this technology and needs to create a link. Ding & Dafoe implicitly assume a GPT's development (2023). The second condition (SC2) is connected to the state of a given innovation ecosystem. Ding & Dafoe argue that an industrial base out of which a GPT arose has to be robust (Ding and Dafoe 2023, 2, 3, 7). A government must be able to draw on a wide base of "[…] engineering talent, rather than star researchers or cutting-edge technical capabilities […]", which is crucial for adapting GPTs to a variety of specific military applications (Ding and Dafoe 2023, 18).

IV. The GPT of Interest: Artificial Intelligence

This chapter aims to identify AI as a GPT and provides a comprehensive overview of military use cases. To count as a GPT, AI must have potential for continuous improvement, be characterised by the potential for pervasive use, and display technological complementarities. The analysis shows that AI meets all three criteria. Military AI involves the development and deployment of AI systems to enhance various aspects of military operations, including intelligence gathering, surveillance, threat detection, decision-making, information warfare, and autonomous systems, thus encompassing a wide range of possible applications. Overall, military AI aims to augment human capabilities, improve operational efficiency, enhance decision-making processes, and increase overall defence capabilities.

A. How AI meets the GPT Criteria

AI possesses significant potential for continuous improvement. This technology is constantly evolving (Hao 2018). As Zachary Lipton puts it, AI "is aspirational, a moving target based on those capabilities that humans possess but which machines do not" (Iriondo 2018). This is also captured in the understanding of what AI actually is. A well-known and vastly cited definition comes from Andrew Moore, former Dean of the School of Computer Science at Carnegie Mellon University and Director of Google Cloud AI. In an interview with Forbes, he defined AI as "the science and engineering of making computers behave in ways that, until recently, we thought required human intelligence" (Moore 2017). Therefore, AI fulfils the first criterion of GPTs.

AI technology has a diverse range of applications. Literature suggests two categories of AI, narrow and general.[4] The former, also "modular" or "weak" AI (Ayoub and Payne 2016), refers to the AI machine which can learn and self-program but only perform a narrow or specialised range of activities. General AI, or Artificial General Intelligence (AGI), is commonly understood as a system able to mimic human awareness and to make decisions concerning multiple domains (Tangredi and Galdorisi 2021). Notwithstanding the debates questioning its usefulness, most researchers agree that there is no clear path to creating AGI in the near future, making narrow AI the current developmental stage of AI systems (Dickson 2023). Following this broad understanding, current AI involves the development of specialised computer programs that perform various narrowly defined tasks by imitating human intelligence with the same, or greater, proficiency as a human (Dickson 2023). In the commercial sector, AI is being used in various industries beyond computer science, including fields like structural biology, transport, and imaging (Cockburn, Henderson, and Stern 2018). Returning to military AI, current applications and research and development (R&D) projects regarding AI-driven systems concern narrow AI (Scharre 2019). Consequently, AI also meets the second criterion.

Lastly, AI displays strong technological complementarities. AI technologies complement and rely on secondary innovations like cloud computing and big data, which provide greater access to larger and more affordable datasets (Brynjolfsson, Rock, and Syverson 2017). Moreover, due to the shared underlying structures and information exchange capabilities of diverse AI systems, advancements in one application of machine learning, such as machine vision, can drive innovations in other domains like autonomous vehicles (Hötte et al. 2022, 11). AI also fulfils the third criterion and can therefore be identified as GPT.

B. What is Military AI?

Commercial AI application possibilities are diverse, and so are the ones in the military domain. Following Rickli and Mantellassi (2023), fields of application regarding this emerging technology can be divided into three categories. First, AI can serve as an analytical enabler due to its ability to analyse large amounts of data (Sayler 2020). This is particularly useful in the field of Intelligence, Surveillance, and Reconnaissance (ISR) known to be prone to "data overload" (Morgan et al. 2020). AI systems not only process more data than humans but are

[4] Some scholars go even further in dividing AI into three or more subcategories, adding „simple" AI as its most basic form, or "super" intelligence capable of providing intelligence that is beyond human capability as AI's highest stage of development (see Tangredi and Galdorisi 2021; Jindala and Sindhu 2022).

also able to uncover hidden correlations. As data grows and diversifies, centralising, analysing, and presenting information concisely is crucial for decision-making. In the fast-paced realm of warfare, AI plays a vital role in empowering platforms to effectively assist decision-makers (Dam 2020). Second, AI can be used as a disruptor. It automates and assists in the production and spread of online disinformation and is capable of undermining trust in democratic institutions and fostering confusion and polarisation. Advances in Natural Language Processing (NLP), the branch of AI that trains computers to comprehend, process, and mimic human language, allows for targeted dissemination of propaganda tailored to exploit individuals' susceptibilities and fears (Horowitz et al. 2018; Rosenbach and Mansted 2018). While manipulation of information is not new, AI becomes a powerful tool of asymmetric warfare. Third, AI acts as a force multiplier. AI is integrated into these systems to ensure faster and more efficient decision-making processes. Beside systems which target and engage autonomously, other AI-enabled systems which possess a smaller degree of autonomy and rely on human operators use AI applications in narrower forms, e.g. for image recognition or target selection (Rickli and Mantellassi 2023). Possible AI-enabled systems include drone swarms, ground-based air defence systems, and loitering munitions.

V. Research Design, Method, and Data

In this chapter, the research design and methodological approach used to address the research question will be elaborated. The investigation conducted in Chapter VII represents a theory-driven empirical analysis. As outlined above, the chosen theory is the EC which is adjusted to GPTs in order to account for distinct characteristics of AI compared to single military technological innovations. A y-centred theory-testing process-tracing analysis will be conducted (Beach and Pedersen 2013). The analysis is grounded in an entirely qualitative approach. The chapter begins by illustrating the chosen method. Next, the data selection will be discussed.

A. Process-Tracing

Process-tracing was selected as a method since it functions as an analytical tool used to draw causal inferences from evidence by conducting an in-depth case study (Beach and Pedersen 2013; Mahoney 2015; Ulriksen and Dadalauri 2016). This method is not aiming at identifying values of variables and measuring their co-variation but rather at comprehending the underlying processes that connect different relevant factors to the ultimate outcome (Gerring 2017; Hall 2003). Process-tracing entails a “mechanismic and deterministic understanding” of causation and therefore differs from other methods such as large-*n* statistical and comparative case studies (Beach and Pedersen 2013, 6). Following this understanding means to conceptualise causal mechanisms as a series of parts composed of entities engaging in activities whereby each part of a mechanism is an individually insufficient but necessary factor to produce the outcome (Beach and Pedersen 2013, 6, 176; Machamer 2004; Machamer, Darden, and Craver 2000). In *Process-Tracing Methods: Foundations and Guidelines*, Beach and Pedersen present three variants, namely theory-testing, theory-building, and explaining outcome process-tracing (Beach and Pedersen 2013, 13). This study aims to test whether a causal mechanism derived from the EC is present in the case of military AI and, consequently, to unpack the process of its development and integration. Accordingly, the method guiding the analysis will be theory-testing process-tracing. Here, the focus is on examining a hypothesised causal mechanism within a population of cases related to a specific phenomenon. The objective is to assess whether the evidence demonstrates if a theorised causal mechanism was present in a single case and if the mechanism functioned as expected under the necessary contextual conditions (Beach and Pedersen 2013, 11, 15, 35).

Conceptualisation in theory-testing process-tracing involves formulating a plausible causal theory and mechanism that explains how the independent variable contributes to the production of the dependent one, along with the relevant scope conditions. Accordingly, process-tracing begins as a deductive approach, utilising existing theoretically established conjunctures and logical reasoning (Beach and Pedersen 2013, 14, 56). This step was conducted in the previous chapter. Additionally, this type of process-tracing incorporates inductive elements, particularly in the operationalisation of empirical tests. Case-specific predictions about the expected evidence that supports the validity of the theory are drawn from existing empirical studies (Beach and Pedersen 2013, 14). Causal inferences about the mechanisms are subsequently made based on the empirical data, testing whether all parts of the deduced mechanism were present in the case and can account for the observed outcome (Beach & Pedersen, 2013, 33, 91).

B. Data Selection

This thesis incorporates various data sources, including grey literature such as policy papers and official reports, primary communications from official and commercial entities, and secondary research literature on military AI development and integration regarding the selected case. The evidence supporting the different stages of the causal mechanism is partly based on examples from past and ongoing projects related to military AI, which are also sourced from journalistic reports. Additionally, conference reports and public speeches are included in the range of documents used for the complementary case study. The empirical data was collected through online research from publicly available sources.

VI. Case Selection

In the following, the case selection will be elaborated. Theory-testing process-tracing involves choosing a case where both the independent variable and the outcome are present, along with the scope conditions that allow the theorised mechanism to operate (Beach and Pedersen 2013, 147, 150, 182). Therefore a typical case is selected, accordingly understood as a "representative of a population of cases" (Gerring 2007, 96). Beach & Pedersen recommend choosing a typical case which was identified in previous large-*n* studies (Beach and Pedersen 2013, 146). As noted in Chapter II, such cross-case analyses have not been conducted yet for military AI. A population of cases will therefore be identified using existing case-study literature.

To select an appropriate case, it is essential to first shed light on the outcome. As noted before, a partial aim of this study is to explain how a state develops and integrates military AI. Beach and Pedersen state that the independent variable and the outcome should be conceptualised using set-theoretical terms instead of variables as these entail the entire range of a concept, including both poles, while a set-theoretical conceptualisation considers their presence or absence (Beach and Pedersen 2013, 148). But successfully acquiring this technology is not an absolute outcome. Two reasons account for that. First, the endeavour of developing and integrating military AI is rather young, starting anew with breakthroughs in machine and deep learning at the beginning of the 2010s (Ding and Dafoe 2023, 17; Stanley-Lockman 2023, 112). Scholars engaged in military AI research note that it is mostly at the beginning of development, even though some types are already used or close to fielding (Ding and Dafoe 2023, 17; Johnson 2020, 28). Second, it lies in the character of GPTs that they are progressively developed, together with accompanying technological innovations (Ding and Dafoe 2023, 4). To conclude, the dependent variable must not be understood as a final point compared to the development of individual military systems but rather as a current snapshot of military AI development and integration. Therefore, it is only possible to select among cases which are deemed key players or most advanced regarding this technology and which possess both the independent variable and the theorised scope conditions.

To start the identification of a case population, states which possess the scope conditions will be described. AI research & development (R&D) has gained ever-increasing momentum in the last decade. The AI market is growing in many states, especially in Europe, South East Asia, and North America (Maslej et al. 2023; Mostrous, White, and Cesareo 2023). But regarding the AI innovation ecosystem, which includes infrastructure, private investment, research development, and talent, there is great variation in a state's commercial sector robustness (Mostrous, White, and Cesareo 2023). The Global Artificial Intelligence Index lists leading countries which include the United Kingdom, Singapore, Germany, France, Canada, India, Japan, Israel, and, finally, China and the U.S. (Mostrous, White, and Cesareo 2023), with the last two being the main players (Bigley 2023; Mostrous, White, and Cesareo 2023) The AI commercial sector is therefore continuously and globally growing but its AI ecosystem robustness is currently concentrated in certain regions.

A similar assessment can be made regarding the independent variable, namely a state's interest in operationalising military AI. More and more states seek to harness the power of AI for military advantage and make efforts to realise its development and adoption. According to DAIO, these states include but are not limited to Sweden, Italy, Australia, the United Kingdom, Germany, Russia, Canada, Turkey, Israel, China, and the U.S. (Schaal 2023). In the book *The AI Wave in Defence Innovation: Assessing Military Artificial Intelligence Strategies, Capabilities, and Trajectories*, the contributing authors additionally shed light on military AI trajectories and strategies in Russia and South Korea (Raska and Bitzinger 2023b). In 2021, an OECD report analysed national AI strategies and policies and showed that France, Korea, Latvia, Turkey, Singapore, United Arab Emirates, China, and the U.S. explicitly identify the defence sector as one priority, underpinning the diverse global interest in the military application of this technology (Galindo, Perset, and Sheeka 2021).

The number of states interested in operationalising military AI is ever-increasing, but comparatively few states actually qualify as leading nations in military AI. Breakthroughs are rather young, and so are official development and implementation attempts. A state needs to have considerably progressed in its attempts to develop and integrate this GPT to be deemed selectable for this study. According to the DAIO, the states which are most advanced in military AI development and integration are Israel, Sweden, the UK, and finally, China and the U.S. (Dolinko and Antebi 2023; Finlan 2023; Kahn 2023; Lee 2023; Payne 2022). This list is by no means exhaustive, as further studies will follow, but it serves as a starting point for the identification of the population of cases.

Finally, the U.S. is selected for the case study due to several reasons. It is the leading nation in commercial AI research and development. Its AI innovation ecosystem is broad and has the necessary infrastructure, private investment, research development, and a broad pool of qualified workforce. In a broader perspective, the U.S. was identified as a "creator" focusing on the development of new disruptive capabilities such as AI (Schlueter et al. 2022). To put it in a nutshell, the U.S. "[…] has both the desire and means to achieve world leadership in defense applications of artificial intelligence […]" with support from political leaders and decision-makers, and underpinned by a rich AI innovation ecosystem (Kahn 2023, 43). Therefore, it represents a typical case with the independent variable, the outcome, and the scope conditions and is deemed appropriate for this analysis.

VII. Empirical Analysis

The empirical analysis is designed to test whether the theorised causal mechanism based on the EC is present in the case of military AI, and if the mechanism functioned as expected. In that way, the process of its development and integration will be unpacked. This chapter is aiming at collecting sufficient evidence for the existence of each theorised part of the mechanism (Beach and Pedersen 2013, 124). To do so requires the operationalisation of the model in a way that permits an evaluation using empirical evidence (Beach and Pedersen 2013, 95). Case-specific predictions about the expected observable manifestations of each theorised part have to be formulated. These predictions serve as indicators of evidence that should be observed if the mechanism is indeed present. The formulation of these case-specific predictions relies on contextual understanding and knowledge of individual cases (Beach and Pedersen 2013, 95).

The key to theory-testing process-tracing is to maximise the inferential power of empirical tests regarding the existence of the different parts of the causal mechanism (Beach and Pedersen 2013, 96). The strength of the test directly influences the ability to update the level of confidence in the presence or absence of these parts within the proposed mechanism. The empirical analysis follows the Bayesian logic (Beach and Pedersen 2013, 96). To evaluate the test strength, both certainty and uniqueness of the predicted evidence must be assessed. Van Evera categorises various types of prediction tests based on these two dimensions, leading to four distinct types: straw-in-the-wind, hoop, smoking gun, and doubly decisive tests (1997, 31-

34). Straw-in-the-wind tests are the weakest type, as such predictions have a low level of both certainty and uniqueness. Passing the test indicates the relevance of a part, yet it does not confirm, and failure does not eliminate it. Hoop tests consist of predictions that are certain but lack uniqueness. If such a test fails, it reduces the confidence in the hypothesis, but finding it does not enable inferences to be made. Smoking gun tests possess a high level of uniqueness but score low on certainty. Passing strongly confirms a hypothesis. Failing does not eliminate but somewhat weakens it. Finally, doubly decisive tests are both highly unique and certain. One should aim to maximise both the certainty and uniqueness of the predicted evidence to maximise the ability to update the confidence in the hypotheses in light of empirical evidence (Beach and Pedersen 2013, 96).

In what follows, each of the theorised parts will undergo systematised testing while adhering to the principles outlined above. In the case of parts one and two of the causal mechanism, all four types of tests will be conducted due to their open description within the EC. However, parts three and four, namely infrastructural and organisational adaptation, are precisely defined and hands-on. Here, only Smoking Gun and Doubly Decisive tests will be conducted.

A. Creating a Link to the Commercial Sector

The first part of the causal mechanism is deduced from the EC adjusted to GPTs. It states that a government must create a link to the commercial sector, and specifically to the relevant GPT players, to be able to draw from its technological capacity and to introduce a GPT into its military sphere. The operationalisation is outlined in Figure 3.

To start, evidence for the Straw-in-the-Wind test is examined. Evidence needed for this test is statements expressing a government's wish to tip into the commercial sector for innovation. This test is not certain as officials do not necessarily publicly state that they lack the capability for innovation, which reveals the weakness and is not unique since this is not necessarily aimed at military AI development. The expected observations are policies and public statements. Accordingly, publicly available policy documents, speeches, and secondary literature will be reviewed. The advancement of commercial innovation led to the launch of the Defense Innovation Initiative (DII) by the U.S. Department of Defense with the goal of sustaining U.S. military advantage by developing and integrating new cutting-edge technologies (Mori 2018, 18; Pellerin 2014). The initiative was officially introduced through a memorandum issued by former Secretary of Defense Chuck Hagel at the end of 2014 (Secretary of Defense 2014).

Figure 3: Operationalisation of the First Part of the Causal Mechanism

Test	Causal Evidence	Expected Observations	Measurement
Straw-in-the-Wind	A government's intent to tip into the commercial sector	Expected to see policies and public statements	Measured using trace and account evidence by reviewing grey and secondary literature
Hoop	Institutionalisation of link between military and commercial sector	Expected to see creation of intermediaries connecting the DoD to the commercial sector	Measured using trace and account evidence by reviewing grey and secondary literature
Smoking Gun	Acknowledgement that those institutions aim to engage with the AI sector	Expected to see official statements identifying that aim	Measured using trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	AI companies engage with those institutions	Expect to see AI companies working together with intermediaries	Measured using trace and account evidence by reviewing grey and secondary literature

Own visualisation, modified and adapted from Collier (2011)

Part of the initiative was the establishment of the Long Range Research and Development Plan (LRRDP) that allowed individuals, ranging from public businesses to private citizens, to submit ideas for next-generation technologies and their integration within the U.S. military (Pellerin 2015). Through this initiative, it was acknowledged that the cutting-edge technology development was driven by experts in the commercial realm. The DII efforts were then embedded in the *Third Offset Strategy* (3OS), which aimed "[…] to offset - or create an overmatch of - China's and Russia's increased capabilities" (Gentile et al. 2021, x). One of the key principles was to explore novel approaches for fostering technological innovations and engaging with the commercial sector, aiming to address the diminishing role of the Department of Defense (DoD) in driving innovation (Kahn 2023, 21). Former Secretary of Defense Ashton Carter outlined the rationale behind the 3OS, stating that "[…] the current erosion of the U.S. technological advantage derives not from adversaries' numerical superiority or superior volumes of investment, but from the increasingly global and commercial nature of the innovation environment and the increasing applicability of commercial technologies to military operations" (Gentile et al. 2021). With the *2018 National Defense Strategy* (NDS), the successor of the 3OS, the government again expressed its wish to connect to the commercial sector by

"[…] expanding access to outside expertise, and devising new public-private partnerships to work with small companies, start-ups, and universities" (DoD 2018c, 8). To conclude, the government expressed its interest in creating a link to the commercial sector on numerous occasions. Given these examples, the first part of the causal mechanism is initially strengthened.

The causal evidence for the Hoop test is defined as institutionalising the link between the military and the commercial sector. This is realised through intermediaries, which are imperative for three reasons. First, they serve as technological horizon-scanning tools to help officials understand how new technologies will impact future operations and guide decisions on when and where to invest in R&D and capability development (Soare and Pothier 2021, 23). Second, they ensure mutual information flows since many entrepreneurs simply lack an understanding of what products would appeal to a defence client, making warfighter input essential (Stanley-Lockman 2021, 487). And third, doing business with government agencies necessitates specialised knowledge (Roberts and Schmid 2022, 355). Intermediaries can be a means of systematising a broader national security innovation ecosystem (Roberts and Schmid 2022, 355; Stanley-Lockman 2021, 487). Therefore, this test is certain, but not unique as such institutions are not necessarily used for military AI development. The expected observation is the establishment of actual institutions overtaking such a role. This is tested using a mix of trace and account evidence which can be found in official documents, secondary literature, and the actual institutions themselves. The U.S. government has created two institutions in this regard. First, it established the Defense Innovation Unit (DIU)[5] as an outreach body with offices in Austin, Boston, and Silicon (Carter 2016b). Within each office, there are three teams that play distinct roles (Mori 2018, 20). The Engagement team enables a two-way exchange between the military and entrepreneurs. The Foundry team collaborates with internal and external engineers to advance technologies through focused design sprints, rapid prototyping, and field trials. And the Venture team identifies emerging commercial technologies and assesses their suitability for potential military and civilian customers throughout the department. To put it in a nutshell, the DIU attempts to bring commercial actors and defence practitioners together to identify opportunities for technological innovation through civil-military collaboration. The second institution is the Defense Innovation Board (DIB), established in 2016. It was formed with the purpose of offering recommendations to the Secretary of Defense and other officials in the DoD regarding the integration of emerging technologies into military operations (DoD 2016). Its

[5] Formerly named Defense Innovation Unit Experimental (DIUx) and redesignated as Defense Innovation Unit (DIU) in 2018 (Mori 2018, 27).

primary objective is to foster closer collaboration between military officials and leaders from the commercial technology sector (Mori 2018, 38). The establishment of the DIU and the DIB are hands-on examples of intermediaries which resemble a government's link to the commercial sector, further underlining the plausibility of this part of the causal mechanism.

In the next step, a Smoking Gun test will be conducted. Here, the intent that those institutions are primarily designed to engage with the AI sector serves as causal evidence. This is highly unique in that it explicitly clarifies the drive for the creation of those intermediaries, but not certain since such information could be held classified. Expected observables are public statements that both the DIU and the DIB mainly focus on the AI sector. The creation of both the DIU and the DIB was based on the 3OS (Ellman, Samp, and Coll 2017, 3; Gentile et al. 2021, 46). Even though it does not explicitly select AI as the predominant focus, leading officials who drove its development did so (Gentile et al. 2021, 2; Stavridis 2021, xi). Deputy Defense Secretary Work, who was responsible for its draft, stated that the primary focus of this strategy is to leverage advancements in artificial intelligence and autonomy and integrate them into the DoD's battle networks (Pellerin 2016). At an event with a focus on the 3OS, he stated that "putting AI and autonomy into the battle network is the most important thing we can do first" (Work 2016). The underlying theory of the 3OS was that the use of AI-enabled autonomous systems would provide U.S. battle command networks with an operational advantage over strategic competitors like China and Russia since these competitors had shifted their focus from destroying combat systems to targeting the network itself (Gentile et al. 2021, 38; Tangredi and Galdorisi 2021, 12). These findings allow for assuming that the DIU and the DIB were primarily established to link the military to the commercial AI sector. The first theorised part of the causal mechanism passes this test.

Commercial companies which are key players in the AI market engaging with those intermediaries is deemed strong causal evidence for a Doubly Decisive test. Such companies engaging with those intermediaries would show that a government successfully created a link to the commercial sector. This is both unique and certain since it embodies the theorised part of the causal mechanism. The expected observable is, accordingly, both the DIU and DIB working together with leading AI companies. It is tested through grey and secondary literature. As previously noted, a key part of the DIU's portfolio is indeed AI, and it was able to engage with commercial AI actors. It has collaborated with companies such as Anduril, Applied Intuition, Databricks, Modal AI, Rebellion Defense, Shield AI, C3 AI and Palantir (Kahn 2023, 30). In doing so, the institution was able to identify key capabilities such as mission forecasting and planning, anomaly detection, complex system controls, and operational decision support within their focus area AI (Defense Innovation Unit 2021). In the case of the DIB, its board partly consists of members from leading commercial AI companies. The DIB was first chaired by Eric Schmidt, former Executive Chairman of Alphabet. Current and former members include Reid Hoffman, co-founder of LinkedIn and Inflection AI, and Amazon's Jeff Bezos (Mori 2018). Furthermore, representatives of companies leading in AI supported the work of the DIB. Numerous commercial stakeholders took part in the *AI Principles Project*, including OpenAI, Microsoft, Facebook, and Google, among others (Defense Innovation Board 2019). Taken together, the link in the form of newly created intermediaries indeed connects the government with the commercial sector and specifically with key AI players.

B. Spin-On of AI Technology

The second part of the causal mechanism claims that a government is now able to adapt AI originally designed for civilian or commercial purposes for military use, thus solving the platform challenge, according to the EC. The operationalisation of this part is outlined in Figure 4.

Figure 4: Operationalisation of the Second Part of the Causal Mechanism

Test	Causal Evidence	Expected Observations	Measurement
Straw-in-the-Wind	Growth of governmental IT capabilities	Expected to see rising public investment in governmental IT capabilities	Measured using pattern and account evidence by reviewing grey and secondary literature
Hoop	Lowering acquisition barriers	Expected to see creation of new procedures to lower such barriers	Measured using trace and account evidence by reviewing grey and secondary literature
Smoking Gun	Lowered barriers and public spending used for AI spin-on	Expected to see financial flows dedicated to military AI projects and the use of newly established acquisition procedures	Measured using pattern, trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	Successful AI spin-on	Completed military AI projects	Measured using trace and account evidence by reviewing grey and secondary literature

Own visualisation, modified and adapted from Collier (2011)

Straw-in-the-Wind test evidence is the growth of governmental IT capabilities. This is not certain since a focus on software-based AI does not necessitate capability growth because no growth could be due to priority shifts, and not unique as AI is not necessarily part of those capabilities. The expected observation is rising investment which will be measured through a mix of pattern and account evidence in the form of publicly available data, grey and secondary literature. According to the Office of Management and Budget of the White House, federal government spending on IT has continuously increased since 2013. It grew from $37 billion in 2013 to $66 billion in 2023, and is estimated to reach $74 billion in 2024 (Office of Management and Budget 2023).[6] To make a case for the DoD, it accounted for over half of the federal IT contract spending, totalling $35.9 billion in fiscal 2019 according to an analysis by Bloomberg Government (Cornillie 2020). Given the evidence found, governmental IT capabilities grew. This is the first piece of solid trace evidence.

Causal evidence for a Hoop test is the creation of low acquisition barriers. The ability to collaborate with non-traditional commercial actors in defence innovation efforts relies on proper transition pipelines in form of procurement and acquisition procedures (Soare and Pothier 2021, 23). To enable a government to spin-on civilian AI into the military, acquisition processes have to be adapted. This evidence is, therefore, certain but lacks uniqueness as this is not necessarily aiming at AI technology spin-on. The predicted observation is the creation of new procedures to lower such barriers. This is tested by trace and account evidence. The Pentagon has streamlined contracting methods for engaging with commercial partners. This includes the Other Transaction Authority (OTA) and the Commercial Solutions Opening (CSO) procedure (Procurement Innovation Resource Center 2018; Stanley-Lockman 2021, 487). OTAs are designed to bypass bureaucratic hurdles and facilitate rapid prototyping. They are intended to provide advantages to commercial companies by offering them a pathway to engage in defence-related projects without the complexities and constraints of the traditional Federal Acquisition Regulations (Stanley-Lockman 2021, 487). The CSO is a competitive business process that enables the DoD to solicit and evaluate proposals for potential solutions to its challenges. It offers a simplified approach to engaging with external entities and assessing their proposed solutions in a more efficient manner (Kotila et al. 2023, 117). Together, they enable the government to improve acquisition processes and lower spin-on barriers. The successful test further strengthens the second part of the causal mechanism.

[6] The analysis explicitly excludes DoD data.

The use of such lowered barriers and public spending actually aiming at AI spin-on serves as causal evidence for a Smoking Gun test. Such evidence shows the government's attempts to spin-on commercial AI into its military and is, therefore, unique. But it lacks certainty since a government could attempt to acquire military AI capabilities from other sources. The government's financial resources dedicated to military AI projects and the use of newly established acquisition procedures are the expected observations. This is measured through official data, secondary, and grey literature. The DoD has been steadily increasing its funding for research and development of AI in recent years. Although specific budget details are not publicly disclosed, unclassified requests indicate a clear commitment to investing in AI (Kahn 2023, 30). The Institute for Human-Centered Artificial Intelligence estimated that in 2021, there were approximately 305 Department of Defense research, development, testing, and evaluation (RDT&E) programs regarding AI technologies. The estimated budget for these programs amounted to around $5 billion (Zhang et al. 2021, 168). In 2021, the Defense Advanced Research Projects Agency (DARPA), a traditional key player in the U.S. defence ecosystem, invested about $568.4 million in AI, which marked a significant increase from its estimated $82 million investment in 2020. For 2022, budgets for AI-related projects was planned to amount to $1.86 billion for the U.S. Navy, $1.7 billion for the U.S. Army, $1.1 billion for the Secretary of Defense, and $883 million for the U.S. Air Force (Zhang et al. 2021, 191). The Artificial Intelligence Exploration Program (AIE) launched by DARPA has adopted the OTAs as a central component. This program aims to undertake high-risk, high-reward projects that show the viability of innovative AI concepts within a timeline of 18 months from award (DARPA 2019). The DIU used both CSOs and OTAs and between June 2016 and September 2021, the organisation successfully secured $20.1 billion in private investments and awarded contracts totalling $892.7 million (Defense Innovation Unit 2021, 4, 7). This test was successful and provides strong support for the second part of the causal mechanism.

Finally, a Doubly Decisive test will be conducted. Here, successful AI spin-on serves as causal evidence. This is both highly certain and unique, as it represents a materialisation of the second theorised part. Expected observations are completed military AI projects. Measurement happens through secondary and grey literature. Several projects have been successfully completed across the U.S. defence establishment, for example, in aerial swarm technology. The Strategic Capabilities Office (SCO) has enhanced the Perdix autonomous micro-drones, originally created by the Massachusetts Institute of Technology's Lincoln Laboratory in 2013, using commercial components. In a successful demonstration in October 2016, 103 Perdix drones were deployed (DoD 2017). Additionally, the SCO, in collaboration with other military organisations, achieved a successful free-flight demonstration of the MALD-X decoy missiles. It involved a large number of collaborative, expendable platforms equipped with advanced electronic warfare techniques. MALD-X was transferred to the Navy for further system development and transition to operational capability (DoD 2018a). In another project, Google Cloud collaborated with Klas Telecom to offer AI technology to U.S. Special Forces. This technology processes captured enemy materials for actionable intelligence. Google sales representatives have conducted demonstrations and pitches to military customers training and deploying forces (Tucker 2018). A core example of a successful spin-on is Project Maven, which was established in April 2017. It has become a prominent case of AI application for defence purposes in the U.S. (Kahn 2023, 23). It aimed to automate and enhance the analysis of video footage from unmanned aerial systems (UAS) using computer vision technology (Gentile et al. 2021, 47). Google was initially the main technological partner in this project but left due to internal protests (Mitchell 2019). Microsoft and Amazon supported the project, and Palantir took over the project lead in 2019 (Brewster 2021; Peterson 2019). To conclude, there are already a number of completed projects which evolved out of the collaboration between public institutions and commercial players. This proves that the established development and acquisition framework yields successful spin-on output and underpins this part of the causal mechanism.

C. Meeting the Adoption Challenge in a Top-Down Approach

After successfully meeting the platform challenge, the government must overcome the adoption challenge in a top-down manner to ensure broad technological integration. This embodies the third part of the theorised causal mechanism. According to the EC, both infrastructure and organisational requirements have to be fulfilled. The National Security Commission on Artificial Intelligence puts it at follows:

> "Even with the right artificial intelligence (AI)-ready technology foundations in place, the U.S. military will still be at a battlefield disadvantage if it fails to adopt the right concepts and operations to integrate AI technologies. Throughout history, the best adopters and integrators, rather than the best technologists, have reaped the military rewards of new technology. The Department of Defense (DoD) should not be a witness to the AI revolution in military affairs, but should deliver it with leadership from the top, new operating concepts, relentless experimentation, and a system that rewards agility and risk."
>
> **(NSCAI 2021, 77)**

1. Infrastructure Adaptation

Ensuring an appropriate infrastructure for the successful adoption of a GPT represents a subpart of meeting the adoption challenge. First, logistics is crucial for sustaining operations (Gilli and Gilli 2016, 60). Second, communication plays a central role in modern warfare (Friedman 2009). Third, military platforms often depend on support from other weapon systems (House 2002). In the case of the technology in question, "[d]ata is the lifeblood of AI" as a former DoD official puts it (Kuzma 2018). Accordingly, a key infrastructural requirement is data logistics – the data management, storage, and communications structures required to train and apply learning algorithms operationally to ensure AI-enabled sensor-to-shooter loops and data streams between the various services and platforms (Blair et al. 2021, 99; Raska 2022, 96). Here, infrastructural adaptation is a hands-on activity. This allows for directly conducting a Smoking-Gun and a Doubly decisive test. The operationalisation is outlined in Figure 5.

Figure 5: Operationalisation of the First Subpart of the Third Step of the Causal Mechanism

Test	Causal Evidence	Expected Observations	Measurement
Smoking Gun	Adaptation of data and management systems for military AI	Expected to see policies and projects to make data interoperable and linked together for AI	Measured using trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	AI actually being trained by newly streamlined and labelled DoD datasets	Expected to see individual military AI algorithms being trained by this data	Measured using trace and account evidence by reviewing grey and secondary literature

Own visualisation, modified and adapted from Collier (2011)

Causal evidence for a Smoking Gun test is efforts to adapt data and management systems for military AI. This is unique as it shows attempts to appropriate existing data resources, but not certain since existing systems could already be sufficient for military AI integration. The expected observations are policies and projects to make data interoperable and linked together for AI. This is measured through secondary and grey literature. The U.S. federal government's efforts to adapt appropriate infrastructure are partly led by the data-readiness evaluation principle, which was established by the Joint Artificial Intelligence Center (JAIC)[7]. Officials

[7] The JAIC was tasked with implementing the DoD's vision and ensuring the coordination of AI activities to maximise the advantages of the Joint Force (DoD 2019, 9).

have to assess the storage and preparation of data to determine its suitability for AI applications and advanced analysis and modelling (Vincent 2020). In a similar vein, Deputy Defense Secretary Hicks emphasised the goal of transforming the DoD into a data-centric organisation with the aim of “improving warfighting performance and creating decision advantage at all echelons from the battlespace to the board room” (Vergun 2021). Significant internal organisational shifts have been implemented by the DoD to effectively align data with AI, address siloed data streams, and enhance data transparency (Kahn 2023, 16). The DoD’s IT environment as such underwent a significant transformation, characterised by a shift towards a cloud-based infrastructure (Peterson 2021). Two concrete examples are the Defense Intelligence Agency (DIA) and the JAIC. The DIA aims to enhance its military intelligence capabilities with the Machine-Assisted Analytic Rapid-Repository System (MARS), surpassing the capabilities of its current Modernized Integrated Database (MIDB), and its development started in 2018 (GAO 2020, 1). The JAIC is overseeing the Joint Enterprise Defense Infrastructure (JEDI) contract, which establishes an enterprise cloud computing network across the federal government. This network is seen as crucial for fully leveraging AI systems and the associated data (Freedberg Jr. 2019). The initiatives aim at enhancing agility, enabling remote capabilities, and serving as the foundation for the widespread adoption of AI within the enterprise. This test was successful and provides strong support for this theorised part.

A Doubly Decisive test will be conducted to make a final point for infrastructural adaptation. Causal evidence is AI actually being trained by newly streamlined and labelled DoD datasets. This is both certain and unique, as it embodies successful infrastructural adaptation. It is expected to observe individual military AI algorithms being trained by such data. This test is measured through grey and secondary literature. Project Maven is again an important example. Here, infrastructural adaptation included triaging and labelling data so the AI algorithms could be trained (Pellerin 2017). This project adopted project management techniques widely recognised as industry standard. Those techniques play a vital role in AI development, as they encompass essential tasks like data labelling, computational infrastructure development, and algorithm integration, which are carried out iteratively and in parallel (Allen 2017). The same data is used in newer projects, such as in the U.S. Army’s Scarlet Dragon to provide targeting assistance for large-scale combat operations (Kahn 2023, 35; Wasserbly 2021). The Marine Corps is actively integrating Project Maven's algorithms into their capabilities and updating legacy weapon systems to align with modernisation efforts (GAO 2022, 21). In sum, AI-ready infrastructure established through Project Maven now serves as a foundation that can be utilised for future algorithmic training in other projects (Allen 2017). In essence, it has contributed to the development of the necessary institutional infrastructure for the adoption of AI. This test has been successful and proves that meeting infrastructural requirements play a key role in the case of military AI, and that the U.S. government is meeting them.

2. Organisation Adaptation

Finally, and according to the EC, a government must develop appropriate codes, practices, doctrines, and a competent workforce organised in suitable formats to successfully integrate a new GPT. This represents the second subpart of the adoption challenge. As Raska points out, "[…] the direction and character of AI trajectories in military affairs will depend on corresponding strategic, organisational and operational agility, particularly how these technologies interact with current and emerging operational constructs and force structures" (Raska 2022, 96). Similar to infrastructural adaptation, organisational changes are hands-on and allow for conducting several Doubly Decisive tests besides a Smoking Gun Test. The operationalisation can be found in Figure 6.

Efforts to organise and oversee broad organisational adaptation for military AI serve as Smoking Gun test. This is unique since it shows attempts for coherent adaptation but lacks certainty because existing institutions could be made responsible for this endeavour. Expected observations are newly created federal bodies devoted to military AI adoption. It is measured through grey and secondary literature. In the U.S., projects like Maven and the JAIC exemplify the government's efforts to accelerate the DoD's AI capabilities. Broad AI integration was not initially possible since existing organisational structures were not well-suited since separate departments and organisations independently worked on AI projects without cross-departmental coordination (Kahn 2023, 25). To prevent further redundancies and inconsistencies, the DoD has reorganised its existing AI structures (Horowitz and Kahn 2022). This reorganisation aimed to establish a more cohesive approach to military AI adoption by creating the Chief Digital and Artificial Intelligence Office (CDAO). The CDAO incorporates the JAIC, the Defense Digital Service (DDS), and the Office of the Chief Data Officer (CDO) (Office of the Deputy Secretary of Defense 2021). This restructuring aimed to promote greater integration and collaboration within the military AI efforts and underlines this subpart. Thus the Smoking Gun test is passed.

Figure 6: Operationalisation of the Second Subpart of the Third Step of the Causal Mechanism

Test	Causal Evidence	Expected Observations	Measurement
Smoking Gun	Efforts to organise and oversee broad organisational adaptation for military AI	Expected to see creation of federal bodies devoted to military AI adoption	Measured using trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	Revision of existing military warfighting approaches for effective use military AI	Expected to see creation of codes, practices, and doctrines focusing on military AI	Measured using trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	Experimentation with AI technology within the military	Expected to see individual conducted experimentation projects	Measured using trace and account evidence by reviewing grey and secondary literature
Doubly Decisive	The development of a competent workforce	Expected to see creation of training structures for educating personnel in AI	Measured using trace and account evidence by reviewing grey and secondary literature

Own visualisation, modified and adapted from Collier (2011)

Causal evidence for the first Doubly Decisive test is the revision of existing military warfighting approaches for effective military AI implementation. This test is certain and unique since military AI is theorised to have a broad impact on the military as a whole and on how wars are fought. Expected observables are the creation of codes, practices, and doctrines focusing on military AI. The FY2019 National Defense Authorization Act (NDAA) mandated the DoD to publish a strategic roadmap outlining the development and deployment of AI. It also required the DoD to establish guidance regarding ethical, legal, and other policies pertaining to the use of AI-enabled systems and technologies in operational contexts (Sayler 2022, 4). To fulfil this, the DoD subsequently adopted five ethical principles for AI, derived from the recommendations put forth by the DIB (DIB 2019). These principles encompass responsibility, equitability, traceability, reliability, and governability (DoD 2020). Military AI is also incorporated into warfighting concepts. In the U.S., an attrition-centric approach to warfare has been reflected in the traditional design of its military, but a decision-centric approach is increasingly seen as the main way of future warfare, and AI lays the foundation for it (Clark et al. 2020). One popular example is the concept of mosaic warfare. It is developed by DARPA to revolutionise how forces are acquired, deployed, and utilised. It involves assembling individual warfighting platforms like ceramic tiles in a mosaic to create a cohesive and effective force package through AI (O'Donoughue, McBirney, and Persons 2021, xi). Another concept is the Joint All-Domain Command and Control (JADC2). JADC2 aims to centralise the planning and execution of operations across various domains to create a highly connected and synchronised military (Sayler 2020, 12-13). The DoD's JADC2 Implementation Plan, released in March 2022, emphasises the use of AI to enable the Joint Force to rapidly "sense", "make sense", and "act" on information across the battle space (DoD 2022). These are examples of new codes, practices, and doctrines which were adapted to military AI and underline organisational changes.

The second Doubly Decisive test is the experimentation with AI technology within the military. To better grasp how a new technology can be implemented best, experimentation with new concepts, force structures, weapons technologies, and warfare methods is crucial (Raska 2022, 68). Hence, this is both certain and unique. Conducted experimentation serves as expected observations. This is measured through grey and secondary literature. In the U.S. military, the Army, Navy, and Air Force have running JADC2 projects (Kahn 2023, 37). In the recent Project Convergence experiment, the U.S. Army employed its AI-powered network called Firestorm to facilitate the direct transmission of intelligence from U.S. Army sensors to Australian and British forces (Lacdan 2022). The Air Force has initiated Global Information Dominance Experiments (GIDE) to enhance commanders' decision-making by leveraging AI and machine learning to integrate information from a global sensor network. These experiments aim to identify significant trends within the data and provide current and predictive information to support informed decisions (NORAD and USNORTHCOM 2021). Those examples show ongoing experimentation efforts with military AI in the U.S. military and underline this subpart.

Finally, a third Doubly Decisive test can be conducted. The development of a competent workforce serves as causal evidence. Upskilling military personnel is essential since having expert personnel in the armed forces enables the broad integration of new technologies (Soare and Pothier 2021, 26). This is, therefore, certain and unique. Established training structures for educating personnel in AI are expected to be observed. This is measured through grey and secondary literature. The DoD has taken some steps in that direction. In April 2020, the JAIC released a comprehensive guide on AI which aimed to assist DoD officials who were tasked with making AI-related decisions but lacked a sufficient understanding of the technology (Allen 2020). In September 2022, it was announced that the CDAO had entered into a contract with

FedLearn, an online educational tool provider, to develop a prototype AI training program (Federal Times Staff 2022). Since the establishment of the CDAO, which absorbed the JAIC, there has been a renewed focus on internal AI education. The CDAO has developed a comprehensive AI education strategy to enhance the overall understanding of AI within the DoD and the armed services (JAIC 2020). This strategy includes the launch of “AI 101” educational pilot programs in February 2022, providing consistent AI education across the organisation (Barnett 2022). The development of the AI strategy involved collaboration from a diverse range of organisations, including multiple offices of each armed service, members of the intelligence community, and the Joint Chiefs of Staff. In total, forty-seven different organisations contributed to its development (Kahn 2023, 41). Those undertakings are rather young but represent an important step towards military AI integration and operationalisation (Kahn 2023, 43)

D. Assessing the Results

The empirical analysis has successfully shown that the DoD has intensified its efforts to incorporate military AI into its military. This includes the establishment of new organisations dedicated to enhancing AI development and adoption, the reorganisation of its internal AI and data infrastructure, and the implementation of appropriate codes, practices and doctrines, personnel training, increased funding, and support for AI projects. These measures reflect the DoD's commitment to staying at the forefront of technological advancements and leveraging AI for military capabilities. The conducted case study provides reasonable grounds for the plausibility of the EC.

VIII. Conclusion

Building on existing theoretical work of military innovation, innovation diffusion, and military AI research, this study attempted to shed light on the process of developing and integrating AI into the military. A theoretically-informed causal mechanism was established and tested within a case study. Based on an analysis of primary and secondary sources, this thesis concludes that the conceptualised process was present in the case of the U.S. and functioned as expected. The government's interest in adding AI to its military portfolio necessitated the creation of a link to the commercial AI sector. Next, it solved the platform challenge by "spin-on", i.e. the flow of technology from the civilian to the military sphere. In a third step, the U.S. government then met the adoption challenge by simultaneously establishing the necessary infrastructure for AI, and by adapting its military organisation to capitalise on the potential of the technology. In sum, this led to the outcome. All parts of the mechanism are individually necessary and sufficient to explain the development and integration of military AI.

This study attempted to address shortfalls in the existing research landscape, which resulted from a lack of combination. Existing research on military innovation and diffusion has primarily focused on the traditional industrial defence sector, neglecting the study of military AI innovation. Conversely, scholars examining military AI innovation have not capitalised on existing theories and have regarded AI as a limited technological advance rather than a GPT. The contribution of this study is twofold. First, it diverges from the conventional focus on narrow technological developments, such as new weapons systems, and instead expands and enhances traditional theorisation in this field. Second, it lays the foundation for a more systematised innovation framework in the case of military AI. This allows for a better understanding not only of how innovation takes place but how the technology will diffuse in the international theatre.

Nonetheless, these findings entail several limitations due to the chosen method. First, no claims of sufficiency can be made based on a single theory test (Beach and Pedersen 2013, 89). This is due to the complexity of the social world, in which multiple mechanisms often contribute to an outcome simultaneously. Theory-testing process-tracing allows for inferring the presence and functioning of a specific mechanism in a case. However, it does not allow for claiming that the mechanism was the sole factor leading to the occurrence of outcome (Beach and Pedersen 2013, 35). Hence, equifinality is assumed (Beach and Pedersen 2013, 153). Furthermore, inferences can only be made regarding the presence of a mechanism in the specific case, and it is not logically possible to claim the necessity of the mechanism.

Due to those limitations, this study can only be a first step towards a systemic understanding of how states pursue military AI. Further in-depth case studies and cross-case analysis could yield fruitful ground for testing the generalisability of the theorised process (Beach and Pedersen 2013, 15-16). Furthermore, new diffusion dynamics could unfold while the technology is maturing. Organisations such as the EU and NATO are undertaking efforts to support military AI development and integration among states (EDA 2022; Stanley-Lockman and Christie 2021). Research on how military AI diffuses within alliances could therefore refine and enrich current academic approaches. Lastly, the conceptualised mechanism could be applied to other technologies, which are close to being a GPT, including nanotechnology, space-related capabilities, and quantum computing which are commercially developed and not confined solely to the great powers (Hammes 2016).

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