

Replacement of the Military's Intellectual Labor Using Artificial Intelligence

—Discussion about AI and Human Co-existence—*

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Abstract

The development of AI, which first began in the 1950s, has been carried out in a way that explores the logical thinking of humans using deductive or inductive inference, but this approach has become the potential and limitations of AI. The introduction of AI by the military, whose full-fledged trials began in the Second Boom of AI development in the 1970s, has today reached a level where AI can replace the thinking and decision making related to the command structure (military personnel). The introduction of such high performance AI will likely have a major impact on approaches to the military (structure and organization). However, AI, which was developed in pursuit of human logical thinking, faces with the weak point of “ad hoc response to inexperienced situations.” However, such response is always required of the military (military personnel) on the battle front or at the scene of disasters. When viewed in this light, the ideal approach of the military (military personnel) for co-existence with AI comes into focus.

Introduction

Today, Artificial Intelligence (AI) is permeating into every corner of our world, and the military is no exception. The military's main interest in AI today focuses predominantly on the development and operation of Lethal Autonomous Weapon Systems (LAWS), or robots sophisticated by AI. From the invention of the spear in Stone Age (around 70,000 years ago) to the 21st century today, people have proactively used technological development for warfare and the development of weapons.¹ Debate over the development and operation of LAWS, too, is basically an extension of this. In other words, although these discussions focus on accountability and the pros and cons of entrusting decisions for attacks to autonomous weapons systems with lethal force, the basis of these discussions is that humans will proactively regulate and control LAWS. Improvements in AI performance may force a change in this paradigm in the future.

The purpose of AI development is to contribute to human's intellectual labor; yet, attempts to reduce the burden of this intellectual labor date back to the invention and use of calculating

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¹ See Ferrill Arther, *Senso no Kigen* [The Origins of War], translated by Suzuki Chikara and Ishihara Tadashi, (Tokyo: Kawade Shobo Shinsha, 1988), pp.24-48 for the development of prehistoric technology of weapons.

tools in ancient Mesopotamia.² In addition, modern computers are believed to have begun from the mechanical calculator that could perform four-arithmetic operations invented by Gottfried Wilhelm Leibniz.³ Today's AI development, however, is largely different from these other technological developments. The main reason for this is the fact that AI technological development today eyes the replacement of intellectual human labor. In the case of the military, this means that the thinking and decision making of commanders and staff organizations can even be replaced with AI. Intellectual activities set mankind apart as the lords of creation, but in this sense, AI has the power to surpass humans.

AI, with its close to 70-year history, did not necessarily pose a threat to human's intellectual activities in the beginning. The development of AI that began in the 1950s has been pursued in a way that explores the logical thinking of humans using deductive or inductive inference. This history of development has become both the potential and the limitation of AI. As a result, this paper will look back on AI's development history as a civilian technology and then debate the replacement of the military's intellectual labor using AI and the co-existence of AI and the military (military personnel). Furthermore, advancements in AI (including Information Technology: IT) are ushering in great changes in military-industry relations, towards industrial superiority.⁴ This paper does not cover military-industry relations, but this fact clearly demonstrates the extent of impacts from AI development.

1. From Supplementing to Replacing Intellectual Labor

Attempts to entrust human's intellectual activities to tools and machines have been made since ancient times. For the longest time, these attempts did not go beyond the domain of "supplementing intellectual work," but the aim of AI development is "replacing intellectual labor." Put another way, the problem was how to carry out abstract human logical thinking using a machine.

(1) Up to the First Boom of AI Development

Attempts to replace human's intellectual labor with machines began in earnest with the development and operation of computers that occurred in the United States during the middle of the 20th century. However, attempts to reduce the burden of intellectual work using calculation tools can be traced back to Mesopotamia three to four thousand years before the Common Era. Regarding the invention of the first mechanical calculator called the "Stepped Reckoner" for four-arithmetic operations by Gottfried Wilhelm Leibniz in the 17th century, Yuma Matsuda said, "Many scientists no longer had the need to endure the difficulty of calculation. This was exactly the moment when mankind was liberated from the labor of calculation."⁵ Such development of calculators became the trigger behind social reforms caused by the series of information sciences also known as "the

² Suzuki Hisao, and Toya Seiichi, *Soroban no rekishi* [The history of abacus] (Tokyo: Morikita Publishing, 1960), p.1.

³ Matsuda Yuma, *Jinko chino no tetsugaku* [Philosophy for artificial intelligence] (Hiratsuka-shi: Tokai University Press, 2017), p.5.

⁴ See Ono Keshi, "Gunsan kankeishi to sorewo meguru shiso [The History of the Military-Industrial Relations and Related Theories]," *NIDS Military History Studies Annual*, no.21 (March, 2018), pp.66-70 for relationship between the military and industries in the IT and AI age.

⁵ Matsuda, *Jinko chino no tetsugaku*, p.6.

intellectual industrial revolution.”⁶

The systemization of logical operation by George Boole that appeared around two centuries after the invention of the “Stepped Reckoner” is said to have migrated the intellectual industry revolution into a new stage.⁷ Logical operation that carries out logical inference using the four arithmetic operations “became the philosophy behind today’s programs,” and as a result, people “have been able to give orders to computers.”⁸ In other words, logical operation provides “a means for combining multiple intellectual work (calculation) following conditions.” Consequently, computers were invented that can automatically carry out logical operation by simply providing algorithms (calculation methods [orders = program]). This system handles variables as an abstract concept and can be seen as “moving one step closer to human’s abstract thinking.”⁹

One of the most famous first computers was Electronic Numerical Integrator and Computer (ENIAC) developed in the United States in 1945. This development project was led primarily by the US Army’s Ballistic Research Laboratory and the University of Pennsylvania during World War II.¹⁰ It was implemented jointly between the military and universities, with cooperation from universities across America. The original purpose of ENIAC development was the preparation of firing tables (correlation table for type of ordinance, angle of elevation, launch explosives, wind, temperature, and humidity, etc.) for indirect shooting. The preparation of one artillery firing table required between 2,000 and 4,000 ballistic calculations. This work took 50 people three to six months even when using a desktop mechanical calculator, but with ENIAC it could be completed in one day by five people.¹¹ In other words, the calculation efficiency was improved between 900 and 1,800 times. However, ENIAC was a huge machine made of 18,800 vacuum tubes and it was 12 meters long, four meters high and weighed 30 tons. It also required a 24-horsepower ventilator for the heat from the vacuum tubes. Vacuum tubes broke down at a rate of about one per day and one hour was required to replace each one. As a result, the utilization rate was only 69%. Coupled with the sheer size and complex structure (around 6,000 switches), this meant ENIAC was rather far from practical.

Attaining AI is based upon the premise of advancements in computers that began with ENIAC. In 1956, an international meeting called the Dartmouth Summer Research Project on Artificial Intelligence was held on the mechanization of intellectual activities. This is where the word Artificial Intelligence (AI) was used for the first time. The development of AI until today is generally categorized into three booms. The time around this conference is considered the First Boom in the 1950s and 1960s. The features of AI around this time can be found in inference and exploration. Syllogism is a simple example of inference, which translates as “If A, then B (minor premise), and if B, then C (major premise), as a result, A is C (conclusion)”. In the late 1950s, a computer program was developed in the United States that carried out theorem of geometry with

⁶ Shinagawa Yoshiya, *No to konputa* [Brain and Computer] (Tokyo: Chuko Shinsho, 1972), pp.194-205.

⁷ Inoue Tomohiro, *Jinko chochino* [Artificial Super Intelligence] (Tokyo: Shuwa System, 2017), pp.60-66.

⁸ Matsuda, *Jinko chino no tetsugaku*, p.6.

⁹ Nagao Makoto, *Jinko chino to ningen* [AI and Humans], (Tokyo: Iwanami shinsho, 1992), pp.2-7.

¹⁰ Herman H. Goldstine, Ch.2. in *Keisanki no rekishi* [The Computer from Pascal to Von Neumann], translated by Ryota Suekane, et al., (Tokyo: Kyoritsu Shuppan, 1979).

¹¹ Shinagawa, *No to konputa*, pp.17-18.

deductive operation of symbolic logic using syllogism.¹²

Meanwhile, exploration involves finding the solution to a problem from among the options.¹³ For example, in the case of the problem of “Move to Z from X via Y,” the solution requires finding the road that leads to Y, among the roads extending in all directions from X. Even after arriving in Y, the same process needs to be carried out. If the location relationship of XYZ is not known, the correct answer must be searched for by considering solutions in a round robin format including roads that do not lead from X to Y or from Y to Z. Another example is the problem known as the “Tower of Hanoi.”¹⁴ It involves a base with three poles sticking up, and several disks with differing diameters and holes in the middle. Prior to starting the game, all the disks are lined up on one of the poles in descending order of the size of their diameter, and they are moved to the pole on the opposite side in the same shape. When doing so, one disk can be moved one time to either of the three poles, but the disks must always be stacked in descending order of the length of their diameter.

A similar problem is the Knapsack Problem where products of differing volumes and prices are placed inside a knapsack with a fixed volume with the objective to maximize the total price of the products placed in the knapsack. These examples of exploration are finite even when there are vast quantities of instances. Consequently, computers can arrive at a correct answer by using a round-robin approach. In this stage, the processing capacity of computers at the time could not make a dent since high speed processing was not possible under the given rules and conditions for problems where the number of instances increased exponentially.¹⁵

(2) The Second Boom and Expert Systems

The Second Boom of AI development that began in the 1970s is symbolized by the development of expert systems that attempt to replace the advice and judgement of experts. This involved users entering logical conditions in the form of “if-then” questions into a specific specialized database to narrow down the data and lead to a conclusion. Compared to the First Boom that was logical inference, the artificial intelligence of the Second Boom was deductive inference, which can also be viewed as “knowledge added to logic.” It is also referred to as “knowledge engineering.”¹⁶

An expert system holds a vast amount of data on the knowledge, experiences and intuition of experts, and by searching this database, the answer of “If A, then B” will be provided. MYCIN, an expert system developed at Stanford University in the early 1970s, was able to correctly diagnose bacterial infections with a probability of 69%.¹⁷ Although this fell short of the probability of correct diagnosis by specialist physicians (80%), it was higher than the results of non-specialist physicians. The system demonstrated better results than specialist physicians in terms of diagnosing bacterial

¹² Nagao, *Jinko chino to ningen*, pp.7-10.

¹³ Matsuo Yutaka, *Jinko chino wa ningen wo koeruka* [Does AI Surpass Humans] (Tokyo: Kadokawa EPUB sensho, 2015), pp.65-71.

¹⁴ For the minimal number of steps in the Tower of Hanoi is illustrated via mathematical induction at high school education level (Takahashi Tetsuo and Nikoshi Miyuki, “Kansu shido no ikkan to shitenno koutougakkou suugaku ‘suuretsu’ no jyugyo puran [Classroom plan for “sequences” in high school mathematics as part of function teaching]” *Kyojyu gaku Tankyu* [Search of Didactic Methods] Hokkaido University, no.22. [January, 2005], pp.97–100).

¹⁵ Furukawa Koichi and Fuchi Kazuhiro, “Chishiki kogaku to dai go sedai computer [Knowledge Engineers and 5th Generation Computers],” *Operations Research* vol.28, no. 6 (June, 1983), pp.3–4.

¹⁶ Nishigaki Toru, *Big data to jinko chino* [Bog data and AI] (Tokyo: Chuko shinsho, 2016), p.60.

¹⁷ Matsuo, *Jinko chino wa ningen wo koeruka*, p.88.

blood infections or meningitis.¹⁸

The introduction of an expert system makes it possible to reduce labor, in addition to increasing information processing speeds; therefore, the manufacturing industry also looked toward them.¹⁹ However, the motivation was not just about reducing labor; the purpose also involved the decline in highly experienced engineers and succession of technology. Northrop Corporation (currently: Northrop Grumman Corporation), which had faced challenges from declining engineers and declining competency, introduced an expert system called ESP, gaining hints from MYCIN, for streamlining manufacturing processes.²⁰ At the time, its F-5 and F-18 fighters were made from between 11,000 and 20,000 parts, and vast amounts of time were required for the manufacturing process formulation of each part.²¹

As a result, the company used ESP to answer the question of “what process to use for which material” around 30 times, whereby systemizing the flow of narrowing down the material and processing format, and then determining the selection of the right machine or tool for the job and correct processing sequence. During the parts manufacturing process formulation, even an experienced engineer had to carefully examine the material and processing based on their experience and knowledge, and then select the tool or machine for subsequent work (experienced engineers prefer using something familiar rather than the most optimal tool or machine) as well as consider the processing sequence. This series of process formulation work required two to three people about one hour. Using ESP, however, this work was able to be performed by a single person in around 10 to 15 minutes. Furthermore, even a less experienced engineer was able to master the work procedures with the same degree of proficiency as a highly trained engineer, including “This material is processed in this way using this machine following this procedure.” In this manner, as the number of engineers declined, Northrup was able to assign engineers freed up by the introduction of AI (ESP) to work on other more difficult work.

The question and answer posed to ESP of “what process to use for which material” is prepared based on the experiences of a highly trained engineer (generalization of experience and knowledge). When turned into data, the knowledge of an expert accounts for a vast quantity of data. Incorporating this vast data into systems supported technological progress in increasing the capacity of memory media. Consequently, underpinned by the high expectations placed in expert systems by business and industry at the time, some 3,000 systems were developed in the United States and 1,000 each in Japan and Europe.²² ESP introduced by Northrup was one of these systems.

¹⁸ Geoff L. Simons, *Jinko chino* [Introducing Artificial Intelligence], translated by Tamura Koichiro and Sato Takeshi, (Tokyo: Kindai Kagaku Sha, 1986), p.210.

¹⁹ Shimura Masamichi, *Jinko chino* [Artificial Intelligence], (Tokyo: Shin OHM bunko, 1989), p.56.

²⁰ Edward Feigenbaum, et al. *Expert company* [The Fifth Generation: Artificial Intelligence & Japan's Computer Challenge to the World], translated by Nomoto Haruyo, (Tokyo: TBS-Britannica, 1988), pp.37-55.

²¹ F-15 is said to be comprised 100,000 components (Chaki Akiyoshi, “Kokuki ijibuhin no hokyu kanri ni tsuite [Supply Management of Maintenance Parts for Aircrafts],” *Boei syutoku kenkyu* [Defense Acquisition Research] vol.3, no. 4 (March, 2010): p.3).

²² Yamaguchi Takahira, “Dai 5-sedai computer kara kangaeru AI project [AI Projects Based on 5th Generation Computers],” *Artificial Intelligence* vol.29, no.2 (March, 2014), pp.116-117.

2. Military-Use AI in the Second and the Third Booms

Full-fledged military-use AI was developed by applying the expert systems of the Second Boom in AI development. These systems left a certain degree of operational track record, but given the limit attached to expert systems, even when supplementing the intellectual work of humans, they did not go as far as replace it. This was followed by the Third Boom of AI that greatly transformed the development concept from around 2010. This boom is still taking place today.

(1) The Second Boom and Military-Use AI

The expert systems of the Second Boom were also developed into military-use systems. In the US Navy's threat assessment and countermeasure planning system, information on the type of target captured by radar, estimated intention of the target, and presentation of responses, etc., were provided to commanders.²³ In addition, RAND Corporation developed Tactical Air Target Recommender (TATR) jointly with the US Air Force as a support system for plan formulation when attacking an enemy air base. TATR is also one type of expert system, and the series of attack plan formulation from selection of target and selection of weapons to use was carried out using the following procedures.²⁴

Initially, TATR assessed multiple enemy air bases. In this process, it first determined the vulnerability and operational capacity of each enemy air base, and later, taking into account the operational situation of the enemy air bases, other relevant matters, and the tactical objective of the US Air Force's air operations, it assigned a priority order for attacks of the enemy air bases. After assigning this priority, it calculated the attack effects on each enemy air base (damages to enemy air bases = extent of reduced operational capacity). In this manner, TATR displayed a list of the enemy air bases in order of attack priority, the attack method believed to be the best, along with the types and numbers of friendly aircraft to send for the attack, and then prepared an attack plan based on the results of these estimates.

In order to perform such a calculation, TATR requires a database to refer to as needed. This database is composed of the attribution of enemy air bases (location, elevation, area, weather info), operational capacity of enemy bases (attack capability, air-defense capability, supply provision capability, damage restoration capability), and detailed information concerning friendly attack aircraft, weapons and ordinance, etc. This database is updated following progress in fighting, and (since the operational capacity of friendly and enemy forces changes with attacks) information collected from the fighting is entered manually. If the damage situation of the enemy is unknown even when implementing the attack plan presented by TATR, damages of the enemy side expected in the attack plan are reflected in the database.

TATR is an expert system. The experience and knowledge of experts is generalized in the system. This is embedded into a program that selects the optimal combination of friendly aircraft type and numbers along with ordinance to use and number after determining the priority attack ranking and target of enemy air bases (aircraft, anti-aircraft weaponry, runways, and various facilities, etc.). It also determines the attack effects (whether the enemy air base will suffer extensive, major or minor damages) during an actual attack using these combinations (aircraft

²³ Donald Michie, and Rory Johnston, *Souzou suru computer* [The creative computer: Machine intelligence and human knowledge], translated by Kimura Shigeru, (Tokyo: TBS-Britannica, 1985), pp.51-52.

²⁴ Description of TATR is based on Monti Callero, et. al., *TATR: A Prototype Expert System for Tactical Air Targeting* (Santa Monica: Rand Corporation, 1984).

type, number and ordinance, etc.) along with the variable of the enemy's recovery speed from damages, based on the experience of experts.

The ultimate goal of TATR is to formulate an attack plan for enemy air bases, but this can also be used in war games (military simulations). For example, the knowledge of experienced operators is reflected in TATR, so operators with little experience are expected to quickly acquire the knowledge of unit operations of an experienced operator through training using TATR. In addition, as preparation for planned operations, it can also be used to identify preparatory items. Furthermore, the system can also be utilized to verify unit composition and consider the information that should be collected before the start of operations.

Attempts were also made to apply expert systems to anti-submarine warfare (ASW), with a certain degree of results achieved (CLASSIFY system).²⁵ In ASW, detecting submarines using sonar is key, but higher performance sonar can also pick up many other sources of sound outside of enemy submarines, so it is extremely difficult work to sort out the target's sound from other sounds. On top of this, this work relies heavily on the rule of thumb of sonar operators, which made it almost impossible to use mathematical processing. The rule of thumb of operators is formed by experience operating sonar and expert knowledge concerning the echoing of soundwaves.

As a result, CLASSIFY is used to obtain information on the intensity and characteristics of active sonar echoes, doppler changes, angular velocity, radar reflectivity, and passive sonar information. Experts in ASW combine this, considering the quality of this information, to detect the target submarine. The problem here is that each expert considers quality based on his or her experience (determination of coefficient for variables), but when reflecting this in a system, only the experience of certain people can be reflected. Put another way, the decision of which information to emphasize during which situation varies by expert, but when building a system, only one of these can be reflected. This is an unavoidable limitation of not only CLASSIFY but any expert system.

The second problem is that targets detected with consideration of quality vary greatly. For example, even when detecting the same submarine, radar reflectivity cannot be used as a determining element if it is underwater, but the same is not true when the submarine is surfaced. In other words, the coefficient of the system's configuration and variables should be changed following the target to be detected, but this system falls into the cycle of having the purpose to detect a target. Having said that, however, the development of CLASSIFY carries great meaning in systemization in the ASW field method (heuristic) for solving a problem by narrowing down solutions based on repetition of logical conditions in the format of "If – then" by system and operator, instead of logical problem solving (algorithm).²⁶ As a result, this enabled, albeit partially, the systemization of submarine detection that had relied on experts' rule of thumb until then.

²⁵ For CLASSIFY, refer Ingemar J. Cox and Lewis J. Lloyd, "Artificial-Intelligence Systems in Antisubmarine Warfare: Results of a Pilot Study with Expert Systems," *Saclantcen Memorandum SM-176* (Dec., 1984).

²⁶ On the other hand, in the initial development of TATR, logicity was desired while heuristic methods were attempted to be eliminated (Monti Callero, et. al., "TATR: An Expert Aid for Tactical Air Targeting" *A RAND Note*, N-1796-ARPA (January, 1982), pp.29-30).

(2) The Third Boom and Deep Learning

However, the Second Boom eventually waned in the middle of the 1990s. Once the amount of knowledge (conditions) entered into a system becomes large, it makes it possible to respond to complex events. However, when this input information is vast, it becomes a hypothesis or guess with probability such as “Based on experience, if A, first it should be B” rather than the firm outcome of “If A, 100% B.” Narrowing down data using this logical condition inevitably causes calculation errors to become larger. Even for logical conditions that are 99% correct, such as the case of ESP, the accuracy even for 30 times repetition is 74% (0.99 to the 30th power) and in the case of logical conditions with 95% accuracy, the accuracy after 30 times is 21% (0.95 to the 30th power). This makes it rather difficult to say these systems can withstand practical use. Furthermore, there are cases where decisions are different among experts even when using the same data, and the conclusion reached by AI inevitably faces such limitations.

More than anything else, the tacit knowledge (intuition and rule of thumb) of people, regardless if they are experts or not, was basically impossible to systemize. A human doctor, based on their tacit knowledge, can arrive at a diagnosis even when only obtaining vague information (e.g., “stomach pain”). AI, however, will be stuck without identifying in detail “the part of the stomach, which organ is experiencing what type of symptoms or condition.”²⁷ AI cannot reach a diagnosis with abstract information such as “the top right of my stomach hurts like someone is pressing it down.”

To overcome this, a collection of anticipated questions and answers between doctors and patients must be prepared by a person beforehand and entered into the AI system. In this process, question and answers are repeated with patients to gradually materialize abstract information, but a great deal of labor is required to create these questions and answers. Even so, if the patient’s answer differs even a little from the expected response, AI will not be able to go any further. In addition, the questions and answers of doctors and patients are created based on “conventional wisdom” shared by people, and in case of developing a system, this conventional wisdom must be included, but it is vast and unclear, making it extremely difficult to systemize explicitly.²⁸

Later, the Third Boom began that continues on from the 2010s to today. Unlike the Second Boom where the correct answer was narrowed using logical conditions (deductive inference), the Third Boom is characterized by identifying the correct answer using statistical processing (inductive inference). In order to increase statistical accuracy, the larger the number of sample data the better (big data), and each of these sample data must be broken down into uncorrelated feature values mutually in comparatively small clusters (components and factors) (deep learning). Furthermore, after breaking down into these feature values, the coefficient of each feature value must be revised correlating with the original sample data, for the abstraction and generalization of sample data. This series of tasks is left to AI (machine learning) to increase the accuracy of decisions. In this process, as a result of vast amounts of data used, AI is nearly able to acquire tacit knowledge, expanding the scope of application (Table 1).

The problem here can be found in the fact that logical explanation of how a decision was reached cannot be obtained even with more accurate AI decisions, including the tacit knowledge

²⁷ Matsuo, *Jinko chino wa ningen wo koeruka*, pp.89-90.

²⁸ Nagao, *Jinko chino to ningen*, pp.180-182.

mastered in this manner. For example, AI such that can beat a prominent professional shogi (chess-like Japanese board game) player learned records of more than 60,000 games played since about four hundred years ago and broke them down into more than 10,000 feature values.²⁹ In addition, it is said that recent shogi software is processing and evaluating the positional information of pieces for upwards of 100 million possibilities.³⁰ Even if the coefficient attached to these variables on the order of 10,000 or 100 million can be demonstrated inductively as a result of statistical processing, it is impossible to explain deductively why a certain value was reached. That is, AI simply presents the highly accurate results. More than likely, this could be the actual state of the tacit knowledge possessed by people.

Habu Yoshiharu, a professional shogi player and holder of seven lifetime titles, refers to this situation as a “black box.”³¹ In other words, AI’s decision making has become invisible to people, and Habu states his concerns about becoming excessively reliant on this, and therein lies the awareness that the “decision making process essentially differs between AI and people.” However, learning amounts are simply incomparable between people and AI, but in terms of “indicating the results inductively,” they are likely the same. Incidentally, the shogi software called Ponanza, which beat Sato Amahiko, former Meijin (champion) titleholder, during a match between professional shogi player and shogi software in 2013, developed by Yamamoto Issei, a professor at Aichi University, has data containing 800 billion moves.³² In addition to records of matches, this data is the result of learning from games played between shogi software competing against each other (a match involving professional shogi players requires several hours, but a match between AI software is finished in only several seconds each time).³³ Certainly, it would likely be impossible

Table 1: Summary of Each AI Boom

		Application scope	Logic
First Boom (1950s to 60s)	Logic deductive inference	△ (Puzzles and games, etc.)	◎
Second Boom (1970s to 80s)	Knowledge deductive inference	○ (Expert systems, etc.)	○
Third Boom (2010s to present)	Statistical (learning) inductive inference	◎ (Pattern recognition & machine translation, etc.)	△

Source: Partially revised the table on p.172 in Nishigaki Toru, *Big data to jinko chino* [Bog data and AI] (Tokyo: Chuko shinsho, 2016).

²⁹ Hoki Kunihiro and Watanabe Akira, *Bonanza VS shoubu no* [Bonanza vs. competitive brain – Will the best shogi software eclipse humans?], (Tokyo: Kadokawa Shoten, 2007), pp.27-28. The oldest existing record of a game of shogi is as old as 1607 (Matsumoto Hirofumi, *Kishi to AI ha dou tatakatte kitaka* [How Have Shogi Players and AI been Competing?], [Tokyo: Yosensha, 2017], p.21).

³⁰ Yamamoto Issei, *Jinko chino wa donoyouni shite ‘meijin’ wo koetanoka* [How did AI eclipse famous people?—Fundamentals of machine learning, deep learning and reinforcement learning as taught by the developer of the world’s best shogi AI software Ponanza], (Tokyo: Diamond Inc., 2017), p.140.

³¹ Habu Yoshiharu and NHK Special News Crew, *Jinko chino no kakushin* [The Core of Artificial Intelligence], (Tokyo: NHK Shuppan shinsho, 2017), p.36.

³² *Newton bessatsu* [Special edition of Newton], (May 2018), p.100.

³³ Each professional player has 9 hours per game in a professional shogi competition (sum of 18 hours), which takes place over two days. To date, the longest thinking time spent on one move was 5 hours and 24 minutes (Japan Shogi Association website: https://www.shogi.or.jp/column/2017/01/post_68.html).

for a human shogi player to learn and analyze such a large amount of data even in one lifetime, but there is believed to be no major difference between shogi player and AI in the thought process leading to tacit knowledge thereafter.

(3) Increasing AI's Thinking and Decision-Making Capability

As discussed above, humans have already been “liberated from intellectual work” by the invention of the calculator and computer. The First and Second Booms of AI development (especially the latter) not only liberated humans from simple intellectual work, but also focused on the perspective of “supplementing thinking and decision-making.” These booms ended halfway, but in the Third Boom currently underway, development has gone beyond supplementing to “replacing thinking and decision-making (intellectual labor).” This means that intellectual labor, which was the bastion of humans, is able to be replaced by AI. Discussions are now underway from all sides about this.

The reason why the replacement of thinking and decision-making is possible first thanks to significant improvements in processing speed (computer performance). In the IT field, instead of conventional progressive technological advances such as these improvements, exponential technological innovations are progressing as indicated by Moore's law.³⁴ This means that vast amounts of data physically impossible for humans can now be processed by a machine instantaneously. In other words, the amount of knowledge used as a basis for decision-making by a system is already greatly superior to that of humans. Vast amounts of data must be handled to carry out work commensurate with a system that can be called artificial intelligence, but until recently the processing speeds of computers had not been enough for it.³⁵

In recent years, improvements in computer performance have made deep learning a reality, and made it possible to utilize vast amounts of data for this purpose. In June 2012, Google successfully developed a program using deep learning methods that can recognize a cat without the help of humans (Table 2). This system operated 1,000 computers for three days to read the data of 10 million photographs to learn which picture is a cat and which is not. However, it is said that using a computer in the 1990s to perform the same work would take more than 6,000 years.³⁶

In addition to this, IBM's supercomputer called Watson, which beat a quiz champion on an American quiz show in February 2011, analyzed data equivalent to 200 million pages at the time, and it did not require three seconds to present the results of its analysis.³⁷ The processing speed of Watson sped up 24 times in the four years since.³⁸ IBM's Deep Blue, which beat a world champion

³⁴ Moore's Law is stated by Gordon Moore, one of the co-founders of Intel Inc., that the degree of integration on IC doubles at every 18 months to 2 years (“Moore's Law at 40, Happy birthday, The tale of a frivolous rule of thumb,” *The Economist*, Mar. 23rd 2005, <http://www.economist.com/node/3798505>). However, the same law also applies to the processing speed of IC, capacity of memory medium, and circuit capacity for wireless data communication, optical communication, and the internet, pointing to the exponential evolution of IT technology as a (P. W. Singer, *Wired for War: The Robotics Revolution and Conflict in the Twenty-first Century* [New York: The Penguin Press, 2009], p.99).

³⁵ Nishigaki, *Bigu deta to jinko chino*, pp.76-89.

³⁶ Ono Kiyoshi, “Deep learning nyumon Introduction to Deep Learning,” *Intec Technical Journal*, vol.17 (September, 2016), p.30.

³⁷ Kozaki Yoji, *Jinko chino kaitai shinsho* [AI Guidebook: Understanding the system and utility of AI from scratch] (Tokyo: Science eye shinsho, 2017), p.67.

³⁸ Hachiyama Koji. “Beikoku ni okeru jinko chino ni kansuru torikumi no genjo [Current Status of AI Initiatives in the USA]” *Information-Technology Promotion Agency NY Report*, (February, 2015), p.3.

of chess in 1997, is said to be able to calculate 300 million moves in one second.³⁹ The shogi software called Bonanza developed by Hoki Kunihiro, associate professor at the University of Electro-Communications, is able to read four million moves in one second.⁴⁰ These results have basically benefited from increasing hardware performance.

The factors of number two are deeply related to number one, but this is because non-standardized data can now be handled. Conventional data entry into a computer involved quantifying non-standardized data (analog) into digital form with the help of people. This can now be analyzed by reading recognition of language along with images, videos and voices as data. Citing an example, in 2015, IBM acquired a company that owns medical information and digital charts for 50 million people followed by a company that manages medical imaging data of 200 million sheets, in order to expand its healthcare business.⁴¹ Incidentally, some 200,000 reference works on cancer treatment are registered in a specialized database every year and these records contain many images. The advancement in AI in recent years has made it possible to analyze non-standardized data such as images and sentences.

The factor of the third is cited as AI's thinking and decision-making is not affected by fatigue like humans. As a concrete example, according to Shai Danziger, et. al., there is research about the relationship between judge rulings and fatigue in Israel.⁴² According to this, as a general theory, rulings handed down at times close to the end of work tend to be stricter on the defendant than those handed down during early hours of the day. In addition, in case of rulings after a recess, rulings

Table 2: Improving AI Capability

Year	Developer	Details
1980	M. Reeve, D. Levy	Moor beats world champion in Othello
1994	University of Alberta (Canada)	Chinook beats world champion in Checkers
1997	IBM	Deep Blue beats world champion in chess
2010	Univ. of Electro-Communication, Univ. of Tokyo, et al.	Akara 2010 beats female titleholder in Shogi
2011	IBM	Watson beats quiz champion on American quiz show
2012	Google	AI automatically recognizes cat
2013	Yamamoto Issei	Ponanza records first overwhelming victory of professional shogi player
2016	Google	AlphaGo beats world champion in Go
2016	National Institute of Informatics et al.	Torobo-kun posts the highest score on a university entrance exam (written portion)

Note: The numbers of cases for each game were; 10 to the 30th power for Checkers, 10 to the 60th power for Othello, 10 to the 120th power for Chess, 10 to the 220nd power for Shogi, and 10 to the 360th power for Go (Japan Science and Technology Agency, "Kenkyu kaihatsu no fukan houkokucho [2015] [Report on research and development – Information science technology field [2015]]" [2015], pp.357-359).

³⁹ Matsubara Jin, *AI ni kokoro wa yadoru noka* [Does a heart reside in AI?], (Tokyo: Shueisha International Inc., 2018), p.64.

⁴⁰ *Newton bessatsu*, p.32.

⁴¹ Japan Health Sciences Foundation, "Iryo bunya ni okeru big data narabini ICT • AI no rikatsuyo no saishindoko [Big data in the medical field and latest trend in ICT & AI utilization], (March, 2017), p.125.

⁴² Shai Danziger, et al., "Extraneous factors in judicial decisions," *Proceeding of the National Academy of Sciences (PNAS)*, vol.108, no.17 (April, 2011), pp.6889-6892.

that were stricter prior to the recess were observed to be eased after the recess. This indicates the possibility that even judges who are trained in correct and impartial rulings cannot avoid the impact of fatigue on their thinking and decision-making.

3. AI Advancements and Replacement of Intellectual Labor in the Military

In the previous section, discussions about practical examples of AI as a support method for decision making focused mainly on the application of expert systems in the Second Boom. However, the AI in the Third Boom that is currently underway transcends “support of decision making” where human’s “decision-making itself (intellectual labor) can be replaced. Below, the author will attempt to examine the replacement of intellectual labor using AI by the military.

(1) Replaceability of the Military’s Functions using AI

Traditionally, labor replacement by computer was limited to routine work for which rules were clear. But, after the First and Second Booms, in the Third Boom of recent years, AI has been able to replace non-routine work. The abstraction and generalization of this non-routine work is made possible with big data. Of course, the progress of hardware that enables instantaneous deep learning of big data and breakdown to uncorrelated feature values (abstraction and generalization) has been vital to this. These are also the core technology underpinning the Third Boom of AI. Carl Benedikt Frey and Michael A. Osborne of Oxford University presented the famous report called *The Future of Employment: How susceptible are jobs to computerisation?* in 2013.⁴³ This report examined the replaceability of 702 occupations based on US Labor Department classifications using AI (including robots) from the middle of the 2010s to the middle of the 2020s, but military occupations were not subject to consideration. As a result, the author compiled the replaceability using AI of occupations similar to each military function after largely categorizing these functions into the three areas of headquarter (staff organizations), combat units, and support units (Table 3). At the same time, the replaceability of each occupation by AI produced by Frey and Osborne is shown side by side.

This merely allocates the predicted value of replaceability by AI of the occupations considered to be close to these military functions. However, from this, certain tendencies can be interpreted. For example, in the near future, there is a low possibility that command and management duties will be replaced by AI, but there is a high possibility for replaceability of duties supporting these. Moreover, even for non-routine duties, the judgement of humans is indispensable for the time being regarding management and supervision. For the most general management duties, replacement by AI will come into view, even for supervisors.

In future military units, the commander will make decisions based on their own experience and intuition (tacit knowledge) while referencing documents prepared by AI. Even if physical work in the field is replaced by AI (robots), the management and supervision will be carried out by humans. Military is active on battlefields and at the scenes of disasters, which requires the frequent occurrence of “ad hoc response to inexperienced situations.” This type of judgement is difficult for AI, but this can be easily forecast from the characteristic of AI in which feature values is analyzed

⁴³ Carl Benedikt Frey and Michael A. Osborne, “The Future of Employment: How susceptible are jobs to computerisation?” *Oxford Martin School Working Paper, University of Oxford* (September, 2013).

using statistical processing of past sample data.

However, according to Frey and Osborne, it remains difficult to use AI to replace occupations that require “1. Non-standardized perception and manipulation,” “2. Creative intelligence,” and “3. Ability to build cooperative relationships with others by adapting to social human relationships.”⁴⁴ Among these, 1) presents technological difficulties of hardware and software, while 2) cannot avoid the reliance of AI decisions on statistical processing of past sample data. In addition, 3) is the ability of personal relations in a human society known as “social intelligence,” which is the most difficult to replace using AI (and the least suitable). Conversely speaking, the hurdles of 1) may be reduced with technological advancements, but for 2) ad hoc response to inexperienced situations poses a major challenge for AI. In addition, examples were introduced of AI creating works of art, but these are nothing more than the “imitations” of past artists’ work (statistically close), and not “artistic creations.” 3) should be viewed as AI occupies a different existence as humans and it cannot be resolved since AI cannot be a member of human society.

Military functions for which computerization is believed to be difficult as indicated in Table 3 truly require all three. Specialized analysis provided by AI will likely become even more accurate in the future, but this analysis assumes that the preconditions will not change from the current situation. For example, AI that can beat the best shogi players learns tens of thousands of matches over the past 400 years and learns more than matches as the result of battles between AI software. The assumptions of these are all the same (9 x 9 board, 40 pieces in total, move of each piece, etc.). However, in the activities of the military (battlefield or scene of disaster, etc.), the assumptions are not uniform, and they change on occasion. In the case of shogi, this would mean the board suddenly expands to 12 x 15 during a match, or the number of pieces increases to 60, and the moves change suddenly (soldiers and spears can move backwards which is not allowed in the current rule, etc.), normalizing “ad hoc response to inexperienced conditions.” It is believed that “the ability to respond to sudden, unpredictable situations inherent in humans” will not be replaced by AI for the next 20 years.⁴⁵

(2) Entry and Analysis of Non-Standardized Data and Staff Functions

The important thing when considering labor replacement using AI is whether input and output is standardized or not. The first computers had to have inputs standardized (entry using punch card), and outputs was inevitably standardized. This means that even in today’s everyday life most computers have had their inputs and outputs standardized. On the other hand, computers have gradually been able to cope with non-standardized input (distinguishing handwritten numbers, etc.).⁴⁶ For example, using the example of Table 2, the input of checkers, chess, shogi and go are

⁴⁴ Frey and Osborne, “The Future of Employment,” pp.25-30.

⁴⁵ Eto Minoru, “Economic classroom AI and work style: The rise of various freelance work.” *The Nikkei*, (February 27, 2018).

⁴⁶ For example, the world’s first handwriting recognizing automatic postal code reading and sorting machine was developed and brought to application by Toshiba in 1967 (Toshiba website: http://toshiba-mirai-kagakukan.jp/learn/history/ichigoki/1967postmatter/index_j.htm).

Table 3: Replaceability of Military Functions by AI (including robots)

Military functions		Resembling occupation	Probability of substitution by AI
HQ (staff)	General Affairs	First-Line Supervisors of Office & Administrative Support Workers	1.4%
		Administrative Services Managers	73 %
	Intelligence	Social Scientists & Related Workers	4 %
		Market Research Analyst & Marketing Specialists	61 %
	Operations	Training & Development Specialists	1.4%
		Business Operations Specialists	23 %
	Logistics	Medical & Health Services Managers	0.73%
		Logisticians	1.2%
	Planning	Urban & Regional Planners	13 %
	Communications	Computer & Information Systems Managers	3.5%
		Information Security Analysts, Web Developers & Computer Network Architects	21%
	Legal	Lawyers	3.5%
		Paralegals & Legal Assistants	94 %
	Adjutant	Executive Secretaries & Executive Administrative Assistants	86 %
Combat Unit		First-Line Supervisors of Fire Fighting & Prevention Workers	0.36%
		First-Line Supervisors of Police & Detectives	0.44%
		Police & Sheriff's Patrol Officers	9.8%
		Firefighters	17 %
		Airline Pilots, Copilots & Flight Engineers	18 %
		Captains, Mates, and Pilots of Water Vessels	27 %
		Police, Fire & Ambulance Dispatchers	49 %
		Transit and Railroad Police	57 %
		Sailors & Marine Oilers	83 %
		Security Guards	84 %
Support Unit		First-Line Supervisors of Mechanics, Installers & Repairers	0.3%
		First-Line Supervisors of Transportation & Material-Moving	2.9%
		Chefs and Head Cooks	10 %
		Air Traffic Controllers	11 %
		Commercial Pilots	55 %
		Transportation, Storage & Distribution Managers	59 %
		Aircraft Mechanics & Service Technicians	71 %
		Heavy and Tractor-Trailer Truck Drivers	79 %
		Cooks, Institution and Cafeteria	83 %
		Laborers & Freight, Stock & Material Movers, Hand	85 %

Source: Made by the author based on Carl Benedikt Frey and Michael A. Osborne, "The Future of Employment: How susceptible are jobs to computerisation?" *Oxford Martin School Working Paper, University of Oxford* (September, 2013), pp.61-77.

Note: Shaded cells indicate replaceability of 50% or higher.

standardized and output is also standardized.⁴⁷ However, the automatic recognition of a cat (2012) had non-standardized input (input images from the Internet without changing), but Torobo-kun (2016) has evolved to the point where it can respond to both non-standardized input and output of a university entrance exam.⁴⁸

However, the command functions and chain of command indicated as difficult to be replaced by AI in Table 3 can be viewed as duties that require non-standardized input and output. Yet, current computers are not fully capable of non-standardized output. In other words, there is sufficient potential for duties that involve the combination of “non-standardized input and standardized output” to be replaceable by AI for the time being. In the military, staff duties are one of the occupations that this combination of “non-standardized input and standardized output” applies to.

Lieutenant-General William G. Pagonis, who commanded the 22nd Support Command during the Gulf War (1991), states that an index card (three inch x five inch) was an effective means of communicating complex information and orders based on his experience in the Gulf War.⁴⁹ In the IT world of today such information exchanges can likely be done by email and even Pagonis himself says he used the index card and email together during the battle.⁵⁰ This is an archetype example of non-standardized information. The handwritten entry on a card (although these cards were also typed apparently), and even email, has a basic format and is non-standardized form of information. The main duty of staff organizations is to organize and categorize this information and then convey and coordinate it to the right departments.

A similar situation occurred during the rescue work following the Great East Japan Earthquake of 2011. At Ishinomaki Red Cross Hospital, which is a disaster designated hospital for the Ishinomaki medical district in Miyagi Prefecture, physician Ishii Tadashi, who was the frontline commander of medical assistance as the “disaster medical coordinator” immediately after the earthquake, faced difficulties in information shortages, organization and conveyance.⁵¹ Ishinomaki City had 300 evacuation shelters, but immediately after the disaster there was no information whatsoever on the hospitalized and injured, as well as the presence of food and water and condition of sanitation and heating. As time passed, however, information soon overflowed and at the same time requests began to emerge that exceeded this information. Most of this information was conveyed verbally (in person or over the telephone) and it was managed by handwritten notes on paper. Later, the Japanese subsidiary of Google systematized this information management as part of its support for disaster relief.⁵² The nature of this information was non-standardized, but data organization had to be performed by the system and input, breakdown and analysis had to

⁴⁷ The go software that can even defeat professional players uses Monto Carlo tree search in its algorithm instead of evaluation function that is used in chess and shogi software (Nikkei Big Data ed., *Google ni manabu deep learning* [Learn Deep Learning from Google], (Tokyo: Nikkei Business Publications, 2017), pp.68–71. As the program chooses moves randomly with high probability of winning, even though there are more number of cases in go than shogi, the program itself is considered rather straightforward.

⁴⁸ Iwane Hidenao and Anai Hirokazu, “Suuri shori niyoru syushi mondai eno chosen [Taking on examination questions via formula manipulation]” *FUJITSU* vol.66, no.4 (July, 2015), pp.19–25.

⁴⁹ William G. Pagonis and Jeffrey L. Cruikshank, *Moving Mountains: Leadership and logistics from the Gulf War* (Boston: Harvard Business School Press, 1992), pp.189-191.

⁵⁰ *Ibid.*, p.189, p.226.

⁵¹ Ishii Tadashi, *Higashi nihon daishinsai, ishinomaki saigaiiryō no zenkiroku* [The Great East Japan Earthquake Full Report on Ishimaki Disaster Medical Treatment], (Tokyo: Kodansha bluebacks, 2012), pp.66-70.

⁵² *Ibid.*, pp.89-93.

rely on people.

Certainly, looking at Table 3, the replacement of labor in the military using AI is believed to be not suitable for command units (staff organizations). However, from the perspective of “input of non-standardized data and breakdown and analysis,” an aspect different from this can be observed. For the military’s staff organizations, the transport and organization of overflowing information in the form of non-standardized data during a contingency occupies a large weighting of operations. During the Great East Japan Earthquake, the command of the North Eastern Army of the Japan Ground Self-Defense Force (GSDF) that functioned as the HQ for the Joint Task Force (JTF-TH) saw a sharp increase in operations for formulating rescue plans, organization, analysis, search, and conveyance of various information, and coordination with relevant departments, while the organization’s manpower was lacking absolutely. Consequently, additional staff were dispatched from various units and were placed in charge of these operations. In this manner, AI, which copes with the input and analysis of non-standardized data, was expected to greatly reduce the burden of the command unit and staff. This applies not only to large-scale disasters, but also to other contingencies with various complex information brought from relevant departments without close interactions during normal times, such as the protection and evacuation of Japanese nationals abroad and protecting the Japanese people from armed attacks.

In addition, Ishii introduced the following during a review committee meeting held after the disaster. The first requirement after a disaster is information collection, and there was a common understanding that the most effective approach for it is that the rescue providers (= rescue information receiver) instruct “the types of information necessary for rescue and information should be collected following the instruction” (this is likely the same today).⁵³ However, a person in charge at Google who worked on the development of the information organization system for evacuation shelters of the Ishinomaki Red Cross Hospital during the Great East Japan Earthquake said at the review committee meeting that “It doesn’t matter what information, please gather every piece of information available. You don’t need to worry about whether information is important or not. It is our job as experts to “prepare” the collected information. My message is to collect all forms of information possible and leave the rest to us.”⁵⁴

This statement directly and easily articulates the processing of information (non-standardized and standardized) by AI within the staff organization. The phrase “all forms of information” mostly refers to non-standardized data, and “‘prepare’ collected information (breakdown and analysis)” is made by AI (‘experts’). In addition, large amounts of data increase the decision-making capability of AI, and information that may not be needed or information that is questioned as important is automatically judged according to a high degree of accuracy.

(3) The Military’s Combat and Non-Combat Units and Advancements in AI

A general trend observed from Table 3 suggests that the replacement of labor by AI (including robots) may follow the trend of “support units > combat units > command units (staff organizations).” In addition, even for combat units and support units, duties related to command and management are believed to have a low possibility of replacement by AI. As discussed in the previous sections,

⁵³ Ibid., pp.94-95.

⁵⁴ Ibid., p.95.

improvements in processing capability of non-standardized data indicate that replacement by AI is not necessarily a low possibility even for command (staff organization) duties in the future. However, in the military, the ratio of support units and command units (staff organizations) is increasing. What type of impact will this tendency and the potential of replacement of intellectual labor by AI have on the organization and structure of the military?

Martin van Creveld argues that the ratio of combat units and supply units in the military cannot easily be determined.⁵⁵ However, John J. McGrath quantitatively indicates that the ratio between combat and non-combat units (tooth-to-tail ratio: T3R) is declining based on trends in the structure of US Army units since World War I. The figure presents a graph of the values calculated by McGrath. Here, the T3R is presented as a ratio calculated by dividing the number of personnel in combat units by that of non-combat units (the sum of command units and support units).⁵⁶ Based on the figure, the main factors for the decline in the T3R are the declining ratio of combat units and the increasing ratio of support units. Furthermore, the ratio of command personnel had continued to increase since World War I, but since the end of the Cold War (1991: Gulf War; 2005: Iraq War) it has declined. However, the value for the Iraq War of 2005 includes all private sector contractors included in support units.⁵⁷ Given this, private sector contractors are believed to be uniformly categorized in support units despite the fact they are responsible for certain command and management functions (supervision, planning and coordination).

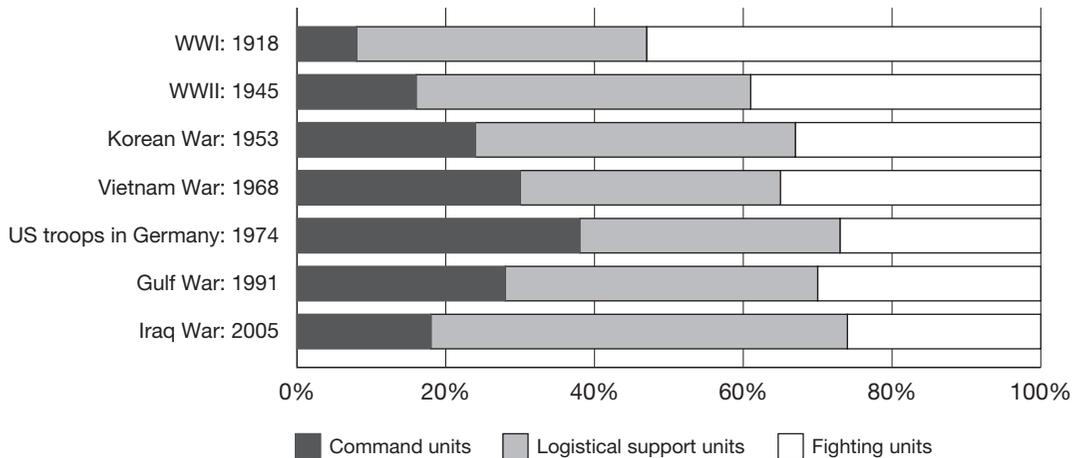


Figure - Ratio of Personnel Belonging to the Command, Logistical Support and Combat Units of US Infantry Divisions (1918–2005)

Note: The value for the Iraq War includes private contractors for logistics support units.

Source: Made by the author based on John J. McGrath, "The Other End of the Spear: The Tooth-to-Tail Ratio (T3R) in Modern Military Operations" *The Long War Series Occasional Paper 23* (Fort Leavenworth, KS: Combat Studies Institute Press, 2007), p.103.

⁵⁵ Martin van Creveld, *Hokiyusen* [Supplying War: Logistics from Wallenstein to Patton], translated by Sato Sasaburo, (Tokyo: Chuko bunko, 2006), pp.384-393

⁵⁶ John J. McGrath, "The Other End of the Spear: The Tooth-to-Tail Ratio (T3R) in Modern Military Operations" *The Long War Series Occasional Paper 23* (Fort Leavenworth, KS: Combat Studies Institute Press, 2007), p.2.

⁵⁷ *Ibid*, pp.52-53.

AI today (Third Boom) has the characteristic of significantly increasing recognition accuracy of non-standardized data. As has already been discussed, this is believed to be linked to the greatly increasing possibility for the replacement of command unit (staff organizations) functions in the military. As indicated in the figure, however, at the time of the Iraq War in 2005, the personnel of the command and management units of the entire military was less than 20% (18%), which was hardly changed from World War II (16%).

Given this, the following can be pointed out as a long-term trend. Support units have seen an uptick in the percentage, but replacement of labor by AI is possible to a certain degree as seen in Table 3. On the other hand, there is believed to be a possibility for replacement by AI for combat units, too. As a result, the downtrend in the T3R is expected to either weaken or reverse into an uptrend. Put another way, the structure of the military, whereby non-combat units have bloated, will perhaps swing back in the future based on the introduction of AI (the weighting of combat units will get larger). There are many discussions about the reduced manpower and elimination of manpower in combat units from the introduction of robots.⁵⁸ However, the replacement of intellectual labor brought about by the introduction of AI (robots) indicates that non-combat units, especially support units are no exception.

Closing – Co-existence of AI and Humans (Military Personnel)

AI development has close to 70 years of history. AI has been commercialized to a certain degree and applied to military-use from around 40 to 50 years ago. The functions of AI at this stage were limited to “supplementing the intellectual labor” of humans, but in the Third Boom of AI development that began around 10 years ago, the “replacement of intellectual labor” of humans until then began to enter the field of view. As indicated in the outcomes of chess, shogi and go matches, AI has already achieved a level that surpasses humans in intellectual games. In view of this, it is believed that AI will be able to “replace the intellectual labor” of humans in the military in the not too distant future.

How will AI and humans (military personnel) co-exist in the future military where most intellectual labor has been replaced by AI (robots)? At the present time, it is no easy task to find the answer to this question, but at the very least the military side, too, likely cannot avoid some form of change in its structure and organization with the introduction of AI. Habu Yoshiharu quoted the remarks of Mogi Kenichiro, a Japanese brain scientist, saying “Modern society is constructed based on the assumption that human IQ is at most around 100.” He continues, “If the IQ of artificial intelligence reached 4,000, [omitted], the approach to society will probably change completely at that time.”⁵⁹ “The possibility that approaches will change completely” also applies to the military, which forms part of human society. These discussions are materialistic, but if the progress of human society could be quantified, it can be said that the speed of IT and AI progress

⁵⁸ A representative work in this field includes P. W. Singer, *Wired for War*. For the mechanical soldiers conceived by Leonard Da Vinci, refer to Taddei, Mario, *Da Vinci ga hatsumei shita robot* [Robot Di Leonardo Da Vinci], translated by Matsui Takako, (Tokyo: Futami Shobo, 2009).

⁵⁹ Habu and NHK Special News Crew, *Jinko chino no kakushin*, p.36.

under Moore's Law greatly exceeds that.⁶⁰

Although not a dramatic change such as replacement of intellectual labor by AI, the capital intensification of the military brought about by the modernization of equipment as indicated in the figure caused the T3R to gradually decline, while the military's structure and organization has become the dependent variable of technological progress.⁶¹ At the same time, Table 3 can be said to predict to some degree the military's structure and organization when AI is capable of replacing intellectual labor. However, humans' psychological resistance to reliance on AI cannot be refuted for the core components of intellectual labor such as decision making. People have pointed out since the time of the Second Boom that this is a major obstacle to the introduction of AI in the military.⁶²

Although its development is progressing at the fastest pace, it appears that AI will not be able to gain the same capacity as humans in terms of "ad hoc response to inexperienced situations" anytime in the near future. As is the case with chess, shogi and go, however, in some localized situations, at the current point in time AI is able to present a faster and more preferable response than humans. Even in such cases, the synthesis of the local, most suitable solution produced by AI is not necessarily the most suitable solution for society as a whole. As a result, the problem of "synthesis error" cannot be avoided.⁶³ Incidentally, the horizon line effect is cited as a further issue of AI (e.g., when a disadvantage occurs, prioritizing actions that do not allow this disadvantage to emerge).⁶⁴ This is not AI-like behavior, which pursues the optimal solution through logic and reason, by not postponing the problem directly and falling into the danger of thinking that the results are the greatest strength, and it also shows the bad habits of humans.

However, Tobe Ryoichi compared the military leaders of the Meiji (1867 – 1911) and Showa (1926 – 1945) periods and stated that compared to the latter with specialized military jobs, the former had elements of broader learning and groundings in the samurai way.⁶⁵ At the same time, he concluded that "military personnel in leadership positions must have not only logical and analytical capabilities, but also have prudence, sagacity and decision-making capabilities from a broader perspective." In other words, compared to the military leaders of Showa who pursued local, specialized, optimal solutions, those of Meiji were able to find the optimal solution holistically and socially. The term holistic likely includes "inexperienced situations," while prudence and intelligence exclude "problem postponement." In addition, "depth of wisdom (= decision-making

⁶⁰ The discussion based on historical materialism that serves as the prelude to the indication here refers to Simone Weil, *Sensou ni kansuru shosatsu* [Investigations into war], translated by Ito Akira in Hashimoto Ichimei, and Watanabe Kazutami eds. *Simone Weil chosaku-syu vol.1* [Works of Simone Weil vol.1, Reflections on Wars and Revolution: Early Critiques], (Tokyo: Shunjusha Publishing, 1968), pp.125-126.

⁶¹ For detail on capital intensive nature of the military, refer to Ono Keishi. "Jinko dotai to anzenhosho [Demographic trend and security]" *NIDS Journal of Defense and Security*, no.19, vol.1 (March, 2017), pp.4-5, pp.13-17, Brian Nichiporuk, *The Security Dynamics of Demographic Factors* (Santa Monica: RAND Corporation, 2000), p.27, p.29, and Paul Poast, *The Economics of War* (New York: McGraw-Hill Irwin, 2006), p.91.

⁶² Randolph Nikutta, "Artificial intelligence and the automated tactical battlefield," Allan M. Din ed., *Arms and Artificial Intelligence: Weapon and Arms Applications of Advanced Computing* (Oxford: Oxford University Press, 1987), p.109.

⁶³ The error in synthesis is an issue in microeconomics, however, there are also risks of similar situations happening in system development (contradiction between systems) (Nagao, *Jinko chino to ningen*, pp.185-187.).

⁶⁴ Habu and NHK Special News Crew, *Jinko chino no kakushin*, pp.86-89.

⁶⁵ Tobe Ryoichi. "Meiji no gunjin to showa no gunjin [Military leaders in Meiji era and Showa era," *Military History* vol.52, no.1 (June, 2016), forward.

ability during unresolved situations)” by which Hironaka Heisuke, a prominent mathematician and Fields Medal laureate, cited as the superiority of the human brain over computers, too, could be viewed as similar.⁶⁶ The starting point for discussing the ideal vision for military units and personnel to co-exist with exceptionally correct and logical AI is believed to be in this area.

⁶⁶ Hironaka Heisuke describes the depth of knowledge as generosity and decisiveness as leap (Hironaka Heisuke, *Gakumon no hakken* [Discovery of studies: mathematicians talk about their thoughts and learning], (Tokyo: Kodansha bluebacks, 2018), pp.51-58.