Concepts and Challenges of Measuring Production of Artificial Intelligence in the U.S. Economy

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Abstract Much of the current literature on the economic impact of artificial intelligence (AI) focuses on the uses of AI, but little is known about the production of AI and its contribution to economic growth. In this paper, we discuss basic concepts and challenges related to measuring the production of AI within a standard national accounting framework. We first present a variety of examples that illustrate how both the production and use of AI software are currently reflected in macroeconomic statistics like gross domestic product and the supply and use tables. We then discuss a broader approach to measurement using a thematic satellite account framework that highlights production of AI across foundational areas, including manufacturing, software publishing, computer and data services, and research and development. The challenges of identifying and quantifying AI production in the national accounts using existing data sources are discussed, and some possible solutions for the future are offered.

Keywords Artificial intelligence, supply and use tables, thematic satellite accounts

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1. Introduction

Artificial intelligence (AI) is defined many ways, though a common underlying theme is technologies that perform tasks by mimicking human-like senses, learning, and actions (Turing 1950; Elham, et al. 2019; U.S. Patent and Trade Office (USPTO) 2020; Grobelnik, Perset, and Russell 2024). While computers have long demonstrated an ability to perform complicated tasks traditionally associated with humans, attention has turned lately to advances in AI capabilities that have shown potential to greatly impact the economy across many industries, such as generative AI. Recent studies have shown use of AI by businesses increases labor productivity in certain occupations, including a recent experiment involving software developers that found the group with access to an AI programmer completed their task 56 percent faster than the control group that did not use AI (Peng, et al. 2023). In another study, customer support agents with access to a generative AI-based conversational assistant were shown to increase average productivity by 14 percent, as measured by the rate of issues resolved in an hour (Brynjolfsson, Li, and Raymond 2023). Still, the percent of U.S. businesses that used AI to produce goods and services was less than 4 percent in 2023 and was heavily concentrated in two sectors: information and professional, technical, and scientific services (Breaux and Dinlersoz 2023). And a recent paper by Acemoglu (2024) estimated AI would have only a modest effect on total factor productivity (TFP) over the next 10 years, increasing TFP by no more than 0.66 percent in that time, suggesting the effects of AI on overall economic production may be limited in the near term.

While much of the literature on the economic impact of AI focuses on the use of AI, little is known about the production of AI, specifically the industries involved in producing AI technology and their contribution to overall economic growth. In this paper, we discuss concepts and challenges related to measuring macroeconomic statistics like gross domestic product (GDP) for AI production using two approaches. In the first approach, we show how both the production and use of AI software are currently reflected in the supply and use tables (SUTs) using a variety of vignettes. Then we discuss a broader approach to measuring production of AI along the supply chain using a typical satellite account framework. In both cases, we note some of the measurement challenges given the existing source data and offer some possible solutions. Analyzing AI-related transactions using these approaches helps convey how economic accountants mechanically view the role of AI in the context of measuring GDP and serves as a starting point for discussion on how to identify and measure AI production using standard national accounting practices.

2. Measuring Production and Use of AI Software in the SUTs

In this section, we first describe two examples that illustrate how the production of AI is currently captured in BEA's GDP statistics using the SUT framework, and conclude with an example of how the use of AI software is reflected in GDP. The SUTs enable one to analyze how individual economic transactions are reflected in all three measures of value added or GDP (production, final expenditure, and income) in a fully integrated, consistent framework. Using the production approach, value added is derived residually as follows:

$$Value\ added = Gross\ output - Intermediate\ inputs$$

Using the final expenditure approach, GDP is measured as the sum of expenditures or purchases by final users:

$$GDP = Consumption + Investment + Goverment\ spending + Exports - Imports$$

Using the income approach, GDP is measured as the sum of income payments and other costs incurred in the production of final goods and services:

$$GDP = Compensation\ of\ employees + Taxes\ on\ production\ and\ imports\ less\ subsidies \\ + Net\ operating\ surplus + Consumption\ of\ fixed\ capital$$

Artificial intelligence is both produced and used by businesses, government, and nonprofit institutions serving households. We do not view AI itself as an asset type, although the pursuit and application of AI each spur capital formation. For example, research and development (R&D) is needed to develop the complex algorithms that underly AI. Those R&D expenses are treated as capital expenditures in BEA's national economic accounts. Moreover, continued R&D in semiconductor manufacturing enables the production of high throughput chips required to execute modern AI algorithms. That R&D, along with advanced machinery required to produce those chips, are all considered capital expenditures. And the production of software applications that embed AI is also treated as capital expenditures. Finally, the production and use of AI are also reflected in intermediate inputs and are captured directly in value added for the producing industries. We sought to provide examples in this section to help illustrate the many ways in which AI-related activity is captured in BEA's economic statistics. In none of the examples do we attempt to capture second-order effects related to the adoption of AI, including changes in productivity, shifts in employment, or other economic effects that are outside the scope of this exercise.

2.1 Production of AI Software for Sale

In our first example, a telecommunications company pays a computer systems design company $100 to develop and implement a new AI-enabled customer service software application. Table 1 shows the derivation of GDP using the production, final expenditure, and income approaches for this example combining information from both the supply and use tables.

Table 1. Simplified Example Showing Production of For-Sale AI Software in the Supply and Use Tables

Products	Intermediate Purchases Industries			Final Expenditures		Product Output
	Computer system design	All other industries	Total	Private fixed investment	Total (GDP)	
Software	0	0	0	100	100	100
All other products	20	0	20			20
Total intermediate	20	0	20			
Compensation of employees	50	10	60			
Gross operating surplus	30	10	40			
Value added (GDP)	80	20	100			
Industry output	100	20	120			120

Using the production approach, the use table shows the computer system design company purchases $20 of intermediate inputs (rent, electricity, maintenance, repair, etc.) in order to produce the AI-enabled custom software application. The supply table shows that output for the computer systems design industry (i.e., the AI software company) is $120. Subtracting intermediate inputs from output equates to $100 in total value added. Another way to think about it is that value added for the computer system design company is $80, value added from other industries that supplied the intermediate inputs is $20, and the sum of value added (GDP) is $100. Under the final expenditure approach, the purchase of the $100 AI-enabled custom software application by the telecommunications company is recorded as private fixed investment in software, contributing $100 to GDP. Using the income approach, value added is the sum of compensation of employees ($60) and gross operating surplus ($40) associated with production of the for-sale AI software, again equating to $100 to GDP.[1] Currently, AI software is not separately identifiable in the SUTs; instead the value of AI is inherently embedded in the value of the software.

2.2 Production of AI Software for Own Account Use

In the second example illustrated in table 2, the telecommunications company develops and implements a new AI-enabled customer service software application in house using existing resources—no new intermediate inputs are required. The telecommunications company will first engage in R&D to develop the AI required for their new AI-enabled customer service software application.

Table 2. Simplified Example Showing Production of AI Software for Own Account Use in the Supply and Use Tables

Products	Intermediate Purchases		Final Expenditures		Product Output
	Industries				
	Telecommunications	Total	Private fixed investment	Total (GDP)	
Software			50	50	50
R&D			50	50	50
All other products					0
Total intermediate					
Compensation of employees					
Gross operating surplus	100	100			
Value added (GDP)	100	100	100	100	
Industry output	100	100			100

[1] For the purposes of these simplified examples, we ignore the role of taxes in these transactions. Additionally, the examples exclude accounting for price changes and are therefore estimates of current-dollar production. To estimate real measures within the SUT framework and GDP, price indexes are used to deflate current dollars to a base year. For example, to estimate private fixed investment in real prepacked software within GDP, we start with receipts data from the Census Bureau's Economic Census to prepare current-dollar estimates. These current dollar estimates are then deflated using a BEA price index based on the Bureau of Labor Statistics Producer Price Index for Software Publishing, Except Games, which is adjusted for quality change by BEA (see Grimm, Moulton, and Wasshausen 2002).

The value of that AI-related R&D is $50 and is recorded as private fixed investment in own-account R&D.[2] Next, the telecommunications company builds the new customer service software application in-house, implementing the AI that was developed as part of their R&D. That software is valued at $50 and is recorded as private fixed investment in own-account software. The creation of a new asset on own account is recorded as gross operating surplus for the creating industry. In this example, the gross operating surplus (and value added) for the telecommunications company is $100.[3]

2.3 Using AI To Produce Software

In our final example shown in table 3, we examine a case where a computer system design company uses an AI-based code generator to produce custom software that is then sold to a third party. The computer system design company pays $25 for the rights to use the AI-based code generator.

Table 3. Simplified Example Showing Use of AI to Produce Software" in the Supply and Use Tables

Products	Intermediate Purchases			Final Expenditures		Product Output
	AI services provider	Computer system design	Total	Private fixed investment	Total (GDP)	
Generative AI programmer		25	25			25
Custom software			0	100	100	100
Total intermediate		25	25			
Compensation of employees	20	55	75			
Gross operating surplus	5	20	25			
Value added (GDP)	25	75	100			
Industry output	25	100	125			125

For this example, we assume the $25 licensing fee covers a 3-month period and is considered an intermediate input as opposed to a capital expenditure. Transactions associated with this purchase are shown in red: a $25 purchase of intermediate inputs by the computer system design company, and $25 of value added attributed to the AI services provider ($20 in compensation paid and $5 of gross

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[2] BEA's estimates of private fixed investment in R&D are primarily based on R&D expenditures data from three National Science Foundation (NSF) annual surveys: the Business Enterprise Research and Development Survey, the Annual Business Survey, and the Higher Education Research and Development Survey. Beginning with 2019, NSF separately identifies AI-related R&D.

[3] For a discussion on how the income associated with own-account investment is recorded, see "Preview of the 2013 Comprehensive Revision of the National Income and Product Accounts,": 14–18.

operating surplus). The computer system design company produces custom software application that is sold for $100. These transactions are shown in green: $100 for private fixed investment in custom software, and $75 in value added attributed to the computer system designer associated with producing that $100 software.

In this AI use-case example, it's tempting to value the generative AI embedded in the custom software at $25, however, it's important to note that that does ignore spillover gains and likely increased productivity associated with using the generative AI programmer. Those gains should be reflected in the computer system designer's gross operating surplus but are not separately identifiable.

3. Measuring the Contribution of AI Production to GDP Using a Thematic Satellite Account Framework

The U.S. Bureau of Economic Analysis produces measures for selected slices of the economy through its system of satellite accounts, which refers to statistics that complement official economic statistics, including accounts for travel and tourism, outdoor recreation, the marine economy, and the digital economy.[4] One use of satellite accounts is to measure areas of the economy that are not easily identifiable under the standard industry classification commonly used to organize U.S. economic statistics, the North American Industry Classification System (NAICS). Satellite accounts can also show how certain areas of the economy change over time and how these areas compare to other sectors of the economy. Since satellite accounts are developed using data and methods consistent with official economic statistics, they can be used to identify what share of the economy is attributable to the satellite account area. For example, recent BEA reports show that the marine economy represented 1.8 percent of GDP in 2022, while the digital economy represented 10.0 percent (BEA 2024; BEA 2023). Each satellite account stands alone, so inclusion of products and industries in one satellite account does not prohibit inclusion from another. In the case of an AI satellite account, certain economic activity would overlap with activity within the digital economy satellite account, such as production of software. As discussed below, some of the data sources used in the digital economy satellite account could be useful in developing an AI satellite account.

Most of BEA's satellite accounts begin with the SUTs, sometimes referred to as "thematic satellite accounts." As discussed, the SUTs show the value of the product that is purchased by consumers, businesses, and government, plus the value that is imported and exported. Developing a thematic satellite account involves three main steps:

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[4] For information on these accounts and other special projects, see the BEA website.

1. Identify relevant product categories within SUTs
2. Isolate relevant shares of economic activity within product categories, when necessary
3. Use the SUT framework to determine economic activity by industry, including contribution to GDP, gross output, employment, and compensation.

Identifying relevant product categories to include in a satellite account (step 1) requires a solid definition of the subject being measured. The rest of this section discusses possible definitions and data sources that could be used to measure production of AI within the SUTs.

3.1 Defining AI Production

Defining the subject of interest is often the most important phase of a satellite account because it provides the overall framework for the new account and influences the goods and services chosen to be part of the resultant economic statistics. An operationalized definition must clearly delineate what products and industries are considered part of AI production. The products chosen as in-scope to a satellite account reflect existing research about the subject of interest, as well as feedback from experts in the private sector, academia, and domestic and international organizations. Table 4 presents a few examples of definitions of AI from U.S. and international government organizations. In general, the definitions mention, at least implicitly, both hardware and software components needed for computing. The computational and prediction processes are also often mentioned, such as machine learning and data analytics in the U.S. Census Bureau (Census) and Organisation for Economic Co-operation and Development (OECD) descriptions.[5] Three sectors in particular appear to be significant from many existing definitions: manufacturing (including accelerator chips), information (including software publishing), and professional and business services (including R&D and computer and data services). In the next section, we consider potential data sources to measure many of these key areas of production.

[5] The OECD has long been engaged in research related to AI measurement, including attempts to develop a meaningful definition of AI. See the OECD AI Policy Observatory website for a list of papers and projects related to AI.

Table 4. Examples of Definitions for Artificial Intelligence

Organization	Definition
Census (2024a)	"Artificial Intelligence is computer systems and software that are able to perform tasks normally requiring human intelligence, such as decision-making, visual perception, speech recognition, and language processing. Types or applications of AI include machine learning, natural language processing, virtual agents, predictive analytics, machine vision, voice recognition, decision making systems, data analytics, text analytics, image processing, etc."
National Institute of Standards and Technology (Elham et al. 2019)	AI technologies and systems "comprise software and/or hardware that can learn to solve complex problems, make predictions or undertake tasks that require human-like sensing (such as vision, speech, and touch), perception, cognition, planning, learning, communication, or physical action."
OECD (Grobelnik, Perset, and Russell 2024)	"An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment."
USPTO (2020)	"For patent applications and grants, we define AI as comprising one or more of eight component technologies [knowledge processing, speech, AI hardware, evolutionary computation, natural language processing, machine learning, vision, planning/control]. These components span software, hardware, and applications, and a single patent document may contain multiple AI component technologies."

3.2 Potential Data Sources to Measure AI Production in the US

The SUTs comprise thousands of product categories that are oftentimes very specific, but this is not always the case depending on the original source data. For example, while the SUTs separately track production of three different types of powered circular saw blades for woodworking (solid tooth, inserted tooth, and other), there is only one general category for engineering services. Given the general nature of many of the SUTs product categories, every BEA satellite account uses external data sources to isolate relevant production in certain areas.[6] The ability to accurately isolate specific production within general product categories in the SUTs depends on availability of consistent and high-quality external data sources. Ideally, data from other government agencies are used because these data are more representative and have a much higher response rate than private data sources. When government data are unavailable, data from private vendors are sometimes used, often for areas related to new technologies. For example, BEA recently introduced quality-adjusted cloud computing price data from 451 Research to supplement producer price indexes from the Bureau of Labor Statistics (BLS) to better measure this growing area of the economy (McCulla, Turner, and Mataloni 2023).

[6] See the BEA website for links to BEA satellite account webpages and related methodology documents.

Though it depends on how the economic production of AI is ultimately operationalized, one approach is to focus on the foundational areas present in existing definitions, specifically, manufacturing of chips, software publishing (own account and for sale), computer and data services, and R&D. Within the SUTs, each of these production areas are included in categories that include non-AI production since there are currently no product categories related solely to AI.[7] The rest of this section highlights possible data sources to isolate AI production within the SUTs for these foundational areas and the price indexes needed for estimating real measures of production.

3.2.1 Manufacturing

Within government statistics, the International Trade Administration (ITA) has trade data that shows dozens of categories of semiconductor manufacturing that could be useful in identifying the imported and exported value of AI-related chips. Similarly, the U.S. Trade in Advanced Technology Products by Technology Group and Country data from the Census have AI products embedded in certain categories that could potentially be useful. However, neither of these datasets could be used directly to quantify AI chip production, since the data categories commingle AI chips with non-AI chips.

Private data sources may be necessary to measure the production of AI chip manufacturing. The International Data Corporation (IDC), a private data firm, sells an “Artificial Intelligence Infrastructure Tracker” that contains revenue information for AI hardware, software, and various related services. IDC data have been used by BEA in the digital economy satellite account to estimate the value of cloud services (Highfill and Surfield 2022). Since purchasing data is sometimes expensive and necessitates special funding, this data source may not be feasible. An alternative is to use revenue information from public financial reports for major chip producers, such as 10-K filings required by the Security and Exchange Commission (SEC) for publicly traded companies like NVIDIA.[8] To the extent that this area of production is dominated by a small number of firms, information on revenue from individual filings may constitute a large portion of the market. However, the level of detail in SEC filings and annual financial reports is not always consistent from year to year or may not show U.S. production separate from foreign production, adding potential complications to relying on financial reports as a primary data source.

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[7] Annex table 1 shows examples of where AI products are currently included within international industry and product classification systems, focusing mostly on manufacturing of chips and software.

[8] See nvidia.com.

3.2.2 Software and Computer Systems Design and Related Services

As with manufacturing, since no standalone categories exist in the SUTs for the production of AI software and relevant computer and data services, private vendor data or public financial information for key companies would likely be needed to measure production in this area. Another possible resource is the Occupational Employment and Wage Statistics (OEWS) data from BLS. The OEWS provides employment and wage information for occupations within industries and have been used in previous satellite accounts as a proxy to isolate production within general product categories. Within the software publishing (NAICS 5132) and computer systems design and related services (NAICS 5415) industries, the OEWS data provide information on a few occupations that are AI-related, such as data scientists, software quality assurance analysts and testers, and database architects (BLS 2022). Although these occupations include non-AI work, these data could still be used for trend analysis and perhaps to serve as a ceiling for potential estimates.

3.2.3 R&D

BEA currently uses spending data from National Science Foundation (NSF) surveys to estimate R&D production in the SUTs. In 2019, the NSF's Business Enterprise Research and Development survey asked about AI-related R&D for the first time. In that survey, 2,590 domestic companies noted positive AI R&D spending for that year (NSF 2022a). While questions related to AI have not been asked consistently since 2019, the survey shows the possibility for these questions to be added to existing NSF surveys. Likewise, it may be possible to update data collections from the National Center for Education Statistics to measure R&D in academia.

AI R&D occurs in both the private and government sectors. In 2018 alone, the Defense Advanced Research Projects Agency (DARPA) launched a $2 billion initiative to continue AI R&D, an area that the agency has been engaged in for over five decades (DARPA 2018). Information on AI R&D spending by the federal government is available via public budget documents for each agency. However, the budget documents are often onerous to parse through and synthesize, potentially leading to missing spending. The NSF also has data on federal spending related to AI R&D in the Survey of Federal Funds for Research and Development that could be useful.

3.2.4 Prices

The price indexes currently used to deflate components within the three categories above are comprised of many different prices, including from the BLS Producer Price Index and Consumer Price Index, the Federal Reserve Board's communication equipment prices, and several BEA-derived indexes that utilize private data sources.[9] Until government agencies collect data specifically on AI products, private data sources would likely be needed to estimate price trends. The impact of prices on growth could be substantial in many areas, especially manufacturing of chips and servers, areas estimated to have experienced substantial price growth in recent years driven largely by AI demand (IDC 2024).

3.2.5 Estimating Overall Output or Trends

The data sources suggested thus far have related to specific products or industries, aligning with how thematic satellite accounts are developed. However, understanding overall trends in AI production would also be valuable for the development of an AI satellite account. The 2019 Annual Business Survey (ABS), conducted by Census for the NSF, asked firms across all industries if they sold business technologies in areas like AI and robotics. About 0.5 percent of all private firms said they sold AI technologies in the years 2016–2018 (NSF 2022b). Again, although these questions are not currently being asked consistently, the 2019 ABS shows the possibility for adding these questions to existing annual surveys. While this information cannot be used directly to estimate production, it could serve as a check against other data sources.

Patents data is another potential option for identifying and understanding general trends in AI production. A paper by the USPTO (2020) noted that the share of all patent applications that contain AI grew from 9 percent to nearly 16 percent between 2002 and 2018. The OECD has also used patents data to understand the types of companies that file AI patents, including the industries that engage in patent fillings and the age and size of those businesses (Dernis et al. 2021). A related OECD paper used patents data to see what types of AI technologies were most prominent in these data, finding autonomous driving and deep learning to be the most common (Calvino et al. 2023). While the patents data may not be directly useful for estimation purposes, they could help identify what types of companies and industries are involved in this activity and indicate where future production may occur.

3.3 Other Considerations for Measuring AI Production

Research, development, and regular production of an official satellite account require dedicated staff resources, including economists, information technology specialists, and administrative personnel. Additionally, many satellite accounts require data purchases from private vendors, and some require contracts with external subject matter experts. Funding for official BEA satellite accounts typically comes directly from budget initiatives approved by Congress or through agreements with other government agencies. A new satellite account often takes years to develop because of the time it takes for domestic

[9] See the *Concepts and Methods of the U.S. National Income and Product Accounts* for information on source data and estimation methods.

and international outreach with subject matter experts to determine definitions and scope; identifying, vetting, and acquiring source data; and preparing, reviewing, and producing the final statistics. The more complicated the satellite account, the more resources are required.

4. Conclusion

In this paper we present basic concepts and challenges to measuring production of AI using a national accounting framework. As with many new or transitioning areas of the economy, AI measurement issues generally relate to defining scope and availability of source data. Although many AI definitions appear similar in concept, extensive research and outreach to subject matter experts would be needed to ensure a comprehensive and operational definition to anchor the development of macroeconomic statistics like GDP. There are often legitimate reasons to include or exclude certain types of economic production in thematic satellite accounts. In the case of AI production, one could potentially argue that construction of data centers should also be included in a satellite account. But perhaps a larger issue is data availability. Since AI production is commingled with non-AI production within the SUTs, external data sources would be needed to isolate economic production of AI to develop satellite account statistics. We note some promising options in this paper, with the important caveat that all datasets have significant downsides. There is always the potential to change or add government data collections to better isolate AI production in the SUTs, but that would take many years to implement and become available for the uses described in this paper.

This paper serves as a starting point for discussing how to identify and measure AI production using standard national accounting practices. This topic is particularly relevant in the United States given recent federal actions to encourage domestic AI manufacturing and research by way of the 2022 CHIPS and Science Act (where CHIPS stands for "Creating Helpful Incentives to Produce Semiconductors") and the 2023 Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence.[10] Accurate and consistent macroeconomic statistics about AI production could provide vital information about how this area contributes to overall economic growth, what industries are involved in production, and how these relationships have changed over time. These statistics could also provide a more comprehensive understanding about the impact of AI on the economy versus research on AI usage alone.

[10] See www.congress.gov and www.whitehouse.gov for details.

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Appendix

Appendix Table 1. Examples of AI-Related Products or Industries Recently Added to International Classification Systems

International Classification System	Product or Industry
2022 NAPCS collection products related to manufacturing of chips	Manufacturing of other semiconductor devices, including semiconductor parts such as chips, wafers, and heat sinks (2033700000) Manufacturing of semiconductor parts, chips, and wafers (2033700018)
2022 NAPCS collection products related to robotic watercraft	Manufacturing of unmanned robotic military ships (including combat ships, troop transport vessels, fleet auxiliaries, and service craft), self-propelled, new construction (2012275006) Manufacturing of unmanned robotic surface and underwater vessels, nonmilitary, new construction (2012300017)
2022 NAPCS collection products to split industrial robots[1]	Manufacturing of industrial robots and industrial robot cells (excluding lifting, handling, loading, and unloading robots) (2016635000) Manufacturing of industrial robots for lifting, handling, loading, or unloading (2016655000)
ISIC Rev. 5 software section for computer programming activities (soon to be final)	Computer programming, consultancy, and related activities (6211)
Central Product Classification (CPC)	Industrial robots and unmanned aircraft
2022 NAICS examples added	Robot programming in custom computer programming services (541511) Artificial intelligence R&D in research and development in the physical, engineering, and life sciences (except nanotechnology and biotechnology) (541715) Various examples of unmanned/robotic vehicles and equipment in existing industries
2017 NAPCS	Manufacturing of unmanned robotic military aircraft, including unmanned aircraft for U.S. military and any other unmanned aircraft built to military specifications (2012100006) Manufacturing of unmanned robotic civilian aircraft (2012125006)

1. In 2027, industrial robots may be split further based on type of equipment (plastics/rubber working, metal working, etc.).