

An Economic Approach to—and Business Application of— Artificial Intelligence

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This research work is motivated by both groups of ongoing unlimited opportunities, challenges, and alarming potentials for abuses, fraud, and spread of disinformation. The bifocal stress of the project is on economic essence and framework for assessment of both potential efficiencies in productivity and potential costs of AI in an economy, industry, or a business unit. The topical issue of the attention extent of AI in business public relations, as a potential perspective to a relevant economic cost-benefit analysis is cited in this research. AI is, in its essence, a technological component of capital in production of goods, services, public relations, and advertising. Hence, the productivity model, cost framework, and profit optimization methodologies are all integrated into a system of interrelated equations. Businesses and dynamic organizations are supposed to devote a more cohesive attention to uncertainties, probabilities, and more importantly, to the extent of presence and/or lack of attentions to the AI capital in search of a sustainable viability and thriving niche in their heavily competitive digital age. Our goal is to strive in compilation of massive data in our prospective research works in a more application-oriented inquiry than this current work.

Keywords: artificial intelligence, public relations, economic optimization, Cobb-Douglas production function, AI-attention economics

Introduction

Considering a business entity, an industry, or an economy, on the one hand, and the traditional capital-labor production function, on the other hand, AI is a major part of capital (K) that has been, and will continue to be, upgraded, promoted, and accumulated by the highly-skilled component of the labor (L) input. While labor broadly constitutes unskilled, skilled, highly skilled labor, managerial and entrepreneurial skills, the entire difference among all would be the quantity and quality of human capital, inclusive of years of schooling, on the job training (OJT), and actual experience.

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Capital component of the production function would broadly encompass physical, debt, equity, human, brand name, trust (ethical), social capital, and location capital. AI, in its essence, would involve a combination of human, financial, physical, and intellectual capital and labor.

Cited Literature

Peterson (2022) on the impact of AI in public relations arena, proposes that it would help in recognizing the individuals' identities, the business names, the types of outputs, services, etc., that would all exist in images. The visual communications related to one's business are also possible to identify and register. One can expect that abuses and creation of disinformation in marketing of both goods and services would be minimized. Also, the quality of journalism, where data and information accuracy are the vital necessity for endurance and success, would be better controlled and promoted.

Medium (July 18, 2024) has summarized the impacts of AI on PR, into nine major advancements, some of which include enhancement of media monitoring and sentiment analysis; revolutionizing media and enabling to keep track of real-time events; data-driven decision making and forecasting; better video production and monitoring; personalizing content creation and distribution for individual journalists.

Daley (2019) adds to the discussion on advantages of AI in marketing. Ramakrishnan (2023), in his *MIT Sloan Management Review*, proposed how to resort to reliable AI solutions when the needed massive or even enough data are not available to a specific business organization.

Focusing this research work on AI application to economic task orientation models, let's start with the highly communicated and applied generative AI models. According to a practitioner, Abdullah (January 5, 2024): "Generative artificial intelligence (AI) models are AI platforms that generate a variety of outputs based on massive training datasets, neural networks, deep learning architecture, and prompts from users." (p. 1).

Stressing on the necessity of lots of quality and domain-specific data, Hosanagar and Krishnan (2024) in *MIT Sloan Management Review* article titled "Who Profits the Most from Generative AI?" proposed that the reasons for the failures or buyouts of most cloud startups were attributable to the advantage of creating specialized generating AI models. Furman and Seamans of Harvard University (2019) also discussed the advantage of the large datasets in creating a barrier to entry and more economic concentration. They have elaborated on AI's impact on labor and productivity, which would involve potential gain and challenges that would come with robotic mix of labor.

While Peterson (October 21, 2022), published on efficiency and efficacy of public relations tasks by incorporating AI into PR, MIT's Ramakrishnan (2023) offered interesting guidance, "How to build good AI solutions when data is scarce", on *MIT Sloan Management Review*.

On the treatment of negative effects of AI, Kerry (February 10, 2020) offered a report on "Protecting privacy in an AI-driven world". He stressed on "three Vs" that would highlight the significance of data: first, volume (larger data) would augment the power and reliability of the needed analyses. Second, variety would facilitate the necessary, though, unexpected new findings and predictability power. Finally, velocity of data and information about almost everything in daily real life would ensure real time analyses.

According to Georgieva (January 14, 2024), 40 percent of world-wide jobs will be impacted by AI in both replacement of some and complementing many others. Hence, she recommends some major balancing policies in an optimal use of AI. Being concerned about potential work losses, she warns that for a better successful AI incorporation into the industries' operational performances, a set of "stronger social safety nets" would be

mandatory, which would include more optimal investment in education, and tax systems to reduce the workers' burden of inequality.

AI's impact on jobs

Most jobs are exposed to AI in advanced economies, with smaller shares in emerging markets and low-income countries.

Employment shares by AI exposure and complementarity

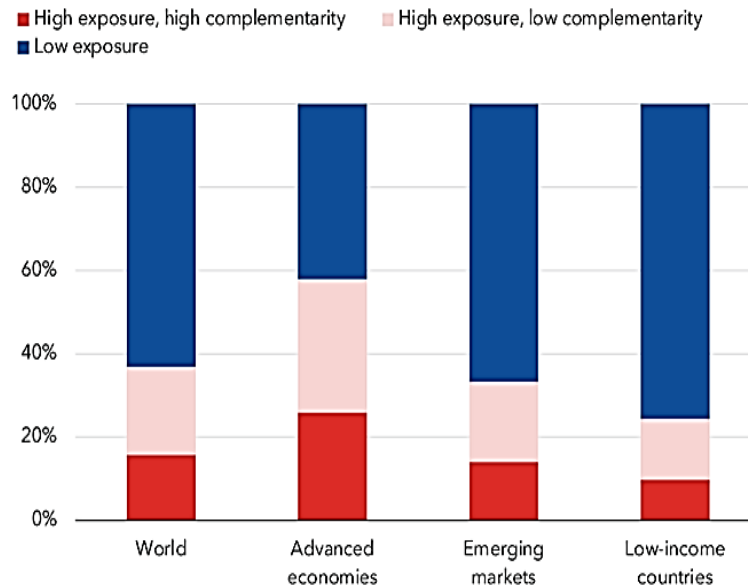


Figure 1. AI's impacts on jobs. Source: IMF.

At the same time, sector-based training, apprenticeships, and upskilling and reskilling programs could play a greater role in preparing workers for the jobs of the AI age. Comprehensive social-assistance programs will be needed for workers facing long-term unemployment or reduced local labor demand due to automation or industry closures.

Meanwhile, Dabla-Norris and de Mooij (June 17, 2024) predict that while the constructive impacts of AI on the jobs and employment after some tough transition periods could be devastating, some social safety nets and protection from disruptive technological changes must be formulated and implemented. Policies such as more reliable unemployment insurance would create an opportunity for displaced workers to find jobs compatible with their skills. Euronews (July 7, 2023) warned the advertisers that just incorporating AI enthusiastically into the advertising industry is not enough. The depth of understanding of the actual and potential implications for sustainability is critical in the long run strategic AI adoption policy. Figures 1 and 2 would signify the exposure of U.S. and world's workers to AI and the necessary policy focus on how to avoid the future devastating effects of the rapid growing adoption of AI.

Some economists have already dedicated some valuable research to AI model making. Some examples are Atashbar (February 24, 2023), Marwala (2023), and Hamzaee and Salimi (September 25, 2023). Meanwhile, Gries and Naude (2020-2022), in their *Modelling Artificial Intelligence*, studied the effects of AI on income distribution and economic growth.

Given that large data would be prerequisite of AI, analyzing the great capacity of blockchain for data storing, and management, hinging on several studies, such as Catalini (April 24, 2017) and Daley (March 1, 2019), Hamzaee and Salimi (September 25, 2023) elaborated the role of applied AI through big data and blockchain on the entire markets, commercial laws, financial regulations, and the digital economies.

On the negative aspects of AI, Dyck, Morse, and Zingales (February 22, 2013) focused on the pervasiveness of corporate fraud. Also, Hamzaee and Salimi (2024), based on a world occupational fraud report, by Dorris (2022), published their latest “An Anti-fraud Policy: A Theoretical Framework for a Prosperity Tripod of Massive Data, Blockchain, and AI”.

Bodungen (March 2024) among many highly sensitive and essential guidelines and remedies, offers many step-by-step recipes and guidelines in *Building Custom Threat Detection Rules in the Evolving landscape of Cybersecurity* within the unlimited domain of cybersecurity, some rules in exploring generic threats, involving each organization’s network and systems that would necessitate certain tailored and elaborated rules for “specific threat landscapes” (Bodungen, 2024, p. 53).

Based on various industry cases studied by Thormundsson (April 5, 2024), the biggest revenue hikes of 240 to 460 billion U.S. dollars from inclusion of generative AI were enjoyed by the high-tech industries.

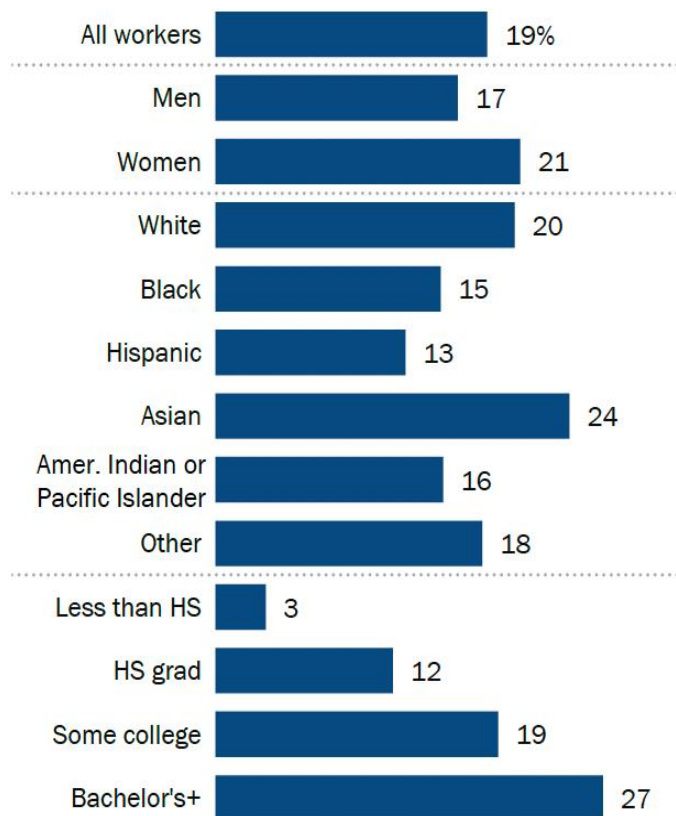


Figure 2. U.S. percentage of workers on jobs most exposed to AI in 2022.

Theoretical Framework

Focusing on the net contributions of AI, one would need to incorporate all the positive and negative impacts of AI into the benefit-loss or revenue-cost analysis. The following list of acronyms would make the entire model easier to follow:

$$Q = a_0 K^{\alpha_1} L^{\alpha_2} AI^{\alpha_3}, \text{ assuming a Cobb-Duglas production function (1)}$$

$$\log Q = \log a_0 K^{\alpha_1} L^{\alpha_2} AI^{\alpha_3} \quad (2)$$

$$\log Q = \log a_0 + \alpha_1 \log K + \alpha_2 \log L + \alpha_3 \log AI \text{ or expressing it}$$

$$LQ = \alpha_0 + \alpha_1 LK + \alpha_2 LL + \alpha_3 LAI \quad (3)$$

where, LQ, LK, LL, and LAI represent the log of quantities of output (Q), capital stock (K), labor (L), and artificial intelligence (AI).

$$\text{So, } q = \alpha_0 + \alpha_1 k + \alpha_2 l + \alpha_3 AI \quad (4)$$

$$AI = \frac{q - \alpha_0 - \alpha_1 K - \alpha_2 l}{\alpha_3} \quad (5)$$

Also, we may re-express (5), AI function, as:

$$AI = -ai_0 + ai_1 q - ai_2 k - ai_3 l \quad (6)$$

where, AI = LAI, q = LQ, k = LK, l = LL

Given a company's budget, equation (6) will help in measuring the impacts of Also, we may re-express (5), AI function, as:

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Given a company's budget, equation (6) will help in measuring the impacts of the size of a company, production wise (q), its capital stock, and labor force, on the adoption of AI:

$$\frac{\partial AI}{\partial q} = +ai_1, \quad \frac{\partial AI}{\partial k} = -ai_2, \quad \frac{\partial AI}{\partial l} = -ai_3 \quad (7)$$

Now from human capital to labor supply:

$$L = l_0 K_{HC} \quad (8)$$

$$K_{HC} = f(\text{PH, ED, OJT, HCI}) \quad (9)$$

human capital production function

$$K_{HC} = k_0 \cdot \text{PH}^{\text{kph}} \cdot \text{ED}^{\text{ked}} \cdot \text{OJT}^{\text{kojt}} \cdot \text{HCI}^{\text{khc}} \quad (10)$$

human capital Cobb-douglas production function

$$L = l_0 k_0 \cdot \text{PH}^{\text{kph}} \cdot \text{ED}^{\text{ked}} \cdot \text{OJT}^{\text{kojt}} \cdot \text{HCI}^{\text{khc}} \quad (11)$$

$$LL = Ll_0 k_0 + \text{kph.LPH} + \text{ked.LED} + \text{kojt.LOJT} + \text{khc.LHCI} \quad (12)$$

which is derived from (8) and (10): how labor is built:

$$l = \lambda_0 + \text{kph.ph} + \text{ked.ed} + \text{kojt.ojt} + \text{khc.hci} \quad (13)$$

which is the log linear of labor generation function:

$$LK_{HC} = Lk_0 + \text{kph.LPH} + \text{ked.LED} + \text{kojt.LOJT} + \text{khc.LHCI} \quad (14)$$

the human capital log-linear function from (9) and (14), will be re-expressed as:

$$k_{HC} = \lambda_0 + \text{kph.ph} + \text{ked.ed} + \text{kojt.ojt} + \text{khc.hci} \quad (15)$$

(13) and (15) are in fact the same, given that the labor supplied would contain the human capital, in their essence.

λ_0 = the constant terms in both generation functions,

HC = human capital (1 for lowest, 10 for highest),

PH = physical health (1 for lowest, 10 for highest),

ED = years of education (1 to 22), OJT = years on the job (1 to 30)

HCI = health care investment, and

Log Variables: $LK_{HC} = k_{HC}$, $Lk_0 = k_0$, $LPH = ph$, PH = physical health (1 for lowest, 10 for highest),

ED = years of education (1 to 22), OJT = years on the job (1 to 30)

HCI = health care investment, and

Log Variables: $LK_{HC} = k_{HC}$, $Lk_0 = k_0$, $LPH = ph$,

LED = *ed*, LOJT = *ojt*

LHCI = *hci*, and *kph*, *ked*, *kojt*, *khc* = the exponents of the 4 variables of the Cobb-Douglas human capital production function.

LED = *ed*, LOJT = *ojt*, LHCI = *hci*, and *kph*, *ked*, *kojt*, *khc* = the exponents of the 4 variables of the Cobb-Douglas human capital production function.

$$K = k_0 \prod_1^8 K_j^{k_j} = k_0 K_{pc}^{k_1} K_{dc}^{k_2} K_{ec}^{k_3} K_{HC}^{k_4} K_{bnc}^{k_5} K_{tc}^{k_6} K_{sc}^{k_7} K_{lc}^{k_8} \quad (16)$$

which is Cobb-Douglas capital production function

where, k_1, k_2, \dots, k_8 are the exponents of all K variables in Equation (16)

Table 1

The Model's Other Symbols and Variables

Variable	Description
Q, LQ, q	output, log of Q = q
K, LK, k	capital stock, log of K = k
k_1, k_2, \dots, k_8	the exponents of all <i>k</i> variables in Equation (7)
ED, OJT, PH; ed, ojt, ph	laborer's education, on the job training, and physical health; log of each expressed in lower case letters
L, LL, l	labor, log of L = l
AI, LAI, AI	artificial Intelligence, Log of AI = AI
A_i , where $i = 1, 2, \dots, 5$	coefficients of AI functions (12) and (13)
all α, β, a_i, k_j	coefficients of the corresponding equations
Subscripts pc, dc, ec, bnc, tc, sc, HC, lc	various kinds of capital: physical, debt, equity, brand-name, trust, social, human capital, location capital
T and t	technology used for AI & data management
dq _i , dq _t	ranked (1-10) quality and quantity of data used in creation of AI

Equation (16) is our capital (Cobb-Douglas) production function, where, each k_j represents the power of each of the 8 kinds of capital for all 8 sorts of considered capital here, $j = 1, 2, \dots, 8$, as: physical capital, debt capital, equity capital, human capital, brand name capital, trust (ethical) capital, social capital, and location capital. Now let's take log from both sides of equation (16):

$$LK = Lk_0 + k_1 LK_{pc} + k_2 LK_{dc} + k_3 LK_{ec} + k_4 LK_{HC} + k_5 LK_{bnc} + k_6 LK_{tc} + k_7 LK_{sc} + k_8 LK_{lc} \quad (17)$$

$$K = k_0 + k_1 k_{pc} + k_2 k_{dc} + k_3 k_{ec} + k_4 k_{HC} + k_5 k_{bnc} + k_6 k_{tc} + k_7 k_{sc} + k_8 k_{lc} \quad (18)$$

where, $k_0 = \log$ of k_0 , $K = \log$ of K , and the 8 k explanatory variables on the right-hand side, represent the logs of their corresponding K variables.

Independently, assuming a Cob-Doiglas AI production function:

$$AI = A_0 \cdot \prod_0^5 AI_i^{A_i} = A_0 AI_1^{A_1} \cdot AI_2^{A_2} \cdot AI_3^{A_3} \cdot AI_4^{A_4} \cdot AI_5^{A_5} \quad (19)$$

where, $AI_i^{A_i}$ for $i = 1, 2, \dots, 5$ are proposed to be 5 various components of AI, which are defined better in:

$$AI = A_0 L^{A_1} K^{A_2} D_{qt}^{A_3} D_{qt}^{A_4} T^{A_5} \quad (20)$$

$$LAI = LA_0 + A_1.LL + A_2.LK + A_3.LD_{qt} + A_4.LD_{qt} + A_5.LT \quad (21)$$

$$AI = ai_0 + ai_1.l + ai_2.K + ai_3.d_{qt} + ai_4.d_{qt} + ai_5.t \quad (22)$$

which is the log-linear (transformed) function, containing logs of (AI): AI , labor (L): l , capital (K): k , Data quality (LD_{qt}): d_{qt} , Data quantity (D_{qt}): d_{qt} and technology (T): t

Given that capital stock was re-expressed into equation (18)

$$q = \alpha_0 + \alpha_1 (k_0 + k_1 k_{pc} + k_2 k_{dc} + k_3 k_{ec} + k_4 k_{HC} + k_5 k_{bnc} + k_6 k_{tc} + k_7 k_{sc} + k_8 k_{lc}) + \alpha_2 (\lambda_0 + kph.ph + ked.ed + koj.t.ojt + khc.hci) + \alpha_3 (ai_0 + ai_1.l + ai_2.K + ai_3.d_{qt} + ai_4.d_{qt} + ai_5.t) \quad (23)$$

Since human capital and labor inputs are the same, one should either keep it as a constitute of capital in the first parenthesis, or just leave it as the labor input in the second parenthesis of equation (23). Let's drop it from our total capital components in equation (23)

above. Also, since human capital (15), and labor (13) are equivalents:

$$l = k_{HC} = \lambda_0 + kph.ph + ked.ed + koj.t.ojt + khc.hci$$

Hence:

$$q = \alpha_0 + \alpha_1 [k_0 + k_1 k_{pc} + k_2 k_{dc} + k_3 k_{ec} + k_4 k_{bnc} + k_5 k_{tc} + k_6 k_{sc} + k_7 k_{lc}] + \alpha_2 (\lambda_0 + kph.ph + ked.ed + koj.t.ojt + khc.hci) + \alpha_3 (ai_0 + ai_1.l + ai_2.K + ai_3.d_{qt} + ai_4.d_{qt} + ai_5.t) \quad (24)$$

Similarly, we substitute equation 18 for K in the last parenthesis of equation (24), while one of the two, human capital component of it - or labor, l , will be dropped out (we chose labor to drop), since labor input, l , is already included in our AI function (last parenthesis).

$$q = \alpha_0 + \alpha_1 (k_0 + k_1 k_{pc} + k_2 k_{dc} + k_3 k_{ec} + k_4 k_{bnc} + k_5 k_{tc} + k_6 k_{sc} + k_7 k_{lc}) + \alpha_2 (\lambda_0 + kph.ph + ked.ed + koj.t.ojt + khc.hci) + \alpha_3 [ai_0 + ai_1.(k_0 + k_1 k_{pc} + k_2 k_{dc} + k_3 k_{ec} + k_4 k_{bnc} + k_5 k_{tc} + k_6 k_{sc} + k_7 k_{lc}) + ai_3.d_{qt} + ai_4.d_{qt} + ai_5.t] \quad (25)$$

Equation (26) will result from some further substitutions:

$$q = \alpha_0 + \alpha_1 k_0 + \alpha_1 k_1 k_{pc} + \alpha_1 k_2 k_{dc} + \alpha_1 k_3 k_{ec} + \alpha_1 k_4 k_{bnc} + \alpha_1 k_5 k_{tc} + \alpha_1 k_6 k_{sc} + \alpha_1 k_7 k_{lc} + \alpha_2 \lambda_0 + \alpha_2 k_{ph.ph} + \alpha_2 k_{ed.ed} + \alpha_2 k_{ojt.ojt} + \alpha_2 k_{hci.hci} + \alpha_3 ai_0 + \alpha_3 ai_2 . k_0 + \alpha_3 ai_2 . k_1 k_{pc} + \alpha_3 ai_2 . k_2 k_{dc} + \alpha_3 ai_2 . k_3 k_{ec} + \alpha_3 ai_2 . k_4 k_{bnc} + \alpha_3 ai_2 . k_5 k_{tc} + \alpha_3 ai_2 . k_6 k_{sc} + \alpha_3 ai_2 . k_7 k_{lc} + ai_3 . d_{ql} + ai_4 . d_{qt} + ai_5 . t \quad (26)$$

Our final reduced form equation will be:

$$q = \beta_0 + \beta_1 k_{pc} + \beta_2 k_{dc} + \beta_3 k_{ec} + \beta_4 k_{bnc} + \beta_5 k_{tc} + \beta_6 k_{sc} + \beta_7 k_{lc} + \beta_8 ph + \beta_9 ed + \beta_{10} ojt + \beta_{11} hci + \beta_{12} d_{ql} + \beta_{13} d_{qt} + \beta_{14} t \quad (27)$$

Companies (industries, as well as countries) can see how, with other things constant, the partial impact of each of the many deterministic components of a consolidated capital, inclusive of human capital, AI, and all other types of capital, can be on the size of the company and its output production, as can be explained in Equations (19)-(22) and (27).

To expand this model to revenue and profit maximization considerations, the following standard equations would follow, based on the above simultaneous and reduced form equations, the following model would be useful:

$$TR = P \cdot Q \quad (28)$$

$$TC = FC + w \cdot L + \sum_{j=1}^7 r_{kj} K_j + \lambda AI \quad (29)$$

$K_j = 7$ forms of capital to be used at r_{kj} per unit cost of each, for $j = 1, \dots, 8$

$\lambda =$ per indexed unit of cost of AI (Artificial Intelligence), $P =$ output price

$TC =$ total cost, $FC =$ fixed cost of production, $w =$ labor wage, $L =$ amount of labor and

$\Pi =$ profit (net earnings)

$$\Pi = P \cdot \alpha_0 K^{\alpha_1} L^{\alpha_2} AI^{\alpha_3} - (FC + w \cdot L + \sum_{j=1}^7 r_{kj} K_j + \lambda AI) \quad (30)$$

$$\Pi = P \cdot \alpha_0 K^{\alpha_1} L^{\alpha_2} AI^{\alpha_3} - FC - w \cdot L - \left(\sum_{j=1}^8 r_{kj} K_j - \lambda AI \right) \quad (31)$$

$$\Pi = P \cdot \alpha_0 K^{\alpha_1} L^{\alpha_2} AI^{\alpha_3} - FC - w \cdot f(ED^+, OJT^+, PH^+, HCI^+) - \sum_{j=1}^8 r_{kj} K_j - \lambda AI \quad (32)$$

Summary and Analysis of Model

Our AI-incorporated macroeconomic model offers many useful and data-incorporated implications for AI production, based on the necessary resources; see Equations (19)-(22). One of the ingredients of AI is labor, inclusive of its all-possible attributes: education, personal health, OJT, and human capital.

Another essential ingredient for AI is capital, expressed in Equations (16)-(18), consisting of a certain minimal amount of it that all individuals possess, physical capital, debt capital, equity capital, brand name, trust, social, and location capital.

Also, AI can be formulated for a general business level, industry wide, or macroeconomic policy consideration, through Equation (7) and differently through Equation (22). One can estimate the impact of each determinant of AI on its size and quality. Considering the determinants of AI in Equation (22), one can estimate the impacts of AI on the output, and income, while in Equation (24) and (25), AI's impacts on costs and profit would be estimated. Obviously, challenges in indexation of data quantity, quality, technology, and other inputs included in Equation (22) are possible to be met well by applying categorical data analysis, in which case, the various categories of qualities and quantities would be determined in, e.g. small, medium, large data as well as low, medium, high quality of data.

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