ROI of AI: Effectiveness and Measurement

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***Abstract*-- Knowing what an AI investment is worth and what determines that value is a pre-requisite for intelligent decision making- in choosing to invest in this field and domain. Investments in advanced transformation like AI, in deciding on the appropriate price to pay or receive in a takeover and in making financial choices when running a business are to be evaluated thoroughly. The premise of computing ROI for such investments, is that we can make reasonable estimates of value, and that the same fundamental principles determine the values of all types of assets, real tangible as well as intangibles. Some investments are easier to valuate as compared to others. Valuation process and effectiveness measurement techniques of new and highly evolving technologies such as AI vary from investment to investment. Also, the uncertainty associated with value estimates is different for different investments and assets, but the core principles and the foundation of valuations remain almost same.**

Keywords-- AI, transformation, business valuation, investment, ROI, measurement, effectiveness

I. INTRODUCTION:

The primary objective of this article is to offer a framework for addressing the question – which measurement approach provides investors/ stakeholders with decision-useful information and why? We utilize valuation frameworks to guide the development of our approach and focus on the information needs to critically assess all perspectives of every tangible and intangible measures.

The terms return on investments (ROI) and business valuations are of great importance. Knowledge about how much an investment is worth is of fundamental value for both the stakeholders of that company and investors to assess future returns. Multiple valuation and measurement models are used to assess on how the asset/ change is expected to realize value for the firm: in-exchange or in-use. How an investment or asset is expected to harness value for the organization is mainly a function of its revenue model, business operations and portfolio.

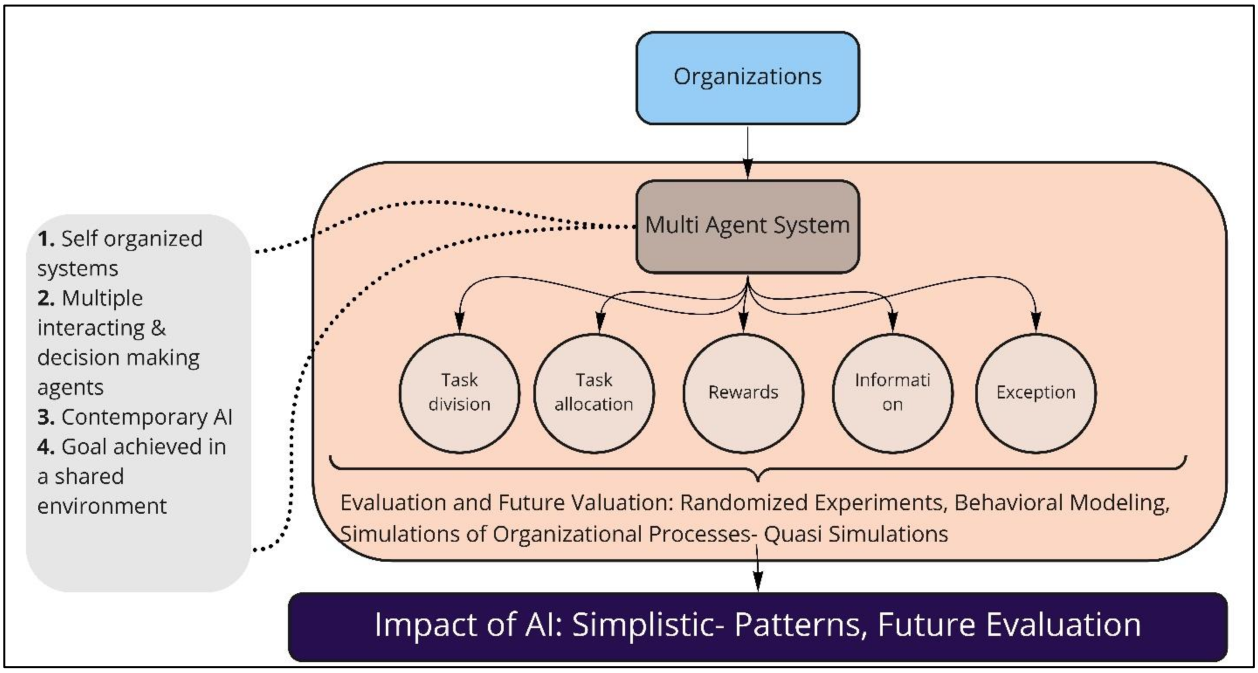

Figure 1: Organization conceptualization- as a multi-agent system

The existing conceptual AI measurement framework provides little guidance on wholistic landscape, which restrict companies' ability to develop correct standardization, benchmarks and standings. We have used an ensemble valuation approach to guide the development of this framework and seek to describe the conditions under which it then offers decision-useful information to investors.

While not explicitly acknowledged in the conceptual framework, it is difficult to rigorously assess the decision-usefulness of these frameworks as it would mean different for different stakeholders.

AI has been a buzzword in recent years. With technology giants like Apple, Microsoft, IBM, Google, Facebook, and Amazon, to name a few, collaborating their research in their

"Partnership in AI", it is exciting to see the development of AI in the next few years and the changes this new technology will bring to the world.

This article analyzes different methods of business valuation. The valuation methodology is presented according to the MDI-R concept (Assets, Income, Intellectual Capital-Market), which in a broad spectrum measures the effectiveness of the company's investments and, in accordance with the current features of good valuation, aims to determine the complete value of the investments.[1] We have also analyzed multi-facet, complex valuation issues as well as factors that may distort the determination of fair value in implementation of these frameworks.

The study is based on inferences from the methodology of business valuation. Hypothesis for the existence of critical parameters of valuation is then verified using practical examples, and thus, allows for broader subjectivity in estimating the value of investments. At the same time, the factors that determine the possibility of the existence of too wide a subjectivity in estimating assets, investments, and services, which is in contradiction with the features of good valuation, are addressed too.

The attempt is made to draw attention to the holistic ways of modern business valuation methodologies and their challenges. Additionally, this article offers the hybrid method evolved from MDI-R, which draws from existing solutions to improve their functionality and applicability.

When starting a valuation or ROI measurement for an AI investment, analysts and business valuators consider three main valuation approaches:

a) Market Approach

b) Income Approach

c) Asset Approach

The Market Approach involves assessment of comparable public companies or precedent transactions. A common shortfall when valuing AI investments in the Market Approach is that comparable companies may not exist or may not be truly comparable to the subject company. For example, while Microsoft and Apple operate in a very similar space, their market capitalizations (i.e., their value) are very different. As a result, the Market Approach needs to be used with caution in valuing an AI investment for a company.[2]

The Income Approach, on the other hand, focuses on the future cash flows available to the subject company. As such, key performance indicators such as revenues, earnings before interest, tax, depreciation, and amortization (EBITDA) and net cash flows are the focus of analysis in this valuation. Of importance are the recurrence of revenues and customer subscriptions as these would drive the future cash flows of the business.

And finally, the Asset Approach is applied to AI investments that are pre-revenue, have minimal or negative cash flows and will not be able to generate any returns on investment in the foreseeable future (e.g., financial forecasts are not available or cannot be reasonably relied upon).[2] In this case, the fair market value of the identifiable assets, net of any liabilities, will form the basis of the valuation.

The valuation will focus on the value drivers specific to the subject company's AI investments. Some consideration factors may include:

a) Stage/lifecycle of the IP

b) Whether any patents exist for the IP

c) Nature of the IP (e.g., subscription-based vs purchase-based)

d) Key management and team

e) Customer quality and retention/attrition rates

f) Target industries that AI is developed to assist

g) Sales pipeline and customer concentration, etc.

With ever growing AI investments, measurement and research framework is sought to quantify the economic impact of AI that would offer substantial benefits in regulating these investments further. Thus far, research finds that a broad range of AI technologies could boost productivity levels and elevate revenue growth trajectories. The exact valuation may vary because researchers have used different methodologies—for instance, considering a narrow or broad set of drivers of economic impact.[2] A large share of AI use cases relates to retrofitting or replacing old capital investments, for instance, embedding technology and processes with smart monitoring and preventive maintenance systems.

Our approaches have tended to estimate the gross potential of AI. The cost of implementation of these technologies into the socioeconomic system or negative externalities such as the impact of major disruptions on socio-economic groups is not considered in this research. Consider, for instance, the cannibalization of old business models through AI-based innovation, or potentially extensive job reallocation due to the adoption of AI. Such negative externalities may be sufficiently large, and affect enough entities, to create the risk of a societal backlash against AI that could limit the full potential anticipated from these technologies.[2]

II. METHODOLOGY I- BACKGROUND:

The pervasiveness of artificial intelligence and its applicability to ever wider solutions and business models represents a strong element of innovation, which can also operate within a portfolio of intangible resources, enhancing their characteristics and potential.

Hence, we do not limit the valuation of AI investments as an entity by itself and measure the direct tangible impact alone. But rather a product and process innovation, intersecting with typical intangible assets such as software, patents (IP), internet-driven and information input data derived from big data or IoT.

The valuation of AI investments in our approach considers:

a) Standard firms, based on traditional business models, which use some AI tools to expand their business or improve efficiency targets

b) Born-digital firms, built around AI and other related technologies

These two typologies of firm interact, sharing an evolving marketplace. Born-digital propose new solutions often as an unconventional answer to well-known problems. On the other hand, Standard firms are shifting to the new technologies to meet demands customer upgrade and appreciation.

The assessment metrics of the business models connected to the AI investment must also consider first their nature: such models can in fact be the basis of entrepreneurial realities for which the AI constitutes the main objective or a mere accessory activity.

The incremental economic and financial marginality induced by AI investments directly influences the evaluation parameters. It should be defined with a perspective that is typical of estimation metrics that project the parameters into the future, their current value, and also the possibility that these parameters can be subjected to significant scalability, with a multiplying impact on the evaluation.

This approach is based on the expected incremental income made possible using AI. We suggest use of differential comparison "with or without" in which the company being evaluated is compared in the presence or absence of AI investment. This in turn is also linked to the financial approach, based on the estimate of incremental cash flows relating to the exploitation of the intangible. One would also consider impact of presumed royalties that the company would collect to license its AI portfolio going forward, explained, and used further in the income method.

For any business or organization, it is appropriate to use valuation methodologies within the scope of the traditional methods of capital, income, mixed capital-income, or market, converge on two criteria:

a) the discounted cash flow method

b) the market method of the EBITDA multipliers

Both these methods lead to the estimation of the business value, intended as the total market value of a company. Further To estimate the specific equity value, one must also consider the net financial position along with the business value.

Business models introducing AI have a positive impact on incremental revenues or on a reduction in costs, with a consequent improvement in economic and financial marginality and greater efficiency. Always from an incremental point of view, the impact on economic marginality can also be examined through differential comparison technique.

AI increases the scope of existing technologies and open new markets. Excess returns are related to the applicability of real expansion and development options, linked to the concept of techno-digital simulations.

It’s a bottom-up approach of valuation that combines the use of real options and big data. This approach uses empirical evidence to reformulate and update the business plans to which the valuation parameters are linked. In this framework, one compares the two typologies together and independently, i.e., companies providing AI services as their core business and companies that limit themselves to using single AI applications to enhance their strategies are analyzed in general and preparative terms.

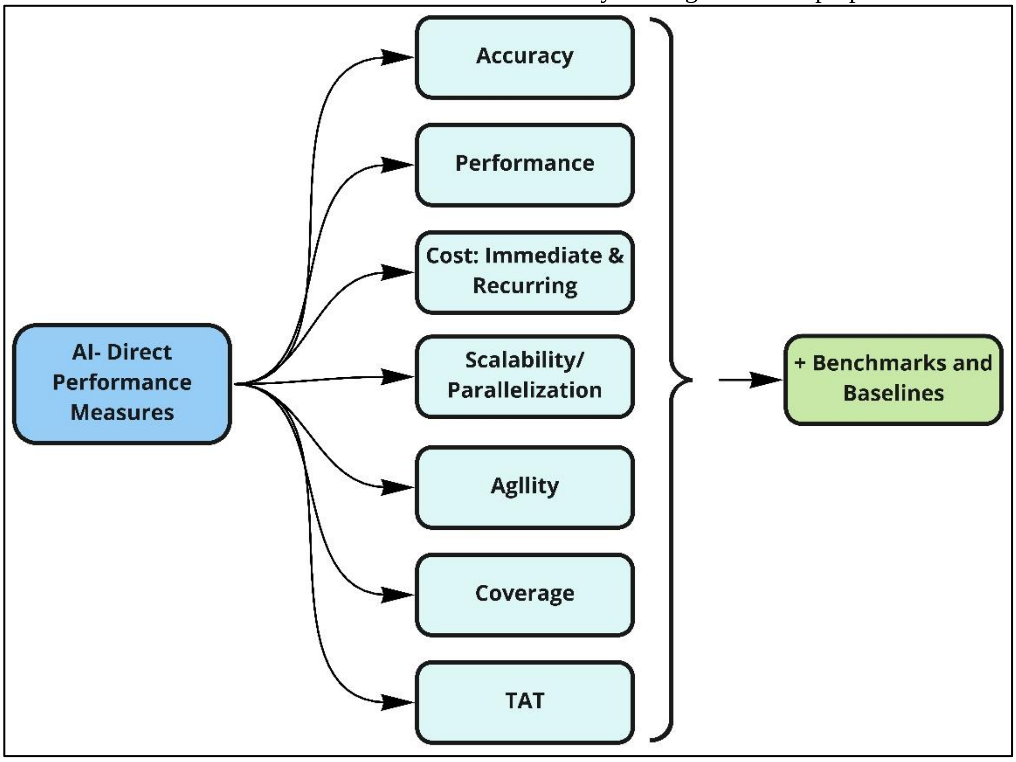

Figure 2: Measurement KPIs: direct- indirect measures for computing total retuns on AI investments

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

III. METHODOLOGY II- APPROACH, DESIGN AND FRAMEWORK

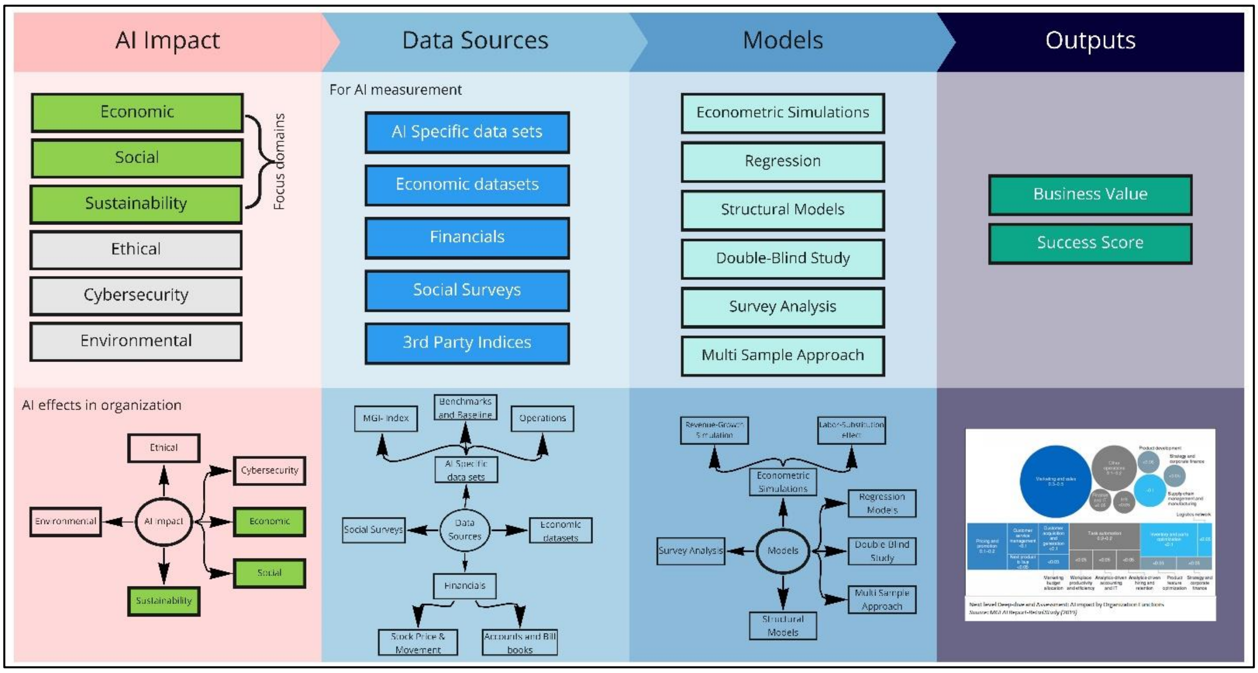

Figure 3: Customized AI measurement framework to holistically assess the tangible and intagible impacts of AI investments

This article focuses on developing a framework to evaluate AI's potential impact on economic activity at the category, sector, company, and worker levels, using simulations. It does not consider other important aspects including ethics and cybersecurity, or the effect of these technologies on sustainability. Nor does it quantify aspects of the consumer surplus that may arise out of using AI technologies, such as saving time or living a healthier life. [3]

Some clarifications/definitions with reference to this article:

a) Definition of AI: AI is notoriously difficult to define due to the conceptual ambiguities of "intelligence." For this article, we take a broad view on intelligence as "the quality that enables an entity to function appropriately and with foresight in its environment." AI can be considered an umbrella term covering a group of technologies that are capable of autonomously performing tasks that, if performed by a human being, would be considered to require intelligence.[3] Characterizing AI precisely is also difficult because the definition tends to change depending on the specific context of research and application.

b) Data sources: In this article, we have used both AI-specific and economic data sets. For AI-specific data, we have analyzed survey studies and their results from MGI's regular survey & the McKinsey annual survey on the extent of digitization in corporations worldwide. The MGI's proprietary database of 400 potential AI use cases across industries and functions is also used in this research to assess the impact of AI investments on the business. For economic data, analyzed socio-economic parameters and statistics from international organizations, the World Intellectual Property Organization (WIPO), the World Bank, the Organization for Economic Co-operation and Development (OECD), the World Economic Forum, Stock markets, Corporate financials, and press releases. Apart from this we have also used other corporate parameters including workforce estimates, R&D expenditures, AI surveys, financial reports, gross profits, and data flows.

c) Approach to AI adoption and full absorption: The concepts of adoption and absorption have been used in various contexts. In this article, an economic entity—notably a company—and its activities is used as a unit for adoption. Adoption of AI is when that entity chooses to invest in one of the five generic AI technologies: computer vision, natural language, virtual assistants, robotic process automation, and advanced machine learning, either for experimentation or for a narrow functional use. Full absorption means that all five generic AI technologies are adopted and integrated into broad enterprise workflows. Full absorption is the stage at which economic benefits tend to kick in and recur. However, full absorption does not mean that there is a fixed range of technologies. New technologies and applications will continue to emerge. Therefore, in this article, the term "full" as opposed to "partial" is used to indicate much broader use of AI technologies than is the case in adoption or a pilot.[3]

d) Simulation and econometrics approach: Economic & financial modeling including regression, causal, structural, and utility based econometric approaches and simulation are used to assess the change in value or the impact of AI for different hypothesis and inputs. We did not limit our study to forecasting outcomes, based on the best evidence collected so far, rather the methodology also simulates the likely impact from AI given different contexts/hypothesis at the category, sector, and company level. For the econometric simulation of firm-level AI adoption and absorption, a double blind and multi-sample approach is used to ensure that the results are acceptable. The solutions are developed, tested, and validated, to estimate and converge, on the dynamics of propensity to adopt and absorb technologies. Consistent dynamics of adoption and absorption is observed in all the survey and samples.

e) Limitations and sensitivities: The firm-level simulation is dependent on the quality of data from the surveys used as inputs, and it should be acknowledged that this framework approach has two potential limitations. First, survey answers depend on the knowledge and perceptions of respondents, and their understanding of AI may vary, possibly affecting the quality of the insights and data gathered in this way. Second, the data set from survey results may be skewed toward early movers. Extrapolating insights from the survey may therefore lead us to overestimate the economic impact because the next wave of companies adopting AI may display different behavior in terms of AI adoption. For these reasons, the result of the simulation from our approach should be interpreted as being the upper bound of estimates of AI's economic impact. However, competitive pressure is a key factor driving up the level of AI adoption. If new companies that are more agile join the AI race more quickly than expected, this could push up the adoption curve. Finally, it should be noted that the simulation is highly sensitive to the results of corporate surveys on AI absorption.[3,4] The adoption and absorption of AI by companies are the foundation of several dimensions of impact modeled, including labor augmentation, substitution, and innovation, as well as transition costs. When new data is gathered, the adoption and full absorption curve and the results of the simulation could also change.

Expanding on the data sources and approach we have assessed the following three types of AI-related indicators:

a) AI investment: The economic impact of AI depends on whether there is sufficient investment to fund new AI initiatives and research and enable greater corporate investment. Investment in AI is growing rapidly but is still largely concentrated in the United States and China. Tech giants such as Google and Baidu spent an estimated $20 billion to $30 billion on AI in 2016. In 2017, according to CBInsights, $15.2 billion was invested in AI startups around the world, and nearly half (48 percent) of that total went to China; 38 percent was invested in the United States. The United States still has more AI startups than China, but China is making considerable headway in striking equity deals in the AI domain. AI-related investment data is compiled from Dealogic, S&P, and Capital IQ. Investment figures include sources of funding such as seed, grant, mergers and acquisitions, private equity, and venture capital.[3]

b) AI research activities: As noted, AI could have a large gross impact if companies use it to create new products and services (beyond simple labor substitution). This framework analyzed AI-related research activities using data on AI-related patents from WIPO, and AI research using AI publications and citations from AI Journal Ranks. These sources do not cover the full range of work being undertaken by companies, because many corporate research laboratories may not fully publish the scope and extent of their research given competitive dynamics. Having said that, it's important to note that many corporate labs are now among the top contributors of AI knowledge for key conferences, including the Conference on Neural Information Processing Systems (NIPS) and the International Conference on Machine Learning (ICML).[3,4]

c) Potential productivity boost from AI and automation: The potential to automate and for AI to be deployed can be driven by the relative costs of machines and wages. Because wages are relatively low in developing countries, the potential to automate is lower. However, in most developed economies, higher wages will likely lead to higher AI adoption and absorption when it substitutes for human labor. Depending on the wage level, economics, and social acceptance, the automation potential, and therefore the substitution effect, may differ. Developed economies tend to have high automation potential, because the business case for AI solutions is easy to justify. The high index reading should be interpreted as high potential to substitute labor rather than a country's strength.[3,4]

The other dimensions looked at in this article are AI enablers. They are the foundations for adoption and absorption of AI (as well as other emerging technologies), and some are likely to correlate with AI-related indicators:

a) Digital absorption: Conventional measures of digital readiness, maturity, or competitiveness of countries tend to focus on digital infrastructure, for example: internet penetration, broadband speed, and affordability for households. However, how companies are developing digital assets and using them across their organization is perhaps the more important precondition for AI effectiveness measurement. We have based it on the technology utilization index, which measures how corporations are using the latest (digital) technologies in each country as a proxy for the ability of companies to absorb digitization.

b) Innovation foundation: The degree of innovation can determine whether an organization is able to develop and commercialize powerful AI solutions. This article assesses overall innovation capacity using data on R&D investment from the OECD and evaluated industry dynamism using data on ICT business-model creation and organizational model creation from the Global Innovation Index. The framework focuses on differences among companies in terms of whether they can use the technologies and create new business models, and whether they can improve their organizational models to absorb technologies.

c) Human capital: Entities need to ensure that they update the skills available not only to ensure that there are sufficient AI specialists, but also to enable large numbers of individuals to work alongside machines. Human capital is critical to the absorption of new knowledge and its real-world applications. This article looks at problem-solving skills using scores from multiple assessment programs.

d) Connectedness & collaboration: Companies with stronger connections to the consumer and world may have better foundations for innovation and are most likely to have increased potential to reap the benefits of AI investments. Connectedness can help companies collaborate and use cross-border data flows to enhance the performance of AI applications and participate in global value chains, as noted.

e) Labor-market structure and flexibility: Widespread penetration of AI will almost certainly displace many existing working tasks. Minimizing the risk of societal backlash will require as smooth as possible a transition to AI by putting in place mechanisms such as transitional support and training for displaced workers.[3,5] Companies that have robust social support and extensive provision of training may be less likely to run into popular opposition to AI at additional cost to its implementation.

This article hence utilizes and is built on multi-layered econometric causal structural model approach (n-layered cross m-factors). Considering factors that affect AI-driven productivity growth, including- labor automation, innovation, and new competition. Micro factors, such as the pace of adoption of AI, and macro factors such as connectedness and labor-market structure, contribute to the size of the impact.

The simulation for this approach examines seven possible channels of impact: (1) augmentation; (2) substitution; (3) product and service innovation; (4) connectedness; (5) wealth creation and reinvestment; (6) transition and implementation costs; and (7) negative externalities. The first three relate to the impact of AI adoption on the need for, and mix of, production (tangible) channels that have direct impact on the productivity of firms. The other four are externalities linked to the adoption of AI and related to the broad economic environment and the transition to AI (intangible effects). These seven channels are not definitive or necessarily comprehensive, but rather a good starting point that collectively provides convergence to the n-layered approach. As AI investments continue to grow, many measurement frameworks emerge and continue to evolve to understand the implications of AI in future.

A. Production channels

These channels translate in direct impact to the firms' productivity in short/ long term.

a) Channel 1- Augmentation: The first dimension relates to increased use of labor and capital. Investment in AI has complementarities for other factors including jobs. For instance, many jobs are likely to be needed to build the AI infrastructure and monitor its operation to ensure its full use. Increased capital investment in AI can create demand for jobs—in both existing occupations and new ones—contributing to output growth. For currently demonstrable narrow AI technologies, human beings are needed to manage and transfer insights from one area of narrow AI to another, in contrast to the necessary capabilities of artificial general intelligence. This additional labor complements the increased capital invested in AI. AI will likely also redefine many existing occupations, augmenting human capabilities and making workers more productive.[6] As machines take over certain activities, workers are freed up to engage in higher-value tasks using AI tools to be more productive or in other tasks that machines are not yet able to perform, regardless of their value.

b) Channel 2- Substitution: Technologies and automated processes that offer better results, cost effectiveness, or both tend to substitute other factors of production. The intensity of substitution depends on the relative costs of inputs. This approach modeled the labor-substitution effect—how AI technology automates human activities and effectively substitutes labor with capital, maintaining the output of goods and services but reducing the labor hours required to achieve that output. The substitution also generates additional productivity gains over time as capital becomes more efficient and productive as it "learns."[3,7]

c) Channel 3- Product and service innovation and extension: Investment in AI beyond what is needed strictly for labor substitution can produce additional economic output by expanding firms' portfolio, increasing channels for products and services, developing new business models, or some combination of the three. This approach suggests that firms' motivation for adopting and absorbing AI relates as much to a desire to develop new products and services as to a bid to boost efficiency through automation. To arrive at a sense of the magnitude of this effect, an extensive set of AI use cases was looked at in detail, and then the relative ratio between the efficiency gained from AI and the magnitude of impact from innovation and market extension is simulated. Innovation often creates new value for a firm as new products and services stimulate consumption. The modeling assumes that

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

the overall economic pie can grow to capture the upside of new value.[3, 4]

B. Externality dimensions

We have established, that production channels produce new economic activity and productivity gains that organizations and researchers tend to take as tangible measure of AI investments. However, one needs to analyze other intangible & external factors, to measure the holistic impact of AI investments. For instance, the AI infrastructure and transition may result in larger collaborative eco-systems between organizations. However, AI investments may also imply negative externalities arising out of transition costs from implementing AI architecture and infrastructure and structural costs associated to loss of competitiveness in firms that do not adopt AI or skillset transition/ replacement to adhere/operate in an AI-based setup. For an exhaustive effectiveness measurement of AI investments, we have included four additional dimensions, positive and negative, to this measurement framework.

d) Channel 4- Gains from collaborative associations: Companies are not insular; they interact in a connected marketplace. Digital ecosystems, data, process, and knowledge sharing helps organizations expand and grow across markets and domains.

e) Channel 5- Wealth creation and reinvestment: As AI contributes to the higher productivity of companies, the increased output from efficiency gains and innovations can be passed to workers in the form of wages and to entrepreneurs and firms in the form of profits. The generation of wealth induced by AI could create spillover effects that boost economic growth. Higher investments in AI translates to better work opportunities with higher per capita income, that boosts economy with higher consumption and overall growth for the society. Such secondary effects or spillovers may develop over time; indeed, they have been a major source of sustained growth in the past.[8]

f) Channel 6- Transition and implementation costs: A range of costs are likely to be incurred during the AI transition for the organization. Companies are likely to restructure their organization as they continue their transition journey. Resulting in multiple costs like: Cost of new technology, infrastructure, and deployments systems, its integration, and associated project and consulting fees. Investment in new skillset & capability development to operate new AI tools, through hiring new workers or upgrade existing workers for new skill sets. Some workers may be displaced by new technologies, and companies might need to pay associated severance cost. Disruptions to society may also incur costs.

g) Channel 7- Negative externalities: AI could induce major negative distributional externalities affecting workers among others. Many economists argue that technology has caused a decline in the labor share in many economies.[3] As firms adopt and absorb AI, pressure on employment and wages is likely to increase, which may depress the labor share of income and potential economic growth—cyclically through lost consumption during periods when individuals are unemployed or retraining, and structurally through a relative income effect. Other costs may have a direct impact on individuals and an aggregated impact on the economy.

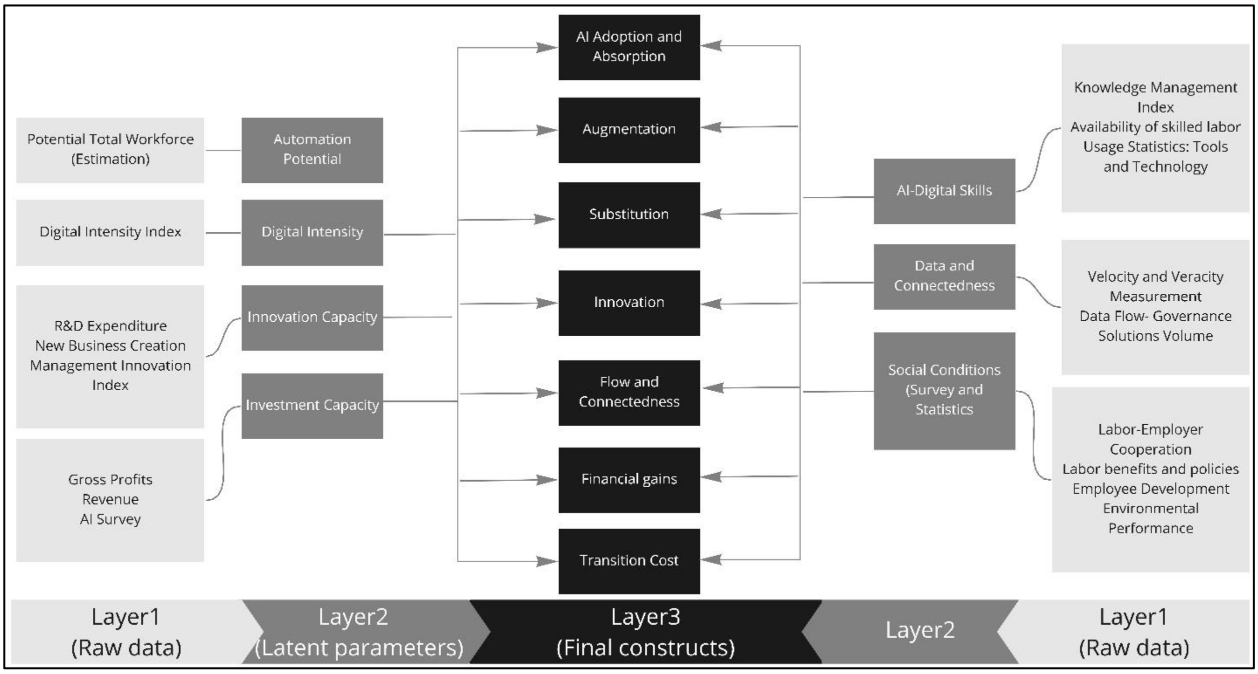

Figure 4: Measurement construct- Layered assessment by creating latent scores for each channel and the data sources used to analyze the return on AI investments

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

IV. METHODOLOGY III: TECHNICAL APPROACH

This research models a set of critical channels through which AI can affect the performance of firms, how this creates spillovers to other overall financial and economic entities, and therefore the aggregate performance of business.

This modeling and simulation rely on two important features. The first feature is the quality of data that provide us with the range of estimates of how AI is perceived by companies and of how they use these technologies economically and strategically. The results of the modeling and simulation will change as one includes other or different data sources for evaluation, and therefore the results presented in this paper may evolve. The second feature of this framework is its inclusion of micro-estimates of the pace of adoption and full absorption of AI technologies. The approach taken in this analysis is based on the premise that AI should be treated as a disruptive innovation that has a strong competitive and strategic rationale for the organizations.

A. *Micro-to-macro approach*

The simulation of the economic impact of AI investments takes a micro-to-macro approach with the following seven steps:

a) Step1: Integrate relevant data sources: Included and harmonized various data sources including surveys, financial reports institutional reports to infer holistic gains for AI investments.

b) Step2: Prepare a foundational data set from econometrics: The article derives an econometric model that links firms' decision to invest to a set of factors from valuation literature on the diffusion of innovation and measurement. This econometric model therefore endogenizes corporate adoption based on the explicit competitive and strategic value of AI, rather than taking a set of older technology adoption curve benchmarks, as MGI research has done in the past.

c) Step3: Simulate "gross" Profit and Revenue impact: In addition to estimating corporate adoption and absorption of AI, the article models economic and financial factors expected to be influenced by this AI investment, namely labor augmentation, labor substitution, product and service innovation, the impact of the global value chain, and the feedback loop in the economy that is, improved productivity leads to additional reinvestment of consumption.

d) Step4: Simulate "net" Sales and Revenue impact: Most existing research on the impact of AI tends to focus on the gross figure. This research models the net impact by taking into account a range of costs related to the implementation of AI, including investment in the deployment of systems and transition costs associated with labor like: displacement, retraining, and rehiring. The analysis also assesses negative externalities such as loss of consumption during unemployment as well as social costs incurred by paying benefits to those who are unemployed during the transition.

e) Step5: Simulate the impact on labor markets. The next step was linking the economic impact with the effect on labor markets, considering different skill and wage levels. It's based on the hypothesis, that various segments of workers based on the tasks they perform (that is, routine versus non-routine, and digital versus non-digital) will experience different shift in employment and wages overtime.

f) Step6: Model variances: After building a foundational model based on regression and causal structural models, the research models variances for paced n-layered distributed latent factors. The research identifies enablers that correlate strongly to factors driving adoption of AI, such as innovation capacity, human capital, and connectedness. It also models parameters such as digital infrastructure, automation potential, and other macroeconomic factors including foreign direct investment (FDI) intensity and unemployment benefits for different markets.

g) Step7: Undertake sensitivity analysis: Finally, the results presented in the main body of the research are ensemble for a multiple set of simulations. Varying effectiveness in driving the change by different parameters is done using sensitivity analysis for significant variables in the research model.

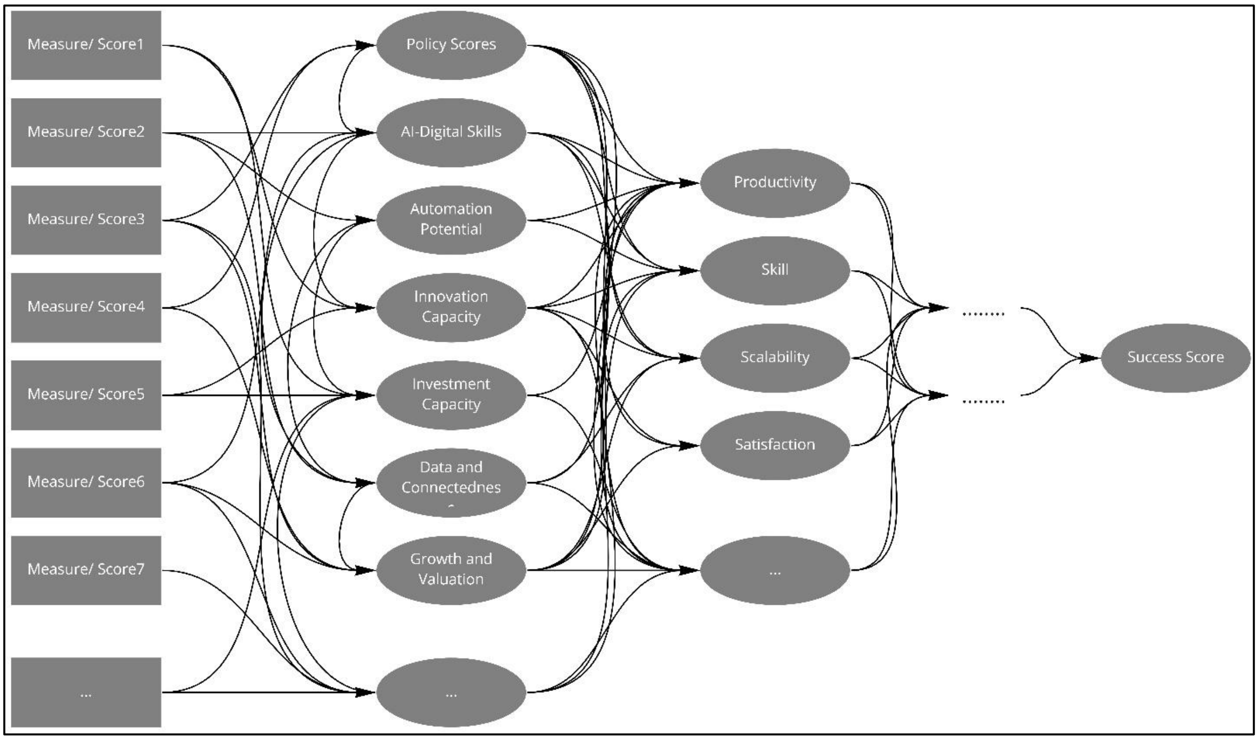

Figure 5: Structural simulation models- causal econometric and combinatorial regression n-layered construct

B. *Survey data*

The research draws on multiple dependent and independent corporate surveys conducted by the company or 3rd party consulting and financial institutions.

The digital survey covers industries worldwide on digital technologies and AI to ascertain the causes of economic impact and the likely pace of that impact. The surveys also present a series of global surveys on economic matters administered independently by global research firms.

The questionnaire is typically cross-checked for systematic correlated bias of answers to ensure its scientific validity. The survey universe is very well defined across companies, sectors and markets that mimic the economy. The typical response rate is checked against a threshold match rate to maintain the data sanctity.

C. *Sampling*

A set of initial tests on the sample are performed to ensure its relevance. While the tests are only indicative, it meets the data acceptance criterion for modeling and simulation purpose.

There are two key tests. The first was to test for answer bias. The second was to confirm the adequacy for certain parameters as established in standard literature. Specifically, the analysis tested whether there is any difference in the sample of answers from the original target of firms by sector and country, with respect to mean difference in key financial metrics (revenue, revenue growth, profit, and profit growth) of respondents and non-respondents. The analysis used a simple one-way test per financial metric, as well as a multivariate logit model of a firm answering or not answering, linked to all the financial metrics. There were no statistical differences in answer rates. Finally, some self-reported biases were tested. In the survey, the order of questions was randomized for half of the sample, and no bias in types of responses was found. However, the econometric results are not sensitive to whether these responses were included, so the full sample was kept as the basis for the simulations.

A few important regularities uncovered in the technology innovation literature were also tested to ensure that they also emerged from the data set. For instance, there is a size bias (size of firms) in AI adoption. For this research, therefore, two indices were built—one for digital absorption and one for AI absorption in which absorption is the proportion of digital technologies and AI used at scale by each firm. A cross-section correlation with firm revenue and employee size was then run. The size-absorption correlation effect is especially strong for large companies with more than 10,000 employees (the coefficient of correlation with employee was $r = 0.56$ for digital and 0.63 for AI).[3,4]

D. *Econometrics of firms' absorption of AI and the impact on their profit growth*

To derive AI adoption and absorption curves, a three-step process was used. The first two steps link firms' competitive advantage and the benefits of AI, demonstrating a strong stock/dynamic effect in which the propensity to adopt at a certain time (t) is the result, among others, of the number of competitors already vested and the stock of other technologies already absorbed. The third step forecasts adoption and absorption at an aggregate level based on the econometric results and the stock effect, which conditions the dynamics at time t+1:

Econometric model: The process of new technology adoption has been widely studied and debated in economic literature over the past 20 years. Applying this literature to the practice of AI adoption, the framework suggests that AI is a function of a set of key predictors, outside of control effects which we note in equation below.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

Pr(AIij)= f (competition, digital capabilities, AI complements, expected profitability,…) (1)

Where Pr denotes the probability by the ith-firm to adopt the cluster j of AI technology, and the probability is a function to be estimated of a vector ultimately composed of the following four key predictors assumed to affect the probability to adopt:

a) Competition: Game theory suggests that the marginal propensity to adopt depends on the extent of competition, or the portion of rivals that has already decided to adopt the technology. However, the effect of competition is not known a priori. If one assumes that the benefit to the marginal adopter from acquiring a new technology decreases with an increase in the number of previous adopters—which is the case with strong first-mover advantage and fixed market potential—then the effect of rivals' adoption may decrease marginal incentives to adopt.[9]
b) Digital capabilities: It is generally assumed in the literature on the diffusion of technology that potential users of a new technology differ from one another on important dimensions so that some firms adopt more (or faster) than others. This heterogeneity is called the rank effect. One group of rank factors refers to general characteristics of firms such as location, size, and industry: larger firms tend to adopt faster, or firms exposed to international competition are more inclined to innovate and adopt new technologies. In addition to the variables in our vector above, we control in our regression for the location of company headquarters, global presence, size, and the main industry in which the company operates.
c) AI complements: As discussed, AI encompasses a multiple set of technologies, which we have grouped in several clusters in this research. There is clearly a point where each cluster acts as a complement to another. For example, when a firm uses AI to automate a process, it will likely combine both advanced robotics and artificial visualization (so that robots can interface with each other). This complementarity in technology diffusion is observed to be high in the case of digital technologies.
d) Expected profitability: Any investment decision in a new technology relies on a business case.

Equation 1 was estimated as a single logit or OLS model or as a system of two equations with, expected profitability. This is estimated for both adoption and absorption, choosing the best fit model.[3]

Its magnitude of impact on adoption and absorption is qualified as high, medium, or low depending on the odds ratio effect on adoption propensity.

In general, the effects are marginally more significant for decisions to adopt than to absorb. Further, AI Complementarity is relatively strong: companies tend to invest in the broad set of technologies. Expected profitability plays a stimulating role, but its impact is lower than any other predictors. Rivalry is a pervasive effect, high significance in the adoption and absorption of advanced machine learning techniques.

E. Simulating company-level economic impact

Multiple data sets were used to simulate the impact of AI investments on organizations. First, financial, and economic data of the company is used to assess the current operating stage with respect to its development and economic structure. As organization profile differs in terms of revenue, share of consumers, and labor share of economic activity. Second, AI-related indicators for each country that are linked to different dimensions of economic impact is analyzed. Variance computation for each organization for all variables, in different markets is modeled. For example, Organization's skillset level may have an impact on augmentation, innovation, and spillovers. While, R&D expenditure, ICT business creation may see higher impact on innovations and wealth generation in many or certain startups and small and medium-size enterprises. Social indicators such as labor-employer cooperation may influence transition costs.

F. Stress testing the economic impact of AI

Various scenarios and causal structures are simulated to assess the sensitivity of AI investments and its impact on different parameters. We observe, for up to ten-percentage-point variations to baseline, parameters like the rate of AI absorption and innovation gains tends to be more sensitive than others:

a) AI adoption and absorption levels: Financial gains and impact due to organizations current or future plans to adopt and absorb AI and its sensitivity scores.

b) Investment in AI: AI investment can be used not only to substitute laborious tasks, but also to develop new business models, products, and services. However, achieving a healthy return on that investment depends on several factors including the company's economic context, regulatory policies, infrastructure available for incubating innovations, and appropriate social safety nets.

c) Innovation capacity: Each organization has different capacity and capability for innovation. Simulated the impact of product and service gains and extension for different gains scenarios.

d) Global data flows and connectedness: The economic potential of AI also depends on the company's participation in data, technology, skillset, and trade flows.

e) Transition costs: Companies can avoid certain costs associated with the displacement of people if they redeploy them rather than let them go, enabling them to shift to other roles by giving them the appropriate skills. The cost of reskilling depends on how effective the program is. Effective programs re-train individuals and get them back into the workforce more quickly, cutting economic cost.

f) Negative externalities due to increased unemployment duration: The duration of unemployment has significant implication on cost.

V. RESULTS

Three of the seven channels stand out: (1) the use of AI-driven automation to substitute existing labor; (2) the application of AI to innovation that creates new and better products and services; and (3) AI-driven competition and the resulting disruption to firms and workers.[3]

The substitution of labor by technology is often assessed from the point of view of the supply side of workers, and rarely from the demand side of firms. Yet, firms adopt technology for economic reasons—resulting more from the productivity boost and gains through AI investments.

Net gains typically increase over time as the performance of these technologies improve—as has been seen in the case of many general-purpose technologies. For instance, the price of electric motors in Sweden plunged by as much as 70 percent during the 1920s. In the case of AI technologies, one observes higher performance over time, with consistent or even lower cost for development and maintenance. For instance, computer vision (an AI tool) in 2011, operated at 75% accuracy; improved its outcomes and solution in subsequent five years to higher accuracy of 95%. Which could be considered at par with—or even better than the information pattern recognition of an average human being, according to Google Brain.[3,4]

AI can make an important contribution by boosting innovation that can then be applied to improve current products and services and create entirely new offerings. The simulation suggests that innovation can contribute significantly to the potential increase in gains in coming years, incremental to immediate or short-term impact.[10]

Impact of AI investment are multifold, as the organizations not only see quick improvement in their top lines with their existing products and services by reaching underserved markets more effectively, also higher gains from input substitution on productivity gains building up over time. The second reason is that, over time, most technologies tend to foster innovation in products and services, boosting non-traditional industries and creating entirely new market space.

Innovation has competitive edge for investors, front-runners capitalize and increase their top-line growth, yet a large portion of gains could be linked to a shift in market share. Organizations with possible cannibalization within their portfolio offerings, are often challenged if they do not redefine their offerings. The firms often require readjusting their cashflows, under higher competitive pressures and are likely to pull their investments off innovations, R&D, new technologies, eventually ending in a vicious circle. This risk is well documented in research related to competitive dynamics in digital markets.

The economic benefits of AI-based automation and innovation are secured at a cost, an element that existing research tends to overlook. The deployment of AI will very likely create a shock in labor markets resulting into costs associated with managing labor-market transitions, especially for workers whose skills are made obsolete or less relevant by AI technologies.[11]

It is difficult to estimate complete cost for the system as its incurred separately and independently in the supply and demand side, and, in many cases, would be interrelated. Moreover, transition costs in one part of the value chain may generate new value in another part; therefore, the items of cost listed in the simulation may not be additive. This current modeling does not account for detailed value redistribution across all the activities. A more complete and robust economic simulation is needed to assess equilibrium and interconnectedness.

Although an annual trend curve is presented here, this is largely for illustrative and simulation purpose. Readers should look at the shape of the curve rather than exact annual figures. This simulation is dependent on the actual level of adoption and absorption by firms, and current firm-level dataset may be skewed towards early adopters. This may mean that the impact shown is an overestimate. One would argue that organizational capabilities and investment capacity for a front-runner would be very different from followers in the category and hence their adoption and absorption would be inherently different.

AI transition is a long-term investment for organization to start reaping its benefits any sooner. The aggregate net impact of AI investments may take off after a period of five to ten years. Reminiscent of the Solow Paradox, the small initial impact may persuade some observers that AI is being overhyped, but this could well lead to misjudgment. The benefits to early adopters of these technologies increase sharply in later years at the expense of non-adopters.[3,4]

In aggregate, and over time, the impact of AI is likely to accelerate, boosting productivity growth. Therefore, companies—and countries—with proactive AI strategies will likely need to be committed for the long haul, as the total net impact may become visible only after a few years.

Micro and macro factors underpin the impact of AI on global economic activity to broadly the same extent. The most material micro factors relate to influences on the dynamics of firms' adoption and absorption of AI. The significant macro factors in our simulated framework include AI investment and research capabilities as well as key enablers, such as digital absorption, human capital, connectedness to global flows, and labor-market structures and flexibility.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

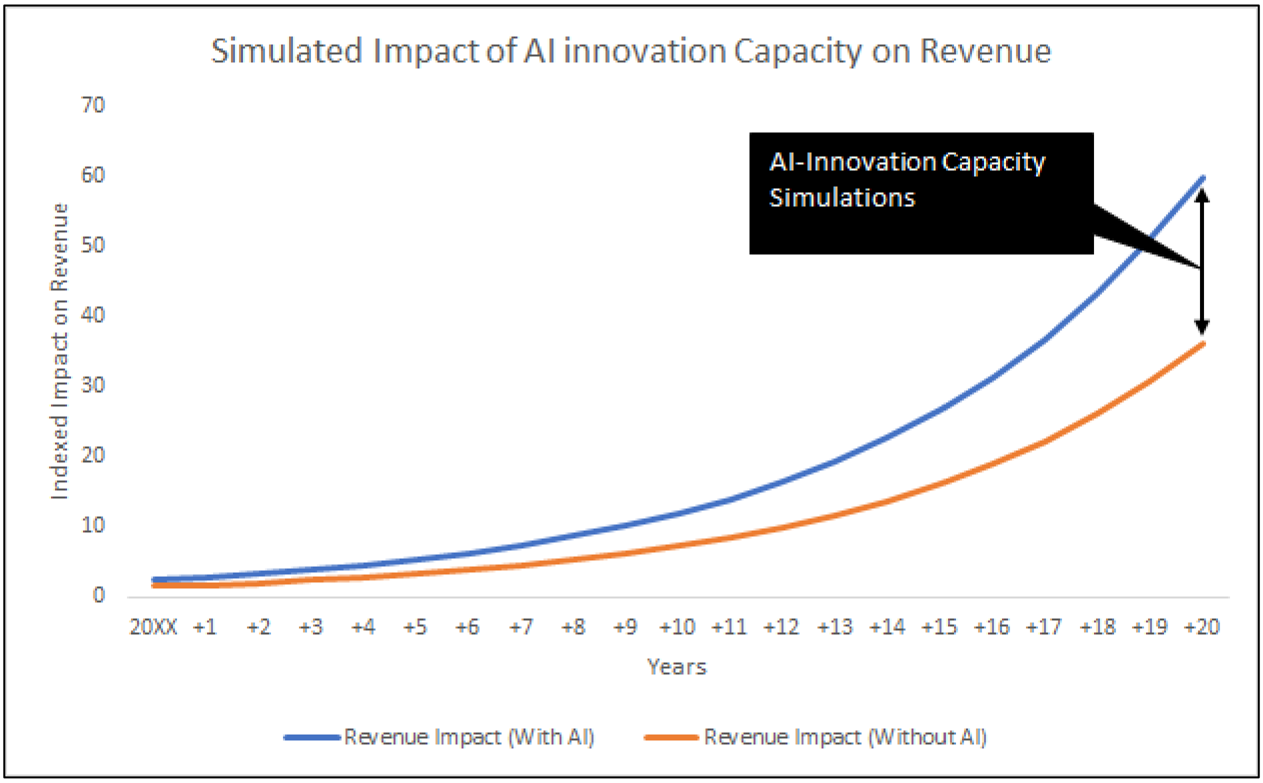

Figure 6: Simulated impact of AI Innovation on an organization's revenue over the years with persistent AI investments (Illustrative)

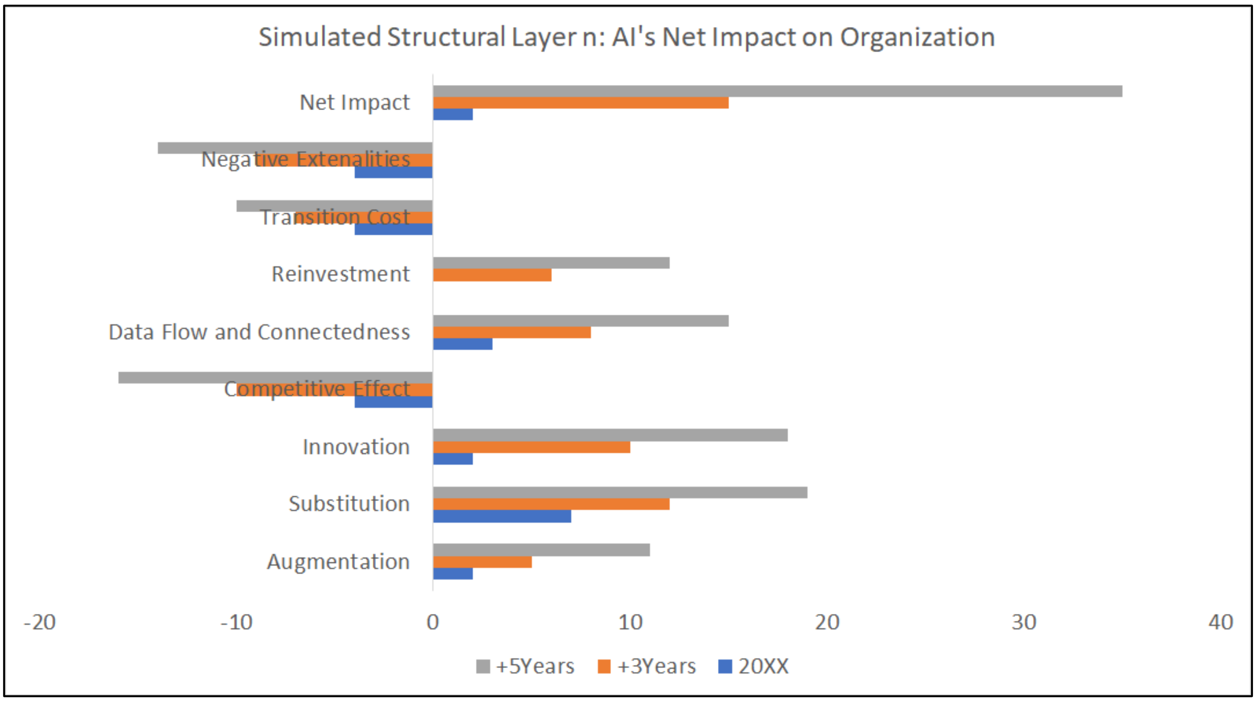

Figure 7:Simulated Impact of AI investment on the channels of measurement over the period of 5 Years using structural n layered approach (Illustrative)

The micro-economic impact of AI investments depends on the rate at which these technologies are adopted & absorbed by organizations. Decisions to invest in these technologies do not occur in silo but depends on interactions of different parameters that determine the economic and competitive case for adoption and absorption.

Early digitization and the competitive race are important determinants of the pace of AI adoption and absorption: Full absorption takes time, as seen in the case of prior generations of digital technology. AI may be adopted and fully absorbed slightly faster—at the high end of benchmarks of the speed at which technologies percolate. AI adoption and absorption could be more rapid because of its versatile applications, including domains where digitization is still underpenetrated, such as the automation of services and smart automation of manufacturing processes. Another reason that AI may be adopted and absorbed more quickly than prior technologies is because of higher ROI. This also

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 05, May-2021

give competitive advantage to overcome significant cannibalization and substitution otherwise. Nevertheless, the adoption and absorption of AI may be bounded by its dependence on the technical infrastructure needed for its effective use. Two aspects worth highlighting are digitization and competition.

a) Digitization: An important factor in the adoption of AI is how strong is the organizations' digital-technological foundation, as this forms the backbone for its effective rollout. Machine learning underpins a large share of AI technologies. Most algorithms require big data infrastructure and a digital architecture.[3] Even with the best technology and infrastructure, organizations cannot generate value and higher performance from AI without the skilled labor and experience necessary to tap into its opportunities and mobilize change through the organization.

b) Competitive pressure: Economists have long been interested in how technology and innovation interact with competition. According to both Schumpeterian and disruptive theory views, the adoption of technology is typically driven by competition and may build a first- to-market advantage if the performance of the technology is strong enough to compensate for all the uncertainty surrounding its introduction. Some economists have shown that competition was the most important driver of PC adoption, for instance. Some companies adopt AI in a preemptive move against perceived fear of disruption from competitors or as a direct response to a new competitor, while others react more slowly.[3,4]

VI. CONCLUSIONS

The impact and ROI of AI is likely to be large, comparing well with other general-purpose technology in history. However, the productivity dividend of AI probably will not materialize immediately. This research finds that AI's impact is likely to build up at an accelerated pace over time, and therefore the benefits of initial investment may not be visible in the short term. The benefits and returns of AI Investments are likely to be distributed unequally, and if the development and deployment of these technologies are not handled effectively, could translate into wider socio-economic differences which can be significantly simulated using the framework developed in this paper.

Predicting the financial and economic impact of AI investments or any disruptive technology is a highly speculative exercise. This is a space of near-continuous discontinuity. It has already been highlighted in many analyses that the scope and pace of AI innovation and deployment depends on several parameters—some more predictable than others—including technical feasibility, the cost of developing and deploying technologies for specific use in the workplace, labor-market dynamics including the quality and quantity of labor and associated wages, the benefits of automation beyond labor substitution, and regulatory and social acceptance. Similar factors are likely to determine the pace of AI adoption. In addition to these factors, competitors enabled by digital technologies can result in disrupting the markets and pose threat to the existing robust incumbent businesses. Technology has accelerated and intensified the natural forces of market competition, and developments are difficult to predict. This research through its framework has built scenarios and extrapolated outcomes using simulations, for quantifiable measurement of impact of AI investments on businesses.

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