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The impact of AI Technological Revolution on traditional microeconomics: Opportunities and challenges

Dr. Lung-Tan Lu
Department of Management, Fo Guang University, Taiwan

Abstract
The technological revolution centered on machine learning and generative artificial intelligence is systematically reshaping the pattern of economic operation from the dimensions of production factors, decision-making subjects, market mechanisms, and behavioral logics. This revolution poses a comprehensive challenge to traditional microeconomics, which is built on the assumptions of rational man, the traditional framework of production factors, and the single human decision-making subject, and relies on core tools such as supply-demand analysis, marginal decision-making, and utility/profit maximization. Focused on the resource allocation behavior of human economic agents, traditional microeconomics is difficult to adapt to the new economic system characterized by human-machine hybrid decision-making, data as a core production factor, algorithm intervention in market operation, and the iteration of information asymmetry. Based on the classical analytical framework of microeconomics, this paper systematically dissects the profound impacts of artificial intelligence technology on core categories including consumer behavior, information asymmetry, price mechanism, market structure, firm production function, labor market, wage distribution, externalities, public goods supply, and institutional governance. It explains the theoretical dilemmas and transformation directions of microeconomics in the AI era, defines the disciplinary connotation of algorithm economics as an emerging interdisciplinary field, and constructs the paradigm expansion path of microeconomics under the human-machine co-constructed economic system. The research shows that artificial intelligence does not subvert the core analytical tools of traditional microeconomics, but promotes its transformation from the classical paradigm to Microeconomics 2.0, which requires the endogenization of algorithms, data, human-machine interaction, etc., to realize the structural supplement and innovation of the theoretical system.

Keywords: Artificial intelligence, microeconomics, data factor, algorithmic economy, market governance, paradigm reconstruction

Introduction

The Evolution of AI Technology and Microeconomics

The digital economy now functions as an essential economic foundation because intelligent technologies have established strong partnerships with this system. The digital economy exists as a main economic factor because AI performs complex economic decisions which transform how businesses function and modify market operations (Brynjolfsson *et al*., 2021) [8]. Machine learning systems underwent multiple optimization processes which resulted in generative AI technology breakthroughs that decreased information processing expenses and prediction and decision-making costs and content production expenses. The economic system now operates through human-machine decision systems which have replaced the previous human-only decision process. The economic factors which used to consist of labor and capital and land now include data and algorithms and computing power.

Microeconomics functions as a core discipline which studies microeconomic agent activities and market balance and resource distribution efficiency while staying connected to technological progress (Mas-Colell et al., 1995) [16]. The Industrial Revolution established the three-factor system which classical microeconomics used to study labor and capital and land resources. Neoclassical economics established a total theoretical framework which used rational man theory and marginal analysis and equilibrium analysis for its foundation. The AI era economic system shows three essential characteristics which create problems for scientists who work with traditional economic models (Goldfarb & Tucker, 2019) [14]. The first characteristic shows how AI developed into an economic agent which now makes independent decisions while working with humans through a human-machine decision system. The production factor system has expanded because data functions as a non-rivalrous resource which organizations can reuse to generate bigger economic benefits. The market operation system now functions through algorithms which perform direct control over supply-demand equilibrium and price determination and resource distribution.

The main elements of traditional microeconomics face three major challenges because of these new market characteristics. The rational man assumption fails because AI systems create new information asymmetries which break down the conditions for perfect rationality and complete information and individual decision processes. The rational agent assumption becomes weak because people face limits when making decisions (Simon, 1955) [24]. Research now studies economic activities which combine human elements with machine operations which traditional consumer behavior theory and firm theory cannot explain. The present research field includes both human agents and algorithmic systems which function as separate entities (Agrawal *et al*., 2019) [3]. The existing theories which study factor markets and price systems and market structures fail to explain new market patterns which data factor pricing and algorithmic pricing and platform monopolies create (Rochet & Tirole, 2003) [21].

The current research focuses on AI effects in individual economic domains which include labor market and pricing system and anti-monopoly enforcement but it fails to develop a complete framework for microeconomic theory. Based on this, this research base its analysis on traditional microeconomics to study how AI affects microeconomics through multiple levels. The research establishes a microeconomic analysis structure which suits the intelligent economic period and creates theoretical support for intelligent economic micro-governance and policy development. The research paper establishes its core contribution through three main achievements. The first achievement provides a detailed explanation about how microeconomic research subjects have grown during the AI period by showing the central importance of human-machine hybrid agents and data elements. The research reveals AI impact mechanisms which affect rational man assumption and consumer behavior and firm theory and market structure so it creates paths to update conventional theories. The research establishes its analytical boundaries through algorithm economics which demonstrates its value to academic fields while it identifies three main paths for microeconomics to develop into "Microeconomics 2.0".

The economic value of artificial intelligence technology is mainly reflected in two core capabilities: predictive optimization of machine learning and content creation of generative AI. Machine learning functions as AI's core technology because it enables systems to learn independently while making better decisions through data-processing methods which operate as prediction systems that adapt based on input information. The main economic worth of this system comes from its ability to decrease information expenses while boosting resource distribution effectiveness which follows the information economics framework (Stigler, 1961; Agrawal *et al*., 2019) [3, 25]. Machine learning finds extensive use in microeconomic studies through its application in demand prediction and price adjustment and manufacturing operations and credit risk assessment: E-commerce platforms use customer behavior information to develop tailored product suggestions which help customers find what they want more quickly; Machine learning helps manufacturing companies optimize their production schedules which leads to lower production expenses; Financial institutions apply machine learning for credit risk assessment which helps them understand hidden information between lenders and borrowers during credit market transactions.

Generative AI technology operates as a revolutionary advancement which transforms the entire field of artificial intelligence. Unlike traditional machine learning which produces classification and regression results through discriminative methods, this technology creates new content and solutions and products by using existing data through large language models and image generation tools and code generation tools. From an economic perspective, the core significance of generative AI lies in reshaping the structure of production factors: it greatly improves the production efficiency of intangible factors such as knowledge, technology, and creativity—significantly enhancing the productivity of intangible capital (Brynjolfsson *et al*., 2021) [8]—breaks the fixed combination boundaries of traditional factors such as labor, capital, and land, and makes knowledge factors a core variable driving economic growth. The research field of generative AI introduces new theoretical concepts which require methods to assess AI content value and systems to add AI components into production processes and methods to establish data ownership rules. The current economic framework faces three fundamental problems which need to undergo basic changes through microeconomic theory because traditional models must evolve into new theoretical systems.

The AI era brought a dual expansion to microeconomics research which now studies two new areas that extend past the traditional boundaries of economic theory. AI expands microeconomics research through two fundamental core expansions which Agrawal *et al*. (2019) and Varian (2019) [3, 27] have identified. The research now studies economic behavior of human-machine systems which combine human and machine elements to function. The field of microeconomics bases its analysis on human beings as the sole decision-making entity because it predicts consumers will chase utility maximization and producers will chase profit maximization. AI systems now control decision-making processes through their ability to process information and their option generation skills which enable them to perform operations that make them function as decision-making entities. AI assistants on the consumer side provide consumption recommendations while they perform automatic transactions based on user preferences and budget limits and current environmental situations which need to include algorithm recommendation variables in consumer utility functions. The production process experiences a shift from experience-based decision-making to data-based decision-making because AI systems perform market data analysis in real time to produce output and pricing adjustments which require new definitions for cost curves and supply functions. Human-machine hybrid decision-making invalidates the premise of "independent decision-making" in traditional theories, and decision-making efficiency no longer fully depends on human rationality but on the matching degree of human-machine collaboration.

The research now explores data factor movement and allocation alongside its previous study of production and consumption behaviors. Data serves as the primary production factor for AI systems because it shows three distinct properties which separate it from conventional resources like land and capital. The economic characteristics of data include non-rivalry and reusability and increasing returns to scale which set it apart from conventional production factors like land and capital (Brynjolfsson *et al*., 2021) [8]. Multiple users can share the same data simultaneously while its worth grows when more users apply it because each additional user entry results in zero extra costs. Researchers need to develop new microeconomic study topics after discovering this characteristic: What methods should economists use to determine data factor values? What are the best methods to control data monopolies? What methods exist to allocate data property rights for reaching Pareto optimality? The current analytical framework which studies traditional factor markets struggles to analyze data factor allocation systems so it needs immediate development of new theoretical models which will define property rights systems and establish efficient resource distribution systems.

Traditional microeconomic theory bases its entire framework on the rational man assumption which predicts that economic agents possess full knowledge and definite objectives and they choose the best options to achieve maximum utility or profit. The AI era has created three major challenges which threaten the validity of this assumption by dismantling the core principles that support it. The perfect information assumption becomes invalid because AI possesses an information advantage which surpasses human capabilities. Traditional theories assume market participants get equal amounts of essential information yet AI-powered platforms and enterprises achieve data advantages which surpass what regular consumers can access through their ability to gather large amounts of data and create detailed user profiles. The perfect information assumption fails to exist because platforms and enterprises which use AI technology create information asymmetry through their ability to gather extensive data and build detailed user profiles which ordinary consumers cannot access (Stigler, 1961) [25]. The perfect information assumption fails because people who lack knowledge about products must choose between options which contradict the ideal rational decision model. Second, the decision-making intervention of AI weakens the premise of independent decision-making. The rational man assumption predicts that economic agents will choose their best options through independent actions yet AI systems use personalized recommendations and algorithmic induction and dark pattern design to modify human choices and control human decision processes. E-commerce algorithms use their programming to show expensive items which lead people to spend money irrationally. The recruitment process encounters problems because recruitment algorithms contain built-in biases which prevent companies from reaching their financial goals. Human decision-making requires fresh evaluation because recruitment algorithms contain hidden biases which stop businesses from reaching their financial goals. The research area of human decision-making autonomy versus rationality finds support through behavioral economics which studies bounded rationality (Kahneman, 2011) [15].

People operate under restricted mental abilities which prevent them from reaching the perfect decision-making ability that perfect rationality demands. People tend to make decisions through limited mental capacity which contradicts the traditional view of perfect rationality in conventional theories. AI systems possess extraordinary computing abilities but they fail to perform value assessments or emotional processing or ethical decision-making because these functions exceed their mechanical rationality boundaries. The economic behavior in AI era remains unexplained by rational man assumption because human-machine rational defects prevent its proper application. The theory of bounded rationality serves as the modern foundation because it shows how human mental boundaries interact with computer system mistakes (Simon, 1955) [24]. The development of AI technology creates an environment which allows microeconomics to develop into Microeconomics 2.0 because this advancement does not eliminate the field of microeconomics. The research field now studies three fundamental propositions which go beyond human resource decision-making because it studies how algorithms impact supply-demand curves and how data property rights should be distributed and how policies should monitor algorithmic systems.

The Basic Framework of Traditional Microeconomics and the Embedding Logic of AI

The foundation of traditional microeconomics consists of three main subjects which include consumers and firms and markets. The core analytical approach of this field consists of marginal analysis according to Varian (2019) [27]. The field establishes utility maximization and profit maximization as fundamental behavioral rules which form a complete system to understand how markets operate (Mas-Colell *et al.*, 1995) [16]. People who buy goods form the demand side because they want to get the most value from their purchases while sticking to their spending limits. The core tools which analyze consumer behavior include indifference curves and demand elasticity and diminishing marginal utility. Businesses which operate as suppliers want to achieve maximum profit through their limited production capabilities and market availability. The main concepts of firm theory consist of production functions and cost curves and market structure theories. Markets function as locations where supply and demand forces meet to distribute resources through price systems. The market structure theories which include perfect competition and monopoly and oligopoly explain how different markets reach their equilibrium state.

AI systems destroy the original "black box" systems which economists used for decision-making at three distinct levels. These three levels represent AI's ability to change how people make decisions in different situations. At the initial stage AI functions as a support system which helps users make decisions to enhance their computer system operations. The basic form of AI exists as a decision-support system which provides users with better performance through its computational power (Agrawal *et al.*, 2019) [3]. AI price comparison tools together with review aggregation systems help people lower their search expenses. Businesses use machine learning to predict customer needs and they adjust their prices based on market conditions. The economic system achieves better alignment with classical theory because AI allows market participants to obtain all relevant information which enables them to identify optimal price points through precise cost-revenue matching. People keep their ability to choose although AI allows economic players to get closer to having all market information. The second level: AI operates as a replacement system which achieves decision transfer through its operation. AI systems perform autonomous decisions which lead humans to define goals instead of making choices. The system performs human decision replacement through algorithmic trading operations which AI executes in specific environments (Brynjolfsson & McAfee, 2014) [6]. Financial markets use AI to handle over 70% of their transactions while smart furniture systems adjust their power settings based on current electricity costs; AI systems perform marginal decision tasks which were previously handled by human operators. The current situation shows behavioral economics' human psychological aspects which include loss aversion and status quo bias break down so decision-making systems switch from human bounded rationality to algorithmic mechanical rationality. The third level: AI changes the objective function to realize endogenous reshaping of preferences. AI systems assist people in their choices while also serving as decision substitutes which transform how economic players select their goals and targets thus breaking away from the standard model of outside preferences (Kahneman, 2011) [15].

Paradigm Transformation of Consumer Behavior Theory Driven by AI

Microeconomics depends on consumer behavior theory as its fundamental area of study. The core principles of traditional theories consist of fixed outside preferences together with full knowledge and separate choice processes and individual utility optimization according to Varian (2019) [27]. The AI era brought new decision environments which people use through recommendation systems and algorithmic pricing and behavioral data analysis systems to create a complete transformation of consumer decision patterns which AI-based recommendation systems now control through their established operational framework (Goldfarb & Tucker, 2019) [14]. The traditional beliefs about consumer behavior become irrelevant because AI-based recommendation systems create new decision environments which help users find products quickly but reduce their ability to explore different options (Goldfarb & Tucker, 2019) [14].

Traditional utility theory assumes that consumers have stable, exogenous, and independent preferences and can achieve utility maximization through price signals and active information search. The core structure of AI recommendation systems opposes this system because these systems generate product recommendations through user behavior tracking which produces "information finding people" that reduces search costs but creates two fundamental theoretical problems through their choice selection methods which both reduce available options and create opposing objectives between platform success and user well-being (Ezrachi & Stucke, 2016) [12].The platform needs to resolve two opposing business needs because it wants to achieve platform success and users want to maximize their utility.

People need their minds to focus because we live in a time when information floods every corner of society. The attention economy theory functions as the main tool which scientists use to study how people behave when they become AI consumers. AI systems need to fight for their limited mental resources which they use to steer human decisions through their behavioral prompts and their user interface elements (Kahneman, 2011; Sunstein, 2015) [15, 26]. The systems fight for user focus by sending customized alerts through their changing user interface and their reminder notifications and their ability to steer users toward choices which harm their future well-being. The practice of behavioral manipulation appears through dark pattern design which includes techniques such as hiding unsubscribe buttons and creating false inventory urgency and default-checking additional services and infinite scrolling recommendations. People make irrational choices because marketers use human mental patterns which include loss aversion and present bias and herd mentality to manipulate their behavior.

Traditional economics assumes that preferences exist outside of economic systems and remain constant through time but AI systems generate consumer preferences by using ongoing interactions which create a decision system that combines human and machine elements. Users and platforms establish a co-evolutionary system through their repeated algorithmic interactions which transform preferences into self-generated choices (Acemoglu & Ozdaglar, 2011) [1]. The revealed preference theory faces challenges because users and platforms establish a co-evolutionary system through their repeated algorithmic interactions which transform preferences into self-generated choices (Acemoglu & Ozdaglar, 2011) [1]. The three algorithmic preference shaping mechanisms include exposure effect and information cocoons which show how algorithms present similar content that boosts consumer preferences through repeated exposure and creates filter bubbles. The second mechanism uses social comparison and normative guidance to help consumers follow social norms by showing them which products "popular recommendations" people have bought. The third mechanism uses dynamic feedback to update algorithms through consumer behavior data which generates new preference patterns that affect how algorithms operate.

New Forms of Information Asymmetry and Market Failure in the AI Era

The core element which leads to market failure in standard microeconomic theory exists through information asymmetry because it produces both adverse selection and moral hazard (Akerlof, 1970) [4]. AI technology produces two different effects on information asymmetry because it solves traditional information asymmetry problems yet creates new algorithmic information asymmetry which leads to institutional risks from big data monopoly control. AI technology helps people reduce information differences by processing data but it creates new information disparities because not everyone can access its algorithms or data sources (Stigler, 1961) [25].

The traditional information asymmetry theory presents two distinct cases which show how adverse selection happens before transactions and causes low-quality products to replace high-quality items because buyers cannot detect product defects in Akerlof's "lemon market." The post-transaction process called moral hazard leads agents to perform dangerous actions because they hide their operations from view in insurance markets through excessive consumption and enterprise managers who follow their own interests. People use their existing coping methods which consist of signaling and incentive mechanism design and information disclosure regulation to handle their restricted ability to process information.

AI technology produces two opposing effects which maintain the existence of both conventional and emerging forms of information inequality. AI technology functions to improve market transparency while it decreases market uncertainty in insurance and used goods sectors (Brynjolfsson *et al.*, 2021) [8] but platforms use their extensive user data to develop algorithm-based information dominance systems (Zuboff, 2019) [28]. The AI system helps users access information which they can process to reduce the difference between what each party knows during their transactions. The used car market uses AI-based image recognition technology to produce vehicle health reports which protect buyers from hidden information about car conditions. Insurance companies use wearable technology together with AI medical monitoring systems to identify risks which leads to reduced insurance fraud and better protection against adverse selection and moral hazard. Medical AI systems for diagnosis have created a situation which reduces doctors' ability to control information but enables patients to make better choices. The unbalanced distribution of AI capabilities forms algorithmic information asymmetry. Through their mastery of AI technology platforms collect exact user behavior information by tracking browsing activities and mouse movements and purchase actions and click patterns. People who use platforms have no understanding about how these platforms determine their prices or manage their inventory or handle their data operations. The uneven distribution of information enables platforms to create individualized prices which extract complete consumer surplus according to Varian

(2019) [27]. The system uses algorithms to modify how information appears which creates an obstacle for buyers to detect unfair market dealings. The system now needs to manage two different types of information asymmetry because it must handle both quantity variations and computational power differences and data storage capacity differences.

The AI era reveals big data monopoly as an institutional system which demonstrates information asymmetry through the existence of few technology platforms that control data collection at an oligopolistic level. The non-rivalry and increasing returns to scale of big data create data network effects which show that larger data sets enable better AI model precision and this attracts additional users who produce new data that produces entry obstacles which form a "winner-takes-all" market system. Big data monopolies create new market problems which include privacy violations and algorithmic price-fixing that challenge the ability of current regulatory systems to handle these issues (Ezrachi & Stucke, 2016) [12].

Algorithmic Pricing, Efficiency of Price Mechanism and Monopoly Risks

Microeconomic theory identifies the price mechanism as its central analytical framework. Traditional economic theories explain price establishment through supply-demand equilibrium according to Mas-Colell *et al*. (1995) [16] while prices perform three essential functions which include information transmission and behavior motivation and resource distribution. The AI age introduced algorithmic pricing as its primary pricing system which operates through dynamic pricing to create instant price changes while transforming price development into an automated system which continuously adjusts prices (Varian, 2019) [27]. The system creates better pricing results but it develops hidden monopoly dangers because algorithms perform silent price agreements which break down both basic economic price models and official anti-monopoly rules. The fundamental principle of conventional price theory depends on supply-demand equilibrium which shows a downward sloping demand curve and an upward sloping supply curve that meet at the equilibrium price point. The traditional pricing system faces three main obstacles which include menu costs and price stickiness and delayed information that prevents prices from changing right away. The market structure of perfect competition forces businesses to accept market prices because they lack any ability to change prices which also applies to monopoly and oligopoly market structures. The traditional price mechanism depends on three basic assumptions which include human choices and restricted knowledge and time delays when prices need to be modified.

Businesses in the AI era depend on dynamic pricing as their primary pricing approach which allows them to automatically modify their prices based on current market supply and demand and customer profiles and time-based factors. The main pricing strategy of the AI era depends on dynamic pricing which allows businesses to modify their prices automatically based on current market availability and demand levels and customer details and specific time periods. The main pricing strategy of the AI era depends on dynamic pricing which allows businesses to modify their prices automatically based on current market availability and demand levels and customer details and specific time periods. Businesses use dynamic pricing to improve their resource distribution performance through their ability to modify prices based on market supply and demand conditions (Cohen *et al*., 2016) [11]. The implementation of dynamic pricing systems which combine market supply and demand data for resource distribution optimization has resulted in negative effects on customer equity because these systems apply price discrimination and customers cannot understand how prices are established (Goldfarb & Tucker, 2019) [14].

The AI era presents algorithmic tacit collusion as the most difficult monopoly form because businesses use AI algorithms to learn from each other while they maintain high prices without any formal agreements. The regulatory system faces a new challenge because pricing algorithms learn to work together through their systems without any direct communication between them (Calvano et al., 2020) [9]. The current antitrust system based on purposeful actions breaks down due to these algorithmic coordination methods. The present anti-monopoly system demands businesses to show mutual agreement before it takes action but algorithmic collusion occurs without any need for human interaction. Multiple business AI pricing systems develop their "tit-for-tat" approach through analyzing public price information which leads them to react to each other's price changes that result in decreased industry earnings yet both businesses gain from maintaining elevated prices until they reach an automatic quasi-monopoly status. The gasoline retail markets in Germany and the United States along with Amazon's third-party seller market have revealed actual cases of algorithmic collusion which created a "law enforcement gap" for standard anti-monopoly authorities. The main paradox of algorithmic collusion exists because transparent market information that supports competition in standard markets creates perfect conditions for collusion to occur in algorithmic markets (Ezrachi & Stucke, 2016) [12].

Reconstruction of Market Structure Under Platform Economy and the Dominance of AI Giants

Microeconomic theory identifies four market categories which include perfect competition and monopolistic competition and oligopoly and perfect monopoly. The four market types in traditional microeconomics stem from how many companies exist and how different their products are and what obstacles block new competitors and what level of market knowledge exists. The market structures exist in three main forms which include competition and monopoly and oligopoly according to Varian (2019) [27]. The platform economy operates as the dominant market system during the AI period because it creates strong network effects which block new competitors from entering the market (Rochet & Tirole, 2003) [21]. The market moves toward oligopoly monopoly because network effects and data barriers and economies of scale work together to shape its development (Brynjolfsson *et al*., 2021) [8]. Platforms achieve "winner-takes-all" results because they gather massive amounts of data and they expand their operations through economies of scale. The market has become highly concentrated which leads to decreased competition between different market players. AI giants have established market control through their multiple dimensions which challenge traditional market structure models. The three key elements which form the basis of their market power include data resources and algorithmic systems and their ability to connect multiple market segments (Varian, 2019) [27]. Their control over multiple market segments creates difficulties for standard industrial organization theory to explain their positions in the market. New businesses face entry barriers because network effects and rising returns enable existing companies to maintain their market control (Shapiro & Varian, 1999) [23]. The current market conditions require new antitrust rules for effective business monitoring.

The standard economic model of perfect competition achieves its operational efficiency through its market structure which includes many buyers and sellers and identical products and unrestricted market entry and exit and full market transparency and prices that match production costs. The platform economy operates under different rules than the traditional market system which follows perfect competition. The platform economy operates under two main characteristics which involve high market concentration that creates a winner-takes-all system where few dominant platforms control most of the market and platforms connect multiple user groups through cross-side network effects which create a positive feedback system that increases both buyer and seller numbers. The platform economy operates as a winner-takes-all system because only a few dominant platforms control most of its market share. The platform economy operates as a winner-takes-all system because only a few dominant platforms control most of its market share. The platform economy operates as a winner-takes-all system because only a few dominant platforms control most of its market share. The platform economy operates as a winner-takes-all system because only a few dominant platforms control most of its market share. The platform economy operates as a winner-takes-all system because only a few dominant platforms control most of its market share.

The market dominance of AI giants (Google, Amazon, Microsoft, Meta, etc.) goes beyond traditional monopoly pricing power because they control three essential dimensions which include data and algorithms and their operational environment. The first dimension of control emerges from their ability to handle vast amounts of complex real-time user data which they use to establish data protection systems that prevent newcomers from accessing comparable data for their AI model development. The second dimension of control emerges from their ability to develop superior algorithms through top talent and their powerful computing resources which they use to establish their core business strength in recommendation systems and pricing and matching algorithms that allow them to direct customer decisions and control market dynamics. The third dimension of control takes shape through their ability to establish complementary product and service networks which they connect to their main platforms to create self-contained data systems that prevent outside competitors from entering their market through their practice of using profits from one business to support another and their practice of selling products together which creates challenges for current anti-monopoly authorities to assess their market dominance.

AI Production Factors and Super-Capital Innovation of Firm Theory

The original firm theory bases its production factors on labor and capital and land while using marginal productivity theory to explain how resources receive their payments. The emergence of AI technology has destroyed the existing system which categorized production factors because traditional production functions used to consist of labor and capital according to Mas-Colell *et al*. (1995) [16]. AI functions as an independent production factor which operates separately from human work and established financial assets while it shows super-capital traits through its ability to work independently and its capacity to learn and its potential to duplicate itself (Brynjolfsson *et al*., 2021) [8]. The development of AI technology has led to a complete transformation of firm theory through its super-capital characteristics which include autonomous operation and learning abilities and self-replication potential. AI functions differently from conventional capital because it learns from experience while producing higher outputs (Agrawal *et al*., 2019) [3]. The diminishing marginal productivity theory faces obstacles to continue as a valid economic theory because AI technology produces learning effects and rising output levels. The measurement of AI's marginal contribution becomes challenging because it produces fundamental changes which affect every aspect of production operations (Varian, 2019) [27]. The system requires factor pricing because it depends on data ownership and algorithm control operations. AI technology creates organizational changes for firms because it replaces basic work tasks and supports the performance of employees who possess advanced skills (Autor, 2015) [5]. AI technology implementation creates business model transformations which affect operational expenses and forward-thinking business plans.7.1 Reconstruction of Production Factors: A Tripartite Framework of Labor, Capital, and AI. The production factors which classical and neoclassical economists use consist of physical and mental labor and capital assets and natural resources which form the basis of the production function Q=f(L,K,T). The introduction of AI breaks this classification, becoming a third independent production factor, and the production function is expanded to Q=f(L,K,A) (A is the stock of AI capital). AI operates independently from traditional factors because it performs all stages of perception and decision-making and execution without any need for human oversight which exceeds the basic operational function of traditional capital. The learning and self-enhancement abilities of AI differ from traditional capital because capital loses value over time yet AI models keep improving through data processing which strengthens their capabilities with every new data point. AI models operate independently as they can duplicate themselves at no cost while they operate throughout various production systems which traditional capital must restrict to a single user.

The theory of marginal productivity states that factor prices match the value of their additional output and perfect competition markets determine wages through marginal work value and capital rents through marginal work value. The theory faces three main obstacles because of AI introduction which affect its existing framework. The first problem emerges because we struggle to find the correct method which will show how AI helps businesses reach their targets. AI systems operate across all production stages which leads to improved overall system performance but prevents us from tracking the production value of individual AI models. The production value of human-machine collaboration depends on their joint performance which produces shared results that affect total output. AI systems create new problems for self-improvement because they enable unlimited performance growth which violates the principle of diminishing returns. The conventional production functions need fixed technology but AI systems perform self-optimization which results in continuous growth of marginal productivity that contradicts the basic assumptions.

The definition of AI as super capital explains its three unique abilities which traditional capital lacks while making it difficult to distinguish between labor and capital resources. AI models demonstrate their ability to optimize themselves through self-enhancement by continuously improving their performance with each new data point which breaks the diminishing returns rule for capital investment and produces rising scale benefits. The system produces two opposing effects because it replaces monotonous work through automation while generating new products and services and business models which break into the area that used to require human mental and creative abilities. Thirdly, AI models exist as intellectual capital which organizations can duplicate without expenses to launch worldwide operations which produces massive business growth and enables them to build substantial cost advantages. The optimization of enterprise factor combinations becomes possible through AI super capital which firms can use for their decision-making process. Organizations need to replace their actual employees who perform routine work with AI technology while they should preserve creative and emotional work and complicated decision-making for their human staff members. The labor market shows different trends between its various sectors because creative work at high skill levels and physical work at low skill levels stays consistent but white-collar positions for middle-class workers face major AI-driven competition and high-skilled workers achieve better salaries through AI collaboration which deepens social economic differences.

Impacts on the Labor Market: Skill Polarization and New Forms of Human-Machine Collaboration

Microeconomics studies the impact of AI technology on present-day work environments which stands as its main operational challenge. The traditional labor market system depends on human work as its main supply factor while wages stem from the extra value which workers produce. The AI era brought automation which now performs smart operations instead of just physical replacements because technological progress has continuously transformed work environments throughout history (Autor, 2015; Frey & Osborne, 2017) [5, 13]. The work environment now depends on skill-based technological advancement which has reached its peak while people must work with machines to perform their jobs. The labor market shows three main features which include skill polarization and structural transformation and human capital reconstruction. The research section 8.1 examines how AI automation systems lead to employment substitution while they transform the fundamental structure of automated systems. The basic difference between AI automation and traditional industrial automation systems exists in their ability to replace human work for physical tasks and intellectual tasks and their ability to perform standard and non-standard operational procedures. The overall impact of AI on work positions remains unknown because it creates two opposing effects on employment numbers. The substitution effect eliminates particular work positions yet the productivity and capital accumulation effects generate new employment opportunities which result in an uncertain total employment impact. The total number of jobs which AI generates remains uncertain because it leads to job losses while creating new positions (Acemoglu & Restrepo, 2020) [2]. The process of technological advancement has shown through history that it does not cause permanent widespread unemployment yet it creates major expenses for restructuring systems. The workforce faces two options when their jobs become dangerous because of customer service and translation work and cashier positions: they either lose their jobs or their pay decreases while they need to acquire new abilities to enter entry-level positions. The task model of microeconomics became an essential analytical framework which helps researchers study substitution effects.

The main framework of labor economics during the last forty years consists of Skill-biased technological change (SBTC) which shows that technological advancement leads to higher demand for skilled workers while decreasing demand for unskilled labor which creates growing wage gaps and social wealth disparities between different skill levels (Autor, 2015) [5]. The AI era has created a combination of SBTC which both increases workplace demands and creates social separation between workers while generative AI technology makes it easier for people to learn particular skills (Brynjolfsson *et al.*, 2023) [7]. The intensification effect shows how high-skilled job roles in AI development and maintenance and auditing work have become more popular while AI tools enable skilled workers to increase their productivity which results in higher wage differences between skill levels. The alienation effect shows how generative AI technology enables people to start working in high-skilled roles which used to require more experience so they can now handle advanced tasks which leads to the disappearance of middle-level work positions. The task model replaces the traditional SBTC framework as a more adaptive analytical tool: technological change affects tasks rather than skills themselves. AI systems perform information retrieval and pattern matching tasks while they also improve creative generation and complex decision-making operations. The total impact of jobs depends on how tasks combine together because AI helps doctors with their diagnostic work but it remains challenging to automate their communication and ethical decision-making responsibilities. The final distribution effect depends on the response speed of the education system, labor system, and redistribution policies.

Reshaping of Wage Determination Mechanism: Skill Premium and Superstar Effect

The standard wage model uses marginal productivity and human capital and compensating differentials to explain wage determination because workers receive payments based on their abilities and their work experience and the current market balance between job seekers and available positions. The standard wage model links workers' earnings to their production value in the market (Mas-Colell *et al.*, 1995) [16]. The AI period brings about a new wage system which distributes compensation through scale-based rewards instead of skill-based payments. The substitution and complementary effects of AI technology create wider differences between skilled and unskilled workers. The data scale creates an unlimited power which makes the superstar effect become more extreme. The current income distribution system shows an extreme pattern of distribution. The market now determines wages through two main factors which include scalability and network effects according to

Rosen (1981) [22]. The implementation of AI technology creates two major effects which result in rising wage differences between workers who possess different skill sets and between employees who have different levels of human capital investment (Acemoglu & Restrepo, 2020) [2]. The implementation of algorithmic management systems has resulted in reduced employee ability to negotiate with their employers. The superstar effect intensifies because top performers use AI technology to achieve unlimited output expansion (Rosen, 1981; Brynjolfsson et al., 2021) [8, 22].The current income distribution system will continue to become more unequal because there are no existing policies which can reverse this trend (Piketty, 2014) [20].

The four main components of traditional wage theory consist of marginal productivity theory which states that wages match the value of extra labor output and human capital theory which views wages as returns from educational and training investments and compensating differentials theory which states that dangerous and strenuous work requires additional wage compensation and efficiency wage theory which demonstrates that better wages lead to improved worker performance. According to traditional theories wages form through human labor characteristics and market supply and demand because labor represents the only available resource for supply.

AI creates three separate ways which lead to increased wage distribution inequality. The first stage of skill polarization creates an expanding wage gap because AI experts with advanced skills receive rising salaries through their complementary abilities yet traditional workers with basic and average skills face unchanging wages which drives the wage gap between these two groups to grow. The second stage involves the transformation of human capital value system which produces rising returns for programming and data analysis skills but decreases returns for repetitive clerical tasks while educational system delays create growing social gaps between different generations. The third stage involves algorithmic employment which reduces employee bargaining power because platforms use AI to determine distribution fees and working hours which leads to wage flexibility and individual wage determination but workers lose their ability to negotiate collectively while their hourly wages become lower. AI technology generates economic advantages which do not create social gaps between people yet governments must establish policies to generate shared economic expansion.

Rosen introduced the superstar effect through his 1981 [22] research which shows that technological advancement allows a small number of outstanding producers to distribute their products across extensive markets while maintaining minimal production expenses and receiving concentrated financial rewards. The AI era has brought an expansion of the superstar effect which now affects all business sectors because top performers use AI technology to expand their production capacity throughout the world (Brynjolfsson *et al*., 2021) [8]. AI technology spreads the superstar effect through three different systems which operate independently from each other. The first system operates through zero marginal cost replication which allows top AI models and content creators to reach millions of users while maintaining near-zero production expenses which leads to market dominance by a few major players. The second system depends on data network effects because leaders enhance their models through increased data access which leads to user growth and positive feedback loops that transform minor advantages into large income differences. The third system depends on personal productivity empowerment because skilled workers achieve team objectives through AI systems which allocate financial rewards to their individual accounts instead of sharing them with their team members thus creating a larger divide between them and common workers. The superstar effect has created an essential influence which makes employee compensation unrelated to their actual work output because it depends on how big the market is and the strength of connection between users instead of following established economic distribution patterns. The government needs to create three policy solutions which include progressive taxation and anti-monopoly regulations and public education funding to stop opportunity inequality from developing through winner-takes-all systems and to spread technological benefits between superstars and common workers.

Externalities, Public Goods Attributes and Institutional Governance of AI

The expansion of AI as a universal technology system creates various positive and negative external effects which affect society at large (OECD, 2019). Institutional economics which forms the base for AI governance studies property rights and governance systems to understand economic systems (North, 1990) [17]. The market requires government intervention through rules and taxes and public spending to achieve balance between individual gains and community advantages and between personal expenses and collective expenses. AI creates two sets of external effects which include both positive and negative outcomes. AI systems spread knowledge which leads to better productivity but they create privacy dangers and cause job losses that harm society (Zuboff, 2019) [28]. Data exhibits quasi-public good characteristics, with non-rivalry and partial excludability (Varian, 2019) [27], creating tension between efficiency and incentives; effective governance includes data rights, algorithm transparency, and antitrust enforcement (OECD, 2019), and AI regulation must balance innovation and risk.

Social benefits from AI technology exceed private benefits because its knowledge spillovers and its ability to lower transaction expenses and its capacity to enhance public sector operational efficiency. The free distribution of fundamental AI algorithms enables better operational performance throughout all sectors of industry. The market uses AI matching systems to decrease the difference between what people know about products and what others understand about them. The development of AI technology in medical field and transportation sector and energy industry creates benefits for public welfare but the market system does not direct enough funding toward research and development activities. Social costs from negative externalities including privacy violations and employment disruptions and algorithmic collusion and information cocoons and algorithmic discrimination exceed the costs that private entities bear. User data gets collected by platforms which then uses it to violate privacy rights while enterprise automation AI brings job losses to workers who must pay the price through their work and personal lives; AI users together with platforms become the main winners from this situation which results in uncontrolled AI market exploitation.

Public goods show their fundamental nature through two main features which include non-rivalry and nonexcludability. Data and AI models exist between private goods and public goods because they function as quasi-public goods which include data that shows quasi-public good properties through its non-rivalry and limited ability to exclude users (Varian, 2019) [27]. The non-rivalry of data is clear: one piece of data can be used by multiple parties simultaneously with zero marginal use cost; excludability can be achieved through encryption and intellectual property rights, but it is difficult to be completely exclusive in practice, making it closer to club goods. Data should be accessible to everyone according to social welfare standards but free access to data reduces the motivation to collect data so privacy protection needs to balance with data sharing through established data trusts and public data pools which function as the best institutional system. AI models exist as dual systems which show both public and private characteristics through their ability to reproduce at no additional cost and their potential to create major beneficial effects through their open nature. The training process demands substantial financial backing which the business closure will deliver to investors for their expected returns. Basic models show public goods characteristics which makes them suitable for government funding because they operate as open source software; application models serve as private goods which market-based systems deliver to create a supply chain structure.

The market requires clear property rights and established rules for operational efficiency according to Institutional economics (North, 1990) [17]. The state needs to perform four essential functions as the institutional provider and public funder and wealth distributor and global partner to create an effective AI governance system which protects data rights and reveals algorithms and stops anti-competitive practices (OECD, 2019). The first element of this system requires privacy protection together with data governance which establishes ownership rights for information while users must receive the ability to access their data and delete it and move it to other platforms. The system needs to make its algorithms visible to users and it must defend the rights and interests of consumers. The system requires anti-monopoly and algorithmic regulation to treat data barriers as entry barriers while it needs to evaluate killer acquisitions and establish a system for algorithmic filing and auditing and stop algorithms from working together to manipulate the market.

Conclusions

The research on AI effects in microeconomics leads to the main theory of paradigm reconstruction which asks if the core structure of microeconomics requires a total overhaul. What methods should I use to identify human-machine hybrid systems during decision-making processes? What is the disciplinary value of algorithmic economics? The section predicts how microeconomics will develop through its analysis of three fundamental components which include paradigm stance and decision-making subjects and disciplinary evolution. Microeconomics faces three different views about its future development which include conservative approaches and radical methods and hybrid strategies according to Goldfarb and Tucker (2019) [14]. The hybrid approach supports scientists to keep their current theoretical framework while they develop new theoretical frameworks which will improve their existing knowledge. Human-machine hybrid agents have reshaped economic decision-making because they function as agents which operate within human-constructed objectives through AI systems according to Agrawal *et al*. (2019) [3]. The field of algorithmic economics studies how algorithms function and how they interact with each other (Varian, 2019) [27]. The field of algorithmic economics combines machine learning techniques with economic theories to investigate economic systems. Future microeconomics will base its core analytical framework on algorithms which will work together with data and human-machine systems according to Brynjolfsson *et al*. (2021) [8].

The academic field presents three distinct positions about how microeconomics should evolve during the AI development period according to Goldfarb and Tucker (2019) [14]. Conservative school: core tools such as supply-demand analysis, marginal decision-making, game theory, and general equilibrium are still valid. The theoretical core of economics remains intact because AI only modifies parameters which include information costs and production function forms in the same way electricity preserved economic principles so textbooks do not require updates. Radical school: AI shakes core premises such as the rational man assumption, exogenous preferences, and uniqueness of decision-making subjects. The existing theoretical framework fails to describe algorithmic pricing and human-machine decision processes and data distribution systems so researchers need to develop an entirely new theoretical framework. Compromise school (hybrid approach): The main analytical structure needs to stay intact while we add new sections about algorithmic behavior and human-machine interaction and data property rights and platform governance to develop theoretical understanding instead of completely rejecting the current system.

Microeconomics based on traditional methods considers people as the only entities which make choices. The AI era demands economic agents to receive new definitions because AI systems now make autonomous choices and people collaborate with machines for decisions and algorithms perform agency functions. Human-machine hybrid agents have established themselves as economic decision-makers according to Agrawal *et al*. (2019) [3] who demonstrate AI systems function as agents which execute human-created goals. AI functions under human-set objectives which make it function differently from economic entities because it lacks personal choices and self-awareness. The system operates under an agency decision-making structure which human designers and users must take full responsibility for all decisions that occur. Human-machine hybrid decision-making serves as the major approach which AI systems process data to create options while humans handle value assessment and make ultimate choices. Decision-making quality depends on three essential elements which include algorithm design and human-machine interaction and trust systems. Human-machine system decision-making models should replace individual decision-making models which follow traditional approaches. The basic theoretical concept which defines responsibility functions as the main framework which should establish the proper allocation of responsibility for algorithmic collusion and algorithmic discrimination and flash crashes in algorithmic trading based on decision-making authority and existing accountability systems while creating a new theoretical base for algorithmic responsibility and expanding incentive systems to work with human-machine systems and maintaining both risk management and responsibility tracking systems.

The AI era brought about algorithmic economics which builds upon microeconomics through its modern theoretical framework that studies economic systems based on algorithmic system behavior and their social network interactions. The field studies economic systems through algorithmic systems which operate according to principles that differ from conventional economic models which treat algorithms as standard operational instruments. Researchers have developed a new field which combines machine learning with economic theory to create Algorithmic Economics (Varian, 2019) [27].The development of this field shows how future microeconomics will merge algorithms with data processing and human-machine collaboration systems to build its fundamental analytical structure (Brynjolfsson *et al.*, 2021) [8]. The research domain of algorithmic economics consists of four main areas. The first area studies algorithmic game theory which focuses on how algorithm-based systems reach equilibrium while they interact strategically through their operations in auctions and financial markets and network routing systems. The second area focuses on algorithmic mechanism design which uses machine learning to find optimal mechanism parameters and to handle systems that have limited rationality. The third area studies algorithmic market microstructure through its examination of high-frequency algorithmic trading systems and their impact on price development and market stability and liquidity availability. The fourth area focuses on developing transparent algorithmic governance systems which solve black box problems through auditable systems.

The development of machine learning and generative AI technology established artificial intelligence as a fundamental production element which now serves as a vital decision-making system that reshapes how microeconomic systems function. The research establishes multiple permanent difficulties which affect both theoretical microeconomic concepts and their actual research targets and their analytical methods and their policy-based decision systems which drives microeconomics to evolve from its classical foundation into Microeconomics 2.0. The core research conclusions of this paper are as follows: Artificial intelligence drives microeconomics to study two new research areas which include decision-making subjects that now consist of human-machine hybrids and production factors which now combine data and algorithms and computing power with traditional resources and the rational man model transforms into human-machine dual bounded rationality and algorithms generate different levels of information access which violate the perfect information assumption. The core categories of microeconomics experience a complete transformation through AI implementation: consumer behavior undergoes a transformation from independent utility maximization to human-machine collaborative decision processes and preferences experience a transition from fixed external stability to algorithm-based internal development and information asymmetry develops from its standard form of adverse selection and moral hazard into big data monopoly and algorithmic collusion and the price mechanism evolves from a fixed supply-demand balance into an algorithm-based dynamic system which creates potential monopoly threats and market structure evolves from four established categories into platform oligopoly monopoly which AI giants use to establish three-dimensional control through their data systems and algorithmic operations and ecological systems and firms have developed production functions which include AI super capital that requires scientists to study marginal productivity theory and the labor market shows workers with different skills and human-machine partnerships create fresh human capital needs and wage determination has evolved to give workers scale rewards instead of skill-based payments and the superstar effect makes income distribution more unequal.

The external nature of AI and its public resource characteristics need special institutions to develop new governance models which must become operational. The government should establish data ownership rules and develop algorithms for transparent operations and enforce anti-monopoly laws and support public AI funding and create redistribution systems to establish social benefits which equal private benefits. The future development of microeconomics will focus on algorithmic economics as its main research direction: The research needs to stop completely abandoning traditional economic theories because it should include algorithms together with data and human-machine interactions while keeping basic economic tools like marginal analysis and supply-demand analysis and game theory and adding new components which include algorithmic behavior and data allocation and platform governance and building an analytical system which humans and machines will create together for the intelligent economy. The research limitations of this paper are as follows: it does not conduct refined empirical analysis on the mathematical model of AI production function, the game equilibrium of algorithmic collusion, and the mechanism design of data pricing; research should continue by studying three different areas which include creating an AI-based production function mathematical model and conducting field research about algorithmic pricing effects on market operations and consumer satisfaction and developing the best system for data ownership distribution and algorithm control. The AI era has transformed microeconomics into a comprehensive study which investigates how resources distribute themselves and how welfare distributes and how institutions function within the human-machine built system. The organization works to advance technology in ways which will enhance public health while creating a unified system that balances operational efficiency with moral principles and social equity.

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