Navigating Wage Inequality in the AI Economy towards Inclusive Growth in the UAE

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The swift incorporation of artificial intelligence (AI) is significantly altering labor markets worldwide, particularly in vibrant economies such as the United Arab Emirates. This research investigates the socio-economic disparities that arise from technological advancements driven by AI, with a particular emphasis on their effects on lower-skilled workers and the Inclusive Wage Growth Index. Through thorough analysis, distinct inequalities are revealed between individuals in high-skill roles and those who are disadvantaged, who encounter obstacles without adequate support. The study underscores the critical necessity for proactive regulatory frameworks to ensure equitable practices within the AI landscape. Collaborative initiatives and ethical governance structures are vital to bridging gaps and promoting inclusive wage growth. This paper promotes responsible implementation approaches aimed at achieving long-term sustainability and collective advancement across various sectors. By tackling complexities and encouraging equality, the research highlights a shared objective of realizing potential for all individuals while enhancing economic resilience and prosperity throughout communities, ultimately benefiting future generations.

Keywords: artificial intelligence, wage inequality, economic dynamics, AL ethics, labor market, policy frameworks, inclusive growth, UAE economy, automation, workforce transformation

INTRODUCTION

The impact of artificial intelligence on the social and economic fabrics of the UAE is an inherently dynamic issue related to a net of economic, tech-driven, policy-based, moral and employment variables. Particularly where critical elements of its social-and-economic fabric come into play, AI is likely to have both opportunities and challenges. These factors influence the trajectory of AI and can help us predict its impact in areas like wage inequality, automation, policy response, ethics & values aligned with AI intervention and job displacement so that we can also find effective strategies to mitigate any negative impacts. Research such as that of Heinrich and Witko (2021) show that wages could become more unequal since the market for high-skilled labor increases while low-skilled workers are exposed to job displacement by Al-driven automation. While the labor market also shows evidence of such segmentation, this is particularly relevant to the UAE where expatriates are high skilled and migrant workers primarily low skilled. As McGaughey (2022) notes, greater mechanization could also shatter existing labor arrangements, resulting in a polarizing effect on the labor market, with jobs available only for those few whose work cannot be automated or routine workers completing simple tasks. UAE is dependent on few labour-intensive sectors so the necessity of policy interventions and management of these changes. Additionally, government policies play a crucial role in mitigating the socioeconomic effects of Al implementation. Robles and Mallinson (2023) argue that effective polices can ensure inclusive integration of AI by investing in education and reskilling, thus providing wider socioeconomic gains. This is resonant in the UAE as the policies used on Al and digital transformation are core tenets of its economic vision.

Finally, ethical considerations to guide the development and use of AI are needed to ensure that where Al is deployed it does so in a manner compatible with our values around fairness, transparency, and equity Taddeo et al. (2021). The idea is that institutes make extremely helpful in mitigating the bias and uncertainties associated with AI systems. Job displacement is the last but one of the most important drivers, i.e. Currie et al. Susskind (2020) shows that Al has the potential to create new jobs, but it would also put workers out of work by replacing tasks associated with routine and low-skill activities. Given the proven potential of Al to displace jobs, one significant challenge will be building a system of workforce development in the UAE that proactively prepares every socioeconomic group for the opportunities presented. All these elements would combine to build comprehensive knowledge of the socioeconomic impact of AI in the UAE and as a solid basis for guiding policymaking that embraces an inclusive, economically equitable and resilient Al-powered future. (Hultberg et al., 2024)

LITERATURE REVIEW

Wage inequality is one of the most pervasive socioeconomic variables affected by AI and, in this respect, we can see it particularly for UAE. The increasing demand for high-skilled labor to be used in capitalistic sectors where the nature of AI Technology is most integrated has been changing wage differentials between skilled and unskilled workers. Many studies point to this gap, as they indicate that the automation and digital transformation of economic sectors is very much in Favor for the skilled labor which indeed can use machines (Heinrich & Witko, 2021). Thus, the gains from AI continue to manifest for high-income professions, whereas low-paying and routine jobs are subject to falling wages or displacement.

One of the theories often associated with the economic impact of Al, is skill-biased technological change (SBTC), which holds that AI advances at a higher return to high -skill high-wage labor while at best reducing returns to low-skill low-wage labor and at worst, displacing them jobless. This only contributes to greater income disparity in the context of the UAE which employs vast numbers of low-skilled migrant labor. Mutascu (2021) supports this viewpoint, explaining that AI automating repetitive operations may redirect firms' investments toward high-skill workers and leave low-skilled employees with little wage growth or even with a threat to their jobs. (Leavy, 2023)

These disparities call for wage-adjusting interventions. Nguyen et al. (2023) proposed that focused governmental actions, including work force training and up skilling initiatives, can alleviate the skills gap allowing low-income labourers to move towards increasingly protected and higher paying positions.

But those interventions are expensive and must be done thoughtfully so that they are accessible to everyone, regardless of income. Meanwhile, in the UAE — where digital literacy and vocational training-oriented initiatives are already underway in Al-related fields — such approaches could be a positive step forward, but the real question is if they can feasibly reach scale to make wage inequality anything less than entrenched.

Furthermore, there is an ethical side of wage disparity resulting from AI as well. According to scholars such as Anakpo and Kollamparambil (2022), the adverse impact of AI on wage inequality seems morally questionable, especially for expatriate labor dependent economies like the UAE. This huge wage gap has ethical implications, and the issue requires a responsible deployment of AI, considering fairness and inclusion. Not that economic policies would be sufficient without ethical standards ensuring populations will benefit from the AI technologies. Only an adequate combination of these two elements is going to take on board wage inequality in the UAE. By unpacking the unique nature of wage disparity driven by Al, policies can be crafted to not only mitigate this gap but also build bridges towards economic inclusivity that will allow for both prosperities of individuals on the socio-economic spectrum.

Theoretical Development

In fact, the interplay between wage equity and parameters including economic dynamics, technological evolution, policy structures, ethical underpinnings, and methodological paradigms has been explored in depth specifically in the emerging context of AI-pervaded economies (Zhang, Palivos, 6 Liu, 2022). Several theories help frame these relationships, illuminating the mechanisms associated with wage gaps and potential tools for improving inclusivity throughout organizations.

Economic dynamics are key in explaining the formation of labor market and wage structures, and several theories have attempted to describe those in detail. According to human capital theory, investments in education and skill development directly influence an individual's earning potential, implying that wage variations often reflect differences in the acquisition of skills (Zhang, 2022). This is further built upon by the dual labor market framework, which points to the two-tiered nature of the labor market where high-paid jobs are concentrated in the primary sector, while secondary industry focuses on low-paying, temporary jobs (Borstad, 2019). These divides are often compounded by macroeconomic conditions or structural inequalities that consolidate persistent wage gaps. Moreover, the theory of demand and supply wage highlights the significant impact of market forces on wage levels, especially in scenarios where technological progress disrupts the conventional dynamics of labor supply and demand (Barbosa, de Lima, & Costa, 2022).

Technological advancements, especially those related to AI and automation, have been the subject of a lot of analysis in terms of skill-biased technological change (SBTC). According to this theory, technological innovation has differential returns, favoring skilled workers and, to a lesser extent, explaining rising inequalities between skilled and unskilled labor, as it differs on its ability to exploit new devices and systems (Hilstob & Massie, 2022). The use of the technology acceptance model (TAM) explains how technology being integrated into workplaces leads to productivity increases which, when taken to an extreme, modifies wage structures (Lane & Williams, 2023). According to Schumpeter's theory of creative destruction, technology changes industries, alters the types of jobs available, and influences wage structures, flooding the labor market with individuals who adapt to new economic circumstances (Rotman, 2023). Industrial relations theories provide valuable insights into how AI technologies impact wage equity by influencing the negotiation of fair wages and workplace policies.

Focus on policy frameworks: The way markets function is greatly influenced by the policy frameworks that are put in place by the authorities to regulate labor markets, which is yet another key aspect that needs to be tackled to address wage gaps. Institutional theory highlights how government and other institutions influence wage regulations and labor market protections that account for lower income inequality (Kliestik, Nagy, 6 Valaskova, 2023). Guided by this behind-the-scènes edge, welfare economics parcels out redistributive approaches toward objected policies and interventions that assist in maintaining viable access to financial opportunities (DEMÏRAL 6 YENÏLMEZ, 2022). The social contract theory implies adding a normative level to it. Combined, thèse theories highlight the need for strong policies that can help address the issue of wage disparities in economies influenced by Al.

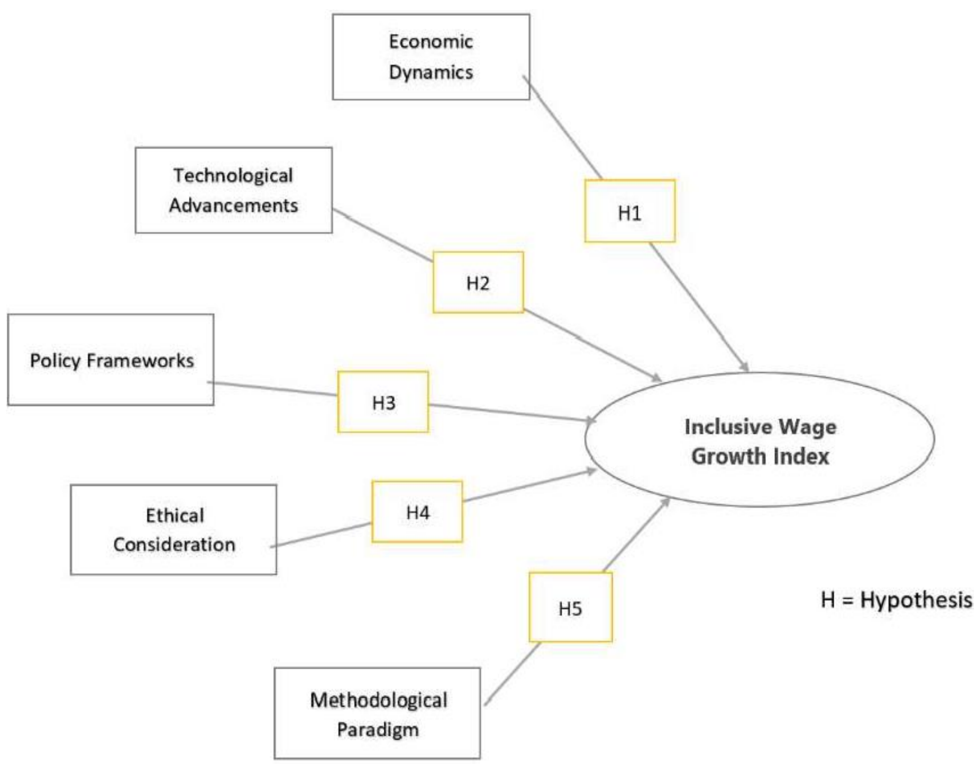
Discussions of wage equity increasingly integrate ethical considerations, especially in areas where technological liberalization can have a debilitating influence on vulnerable demographics. Deontological ethics argue that employers and politicians have an ethical responsibility to ensure equitable AI deployment, whereas utilitarian ethics assess wage policy based on how well it maximizes social welfare (Hilstob 6 Massie, 2022). The fairness and inclusion framework emphasizes the principles of fairness and inclusion in the allocation of resources across various AI-generated economies, pointing out the ethical obligations to address wage gaps. These ethical theories offer a moral basis for resolving wage differentials, particularly in labor markets complicated by substantial deviation. Building on systems theory, it considers the role of economic, technological, and social systems and insists on integrated and holistic solutions to wage policy. Using Structural Equation Modeling (SEM) is a useful statistical approach to examine causal relationships among variables, and SEM has been shown as a capable tool to disentangle wage disparity drivers (Zhang, 2022).

Adaptive systems theory bolsters the argument for responsive policies that address wage gaps in dynamic environments. There are some interdisciplinary approaches that incorporate economic, technological, and social dimensions—such as sociotechnical systems theory, the capability approach, and theories of the circular economy—to offer a more holistic lens for exploring wage equity in AI-driven contexts (Lane & Williams, 2023).

Together, these theoretical frameworks provide insight into the multifaceted nature of wage equity dynamics within the AI-driven economy. Unpacking the interplay of economic, technological, policy, ethical, and methodological dimensions, the factors for bridging the wage gap in the AI economy can be elucidated.

Research Framework and Hypotheses Development

FIGURE 1



Economic Dynamics

The economic aspects of AI-induced wage disparity are significant in any context, but especially notable within the high-paced developing world of the UAE (Shayegh et al., 2023).

With productivity and operational efficiency structure that will impact overall Industries sectors providing growth in an economy along with gaining competitive advantage to this adopting industry

(Wang, Cui, & Chang, 2023). Yet this economic benefit accrues heavily to high-skill workers—with the skills and knowledge to run, manage, and operate AI. Such a socioeconomic stratification creates a winner-takes-all setting for the limited benefits of Al- driven growth, where high-skilled professionals are rewarded the most while low-skilled workers suffer from stagnant or declining wages (Nguyen et al., 2023; Giering et al., 2021).

But the UAE is particularly labor intensive, with an economy that depends on foreign workers in sectors such as construction, retail, and hospitality—areas of the economy that may be more susceptible to AI automation. Mutascu (2021) points to the higher demand for high-skill roles caused by AI, which exacerbates wage inequality by crowding out low-skill jobs. As a result, this transition amplifies economic disparities in the sense that Al-driven productivity boosts profits of businesses but may replace low-income jobs - causing both issues of precarious employment and income inequality within the economy (Bowler-Smith, 2021).

Additionally, with the continued implementation of AI systems in day-to-day sectors, productivity benefits become concentrated amongst the high-income high skill workers who already enjoy economic gains (Wang et al., 2024). In the UAE, this setup reinforces a sharp divide between nationals holding high-skilled positions and migrant workers occupying low- skilled jobs, thus wage disparity is extremely visible. Intrinsically, the method of execution of Al in the UAE may aggravate this gap (Heinrich & Witko, 2021).

Policymakers should thus plan for redistributive economic policies and education programs to offset the inequality created by this change, allowing low-skilled workers to enter the new digital economy. Some of these costs can be countered with such investments in training and upskilling for those workers, so our growth model is further imbued with inclusivity. These interventions, would guarantee that AI contributes to all socioeconomic classes in the UAE, helping sustainable development goals and diminishing wage polarization in the labor market (Reis et al., 2020; Davis et al., 2021).

Hypothesis I. *There is a significant positive relationship between economic dynamics and the inclusive Wape 6rowlh fndex in the UAE's Al-driven economy.*

Technological Advancements

By this lens, the rise of artificial intelligence (AI) presents a double-edged sword, with rapid technological advancement benefiting skilled workers at the expense of those less well- equipped (Bera & Rahut, 2024). This issue, known as ‘technology-driven inequality," happens when the skill requirements to use and supervise technology-like AI tools-are so specialized that lower-skilled workers are priced out of their wage market, affecting wages and employment levels (Ismail et al., 2023). Recent innovations fuelled by AI are geared towards automation and now less human involvement is needed to perform repetitive tasks. As a result, jobs in manual routine chores are more insecure and lower wage as these become replaced by humans through AI (Bowler-Smith, 2021).

The UAE, home to some of the world's most ambitious AI deployment strategies spanning across sectors such as healthcare, finance and public services has only exacerbated this chasm (Liu et al., 2024). At the same time, high-skilled workers who are skilled in using these technologies command greater demand, higher wage levels and lower job instability. They provide the value of their expertise in a world dominated by AI. Conversely, low-skilled workers are left behind, unable to move into Al-supported jobs and with limited career paths within their sectors (Reis et al., 2020).

That polarization creates an economic climate in which wage inequality becomes more deeply embedded around specialized knowledge. Second, many low-skilled jobs — especially those which migrant workers tend to fill — are also at high risk of automation, making technology-driven wage inequality a particularly pernicious problem (Asravor 6 Sackey, 2023). Chain or scripted tasks characteristic of jobs in the retail, hospitality, and various other service industries — which churn about half of the UAE's low-paid employees — are very vulnerable to artificial intelligence-based replacement (Lima et al., 2021).

According to Bessen et al. (2021), this substitution of tasks with AI technologies caps the upward mobility of low-income workers, thus restricting them from wage growth and job openings. To prevent technology from deepening pre-existing socioeconomic gaps in the UAE, this transition will require initiative-taking measures — encompassing upskilling initiatives and training programmes that are accessible to all — to create a more equitable technological workforce that can adapt to change.

Hypothesis 2: *Technological advancements in AI contribute to rape inequality but their effect on the Inclusive Wape Growth Index is moderated by skill adaptation and labor market restructuring.*

Policy Frameworks

Wage-price fills in the wide gap of artificial intelligence (AI) connected with inequality on wage can be altered by moderating policies. UAE government policies have shown a stronger focus on digitalisation and AI as economy driving forces to promote economic growth and increase productivity (Muhammad, Khan, & Sardar, 2023). Policymaking on wages must therefore be speeding up alongside technological development, if we want to avoid leaving large portions of society behind in a new digital economy (Kongshoj, 2023). Reskilling and upskilling policies play a vital role in preparing low-income workers for the new jobs created by AI technology as it transforms the labor market (Anakpo 6 Kollamparambil, 2022). A concrete policy that would work is creating adequate vocational training for workers to move up the value chain in an economy more powered by AI (Mack, 2024). Providing access to lifelong learning and working in conjunction with educational institutions to deliver courses focused on digital literacy and AI skills sets the foundation for low-skilled workers to progress into higher-paying jobs according to (Nguyen et al., 2023). Policies promoting continuing education and digital competencies are instrumental in narrowing the wage gap, because they equip workers with skills that correspond to market demands (Franșoise et al., 2022). A third key component of policy to hem in wage inequality is to encourage firms not just to want capital investment for its own sake — but also specifically human capital investment. Tax breaks or subsidized programs for businesses that provide training and development programs ensures employees at all levels of skill have the necessary tools to adapt to technological changes. In addition, equally critical is equitable access to technology and educational resources. By ensuring access to the global digital economy, the implementation of inclusive access policies enables marginalized groups to participate in an unbounded landscape of economic opportunity that helps level wage disparities and provides a clear pathway for social mobility. The UAE government has done a commendable job here through national initiatives like digital skill-building workshops and training programs across the nation. Although such efforts are incremental progress, Heinrich and Witko (2021) argue that policies must be "deeply entrenched" rather than "episodic" in order to create lasting change. Efforts must continue toward creating a flexible labor supply, ensuring that wages rise across the spectrum of job quality, and designing an economy which enables AI- generated gains to be distributed fairly. Policymakers will need to ensure that their policies not only meet the immediate needs of workers but also prepare for potential labor supply related challenges that are on the radar screen.

Hypothesis 3. *Policy frameworks, including labor regulations and wage policies, have a direct positive impact an the Inclusive Wape 6ro 'Ih Index, mitipatinp rape disparities in the Af*

Ethical Considerations

Wage inequality exacerbated by artificial intelligence (AI) raises ethical concerns, particularly in a diverse labor market like that of the UAE (Koehn, 2024). With AI tech automating processes and optimizing operations, access to these advantages becomes a key component of systemic fairness (or lack thereof). This asymmetrical allocation can bring about additional economic stratification where skilled labor, in a higher income class, enjoys the benefits and low-skilled labor experiences stagnation in wages or even job loss (Svane 6 Frandsen, 2024). However, these ethical dilemmas are especially concerning in the case of economic sectors with the potential for automation by AI, where low-income workers may endure the most of negative consequences— deepening wage disparities (Davis et al., 2021; Mutascu, 2021).

A framework that emphasizes inclusive, fair deployment of AI can serve as an important tool for remedying these inequities (Redhead et al., 2024). It should be such that every employee is rewarded fairly and has a chance for upskilling and career growth (Goglin, 2023). For instance, Mutascu (2021) similarly argues that "AI should be embraced in line with principles of justice" by incorporating ethical and moral into design to avoid some social marginalization or socio-economic exclusion (Triantari 6 Vavouras, 2024). This means advocating for policies that protect the incomes and rights of low-income workers, thereby also encouraging a fairer share of the economic benefits of AI.

A different important ethical issue in minimizing wage inequality is transparency. While deploying AI, organizations and policymakers should strive for transparency especially when it affects wage rates and employment slots. Proper communication about the effect of AI on jobs and salaries increases trust among workers and fosters less of a sense that AI is a risk to their livelihood. Transparency can also initiate discussions that are more informed and promote labor market access, provided there are ethical guidelines that require it (Brendel et al., 2021; Nguyen et al., 2023). Furthermore, ethical AI policies should consist of ways to monitor technology's impact on society as a whole and modify the approaches in use as needed to prevent any group from being overly harmed. This will require strengthening initiatives to offer those most at risk of falling behind because of automation with targeted training and support. This kind of ethical use i.e. ethic deployment of Al can make the income scenario much fairer and keep the ethics of social justice live because we will consider all socioeconomic strata in such a way. A middle ground that would bolster public confidence in technology adoption, while also guaranteeing that Al-powered developments benefit everyone at all levels of society.

Hypothesis ñ: *Strong ethical considerotioris in Al deployment positi eff influence Voir orage distribution, leadinp to a hipher inclusive Wape 0row'th Index.*

Methodological Paradigm

The methodological approach to studying wage inequality impacted by AI involves a multi-dimensional analysis that combines quantitative data with qualitative insights (Smela et al., 2023). To comprehensively understand how AI affects wage structures, researchers often employ econometric modelling, case studies, and surveys targeting different economic sectors (Goretzko, Pham, 6 Bühner, 2021). Quantitative Methods: A quantitative approach could involve regression analysis to investigate the relationship between AI adoption and wage changes in different skill categories (Borsboom et al., 2021). Econometric models, for example, can illustrate the increase in wage inequality between high-skill and low-skill workers as AI technologies are increasingly adopted into the economy (Nguyen et al., 2023). Longitudinal Data: Longitudinal data in the context of the real-time wage impacts of AI would provide compelling evidence over how and when those wage differentials might widen or close as AI increases its penetration throughout sectors (Peters et al., 2021). Such research enables tracking employment shifts and wage changes and measuring job displacement attributable to automation. This mean, all they really need to do is collect a bunch of historical wage data from the industries where AI is still relatively early on in adoption - manufacturing, logistics, healthcare, retail etc. (Devezer et al., 2021)

According to Mutascu (2021), however, these data sets must be used to build a narrative on how wages are displaced by AI adoption so that timely and effective policy interventions can be developed for negative impact mitigation. Interviews and focus groups on the qualitative side may offer more personal stories about the effects of AI on workers' lives, both advantageous as well as harmful. It is qualitative data that enables others to perceive the human component of wage inequality, which quantitative data are too blunt to convey. This data might indicate whether workers consider themselves secure or endangered by Al's presence and what drives their perception of changes in wage.

Comparative studies are also warranted, such as between countries neighbouring the UAE or in similar contexts of Al adoption and diffusion (other than amongst the GCC countries). Such studies can shed light about whether the trends of wage inequality that are observed here in the UAE are an isolated phenomenon or part and parcel of a broader regional or even global trend (Brendel et al., 2021). Combining qualitative interviews with quantitative analysis within a mixed-methods approach is useful because it combines statistical findings derived from large datasets with the gained insight of workers themselves to deliver an integrated picture of how Al-induced changes affect wages.

By including both quantitative data analysis and qualitative input, the research is well- rounded and useful for developing policies aimed at achieving wage equity. Such a methodological framework enables conclusions with high robustness, to design measures and policies aimed at overcoming wage inequality driven by AI in the UAE.

Hypothesis S. *The methodological paradigm used to assess w'oge structures and AT's economic impact significantly effects the measurement and improvement of the inclusive Wage Grourth Index.*

RESEARCH METHODOLOGY

Data collection from consumers primarily utilizes online questionnaires, supplemented by a small number of offline hard copies. Initial testing was conducted with 20 participants to refine the questionnaire. The final version comprised eighteen questions aimed at assessing general perceptions regarding Economic Dynamics, Technological Advancement, Policy Frameworks, Ethical Considerations, and Methodological Paradigms. Additionally, four questions were designed to collect demographic information such as gender, age, nationality, region, and job profile. Responses were evaluated using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

The data was gathered from Middle Eastern professionals—leaders, innovators, and changemakers—across various sectors in the Middle East as well as Europe and North America. This unique group includes seasoned experts alongside emerging executives who are actively shaping the future landscape of their region. Comprising resilient leaders predominantly in their thirties from diverse industries such as finance and technology, they are skilled at tackling intricate market challenges while serving as key decision-makers guiding organizations toward sustainable growth and competitiveness.

This professional cohort represents a synergy of experience and innovation; established leaders mentor newcomers while younger professionals introduce fresh insights into conventional issues. Data obtained through the questionnaire was analyzed using ADANCO 2.0 to develop a process model grounded in variance-based structural equation modeling (SEM). This approach is favored for its ability to model relationships among independent variables while addressing various forms of measurement error for comprehensive theory evaluation.

Measurement Model

To assess common method bias, confirmatory factor analysis was performed (Chang et al., 2010). The model's fit was evaluated using ADANCO 2.0; results indicated that the standardized root mean square residual (SRMR) value was 0.0296—a figure below the generally accepted threshold of SRMR • 0.08 (Hu & Bentler, 1999).

Testing hypotheses involved conducting t-tests (Armstrong 6 Overton, 1977), treating respondents lacking demographic data as non-respondents (Kam & Meyer, 2015). No significant differences were found across all the constructs' data sets. Reliability assessments were carried out utilizing Cronbach's alpha (a) and Jbreskog's Rho (pc), both yielding acceptable values significantly surpassing 0.7 (Cronbach, 1951), as detailed in Table.

The research model's validity was assessed by examining convergent validity through factor loading metrics along with composite reliability measures (Hair et al., 2016). Per Hair et al.'s recommendations (2016), thresholds for convergent validity included factor loadings above 0.7, average variance explained exceeding 0.5 (AVE › 0.5), and composite reliability over 0.7 (›0.7)—all criteria met according to Table 2.

Discriminant validity was evaluated by comparing correlations among constructs against their respective AVE square roots based on Fornell and Larcker's guidelines (1981). To ensure model reliability further evaluations were conducted using Cronbach's alpha (Cronbach, 1951; Sijtsma, 2009) alongside Jöreskog's Rho for composite reliability assessment (Wertz, 1978). Convergent validity examiner how closely two measures should hypothetically relate; an adequate average variance extracted value must be 1 0.5 per Campbell & Fiske's standards (1959; Carlson & Herdman, 20J2).

TABLE 1
RELIABILITY

Construct	Dijkstra-Henseler's rho (pA)	Jöreskog's rho (p,)	Cronbach's alpha(a)
Inclusive Wage Growth Index	0.9006	0.9002	0.9001
Economic Dynamics	0.8699	0.8682	0.8680
Technological Advancement	0.8296	0.8294	0.8293
Policy Frameworks	0.8061	0.8011	0.7986
Ethical Considerations	0.8234	0.8232	0.8232
Methodological Paradigm	0.8656	0.8600	0.8601

TABLE 2
CONVERGENT VALIDITY

Construct	Average variance extracted (AVE)
Inclusive Wage Growth Index	0.7505
Economic Dynamics	0.6874
Technological Advancement	0.6185
Policy Frameworks	0.5743
Ethical Considerations	0.6082
Methodological Paradigm	0.6730

TABLE 3
DIRECT RELATIONSHIPS

Statistics		
Multiple R		0.8681
R Square		0.7536
Adjusted R Square		0.7500
Standard Error		0.4408
Observations		349

ANOVA

	df	*:!fi:fi*	*M:fi*	*F*
Regression	5	203.8380939	40.767619	209.8087047
Residual	343	66.64782216	0.1943085	
Total	348	270.485916		

Intercept	0.0361	0.1365	0.2647	0.79143
Economic Dynamics	0.2639	0.0528	4.9952	0.00000
Technological Advancement	0.1770	0.0529	3.3475	0.00091
Policy Frameworks	0.3085	0.0606	5.0956	0.00000
Ethical Considerations	0.1846	0.0444	4.1620	0.00004
Methodological Paradigm	0.0837	0.0373	2.2431	0.02553

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Coefficients Errar f:!fifaI P-sa/tie

Structural Model

To evaluate the hypotheses, as illustrated in Fig. 1, the process macro was employed, implementing an indirect bootstrapping technique (Preacher & Hayes, 2004, 2008). The results of the bootstrapping analysis revealed that nearly all relationships were statistically significant, consistent with the findings of Preacher and Hayes (2012), as shown in Fig. 2. The study concludes that the mediation effect has statistical significance; consequently, while all ten hypotheses received support, some were only marginally supported, whereas others demonstrated strong support, as detailed in Table 3.

FINDINGS AND DISCUSSIONS

The analysis and discussion of the findings are provided below in line with each of the study hypothesis and its results. Table 3 provides a summary of the results of the hypothesis testing in the study.

Hypothesis 1: *There is a sipniticant positive relationship between economic dynamics and the inclusive Wape 0raw'fh Undex in the UAE's Al-driven* economy(t = 4.9952, § = 0.2639, and P • 0.05) was strongly supported.

The transformation of the UAE's economy through AI has markedly affected wage structures, especially in sectors undergoing swift digital advancements (Müller, 2022). The adoption of Al technologies has resulted in greater productivity and economic advancement; however, thèse advantages are not uniformly experienced across all segments of the workforce (Zhang et al., 2022). Professionals with high-level skills in Al-focused roles have witnessed considerable increases in their wages, while those with lower skills have encountered stagnation or job displacement (Lane 6 Williams, 2023). For instance, DP World's logistics division has made substantial investments in AI automation to enhance supply chain efficiency, contributing to wage disparities (Demiral 6 Yenilmez, 2022). In a similar vein, Al trading algorithms at institutions such as Mubadala Investment Company have improved operational efficiency but have altered job frameworks in a way that disproportionately benefits skilled professionals (Benzell et al., 2021). Should advancements in AI outstrip wage growth rates, existing inequalities may escalate further, thus, ongoing policy adaptations and workforce reskilling initiatives become crucial (Hilstob 6 Massie, 2022).

Hypothesis 3: *Policy Frameurorks, includirip labor repulations and cape policier, ha e a direct positive impact on fhe Inclusive Wape l9roiw'th Index, m///pa//np rape disparities in the Af economy(t • 5.0956, § = 0.3085, and P • 0.05) was strongly supported.*

Effective regulatory frameworks and labor policies are integral to addressing wage inequities arising from advancements in AI technology. The UAE government has enacted various policies designed to uphold fair wages and protect employment rights within industries driven by artificial intelligence (Civriz & Öz., 2022). Initiatives related to governance frameworks for AI and labor protections contribute toward equitable wage distribution across diverse employment sectors (Khaskheli et al., 2023). Notably, adjustments made to the UAE's Wage Protection System aim at ensuring fair compensation practices within industries heavily reliant on artificial intelligence (lonescu.,2019). Furthermore, efforts such as the Dubai Future Foundation's creation of ethical guidelines for deploying artificial intelligence advocate responsible business practices involving technology use (Autor, 2022). Nonetheless, it is imperative that thèse policies are regularly updated so they remain aligned with advancements in artificial intelligence; otherwise, certain sectors could experience uneven fluctuations regarding wages attributable specifically due to their influence over business models employed (Barbosa et al., 2022). By developing comprehensive approaches toward policy formation around artificial intelligence applications, the United Arab Emirates can serve as an exemplary model demonstrating how productivity gains facilitated by such technologies might translate into just remuneration opportunities for wider populations—but continual oversight over labor conditions will be critical moving forward (Lane 6 Williams, 2023).

Hypothesis 4: *Stronp* e/ù/va/ *considerafions in Al deploymenl positively influence fair iw'ape distribution, leading to a hipher Inclusive Wape 0rowth Undex* (t = 4.1620, § = 0.1846, and P • 0.05) was strongly supported.

Ethics concerning how Artificial Intelligence gets implemented plays an essential role when it comes to controlling wage discrepancies along with protecting fairness across various labor markets. Transparency surrounding decision-making processes utilized by said systems need attention alongside maintaining focus upon inclusivity preventing any form discrimination based upon algorithmic biases present (Rotman, 2023). In response, the United Arab Emirates introduced its own set standards known as "Al Ethics Framework" aiming promote accountability while fostering responsible usage throughout businesses (Héry et al., 2022). Within the finance sector specifically concerns arose regarding possible discriminatory tendencies detected amongst automated credit scoring systems which prompted regulators to enact safeguard measures to ensure equitable lending practices (Kliestik et al., 2023). Similarly, recruitment mechanisms relying heavily upon machine learning faced scrutiny alleging potential bias prompting corporations to adopt ethical hiring protocols (Hilstob & Massie, 2022). However, should there lack rigid enforcement alongside standardization applied universally we could find ourselves facing persistent challenges associated with unequal payment outcomes stemming directly from Als involvement thus establishing stringent guidelines could help cultivate more equitable distributions ultimately enhancing inclusionary aspects tied into economies structured around Artificial Intelligence (Dawid & Neugart, 2023).

Hypothesis 5: *The melhodolapical paradigm used la assess wape structures and AI's economic impact sipnificanlly affects the measurement and improvement of the fnclusive Wape 0rowth Index(t • 2.2431, § = 0.0837, and P « 0.05) was strongly supported.*

Accurate evaluations concerning how Artificial Intelligence affects overall economic landscapes stands pivotal aiming understand emerging trends surrounding salaries whilst also enabling formulation effective interventions needed address issues encountered presently/traditionally faced models fall short capturing complexities offered up due technological advances necessitating more sophisticated analytical methods (Petroleka et al., 2023). The UAE adopted cutting-edge analytics powered through utilization advanced data insights aimed at refining assessments pertaining labor market dynamics (Lima et al., 2021). The Ministry Economy initiated using machine learning tools assisting identification tracking shifts occurring regarding employment statistics coinciding with variations noted above (Webb, 2019). Moreover, prediction analytics played crucial role shaping urban planning strategies evaluating influences stemming from Als role determining future job allocations spread evenly throughout differing sectors (del Carpio et al., 2022). If existing methodologies fail adequately to incorporate evolving realities presented via developments associated then policymakers might struggle implementing appropriate measures counteracting negative ramifications affecting pay scales thereby enhancing methodological foundations shall prove key guiding principles steering forward comprehensive agendas designed improve inclusiveness targeting wages effectively (Estlund, 2023).

CONCLUSION, IMPLICATIONS, AND FUTURE RECOMMENDATIONS

Conclusion

The incorporation of artificial intelligence (AI) into the economy of the UAE has significantly altered labor market dynamics, introducing both opportunities and challenges regarding wage distribution. This research explored how economic factors, technological progress, policy frameworks, ethical dimensions, and methodological approaches shape the Inclusive Wage Growth Index (IWGI) in economies influenced by AI. The results indicate that economic transformations driven by AI have considerable implications for wage inequality, especially in labor-intensive markets like the UAE. Although AI can enhance efficiency and promote economic growth, it may also widen wage gaps unless policies and skill development strategies keep up with technological changes. To tackle these disparities effectively, it is crucial to implement proactive measures in education, policy formulation, and ethical governance of AI to ensure growth that is both inclusive and sustainable.

Theoretical and Practical Implications

Theoretical Contributions

This research enriches existing literature on labor economics influenced by Al by merging perspectives from economics, technology, policymaking, ethics, and methodology to evaluate wage inequality. It enhances theoretical insights into how Al affects wage structures while reinforcing concepts such as skill-biased technological change (SBTC) and creative destruction theories. Additionally, this study emphasizes the importance of policy frameworks in reducing wage disparities, supporting institutional theory along with welfare economics principles. The ethical aspect of deploying Al is also highlighted within deontological and utilitarian ethics contexts to promote equitable wage distribution. By offering a multi-faceted framework, this research presents a holistic approach to understanding wage inequality in an Al-driven economy.

Practical Implications

From a policy-making and organizational perspective, the findings underline the necessity for strategic workforce planning alongside targeted reskilling programs and fair wage policies to address disparities arising from AI integration. Governments are encouraged to adopt initiatives that foster digital literacy, provide training in Al technologies, and support lifelong learning opportunities for workers transitioning into roles heavily impacted by AI advancements. Moreover, organizations must establish transparent governance frameworks for Al applications to reduce biases associated with hiring practices or compensation structures. It is also essential to refine models used for assessing wages driven by Al to ensure accurate evaluations of wage inequalities that facilitate evidence-based interventions in policymaking. While the UAE's AI Strategy 2031 exemplifies proactive steps taken in this direction, ongoing adjustments are necessary to prevent increased technological displacement from further widening income gaps.

Future Recommendations

Based on this study's findings, several recommendations can be made to promote inclusive wage growth within economies shaped by Al:

- Investment in Reskilling Programs: Collaboration between government entities and private sectors is vital for large-scale upskilling initiatives aimed at equipping workers with relevant competencies related to Al technologies as a means of bridging the income gap between varying skill levels.

- Adaptive Wage Policies: Policy revisions should be implemented to ensure that wage increases align with economic expansion driven by AI developments so as not to contribute towards income polarization.
- Ethics and Transparency in Al: Governance frameworks concerning artificial intelligence should prioritize fairness across labor markets while addressing potential biases present during recruitment processes or salary determinations.
- Strengthened Labor Market Regulations: The introduction of robust labor laws accompanying AI deployment will help protect employee rights while providing safety nets for those affected by automation.
- Cross-Sector Collaboration: Public-private partnerships should be encouraged to enable knowledge sharing along with strategies aimed at economically including all segments of society within an environment propelled by artificial intelligence.

Limitation and Future Research Directions

While this study offers significant insights into how AI impacts wage inequality issues specifically within the UAE context; there are limitations involved as well: first being its primary focus on one nation which may limit its applicability across diverse global economies characterized differently concerning their respective labor markets impacted by similar technological advances—future analyses could benefit from comparative studies examining multiple nations' experiences regarding global trends associated with wages amid increasing integration of Als across sectors; secondly although incorporating various theoretical perspectives bolsters understanding empirical validation through real-time data specific towards labor affected directly via Als would enhance overall robustness—longitudinal studies tracking evolving aspects related specifically towards wages over time could yield additional nuanced findings regarding industries highly reliant upon such technologies; lastly exploring external elements including cultural impacts gender-related pay gaps remote working conditions resulting from implementations involving Als remain areas warranting further exploration ensuring comprehensive insight when addressing influences surrounding contemporary wage structures.

Final Remarks

The profound impact that artificial intelligence has on workforce landscapes cannot be overlooked simultaneously presents avenues leading toward economic advancement coupled alongside obstacles pertaining particularly towards inequitable distributions amongst differing groups contingent upon socioeconomic factors influencing said landscapes ahead. Aligning innovations derived from advancements witnessed through Als alongside inclusive strategic approaches adopted within workforces remains critical; thereby allowing policymakers alongside organizations alike ensuring shared benefits accrue widely among populations served therein! This investigation accentuates urgency tied closely surrounding necessary interventions required aimed at mitigating adverse effects stemming forth due primarily resultant outcomes born out-of-their-deployment scenarios wherein continuous efforts directed strategically enable ongoing developments around workforce capabilities lead ultimately toward establishing balanced environments promoting equity throughout respective job markets—both locally herewith in UAE borders extending outward alike globally.

REFERENCES

Anakpo, G., & Kollamparambil, U. (2022). The impact of artificial intelligence on labor market outcomes: Evidence from emerging economies. *Journal of Labor* 6ooopm/os, J//(3), 678- 701.

Armstrong, J.S., & Overton, T.S. (1977). Estimating nonresponse bias in mail surveys. *Journal al Ivlarketing Research,* N(3), 396-602.

Asravor, R.K., & Sackey, F.G. (2023). Impact of technology on macro-level employment. *Socíal lndicators Pesearch*, *168*(1-3), 207-225.
Autor, D. (2022). *The labor market impacts of fechnolopical chanpe. From unbridled enthusiasm la qualiI'ed optimism fa vasf uncertainly* (No. w30074). *National Bureau of Economíc* ***Peseorch.***
Barbosa, C. E., de Lima, Y. 0., 6 Costa, L. F. C. (2022). Future of work in 2050: Thinking beyond the COVID-19 pandemic. *Eurapean Journal af Futures Pesearch, ///*(25).
Bera, S., & Rahut, D. (2024). Technology development pathways: Enigmas of appropriate technology choice. *Discover Suslainabilily, 5(I), 45.*
Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2021). Al and automation: Implications for wages and employment. *Journal of Economic Perspectives*, J'S(2), 97–118.
Bilawal Khaskheli, M. et al. (2023). Technology advancement and international law. *Fronliers in Marine Science.*
Borsboom, D. et al. (2021). Theory construction methodology. *Perspectives on Psychological Science*, *I6*(4), 756–766.
Borstad, M.R. (2019). Aferfs *of'* ferAnafopiraf *dezelaR•ient on w'age inequality' and underemployment in the service sector Calil'ornia State* £fnirersify, Los Angeles.
Bowler-Smith, C. (2021). The role of Al in labor market disruptions: Challenges and policy responses. *y fi'‹:fiocieIy*, *36(4j,* 5¢3–567.
Brendel, A.B., Lutz, C., & Riedl, R. (2021). Ethical implications of Al-driven labor markets: A fairness and inclusion perspective. *Journal of Business Ethics,* /d (3), ñ39-¢56.
Chang, S.J., van Witteloostuijn, A., 6 Eden, L. (2010). Common method variance in international business research. *Journal af fnlernalional Business Studies*, 4/(2), 178–184.
Civriz, M., & Üz, s. (2022). Opportunities and threats analysis of Industry 4.0 under the concept: Neo-Ludism. *Journal af lnlernalional Trade, Lopislics and Law*, dt2), 108–124.
Cronbach, L.J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 6(3), 297–334.
Currie, G., Tushman, M., 6 Susskind, R. (2020). Job displacement and Al: A workforce adaptation strategy. *MIT Sloan Management Peview, 6f(4),* 27-39.
Davis, R., Hernàndez, G., & Reis, R. (2021). Al and workforce transition: The role of public policy in mitigating displacement risks. *journal of Public Policy fi‹ Marketi“np,* Pô(2), 201–218.
Dawid, H., 6 Neugart, M. (2023). Effects of technological change and automation on industry structure and (wage-) inequality: Insights from a dynamic task-based model. *Journal of* Evo/o//onary Economics, '/1), 35–63.
del Carpio, X., Cuesta, J. A., Kugler, M. D., Hernández, G., & Piraquive, G. (2022). What effects could global value chain and digital infrastructure development policies have on poverty and inequality alter COVID-19? *Journal of Pisk and Financial Management*, /S(2), 43.
DEMiRAL, D. G., & YENiLMEZ, M. 1. (2022). How robots' uptrend affects the economy and the future. FZîne//m ze *Ekanami Derpisi*, /Q2), 347–363.
Devezer, B., Navarro, D. J., Vandekerckhove, J., & Ozge Buzbas, E. (2021). The case for formal methodology in scientific reform. *Poyal:fiocieIy Dpen :ficience, 8(3), 2DD805.*
Estlund, C. (2023). Losing leverage: Employee replaceability and labor market power. L/. I'll/. *L. Re z., 90,* 637.
Forrest, J. J., 6 Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Markefinp Research,* /d{1), 39–50.
Giering, S., Nguyen, T., & Heinrich, K. (2021). The socioeconomic impacts of Al: A systematic review of economic and workforce effects. *Artificial fnfellipence Peview, 54(\),* 23–56.
Goglin, C. (2023). The ethics of artificial intelligence. *journal ofBusiness* milles, *I80(3), 623–*
Goretzko, D., Pham, T. T. H., & Bühner, M. (2021). Exploratory factor analysis. *Current Pspcholapy', CO*, 3510-3521.
Hair, J.F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). *:fiape Publications.*

Heinrich, C. J., 6 Witko, C. (2021). AI, automation, and labor market inequality: A policy response framework. *facial Science Pesearch, 95,* 102531.

Héry, M., Malenfer, M., de Jouvenel, F., & Grzesiak, L. (2022). Medium-term consequences (5 years) of the COVID-19 crisis on work organization and occupational risks: A prospective study. *European Journal of Futures Research,* /d{1), 1-14.

Hilstob, K., 6 Massie, A. (2022). Artificial intelligence and labor: Perspectives from organized labor in Canada. *Labour,* 9/7, 223-253.

Hultberg, P. T., David, S. C., Kamalov, F., & Smail, L. (2024). Comparing and assessing four Al chatbots' competence in economics. *PLoE One, I9(5).*

lonescu, L. (2019). Should governments tax companies' use of robots? Automated workers, technological unemployment, and wage inequality. *Economics, Management, and financial Markets,* lb(2), 64-69.

Ismail, 1. S., Ghazali, N., Hamid, N. A., Abdullah, N., & Palil, M. R. (2023). The impact of technology acceptance on SMEs' business resilience. Ecooom/c *Affairs, 68(3), U2l-I529.*

Kam, C. C., & Meyer, J. P. (2015). How careless responding affects cross-cultural research: Identifying problematic data and explaining variance. *Journal of Cross-CulturalPsycholopy,* I/(10), 1349-1368.

Kliestik, T., Nagy, M., & Valaskova, K. (2023). Global value chains and Industry 4.0 in the context of lean workplaces for enhancing company performance and its comprehension via the digital readiness and expertise of workforce in the V4 nations. *Mathematics,* //t3), 601.

Koehn, D. (2024). Narrative business ethics and Aristotelian virtue ethics. *Journal of Bu«ine« Ethic«, i89(4), 7az-779.*

Kongshaj, K. (2023). Social policy in a future of degrowth? *Humanifies ‹fi Social Sciences Communications*, *ID(I), OGD.*

Lane, M., & Williams, M. (2023). Defining and classifying AI in the workplace: Challenges and implications. *Journal of Industrial Relations,* d (1), 67–85.

Leavy, B. (2023). Understanding the fundamental economics of Al. *:fiłrałegy ‹fi Leadership,*

Lima, Y., Barbosa, C. E., dos Santos, H. S., & de Souza, J. M. (2021). Understanding technological unemployment: A review of causes, consequences, and solutions. *:fiocieties,* /#2), 50.

Liu, Y., Lei, P., Shen, B., & He, D. (2024). Green technology advancement and carbon emissions. *:ficienIific Reparls, ł4(ł), 2DDO.*

Mack, A. (2024). Foreign policy and security. *The Journal of Australian Political Economy,*

Margaux Franşoise et al. (2022). Evidence-based policy-making during uncertainty. *Archives of Public Health, 8D, I-5.*

McGaughey, E. (2022). The impact of AI on labor law and employment rights: Balancing progress with fairness. *Cambridge Journal of Economics,* 16(4), 899-923.

Muhammad, A. K., Khan, Z., 6 Sardar, F. S. (2023). Monetary policy effectiveness in Asian economies. *Journal of Financial Economic Palícy, f5(3), 22á-247.*

Müller, P. (2022). Austrian foreign policy and EU economic policies. *Österreichische* ż'e//srńc//? *Für Polílíkiw'issenschafł, (4), 19-25.*

Mutascu, M. (2021). Al and wage inequality: Economic implications of automation. *Af 6 :fiacieły,* 'g2), 185–200.

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and information Technologies, 28țń),* ń221- *424\.*

Nguyen, T., Reis, R., & Davis, R. (2023). Al-driven wage inequality and labor policies: A review of global trends. *World Development,* /S4, 105842.

Peters, M. D. et al. (2021). Scoping reviews: Reinforcing and advancing methodology. 6ys/ema//r *Review's, IO, I-6.*

Petroleka, M., Sano, Y., Shah, K., Marshall, R., Haines, C., Weber, K., 6 0liva-Velez, D. (2023). Towards 2050: Megatrends in industry, politics and the global economy 2023 edition. *BMX Pesearch.*

Preacher, K. J., & Hayes, A. F. (2012). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Persanalify Psychaloyy Compass,* d(6), 372-382.
Redhead, C. A. B. et al. (2024). Using symbiotic empirical ethics in clinical decision-making. *BMC Medical Ełhics, 25, I-I5.*
Robles, M., & Mallinson, T. (2023). AI governance and labor market policies: A comparative analysis. /n/ecna//ona/ *Jaurnal of Policy Analysis,* ź'Ą3), 311-329.
Rotman, D. (2023). ChatGPT is about to revolutionize the economy. We need to decide what that looks like. *MOT Technology Pevier.*
Shayegh, S., Reissl, S., Roshan, E., & Calcaterra, M. (2023). An assessment of different transition pathways to a green global economy. *Communications Earth fi‹ Environment, 4(I), 448.*
Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of Cronbach's alpha. *Psychometrika,* (1), 107-120.
Smela, B., Toumi, M., Świerk, K., Clement, F., Biernikiewicz, M., Clay, E., & Boyer, L. (2023). Rapid literature review methodology. *Journal af Markef Access fi‹ Heallh Policy, Ił(I).*
Svane, M. S., 6 Frandsen, S. (2024). Ethical sales cultures in retail banking. *Journal of Business Ethics, I89(2), 269-286.*
Triantari, S., & Vavouras, E. (2024). Decision-making and corporate social responsibility.
Wang, J., Cui, M., & Chang, L. (2023). Evaluating economic recovery by measuring the COVID-19 spillover impact. *Economic Chanpe and Restrucfurinp, E6(3), f629-I65D.*
Wang, Z., Lin, S., Chen, Y., Lyulyov, 0., & Pimonenko, T. (2024). The digital economy and real economy: *:fiustainability, I6(f3), fi769.*
Zhang, X., Palivos, T., & Liu, X. (2022). Aging and automation in economies with search frictions. *Jaurnal of Population Economics,* 75{2), 621-642.