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Industry 5.0: The Impact of Artificial Intelligence and Blockchain in Financial Sector

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Abstract

Advanced companies have promptly incorporated artificial intelligence (AI) and blockchain functionalities into their service networks, significantly transforming the way their specific sectors see the execution of services. There have been a few studies on the use and combination of AI and blockchain, this study attempts to investigate how Artificial Intelligence (AI) and Human Intelligence (HI) are integrated in the banking sector under Industry 5.0. The study used a mixed-method approach, combining quantitative and qualitative investigation of ten leading financial institutions in various nations to determine how often AI and HI are used. Information for this study was obtained from publically available sources, company records, and primary surveys. PLS-SEM was utilised for the primary data analysis in this study, which focused on how AI-HI collaboration affects customer support and personnel well-being. According to the study, AI-HI collaboration greatly improves employees well-being but has no effect on customer satisfaction while considering moderating factors like task difficulty. Although not considerably, AI explainability improves results, highlighting the need for more openness and knowledge. The study's concentration on big financial institutions, which might not be typical of the industry as a whole, poses limitations. Future studies must to take into account a bigger sample size, as well as new markets and smaller businesses. The research findings hold great significance for policymakers and business leaders who seek to enhance human-AI collaboration and guarantee ethical and transparent AI implementation in the financial services sector.

Keywords
Artificial Intelligence, Blockchain, Financial Services, Human Centric, Customer Behaviour.

1. Introduction
The fourth industrial revolution, often known as Industry 4.0, is revolutionising industries all around the world. It is distinguished by the emergence of digital technologies like artificial intelligence (AI), big data, the Internet of Things (IoT), and cloud computing. These technologies facilitate the next phase of automation, connectivity, and intelligence in manufacturing processes. The financial industry is not exempted to these transformational pressures. In fact, Industry 4.0 has the potential to profoundly disrupt and transform financial institutions' operations (Lee, et al. 2018). Businesses have been urged to embrace Industry 4.0 technologies in order to grow their clientele and profits over the past decade (Naeem & Di Maria, 2022).

While technology is portrayed as a method of increasing efficiency and productivity in order to improve competitiveness in the global market, the notion of Operator 4.0 emphasises the use of such technology to achieve a specific level of human-centricity. Operators 4.0 are those who will be aided by technology that provide relief from physical and mental stress without jeopardising production objectives. (Romero et al. 2016; Romero, Stahre, and Taisch 2020; Kaasinen et al. 2020). Though companies are still trying to embrace I4.0, the next revolution, or I5.0, is already taking place and bringing with it the managerial challenge of investing in I4.0 technology while pursuing a vision that is sustainable, resilient, and based around the needs of people. Beyond efficiency and productivity as the only goals, I5.0 presents a strategy that upholds the social duty and commitment of the smart sector to society (Rupa & Saif, 2022).

According to a recent McKinsey & Company (2023) report, the integration of AI and blockchain technology is transforming the banking industry, allowing businesses to improve operations, manage risks, and unlock new revenue streams. Financial institutions may use AI's data analysis, machine learning, and predictive modelling skills, as well as blockchain's decentralised and immutable ledger system, to transform processes ranging from payments and settlements to regulatory compliance and fraud detection.

The Impact of AI Innovation on Financial Sectors in the Age of Industry 5.0 emerges as a crucial resource, speeding up innovations that will influence the future of finance (Irfan et al. 2023). Industry 5.0 is envisioned in tandem with the current industrial revolution (Xu et al. 2021). This emergent paradigm emphasises human-centricity, human-machine collaboration, and prioritising societal well-being. The precise effects of Industry 5.0 on the financial industry are still being investigated, but it has the potential to further revolutionise sectors such as financial inclusion, risk management, and customer experience Thoi, D. S., Nghiem, P. T., and Huynh, V. N. (2021).

1.1 Industry 4.0

As part of the German industrial strategy, Klaus Schwab unveiled the notion of "industry 4.0" in 2016 (Xu et al., 2021). It provides an innately accessible platform that makes administration easier Optimising the operational decision-making process and digital transformation to increase customer satisfaction and return on investment (Alvarez-Aros & Bernal-Torres, 2021). As a result, data are increasingly crucial to business strategy (Limba et al., 2019). Leveraging large data sets to get business and market insights is a key component of I4.0 technologies. This might be related to managing infrastructure, coming up with better ways to offer services, or improving manufacturing efficiency (Ghobakhloo, 2020). I4.0 assists companies in streamlining operations through process automation (Huang et al., 2021). Automation, big data, blockchain, IoT, cloud-based platforms, robotics, and predictive analytics are some of the I4.0 technologies that academics, practitioners, and governments are becoming more interested in (Misra et al., 2021). They provide an advanced and networked platform by merging software for data integration, transmission, and algorithm processing with hardware (Atif et al., 2021; Frank et al., 2019).

1.1.1 Artificial Intelligence

I4.0 also includes artificial intelligence (AI) as a critical technology. It comprises the creation of clever devices to assist in the interpretation of enormous volumes of data collected from several machines at different phases of the production process. In order to help with real-time decision-making, these data are then categorised to find patterns and connections between different sets of acquired data (Dhar Dwivedi et al., 2024).

1.1.2 Blockchain

The Fourth Industrial Revolution was propelled by blockchain-driven digital change. The blockchain is essential to an intelligent factory because it allows the control and decision-making system to be decentralised and allows manufacturing process adjustments to accommodate growing demand (Rupa & Saif, 2022). The locations of the system and device connections are among its features. By connecting and organising the human force, production tools, commodities, logistics, and IT systems, it is possible to increase production viability and optimise resource utilisation. Real-time embedded data can offer a path for making decisions. Moreover, while decentralisation permits automated decision-making, intelligent participants make this possible (Maddikunta et al., 2022).

1.2 Objectives

This study aims towards accomplishing the following objectives:

- Assessing Human-AI collaboration on employee well-being.
- To evaluate customer-facing applications using explainable AI that is transparent and trustworthy.
- Examine the task complexity impact on customers as well as employees of the institution.
- Upskilling and Reskilling the Workforce for Industry 5.0: The Future of Work in Finance.

A systematic literature review (SLR) was carried out, assessing 160 research publications, in order to accomplish the aforementioned study goals and precisely address the research issues. With the focus of the Industry 5.0 landscape, which focuses enhancing human capital's skills rather than substituting it with robots, this review seeks to objectively determine the function of the Industry 4.0 nexus in improving resource efficiency in the finance industry.

2. Literature Review

The financial sector is currently going through a massive transition, propelled by the convergence of artificial intelligence (AI) and blockchain technology. This literature review looks at the individual and combined effects of these disruptive factors on different financial services.

Industry 4.0 entails integrating intelligent devices and systems while improving industrial processes to increase productivity. According to Luthra and Mangla (2018), Industry 4.0 promotes strong technology, novel approaches of working, and the value of connecting with others. Industry 4.0 enhances plants and factories across industries and services, as well as societal roles. Industry 4.0 is defined as the automation and data sharing of industrial technologies and processes, including Cyber-Physical Systems (CPS), the Internet of Things (IoT), Cloud Computing, Cognitive Computing, and Artificial Intelligence (Lee et al. 2018).

The literature primarily portray Industry 4.0 as technical changes for industrial enterprises. The impact of the industrial revolution may be seen in various aspects of the market, both large and small. Technological advancements have impacted all aspects of the value chain, altering competition and consumer expectations (Saniuk et al., 2020). The increasing adoption of Industry 4.0 technology and a shift towards dehumanising manufacturing methods raises worries among workers, society, and governments. Manufacturing technologies in Industry 4.0 are integrated, advanced, and durable. Sensors monitor machine activity, while communication networks enable data reporting and simulation. The functions of current employees are hardly discussed. Multiple research studies (Romero et al., 2016) fatigue the need of including human elements into future industrial development models. Furthermore, others think that limiting technological resilience is insufficient. Resilience should apply to the entire value chain, procedures, and business models. As a result, in 2019, there was a discussion around the concept of Industry 5.0. Longo et al. (2020) advocate restoring the human factor in industry by encouraging collaboration between humans and intelligent production systems. This strategy blends automation's speed and precision with human cognitive abilities and critical thinking.

Industry 5.0 emphasises the relationship between humans and machines (Özdemir & Hekim, 2018). Demir et al. (2019) report that intelligent gadgets connect humans and machines in smart industries. The world of technology, customisation, and advanced manufacturing is rapidly evolving. Robots are becoming increasingly significant due to advancements in artificial intelligence and brain-machine interface technology (Juel, W.K., et al., 2020). According to Moradi (2019), robots now collaborate with humans rather than compete directly. Industry 5.0 is going to bring unprecedented difficulties to human-machine interaction (HMI) by introducing automation into people's daily lives. Industry 5.0 is predicted to increase job opportunities in HMI and HCF. According to Martynov et al. (2023), Industry 5.0 will create opportunities in intelligent systems, artificial intelligence, and robotics, as well as programming, maintenance, training, planning, repurposing, and building new automated systems. Industry 5.0 strives to raise living standards and stimulate innovation through high-quality custom-made products and services, resulting in more environmentally friendly production and consumption.

According to a literature study and forecast analysis, Industry 5.0 prioritises human-centric, sustainable, and resilient development (Romero et al., 2016; Felsberger & Reiner, 2020). To effectively deliver prosperity, industries must address social, environmental, and societal challenges. Industry 5.0 is based on a symbiotic link between technological, social, and environmental sectors. Industry 4.0 prioritised technology, whereas the next phase will focus on industry workers who perceive automation as a threat to their jobs. Industry 5.0 brings together technology for commercial success with social and environmental responsibilities (Gorodetsky et al., 2020). This includes prioritising workplace safety, employee wellbeing and human-machine interaction. Industry 4.0 has been defined as the integration of automation and information technology, data exchange, cyber-physical systems, and new production processes. It also addresses value chain changes and product personalisation options. All of this is part of a wider process known as digital transformation. According to Kagermann (2016), digitalization is the cornerstone of Industry 4.0. Industry 4.0 encourages synergy between ICT and OT. The synergy of IC and OT technologies was to be realised in Industry 4.0. Industry 5.0 recognises the need to digitise communities, economies, and industries (Doyle-KEnt & Kopacek, 2019).

To optimise company and supply chain processes, Industry 5.0 demands extensive digitalization. Industry 5.0 emerged from Industry 4.0, a megatrend. The Industry 5.0 paradigm highlights the incorporation of artificial intelligence into everyday activities. Some experts believe that "Society 5.0" (Super Smart Society) is a more accurate term than "Industry 5.0" (Elim & Zhai, 2020). Society 5.0, unlike Industry 4.0, addresses social issues in both real and virtual spaces. Society 5.0 is a society in which people actively use advanced technologies in their daily lives. According to John et al. (2020), advancement in business, health care, and other professions should prioritise the benefit and convenience of all stakeholders.

The combination of artificial intelligence (AI) and blockchain technology has received a lot of attention in recent years, with academics as well as professionals recognising its potential to revolutionise the finance industry. A survey of the literature finds a growing corpus of research on many elements of this convergence, including its impact on financial services, regulatory frameworks, market dynamics and human-centred industry. Based on that below mentioned conceptual framework is created (Figure 1):

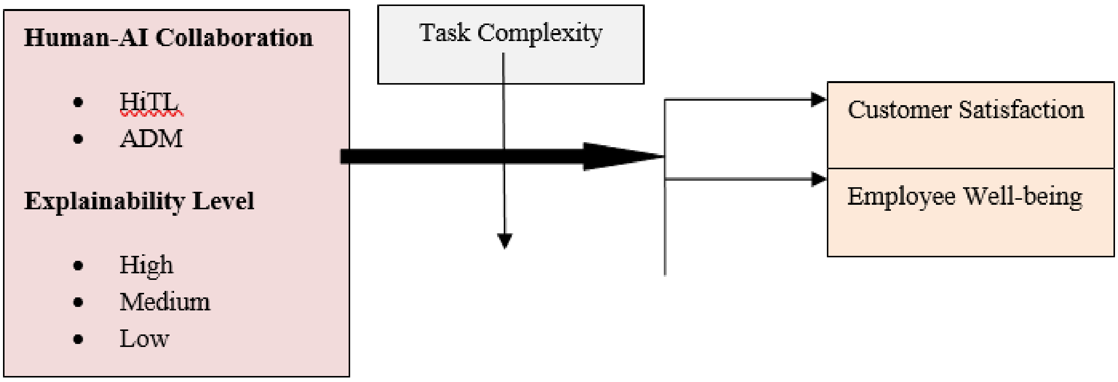

Figure 1. Conceptual Framework

This framework looks at how AI and HI function together in the financial industry, with an emphasis on explain ability levels and task complexity. It investigates the effects of this cooperation on revenue generation, client happiness, and staff welfare. The framework seeks to improve strategic decision-making, transparency, and efficiency by comprehending these dynamics; ultimately, this will improve organisational outcomes and the customer experience.

2.1 Hypothesis Development

H1: Customer satisfaction will be better at higher degrees of human-AI collaboration than at lower ones (ADM).

According to the theory, customer satisfaction improve when people and AI systems collaborate closely, utilising their combined capabilities. When human judgement is combined with AI's data processing powers, decision-making can be more efficient than with automated decision-making (ADM) models, which mostly rely on AI with minimal human input.

H2: Enhancing the explainability of AI recommendations will have a favourable effect on customer trust and satisfaction.

According to this theory, clients are more likely to trust AI systems and feel happy with the services they receive provided they are given comprehensible, transparent explanations for their recommendations. Explainability lowers doubt and boosts users' trust in the technology by assisting them in comprehending the reasoning behind AI judgements.

H3: Employee well-being will be higher in collaborative models with high explainability than in ADM models with low explainability.

This hypothesis states that working in circumstances where AI recommendations are both highly explicable and collaborative will improve employee well-being (e.g., lower stress, increased job satisfaction). In contrast to workplaces with automated decision-making (ADM) and low explainability, which can breed mistrust and confusion, employees can feel more in control, comprehend and trust AI judgements better, and perform more meaningful work in such circumstances.

H4: Task complexity will mitigate the impact of explainability and collaboration on customer satisfaction, and staff well-being.

This hypothesis admits that there are situation-specific variations in the impact of AI explainability and collaboration on financial performance, customer happiness, and staff well-being. The level of intricacy and diversity of the activities, as well as the industry sector (a particular business domain such as banking), might impact the efficacy of explainability and collaboration. For example, the demand for explainability may be more critical in highly regulated or complex industries, but less critical in simpler or more direct enterprises.

3. Methodology

The research design used in this study is mixed method approach, it includes a survey through questionnaire and also used publicly available data from corporate websites, industry news sites, and research papers; it also includes a review of the literature and case studies of ten notable financial institutions. In order to evaluate the effects on customer satisfaction, and staff well-being, the study analyses data related to the integration of AI and HI in the selected institutions, with a particular focus on AI explainability and human-AI collaboration.

3.1 Sample Size for Secondary Data Analysis

For this research on human-AI collaboration and explainability in Industry 5.0, concentrating on 10 top firms provides a strategic and justified sample size, even if a genuinely representative sample for the entire financial industry would need a far greater number of institutions. Selected ten companies are mentioned below:

- JP Morgan Chase (USA)
- HSBC (UK)
- Allianz (Germany)
- Ping An (China)
- Barclays (UK)
- Citigroup (USA)
- UBS (Switzerland)
- Standard Chartered (UK)
- BNY Mellon (USA)
- Banco Santander (Spain)

These ten businesses comprise some of the biggest and most powerful financial institutions. Their endeavours and difficulties are probably going to be similar to those of other industry participants, therefore their experiences are quite applicable.

3.2 Sample Size for Primary Data Analysis

A total of 96 responses are gathered for this study using questionnaires from the staff members of 10 selected companies, i.e. JP Morgan Chase, HSBC, Allianz, Ping An, Barclays, Citigroup, UBS, Standard Chartered, BNY Mellon, Banco Santander. Also the selected firms offer a wide range of financial services (insurance, retail banking, wealth management) and geographical areas (USA, Europe, Asia, Africa, Australia). This diversity makes it possible to investigate the potential effects of industry sector and regional differences on explain ability techniques and human-AI collaboration.

3.3 Data Collection

- **Company Website:** Each company listed has an official website to find information about their AI and Blockchain initiatives, as well as their focus on human-centricity from sections on innovation, technology, or corporate social responsibility.
- **Industry New Sites:** Financial publications such as American Banker, Financial Times, and Forbes regularly release articles about the use of AI and Blockchain by financial firms.
- **Research Reports:** Reports on the future of finance and the role of AI and Blockchain are frequently released by consulting firms such as Accenture, McKinsey, or Deloitte.
- **Questionnaire:** It used as a research instrument for a survey of employees from selected companies.

4. Data Analysis & Discussion

Based on information gathered from company reports, websites, and research reports, the chat below illustrates how company combine artificial intelligence (AI) and machine learning (HI) in their work:

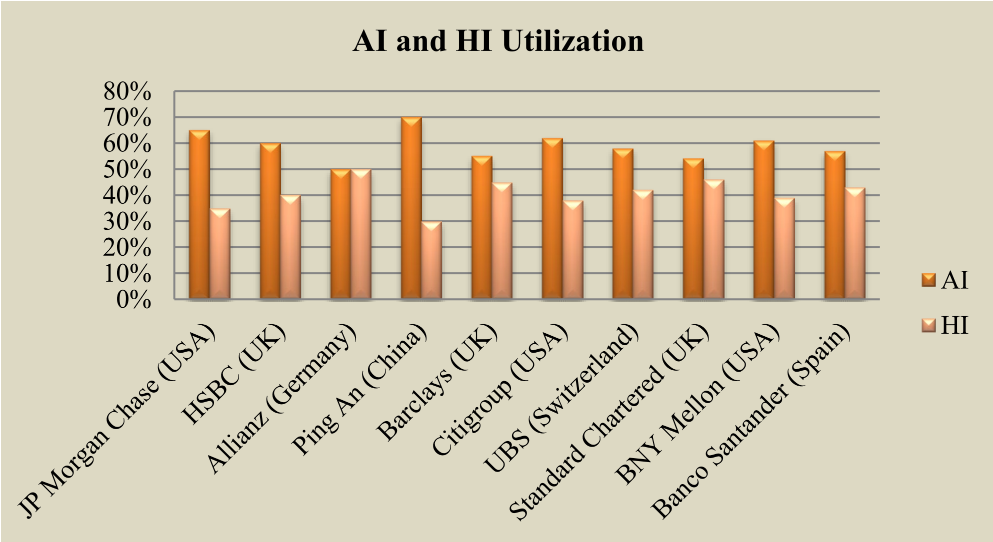

Figure 2. AI and HI Utilization in Companies

Significant heterogeneity across different locations and institutions is revealed by the data on the use of AI and HI in key financial businesses. With the greatest AI utilisation of 70%, Ping An from China is in the lead and shows a significant reliance on artificial intelligence. As an example of a balanced strategy, Allianz, a German company, distributes AI and HI equally, at 50% each. American businesses with high AI utilisation rates—between 61% and 65%—include JP Morgan Chase, Citigroup, and BNY Mellon. These numbers are indicative of a trend towards automation and cutting-edge technology. Even though their levels of integration are a little lower, UK-based institutions like HSBC, Barclays, and Standard Chartered also show significant AI integration. Significant AI use is also seen at other European banks, such as Banco Santander in Spain and UBS in Switzerland. Although the degree of adoption varies throughout organisations and countries, the data generally points to a general trend towards growing use of AI in the financial sector (Figure 2).

For primary data analysis in the present research, the PLS-SME method is employed among the several statistical techniques that are available. The analysis of research models with multiple variables, including unobserved variables, measurement errors, and advanced econometric models like confirmatory factor analysis, is made possible by the more potent partial least square path model-structural equation model (PLSM-SEM) technique (Zhenwei, 2023).

Table 1. Path Coefficients

Variable Relationship	Original sample	Sample mean	Standard Deviation	T Statistics	P Values
AI and HI Collaboration -> Customer Satisfaction	0.269	0.225	0.205	1.312	**0.190**
AI and HI Collaboration -> Employee Well-being	0.431	0.427	0.207	2.086	**0.037**
Explainability Level -> Customer Satisfaction	0.113	0.101	0.177	0.637	**0.524**
Explainability Level -> Employee Well-being	0.306	0.279	0.178	1.718	**0.086**

Task Complexity -> Customer Satisfaction	0.081	0.075	0.099	0.816	**0.414**
Task Complexity -> Employee Well-being	0.047	0.046	0.084	0.554	**0.580**
Task Complexity x AI and HI Collaboration -> Customer Satisfaction	-0.415	-0.311	0.200	2.073	**0.038**
Task Complexity x AI and HI Collaboration -> Employee Well-being	-0.091	-0.061	0.144	0.804	**0.422**
Task Complexity x Explainability Level -> Customer Satisfaction	-0.036	-0.024	0.102	0.350	**0.726**
Task Complexity x Explainability Level -> Employee Well-being	-0.014	-0.007	0.087	0.156	**0.876**

AI and HI Collaboration and Customer Satisfaction: With a T-statistic of 1.312 and a p-value of 0.190, the path coefficient between AI and HI Collaboration and Customer Satisfaction is 0.269. The lack of statistical significance may be attributed to the influence of unmeasured external factors or to fluctuation in customer views, despite the positive path coefficient suggesting a positive link. The demonstrated impact of AI and HI collaboration may be lessened if other variables, such service quality or customer expectations, have a greater influence in determining customer satisfaction.

AI and HI Collaboration and Employee Well-being: With a T-statistic of 2.086 and a p-value of 0.037, the path coefficient of 0.431 between AI and HI Collaboration and Employee Well-Being indicates a significant positive relationship. It demonstrates how the AI-HI collaboration benefits the organization's employees. AI handles tasks on behalf of the workers and lessens their workload, which in turn makes the workers more satisfied and at ease with their jobs eventually has an impact on their wellbeing.

Explainability Level and Customer Satisfaction: The relationship between Explainability Level and Customer Satisfaction appears to be positive, as indicated by the path coefficient of 0.113. The finding is not statistically significant, though, with a p-value of 0.524 and a T-statistic of 0.637. A potential reason for this lack of relevance is that customers may not be fully aware of or comprehend the underlying AI processes. Customers' happiness with AI explainability may be negligible or nonexistent if they do not completely understand its ramifications.

Explainability Level and Employee Well-being: The relationship between Explainability Level and Employee Well-Being has a positive path coefficient of 0.306. The p-value of 0.086 and the T-statistic of 1.718, however, suggest that this link is not statistically significant. Explainability may have an impact on worker well-being, according to this nearly significant result, but it's possible that other factors—like workload or job security—will have a greater affect. The result's marginal character also suggests that a stronger correlation might be found with a bigger sample size.

Task Complexity and Customer Satisfaction: Task Complexity and Customer Satisfaction have a path coefficient of 0.081, a T-statistic of 0.816, and a p-value of 0.414. These findings demonstrate that there is no statistically significant relationship between task complexity and customer satisfaction. This might be due to the possibility that clients are unaware of or unaffected by the intricacy of activities handled by AI or employees. Rather than being primarily concerned with the intricacy of the underlying tasks, their pleasure might be more directly linked to the final product or the overall service experience.

Task Complexity and Employee Well-being: Task complexity and employee well-being have a poor relationship; a p-value of 0.580, a T-statistic of 0.554, and a path coefficient of 0.047 all show no discernible relationship. This lack of relevance could be attributed to the likelihood that workers have become accustomed to differing degrees of task complexity through experience, or that other elements—like work environment, management support, or employee autonomy—have a greater impact on workers' well-being.

Task Complexity x AI and HI Collaboration and Customer Satisfaction: A significant moderating effect is shown by the interaction term's negative path coefficient of -0.415, T-statistic of 2.073, and p-value of 0.038. This suggests that the beneficial impact of AI-HI collaboration on customer satisfaction declines with task complexity.

Task Complexity x AI and HI Collaboration and Employee Well-being: With a path coefficient of -0.091, a T-statistic of 0.804, and a p-value of 0.422, the interaction term for employee well-being is not significant. It's possible that this is because the advantages of AI-HI collaboration in lowering employee stress or burden don't always change with task complexity, or that the study's complexity levels don't challenge participants enough to have a substantial impact on their wellbeing.

Task Complexity x Explainability Level and Customer Satisfaction: With a p-value of 0.726, a T-statistic of 0.350, and a path coefficient of -0.036, the interaction term exhibits non-significant effects. This indicates that explainability has a greater influence on customer satisfaction than task complexity, presumably because customers are more focused on the result than the complexities of the work and its explanation.

Task Complexity x Explainability Level and Employee Well-being: Similarly, the non-significant interaction effects with employee well-being (path coefficient = -0.014, T-statistic = 0.156, p-value = 0.876) suggest that the interaction between task complexity and explainability level does not significantly affect employees' well-being. This might be the case because, when faced with challenging assignments, workers may depend more on their intuitive judgement and real-world experience than on detailed explanations (Figure 3).

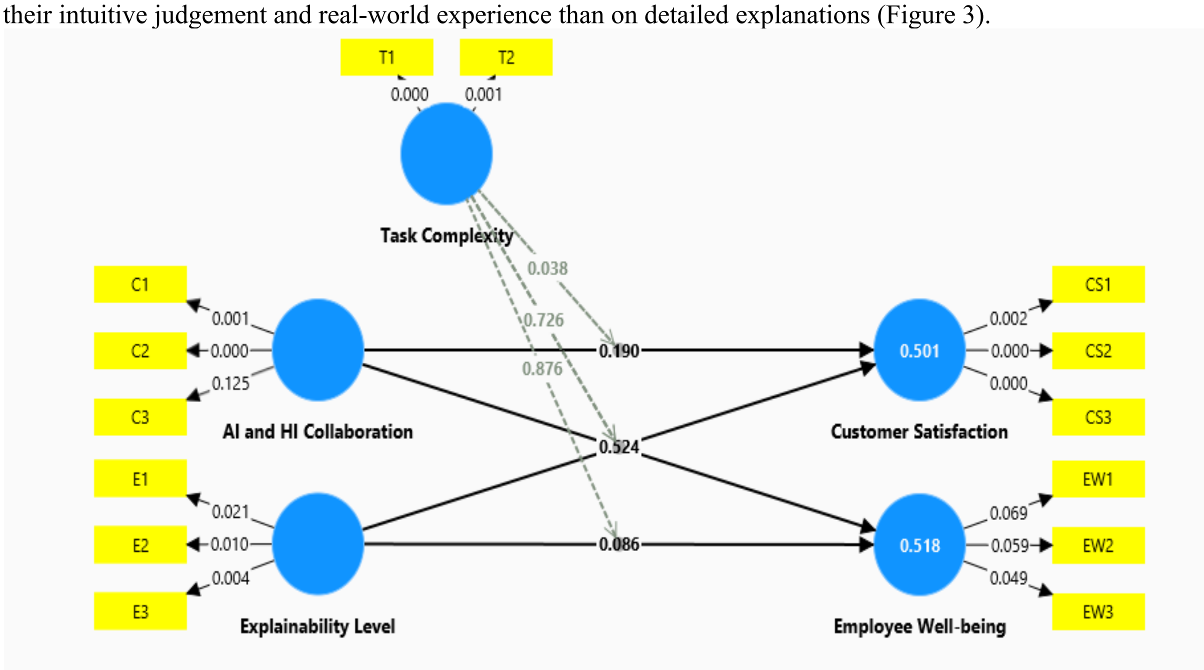

Figure 3. PLS-SEM Model

The PLS-SEM model presents a visual representation of the correlations between AI and HI Collaboration, Explainability Level, Task Complexity, Customer Satisfaction, and Employee Well- Being. In the path coefficients table, the model identifies the direct paths and interaction effects that are examined. Although the non-significant paths point to areas that might need more research or have less of an influence, the major paths highlight areas where AI, HI Collaboration, and Explainability Level are crucial in affecting customer and employee results (Figure 4).

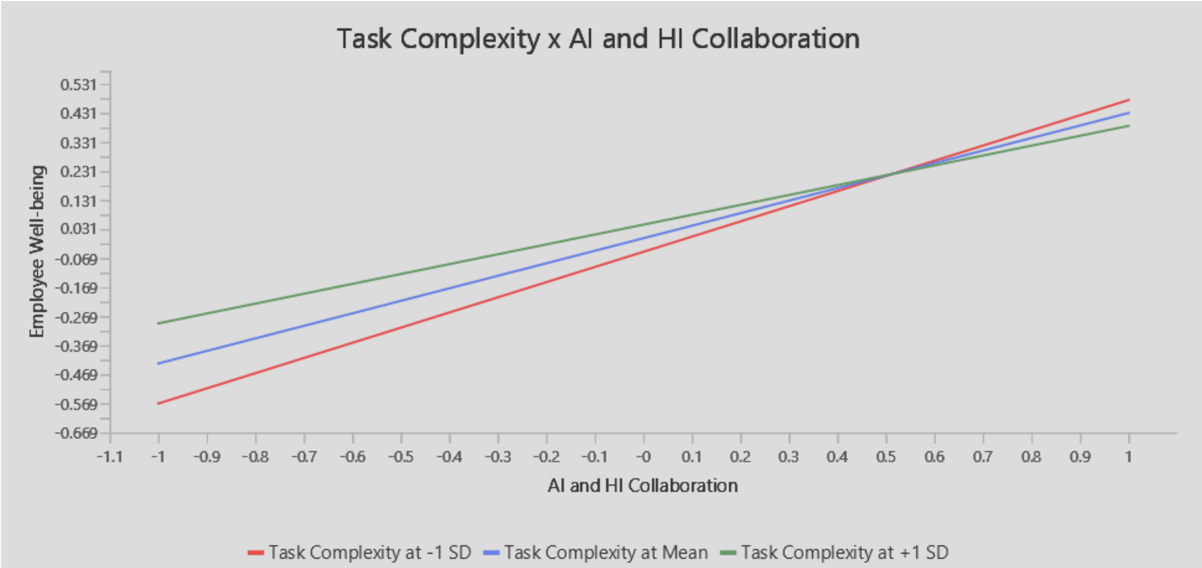

Figure 4. Slope Analysis

Slope analysis in Graph 1 shows how Task Complexity and AI-HI Collaboration interact to affect Customer Satisfaction. The graphic would demonstrate that the beneficial impact of AI-HI Collaboration on Customer Satisfaction decreases with increasing Task Complexity, in line with the strong negative interaction term seen in the path coefficients. This implies that whereas AI-HI collaboration typically improves customer happiness, it becomes less successful when dealing with increasingly complicated task circumstances.

4.1 Findings

The findings of the research indicate a complex interaction between HI and AI in the context of Industry 5.0 in the financial industry. Although there is a positive association between customer happiness and the collaboration of artificial intelligence and human intelligence, this effect is not statistically significant, suggesting that other factors—like task difficulty and service quality—may have a greater influence on customer views. On the other hand, there is a noteworthy correlation between employee well-being and AI-HI collaboration, indicating that when AI is properly integrated with human efforts, it can successfully decrease workload and improve job satisfaction. This demonstrates how AI may benefit employees and enhance their well-being within the company.

The study also reveals that, however these impacts are not statistically significant, the degree of explainability in AI systems significantly influences staff and consumer well-being. This implies that even though it is desired, openness in AI judgements may not have as much of an influence unless customers and staff completely comprehend and have faith in the AI systems. A noteworthy moderator that also comes into play is job complexity, especially when it comes to the connection between customer happiness and AI-HI collaboration. The favourable impacts of AI-HI collaboration on customer satisfaction decrease with work complexity, suggesting that more complicated tasks may call for more human judgement and involvement—something AI cannot supply alone.

4.2 Limitation of the Study

- Even if concentrating on ten elite institutions yields insightful information, it may not be entirely representative of the financial sector as a whole, especially when it comes to smaller firms or those operating in emerging nations. For improved generalizability, larger sample sizes may be investigated in future studies.
- The research sample size was selected with fewer individuals who were distributed unevenly geographically; hence it may not yield reliable results.

5. Conclusion

The study advances knowledge on how the financial sector's main outcomes under Industry 5.0 are impacted by the collaboration of AI and HI. The results indicate that although AI can improve employee and customer happiness, its usefulness varies depending on the environment, especially when it comes to task complexity and the degree of explainability offered. It is critical for organisations looking to get the most out of AI to strike a balance between AI's capabilities and human judgement, particularly in complicated and high-stakes situations. The benefits of working together on AI-HI projects can also be increased by enhancing AI explainability and encouraging staff and customer comprehension of AI operations. To build on these findings, future studies should investigate these dynamics in various settings and with bigger, more varied populations.

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