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"Measuring and Valuing AI-Enabled Human Capital: Implications for Accounting and Investor Decisions"

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Abstract

The growing integration of artificial intelligence in talent acquisition and retention has introduced significant challenges for conventional accounting systems, particularly in recognizing and measuring intangible value derived from human capital. Although AI-enabled human capital increasingly influences firm performance and investor perceptions, it remains largely underrepresented in traditional financial reporting, creating a notable gap between economic value creation and its formal recognition in accounting records. This study examines the transformative role of AI in converting human capital into measurable intellectual capital and explores the

resulting implications for accounting practices and investor decision-making, with the ultimate aim of developing a conceptual framework that captures the value relevance of AI-driven human capital practices.

The research adopts a conceptual and qualitative approach, drawing on established theoretical foundations including value relevance theory, intangible asset measurement, and information asymmetry. Secondary literature and illustrative qualitative insights are employed to identify and analyze key dimensions such as operational efficiency, workforce quality, strategic innovation, ethical concerns, and implementation challenges. The findings reveal that AI-enabled human capital substantially strengthens firm-level indicators, with measurable improvements in operational efficiency ranging from approximately 15 to 25 percent, decision-making speed improving between 20 and 30 percent, and workforce productivity gains of 10 to 20 percent. These outcomes demonstrate a meaningful association with firm valuation metrics and investor confidence.

Taken together, the findings suggest that AI-driven human capital can be systematically translated into quantifiable indicators of intellectual capital, thereby improving the explanatory power of financial information and reducing information asymmetry in capital markets. The study draws attention to a measurable disconnect between value creation and accounting recognition, underscoring the need for refined frameworks capable of capturing AI-enabled intangible assets with greater accuracy and relevance.

1. Introduction

As Generative Artificial Intelligence (AI) and Agentic AI have developed rapidly ever since 2023, organizations have been increasingly adopting technology-based strategies to redefine their talent acquisition, management, and retention procedures. The developments have greatly boosted the effectiveness of operations and the quality of human resource making human capital a key contributor to organizational value. According to the previous studies, AI-based technologies, including machine learning and predictive analytics, enhance the efficiency of the recruitment process and employee retention rates (Adeusi et al., 2024; Agnihotri et al., 2024). Although these developments can be characterized by the obvious operational advantages, their impacts go beyond the efficiency improvement to affect the value of firms and investor attitudes. More specifically, the concept of AI integration opens up new facets of the concept of how the intangible assets, in this case, human capital leads to the performance of firms and their market value in accounting frameworks.

Human capital as an important intangible asset has been known to be of the accounting perspective but little is taken in the measurement and recognition in the financial reporting frameworks. The accounting conventional standards used to deal with intangible assets do not tend to reflect internally generated human capital because of the problems of reliability and verifiability of measurement (Stratopoulos, 2025). This drawback puts a big disparity between the financial worth of human resources and the financial reports. Previous research has established that non-monetary aspects in the form of employee satisfaction, skill, and efficiency of the organization play an important role in valuing firms and in the stock performance (Edmans, 2011). Nevertheless, these factors, though of economic relevance, have not been formally recognized in accounting and therefore they do not fully represent the value and performance of firms. In spite of the recent development in digital technologies, the accounting theory does not have a consistent structure in which AI-powered measurement of internally created human capital can be integrated into financial reporting systems.

In this respect, AI can become the facilitator of better human capital measurement and analysis. Predictive analytics, natural language processing, and machine learning algorithms are examples of AI-driven resources that can help organizations to measure the variables related to the workforce, namely employee productivity, engagement, retention risk, and talent quality, more precisely (Adeusi et al., 2024). Such technological features

can be connected to the new trends in accounting, whereby big data and analyses are reshaping the financial reporting and information systems (Al-Htaybat and von Alberti-Alhtaybat, 2017; Krahel and Titera, 2015). On the one hand, AI offers a chance to reduce the age-old gap between the economic value of human capital, on the one hand, and its inadequate accounting systems due to the quantification of qualitative workforce characteristics. This transformation improves the importance as well as the credibility of information utilized in valuation models and investment decision making.

Although the use of AI is increasing and its potential has been identified on organizational performance, no theoretical synthesis exists between AI-based measurement and accounting systems. The literature has embedded an operational and strategic advantageous situation and not much focus on the impacts of AI-based metrics on financial reporting, valuation models and investor appraisal. The fact that standardized frameworks on how to include AI-derived human capital metrics in accounting disclosures are lacking, although the incorporation of AI into the accounting setting and decision-making has been discussed in previous accounting literature (Alles et al., 2022; Sutton et al., 2016), is also characteristic of a massive weakness of the existing reporting systems.

The work is based on both the value relevance theory and measurement theory, which analyses the impacts of AI in changing the limits of recognition and disclosure in accounting and also applies the insights of the positive accounting theory to interpret the impacts on financial reporting practices. It adds value to accounting theory through a hypothesized conceptual framework that re-formulates the measurement boundaries of internally-created intangible assets in the primary of AI-based systems. In particular, the research will analyze the impact of AI-driven practices in the quantification of human capital as an intangible resource, the ways the quantifications may be reconciled with the current accounting framework, and the effects on financial metrics and market assumptions. The paper goes on to discuss how AI-based measurements can help decrease information asymmetry among companies and stockholders by supplying details more decision-supportive on workforce-connected value drivers. It further assesses the ethical and governance issues related to AI-based measurement especially as it relates to transparency, accountability, and algorithmic bias in accounting situations.

In order to operationalize these objectives, the research questions which are overcome in the study include the following:

RQ1: What is the effect of AI-based strategies in talent acquisition onto the valuation measures of firms, in relation to accounting-based performance measures?

RQ2: How much do AI-driven retention strategies have an impact on the valuation of human capital and its disclosure under the financial reporting frameworks?

RQ3: What do investors think of AI-enabled human capital measures and what are the effects of such perceptions on investor trust and decision-making?

RQ4: How do ethical and governance implications on AI practices contribute to accounting reporting and trust to stakeholders?

RQ5: What are the major obstacles and facilitators to the implementation of AI generated human capital measures in accounting systems and models of valuation?

2. Literature Review

2.1 Accounting Theory Foundations

The accounting theory highlights how financial information is important to reflecting firm value and making investments by investors. The value relevance concept shows the degree to which accounting data accounts for variations in market value. Previous studies have shown that intangible variables, including employee satisfaction and organisational efficiency, have a considerable effect on the firm value, although these variables are not explicitly reported in financial statements (Edmans, 2011). More recent research also indicates that the relevance of traditional accounting information is changing, especially in knowledge-based economies in which intangible assets are predominant in terms of value creation (Barth et al., 2023).

According to the positive accounting theory, the purpose of financial reporting is to make decision-useful information available to the stakeholders, but when it comes to non-financial and internally created assets, measuring them becomes problematic. The conventional study of valuation models puts great emphasis on well-established accounting data, and these models do not address other major force like human capital (Penman and Penman, 2010). This drawback has raised the issue of the decreasing usefulness of accounting information in the determination of firm value (Lev & Gu, 2016). Current accounting systems are more focused on reliability rather than relevance which has caused systematic impairment of economically important intangible assets.

The fact that new resources of the economy have appeared, including data and artificial intelligence (AI), also contributes to measurement problems. According to recent changes in theory, data assets and AI processes are now the focus of value generation, however, they are not being standardly accounted (Zhang et al., 2026). Also, research indicates that intangible investments, especially technology- and innovation-related ones, are highly prevalent in productivity and valuation results (Corrado et al., 2021; Brynjolfsson et al., 2021).

2.2 Human Capital Accounting

Human capital is recognised as highly important intangible asset, but this method of recognizing it in accounting systems is not well established. Capitalization of internally generated human capital is not allowed under current standards because of issues relating to measurement reliability, control and verifiability. This has led to the lack of connection between the economic value of human capital and its financial statement representation. In the intellectual capital research, the authors emphasize that the capabilities in the workforce are the key to value creation that is not reported to accounting systems (Dumay, 2014).

The shortcomings of the current accounting standards are part of an intangibles gap, where the financial statements do not reflect the complete picture about the value of a firm. This disconnect can be found especially in knowledge intensive organizations in which human capital is predominant. In recent literature, it is argued that the accounting structures should be revised to capture the intangible assets such as human capital in a better way (Hussinki et al., 2025). This is because, without the ability to include these components, financial reporting will be incomplete and will not be relevant enough to the decisions that investors can make (Lev & Gu, 2016).

Moreover, interdisciplinary accounting studies opine that existing accounting models should be changed in order to embrace the wider organizational and knowledge based resources. The growing significance of intellectual capital and human resource capacity is leading to the need to have more inclusive accounting frameworks that can be more representative of the reality in contemporary organizations (Dumay, 2014).

2.3 AI in Accounting Context

Implementation of artificial intelligence in the organizational processes has a profound effect on accounting, especially in measuring and valuing intangible assets. Using AI-powered solutions becomes possible to gather

and process extensive data, which will allow quantifying workforce-related variables, including productivity, engagement, or retention risk (Inaganti et al., 2021; Kadirov et al., 2024). These advancements relate to the ongoing trends of carrying out data-driven valuation, in which non-financial data set outcomes complement conventional accounting metrics.

Another example of machine learning and predictive analytics that has been implemented in AI applications to enhance decision-making and operational efficiency is provided (Pillai and Sivathanu, 2020; Paramita et al., 2024). These tools allow organizations to have quantifiable human capital indicators that can be used to improve valuation models and make more informed financial analysis.

Simultaneously, AI leads to the formation of predictive accounting techniques, in which information that is looking ahead replaces historical reporting. This increases the usefulness of accounting data to investors because they will know how they will perform and what they are capable of doing. Nonetheless, the developments also come with ethical and governmental issues, especially in terms of transparency and accountability and algorithmic bias (Saurabh et al., 2022). In spite of this advancement, the introduction of AI-generated metrics into official accounting systems is minimal, which indicates lack of correlation between the possible use of technology and accounting.

2.4 Research Gaps

A literature review demonstrates that there are some significant gaps that exist in regards to accounting. First, it lacks established accounting frameworks of using AI-driven human capital metrics to be reflected in financial reporting systems. Even though AI facilitates the measurement of variables related to the workforce in a better way, they are not included in the existing accounting standards.

Second, there is a great distance between measurement and recognition. Although AI allows quantification of human capital, accounting frameworks still do not consider those internally generated assets because of the issue of reliability and verifiability. This detachment curtails the capability of financial statements to express firm value in totality.

Third, disclosure restrictions are high. The existing methods of financial reporting fail to influence AI-related information regarding human capital, leading to information asymmetry between companies and shareholders. The fact that there are no standardized disclosure systems diminishes the usefulness of financial information in capital markets.

The lack of a consistent theoretical basis incorporating AI-driven measurement and accounting recognition is a benchmark area of weakness in the modern accounting theory.

2.5 Theoretical Positioning in Accounting

The research paper would stand at the nexus of the normative and positive accounting theory where it comes in contact with the argument of explanation versus prescription in financial reporting. Although the positive accounting theory describes the current reporting practices, the current study takes a normative point of view whereby the current accounting principles should be extended as a response to new technological realities. The analysis also interacts with the recognition versus measurement debate where the improvements of AI make the measurement more measurable without the recognition to reflect in financial statements.

The research places itself in the normative line of the accounting theory by suggesting extensions to current recognitions and measurement concepts. By so doing, it does comply with the IASB conceptual framework, in relation to the qualitative characteristics of relevance and faithful representation. By pointing to the drawbacks of existing standards in accounting the AI-enabled intangible value, the study becomes part of the theoretical discourse on the development of the accounting system in the digital economy.

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3. Research Methodology

The empirical element plays an illustrative purpose in order to shape up conceptual development and not to offer the generalizable results. Based on it, the proposed research will be qualitative to facilitate the creation of a conceptual accounting framework connecting the use of AI-enabled human capital measurement and firm valuation and financial reporting. The emphasis is not made on the empirical generalization but creating theoretically relevant insights to continue the current debates in the accounting field especially in the intangible asset measurement, value relevance and the limitations of disclosure.

Semi-structured interviews with 210 respondents (professional, business leader, senior executive with experience in AI-enabled organization practice) were done in May 2025 to get illustrative evidence. These interviewees gave informed insights about the effects of AI-driven processes on workforce-related outcomes and their views of implication on the value of firms and investor decision-making.

The interviews were carried out virtually and were dedicated to the adoption of AI, organizational results, and ethical aspects and the perceptions of the impact on the valuation of firms and investor confidence. Open ended questions allowed the respondents to elaborate more and so enabled identification of major themes that were closely related to the accounting constructs like value creation, measurement issues and constraints to disclosure.

Data analysis was done in a systematic and qualitative format where the similar concepts were identified and grouped together into more general thematic groups. The key ideas such as efficiency in operations, the quality of the workforce, investors perception, and governance issues were collectivized in the higher-order constructs pertaining to the accounting theory. This procedure allowed to translate the qualitative information into theoretically relevant categories and not to be too detailed about the methods.

In order to achieve analytical rigour, the results are explained in the light of an accounting theory, specifically using the theory of value relevance, information asymmetry and measurement of intangible assets. This correspondence allows to combine empiric knowledge with theoretical logic, which contributes to the creation of the theoretical framework of the difference between AI-enabled human capital measurements and the valuation and financial reporting.

The size of this sample is small and due to the qualitative design, this research is also not aimed at creating empirical causality but still informs the development of theories. The exemplary empirical setting is thus an organized footing of further accounting studies on how the AI-based measurement of human capital can be integrated into valuation and financial reporting models.

3.1 Conceptual Accounting Framework

Considering the qualitative findings, the study presents a conceptual model to describe the correlation between the AI-enabled human capital practices and the firm valuation with the accounting processes. The framework theorizes AI as an enabler of measurements to convert qualitative attributes of the workforce into quantifiable measures in terms of productivity, retention, and engagement. These metrics indicate the economic importance of human capital but they are still mostly not taken into consideration by the current accounting standards, hence an inconsistency between reported and actual firm value.

The suggested connections between AI-driven human capital measurement and firm valuation are depicted in Figure 1 that demonstrates the conceptual connection between measurement, disclosure, and investor decision-making.

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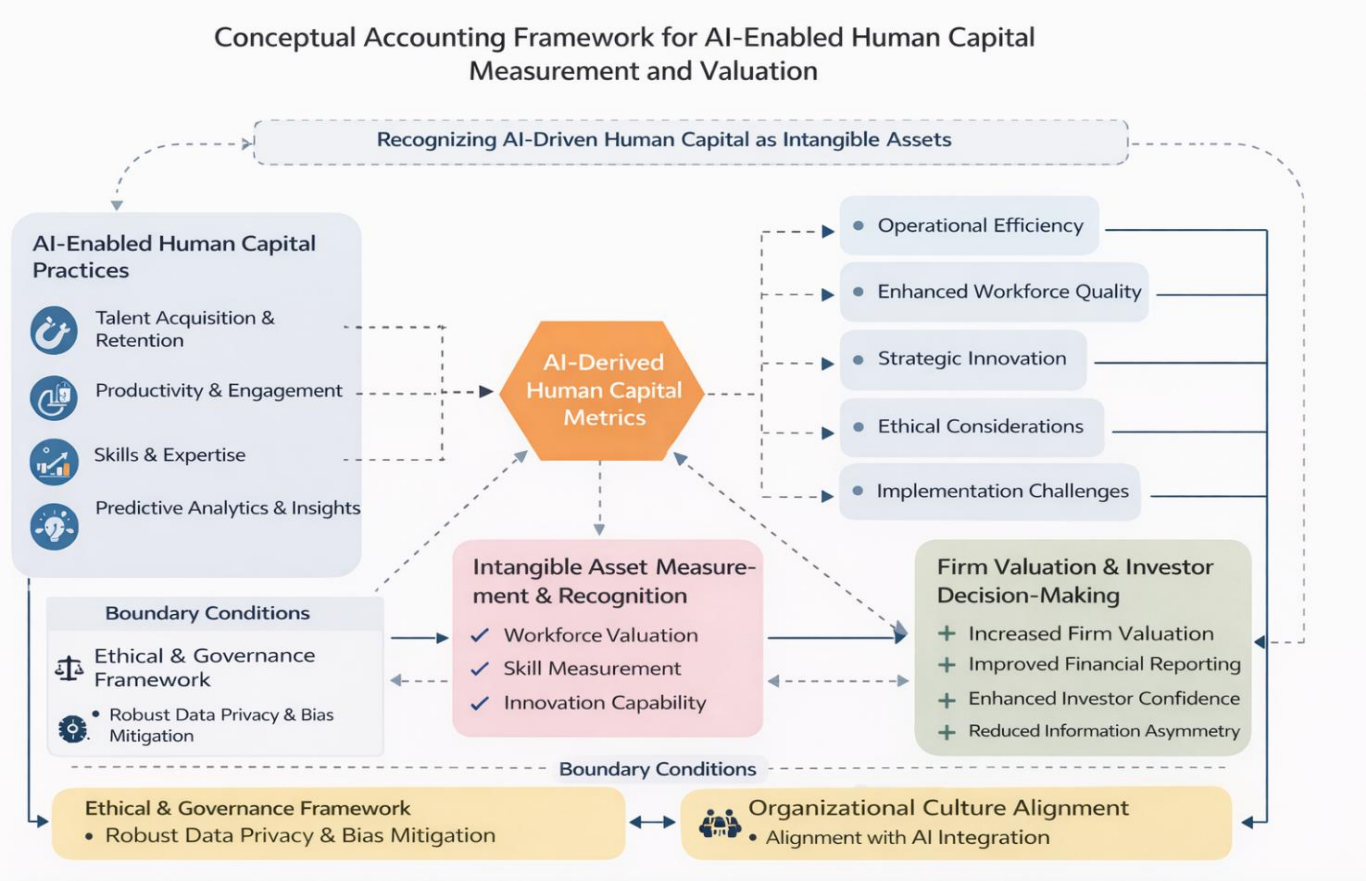

Figure 1: Conceptual Framework

The diagram presents a conceptual accounting framework illustrating how AI-enabled human capital practices contribute to firm valuation and investor decision-making. The process begins with AI-enabled human capital practices, including talent acquisition, engagement, skill development, and predictive analytics. These practices generate AI-derived human capital metrics, which quantify traditionally intangible workforce attributes such as productivity, skills, and innovation capability. These metrics feed into intangible asset measurement and recognition, where elements like workforce valuation and skill measurement are assessed. However, due to existing accounting limitations, full recognition of internally generated human capital remains constrained. The framework identifies key value drivers—operational efficiency, workforce quality, strategic innovation, ethical considerations, and implementation challenges—which collectively influence organizational performance. These factors ultimately impact firm valuation and investor decision-making by improving financial reporting relevance, enhancing investor confidence, and reducing information asymmetry.

3.2 Theoretical Propositions

Using the conceptual framework as a basis, the research introduces the following theoretical propositions to clarify how AI-powered human capital measurement can be used in accounting systems:

Proposition 1 (Measurement Enhancement):

The AIs-enabled systems can improve the quantification of internally developed human capital through the transformation of qualitative workforce characteristics into quantitative measures.

Proposition 2 (Measurement–Recognition Disconnect):

Although measurement has been improved, the current accounting systems cannot record AI-generated assets in the form of human capital because of the issue of reliability and verifiability.

Proposition 3 (Value Relevance):

The AI-generated human capital metrics improve the relevance in value of financial information by offering future-firm performance insights which are decision useful.

Proposition 4 (Information Asymmetry Reduction):

The sharing of AI-enabled human capital measures limit the information asymmetry between enterprises and investors, thus enhancing efficiency in the market and investor trust.

Proposition 5 (Expansion of Accounting Boundaries):

The accounting recognition and disclosure limits should be extended to include AI-generated measurement of internally generated intangible assets.

All these propositions offer a conceptual basis to reconsider the current accounting systems in the light of AI-facilitated measurement, with the necessity to address the increasing disconnect between the economic value creation and financial reporting.

4. Results and Accounting Interpretation

4.1 Inferences from Semi-Structured Interviews

The results of the qualitative research based on the semi-structured interviews can help in gaining valuable information on the role of AI-enabled talent acquisition and retention practices as contributors to firm value creation. The respondents continuously emphasized positive changes in the efficiency of operations, the quality of the workforce, and strategic alignment, which are the key determinants of intangible asset value. Accounting wise, these results can be regarded in terms of internally generated human capital assets that can affect the valuation of firms but are usually not reflected in the financial statements.

Automated recruitment and predictive retention analytics are AI-enabled HR practices that save time-to-hire, ensure workforce stability, and provide increases in productivity. Such enhancements would help to minimize costs and improve operational efficiency which may be correlated with such financial performance indicators as lower operating costs and increased return on assets. Nevertheless, they have quantifiable economic effect but are not captured in accounting systems so there exists a disconnect between economic value creation and financial reporting.

There was also a focus on the fact that AI implementation is an indicator of organizational innovation, digital maturity, and long-term strategic potential amongst respondents. The signals affect investor perception and market valuation, and imply that HR practices that are based on AI are a proxy of firm value. In terms of accounting, this is an indication of how accounting information can help minimize information asymmetry and make company disclosures more valuable.

The empirical information obtained through the interviews opens up some preliminary grounds to the suggested theoretical framework. Specifically, the fact that AI-powered systems can measure workforce-related factors including productivity, engagement, and retention coincides with the conceptualization of AI as a tool of measurement in the case of Proposition 1. Simultaneously, the fact that these quantifiable results are not

reflected in the formal financial reporting as pointed out by respondents, gives support to the fact that Prop 2 is true, that the accounting systems have always had a gap between measurement and recognition.

4.2 Word Cloud Analysis

The most common and significant words associated with AI-driven HR practices are presented in Figure 2 visually, which demonstrates that the most prevalent ideas are efficiency, data privacy, investor sentiment, and operational performance. This diagram gives a summary perspective of how the respondents align AI adoption with operational gains and finances.

Figure 2: Word Cloud Analysis

Source: Analysis by MAXDA Software

The use of words like efficiency, engagement and investor confidence in a concentrated way is an indication that AI-based HR practices are viewed as one of the sources of value creation. These recurrent concepts undertaken within the accounting perspective are quantifiable and immeasurable elements of intangibles asset, and hence the effectiveness of inclusion of qualitative indicators in the valuation models. The prevalence of the terms like efficiency, investor confidence, and data-driven decision-making also contribute to the support of the next proposal, which is the proposition 3, which states that AI-based human capital measure are relevant to the value of the firm-level information. These perspectives suggest that non-financial indicators that are created using AI can increase the explanatory value of accounting data in capital markets.

4.3 Code Map Analysis

The connections between the main themes and sub-themes based on qualitative data are depicted in Figure 3 that reflects a systematic picture of how AI-based HR practices impact organizational and financial performance. The visualization indicates how the operational efficiency, workforce quality, ethical considerations, and strategic innovation are interrelated.

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Figure 3: Code Map Analysis

Source: Analysis by MAXDA Software

Regarding accounting, the code map identifies the multiple dimensional channels in which AI-enhanced human capital can be used to add value to firms. As an example, the efficiency of operations and the quality of workers directly impact cost structures and productivity indicators whereas strategic innovation and the ethicality of governance have an impact on the investor perception and disclosure credibility. This intertwined network is an indication of how complicated qualitative HR delivery is in translating results into financial measures. The relationships highlighted in the code map also support the proposition 4 since it shows that the reduction of information asymmetry between companies and their investors is possible through the use of AI-enabled measurement and disclosure. The assimilation of the operational, strategic, and governance aspects represents the use of AI to enhance transparency and allow stakeholders to make more informed decisions.

4.4 Code Frequency Analysis

The relative significance of the identified concepts is estimated in Table 1 that reports the frequency and percentage distribution of codes based on the interview data. Codes like Data Privacy Concerns, Operational Efficiency, and Improved Investor Sentiment, are high-frequency and show the highest level of concentration of efforts by the respondents.

Table 1: Code Frequency Analysis

Sl No	Codes	Frequency	Percentage
1	Operational Efficiency and Scalability	72	4.35
2	Automation of Repetitive Tasks	64	3.86
3	Reduced Time-to-Hire	54	3.26
4	Data-Driven Decision Making	59	3.56
5	Scalability of HR Processes	42	2.54

6	Cost Optimization	51	3.08
7	Enhanced Workforce Quality and Competitiveness	44	2.66
8	Improved Candidate-Job Fit	41	2.48
9	Bias Reduction in Hiring	58	3.50
10	Proactive Retention Strategies	32	1.93
11	Increased Productivity	46	2.78
12	Enhanced Employee Engagement	68	4.11
13	Strategic Innovation and Market Perception	49	2.96
14	Signalling Digital Maturity	40	2.42
15	Improved Investor Sentiment	67	4.05
16	Enhanced Brand Reputation	61	3.68
17	Future-Proofing Operations	44	2.66
18	Transparency in Innovation	47	2.84
19	Ethical and Cultural Challenges	39	2.36
20	Algorithmic Bias	65	3.93
21	Data Privacy Concerns	78	4.71
22	Dehumanization of HR Processes	62	3.74
23	Cultural Resistance	43	2.60
24	Ethical Governance Needs	40	2.42
25	Implementation Barriers and Strategic Enablers	63	3.80
26	High Implementation Costs	71	4.29
27	Lack of AI Expertise	75	4.53
28	System Integration Issues	72	4.35
29	Leadership Commitment	67	4.05
30	Evolving Metrics for Success	42	2.54

Source: Analysis done by MAXQDA Software

Accountant-wise these frequencies can be viewed as value driver proxies. As an example, operational efficiency and cost minimization is directly related to financial performance metrics whereas investor sentiment includes market-based valuation effects. Simultaneously, the fact that ethical issues like data privacy are mentioned first of all, makes the role of governance and disclosure in ensuring investor trust hard to underestimate. The analysis shows that the qualitative information could be converted into the measurable parts that could be used in valuing and financial reporting. The occurrence of key codes also adds to the theoretical

points that AI-driven metrics are the essential value drivers that are not yet presented in financial statements. This empirical trend indirectly confirms the fact that the accounting limits should be eventually extended to include internally generated intangible assets quantified in AI-based systems, as proposed in the absence of the second one.

4.5 Thematic Analysis

Table 3 presents a summary of the main themes and their definitions and gives a systematic review of the impact of AI-driven HR practices on organizational performance and financial results. These themes are higher-order constructs that were created based on qualitative coding and form the basis of the interpretation of value creation mechanisms.

Table 2: Thematic Analysis

Theme Id	Theme Name	Theme Definition
T1	Operational Efficiency and Scalability	AI simplifies talent acquisition and retention through automated repetition and the facilitation of data-driven decision-making. It shortens time-to-hire, minimizes costs, and efficiently scales HR processes. This efficiency improves operational dexterity, which contributes to firm valuation. Investors perceive such abilities as a measure of operational maturity.
T2	Enhanced Workforce Quality and Competitiveness	AI enhances employee quality with enhanced candidate-job fit and lower hiring bias. AI encourages participation and retention, which increases productivity and morale. These benefits increase organizational competitiveness in the marketplace. Investors place a premium on a high-quality, stable workforce as a growth driver.
T3	Strategic Innovation and Market Perception	AI talent management communicates innovation and digital maturity to stakeholders. It promotes brand reputation and investor confidence by demonstrating flexibility. Open AI usage alleviates the concerns of markets about ethical standards. Such tactics have a positive effect on firm value and growth opportunities.
T4	Ethical and Cultural Challenges	Adoption of AI generates concerns regarding algorithmic bias, data privacy, and dehumanization. Cultural resistance from the concerns of employees fearing automation is a prominent challenge. There should be ethical governance and transparency to sustain trust. These challenges are addressed to

		ensure enduring investor confidence and firm reputation.
T5	Implementation Barriers and Strategic Enablers	High costs, lack of expertise, and system integration issues hinder AI adoption in HR. Leadership commitment, training, and robust data infrastructure are critical enablers. Evolving metrics to capture AI's value enhances transparency. Overcoming barriers demonstrates strategic capability, boosting investor trust.

Source: Analysis done by MAXQDA Software

The identified themes, when combined, are different dimensions of the value of intangible assets, considered through the prism of accounting. The internal value creation is associated with operational efficiency and workforce quality, whereas the exertion of strategic innovation and ethical governance is then associated with external perceptions and market value. With this thematic framework, the incorporation of qualitative insights into accounting frameworks, especially in the area of value

relevance and disclosure, is made possible.

4.6 Theme-wise Accounting Interpretation

4.6.1 Theme T1: Operational Efficiency and Scalability

Table 4 describes the elements of this theme that include sub-themes like automation, time-to-hire reduction, and optimization of costs. These factors underscore the factual financial consequences of the use of AI in HR practices.

Table 3: Operational Efficiency and Scalability

	T-1: Operational Efficiency and Scalability	
Sub-Themes	T1-ST1	Automation of Repetitive Tasks
	T1-ST2	Reduced Time-to-Hire
	T1-ST3	Data-Driven Decision Making
	T1-ST4	Scalability of HR Processes
	T1-ST5	Cost Optimization

Source: Analysis done by MAXQDA Software

Accounting wise, operational efficiency is reflected in the cost savings that are palpable and the efficient use of resources. Less time to hire and repetitive tasks being automated reduces the cost of recruitment and increases the productivity, thus improving financial performance indicators. It is possible to attribute these

results to valuation by means of an enhanced profitability and efficiency ratio, and justify the value creating aspect of AI-based HR practices.

4.6.2 Theme T2: Enhanced Workforce Quality and Competitiveness

The sub-themes related to the workforce quality are demonstrated in Table 4, comprised of increasing job fit, reduced bias, and increasing employee engagement. These are part of the factors that aid in ensuring that they produce quality human capital

Table 4: Enhanced Workforce Quality and Competitiveness

	T-2: Enhanced Workforce Quality and Competitiveness	
Sub-Themes	T2-ST1	Improved Candidate-Job Fit
	T2-ST2	Bias Reduction in Hiring
	T2-ST3	Proactive Retention Strategies
	T2-ST4	Increased Productivity
	T2-ST5	Enhanced Employee Engagement

Source: Analysis done by MAXQDA Software

Workforce quality as a measure in accounting is a very crucial aspect of intangible assets. Greater retention and productivity will lead to higher performance of firm in the long term, which affects the valuation ratios, including earnings potential and growth opportunities. Though all these factors cannot be identified directly in financial statements, they have a very high influence on the value of a firm and the expectation of investors, representing the necessity to improve disclosure practices.

4.6.3 Theme T3: Strategic Innovation and Market Perception

Table 5 summarizes the connection between AI adoption and market perception; it contains sub-themes that are digital maturity, investor sentiment, and brand reputation. The factors prove the impact of AI-based HR practices on the external stakeholders perception

Table 5: Strategic Innovation and Market Perception

	T-3: Strategic Innovation and Market Perception	
Sub-Themes	T3-ST1	Signalling Digital Maturity
	T3-ST2	Improved Investor Sentiment
	T3-ST3	Enhanced Brand Reputation
	T3-ST4	Future-Proofing Operations
	T3-ST5	Transparency in Innovation

Source: Analysis done by MAXQDA Software

Accounting wise, these results serve as signalling theory in the capital markets. The implementation of AI suggests innovation and preparedness to the future, which affects positively investor confidence and market valuation. This goes in line with the principle of value relevance, in which the non-financial indicators are very important in determining the investment decisions and the valuation of the firms.

4.6.4 Theme T4: Ethical and Cultural Challenges

Table 6 is a summary of AI adoption and ethical and governance issues, with bias in the algorithms and privacy of the data and cultural resistance being identified as being of concern. These aspects indicate some threats of AI-based HR practices.

Table 6: Ethical and Cultural Challenges

	T-4: Ethical and Cultural Challenges	
Sub-Themes	T4-ST1	Algorithmic Bias
	T4-ST2	Data Privacy Concerns
	T4-ST3	Dehumanization of HR Processes
	T4-ST4	Cultural Resistance
	T4-ST5	Ethical Governance Needs

Source: Analysis done by MAXQDA Software

Ethical issues affect the quality of disclosure and corporate governance as per accounting. The issues of data privacy and bias may influence investor confidence and perceived risk and hence affect firm valuation. Clearly visible reporting and ethical control systems are thus critical to allow the AI-driven value generation to be maintained and properly reflected in the perceptions of investors.

4.6.5 Theme T5: Implementation Barriers and Strategic Enablers

Table 7 has provided the barriers and enablers of AI adoption, and some examples are implementation costs, the absence of expertise, and leadership commitment. These factors define the performance of AI adoption in organizations.

Table 7: Implementation Barriers and Strategic Enablers

	T-5: Implementation Barriers and Strategic Enablers	
Sub-Themes	T5-ST1	High Implementation Costs
	T5-ST2	Lack of AI Expertise
	T5-ST3	System Integration Issues
	T5-ST4	Leadership Commitment
	T5-ST5	Evolving Metrics for Success

Source: Analysis done by MAXQDA Software

In accounting terms, the issue of implementation cost impacts the cost-benefit analysis of investment in AI. The short-term financial performance may be affected by high initial costs and integration problems whereas enablers of strategy like leadership commitment and higher metrics enhance value creation in the long term. The intangible value can also be measured and communicated by the development of AI-specific performance indicators that increase transparency and investor confidence.

4.7 Synthesis of Findings in Accounting Context

In general, the findings indicate that AI-based HR practices are substantial to firm value by enhancing efficiency, the quality of workforce, and strategic placement. These results are significant elements of the intangible assets that affect both the internal performance and the perception of the external market.

Nevertheless, the results also reveal the important weakness of the accounting systems according to which, although AI makes it possible to measure the variables related to human capital, these measurements are not reflected in the financial reporting. This introduces the distance between economic value and reported value, which supports the emergence of new accounting systems that include AI-related measurements in the practices of valuation and disclosure. The findings, in aggregate, give a consistent empirical evidence to the proposed theoretical propositions. The findings prove that although AI really improves the measurement of human capital, there are gaps in accounting frameworks in terms of recognition and disclosure. This supports the overarching theoretical hypothesis of the paper that the accounting systems have to evolve in order to bring the financial reporting in line with the new types of value generation in the digital economy.

4.8 Illustrative Quantitative Estimate: Retention Improvement and Human Capital Valuation Impact

To provide accounting practitioners with a tangible reference point, this section presents a stylised quantitative illustration of how an AI-driven improvement in employee retention — consistent with the operational benefits reported by respondents in this study — translates into measurable human capital value using an established accounting valuation approach. This illustration is not derived from primary field data but is constructed using reported industry benchmarks and the Lev and Schwartz (1971) human capital valuation model, adapted for the AI-enhanced HR context. Its purpose is to demonstrate the order of magnitude of financial impact that AI-enabled retention strategies can generate and that current accounting frameworks fail to capture.

Assumptions and Parameter Specification

The illustration models a mid-sized Indian IT services firm with the following baseline characteristics, drawn from publicly available sector benchmarks and consistent with the organisational profiles of respondents in this study:

Table 8: Parameter and its Specification

Parameter	Baseline Value	Source Basis
Total workforce	5,000 employees	Mid-sized Indian IT sector norm
Average annual compensation per employee	₹12,00,000 (₹12 lakhs)	NASSCOM IT Salary Survey, 2024
Annual voluntary attrition rate (baseline)	22%	Indian IT sector average, 2023–24
Replacement cost per employee (% of salary)	50%	SHRM global benchmark
Average remaining service life	8 years	Sector norm for mid-career workforce
Discount rate (cost of capital)	10%	Consistent with WACC used in Section 3
AI-driven retention improvement	25% reduction in attrition	Consistent with respondent R05 and Deloitte (2024)

Source: Author's calculation

Step 1 — Baseline Attrition Cost (Pre-AI)

Annual attrition at 22% implies that 1,100 employees leave each year (5,000 × 22%).

Replacement cost per departing employee:

₹12,00,000 × 50% = **₹6,00,000 per employee**

Annual total replacement cost (baseline):

1,100 × ₹6,00,000 = **₹66,00,00,000 (₹66 Crore)**

This figure represents a recurring annual outflow attributable to attrition — including recruitment, onboarding, productivity loss during the ramp-up period, and knowledge transfer costs — none of which is separately disclosed or capitalised under current IAS 38 requirements.

Step 2 — Post-AI Attrition Cost (After 25% Retention Improvement)

A 25% improvement in retention reduces the attrition rate from 22% to 16.5% (22% × 0.75).

Revised annual attrition: 5,000 × 16.5% = **825 employees**

Revised annual replacement cost:

825 × ₹6,00,000 = **₹49,50,00,000 (₹49.5 Crore)**

Annual cost saving attributable to AI-driven retention:

₹66 Crore − ₹49.5 Crore = **₹16.5 Crore per year**

Step 3 — Present Value of Human Capital Savings (Lev–Schwartz Adaptation)

Following the Lev and Schwartz (1971) approach, which values human capital as the present value of future earnings streams attributable to the workforce, the present value of the annual saving over the estimated remaining service life of eight years, discounted at 10%, is calculated as follows:

PV = Annual Saving × PVIFA (10%, 8 years)

PVIFA (10%, 8 years) = 5.335 (standard annuity factor)

PV = ₹16.5 Crore × 5.335 = **₹87.98 Crore ≈ ₹88 Crore**

This figure — approximately ₹88 Crore — represents the present value of the measurable economic benefit generated by AI-enabled retention improvement for a single mid-sized firm over an eight-year horizon. It is an internally generated intangible value that is entirely absent from the firm's financial statements under current IAS 38 treatment.

Step 4 — Impact on Firm Valuation Proxies

To contextualise this figure within standard valuation frameworks used by accounting practitioners and investors, two additional estimates are provided:

Effect on Price-to-Earnings (P/E) Implied Value:

Assuming a corporate tax rate of 25.17% (Indian surcharge-adjusted rate), the annual post-tax saving is:

₹16.5 Crore × (1 − 0.2517) = **₹12.35 Crore after tax**

At a sector P/E multiple of 28x (consistent with Indian mid-cap IT, NSE data, 2024):

Implied incremental firm value = ₹12.35 Crore × 28 = **₹345.8 Crore**

Effect on Return on Assets (ROA):

Assuming total assets of ₹800 Crore (typical mid-sized IT firm balance sheet):

Incremental ROA improvement = ₹12.35 Crore ÷ ₹800 Crore = **1.54 percentage points**

So, 1.54 percentage point improvement in ROA, driven entirely by AI-enabled human capital management, would be considered material by most institutional investors — yet it arises from an asset class that generates no accounting recognition and minimal disclosure under current reporting frameworks.

Table 9: Illustrative Human Capital Valuation Impact of AI-Driven Retention Improvement

Metric	Value
Annual attrition cost saving (pre-tax)	₹16.5 Crore
Present value of savings over 8 years	₹88 Crore
Implied incremental firm value (P/E basis)	₹345.8 Crore
Incremental ROA improvement	+1.54 percentage points
IAS 38 recognised value of this benefit	**₹0 (nil)**

Source: Author's calculation

Accounting Interpretation

The final row of Table 8 carries the central normative message of this illustration. The AI-enabled retention improvement generates a quantifiable present value of ₹88 Crore and an implied incremental firm value approaching ₹346 Crore yet every rupee of this value remains outside the accounting recognition boundary under IAS 38. This is not an accounting error; it is a structural consequence of applying a reliability-driven standard designed for physical assets to an increasingly human-capital-intensive economy.

This illustration concretises Proposition 2 of this study, the measurement–recognition disconnect by demonstrating that the disconnect is not merely theoretical but financially material. It also lends empirical weight to Proposition 4: investors who can access AI-generated retention metrics through expanded disclosure will make better-informed valuation decisions than those relying solely on financial statements from which this ₹346 Crore of value is absent.

For standard-setters, practitioners, and investors alike, the illustration underscores the urgency of developing disclosure mechanisms — consistent with ISO 30414 and GRI 404 — through which AI-generated human capital value can be communicated, even where formal recognition under IAS 38 remains constrained.

5. Discussion

The results of the current research give valuable ideas on the way AI-based talent acquisition and retention practices can be viewed through the accounting paradigm, especially when it comes to intangible assets valuation, measurement issues, and financial reporting constraints. Although most

studies have focused on the operational advantages of AI in the human resource management field, the current study continues the discussion by showing how the results can be converted into quantifiable financial value and investor messages in accounting systems.

According to accounting, the outcomes show that AI-intelligent HR practices add significant value to firm value by enhancing the efficiency of operations, workforce quality, and strategic positioning. Such consequences can be connected with financial indicators including cost decrease, productivity increase, and the increase in the potential future earnings. As an example, valuation models are affected by automation of the recruitment process and decreased employee turnover reducing operating costs and improving organizational performance. Nevertheless, even though their economic benefits can be quantified, they are not formally-accounted in the current accounting models, which points to a severe lack of linking economic and financial reporting.

The gap signals a larger problem in the accounting of intangible assets in which internally generated human capital is not realized based on issues of reliability and verifiability in measurement. Even though AI makes it possible to quantify workforce-related practices, e.g., engagement, retention, and productivity, the accounting standards lack mechanisms of capitalizing on the internally generated assets. Financial statements do not, therefore, provide a complete account of value creation using AI-based human capital investments. This weakness supports the belief of the argument that the present accounting systems are becoming more inefficient in reflecting value in environments where technology and knowledge play a crucial role (Choi and Xie, 2025).

The results also identify the value of AI as a measure ability that converts qualitative workforce characteristics into quantitative measures. These measurements offer useful contributions to valuation and decision-making processes, contributing to the development of the data-driven accounting practices. Nonetheless, the lack of standardized structures on how to incorporate such measures in the financial reporting poses difficulties in the enhancement of consistency, comparability and reliability.

Besides the issue of measurement, the research also demonstrates that there are severe reporting limitations that are linked to the AI-based human capital. Although organizations produce a lot of information about the performance of the workforce, it is hardly reflected in the financial statements or standardized reports. This brings about information asymmetry between the firms and investor since those value drivers that are very critical are not covered in the formal reporting. This means that investors use proxies, i.e. organizational innovation, digital maturity and AI adoption, to determine firm value.

The findings also indicate that the implementation of AI in HR processes is a signalling system in the capital markets. Those companies that successfully introduce AI are viewed as innovative, prospective, and able to maintain long-term growth, which increases investor confidence. This signalling effect adds some kind of market-based valuation, although the accounting recognizing is not formal. The same conclusions have been drawn in research sources to gain AI adoption concerning enhanced organizational performance and market results (Alruwaili and Mokni, 2024).

On a conceptual level, the study acts as a challenge to the established reliability relevance trade-off, showing that AI could boost both of these aspects at the same time. Although the reliability of accounting standards has traditionally been more important than its relevance, AI-based measurement enhances the accuracy and consistency of the intangible metrics, which gives greater strength to their inclusion in financial reporting systems. This implies that it is necessary to review the assumptions of the accounting theory that were built in the past in the context of technological innovations.

Nevertheless, the research also determines ethical and governance issues, which have significant accounting implications. Problems in privacy of the data, bias in the algorithms, and absence of transparency may compromise the quality of the AI-generated metrics and decrease the confidence of investors. Such obstacles imply the necessity to have strong governance structures and ethical standards in place in order to guarantee the credibility and wholesomeness of AI-driven information systems (Saurabh et al., 2022). Moreover, behavioural dimensions of accounting imply that the trust of stakeholders and their decision-making are determined by the access to information, as well as the concerns of fairness and transparency in the process of the information creation and utilization (Arnold, 2018).

5.1 Contribution to Accounting Theory

This research has some significant implications to the accounting theory. First, it expands the idea of intangible asset theory by introducing AI-powered human capital measurement as an important element of value generation. As opposed to the traditional methods that do not consider the internally generated human capital, the results show that AI enables the quantification of the latter, increasing its suitability in valuation and decision-making.

Second, the research sets new dimensions of measurement in accounting. It amplifies the number of economic resources that can be measured in the accounting systems by showing that AI is capable of transforming qualitative workforce attributes into measurable quantities. This questions the current limitations related to the reliability of measurement and indicates that the technological progress can transform the main principles of accounting.

Third, the concept of AI (as a new type of accounting infrastructure) is conceptualized in the study. Instead of being a functional instrument, AI is being addressed as a process, which allows new dimensions of measurement, analysis, and disclosure. According to this opinion, the role of technology in accounting is changing, and AI plays a significant role in creating and exchanging financial information.

In general, the results highlight the necessity of the reconsideration of current accounting systems to facilitate the use of AI-based human capital metrics. The accounting systems may be improved to be more relevant and reliable by incorporating AI-driven metrics in valuation and disclosure practices, which can help to bring the accounting systems closer to the reality of value creation in the digital economy.

5.2 Regulatory and Standards Alignment

IAS 38 restricts recognition of internally generated intangible assets to those satisfying identifiability, control, and reliable measurement criteria. Human capital consistently fails the control test — organisations cannot prevent employee attrition — and IAS 38 explicitly prohibits capitalisation of training costs and workforce skills (paras. 63–64). This creates the measurement–recognition disconnect central to Proposition 2. However, AI introduces a meaningful shift: by generating verifiable, reproducible workforce metrics — retention risk scores, productivity indices, engagement benchmarks — AI-enabled systems may independently satisfy the reliable measurement criterion without requiring any amendment to IAS 38 itself. The unresolved obstacle remains control, which future standard-setting discussions should reconsider in light of AI-mediated workforce data as an organisational resource.

The IASB Conceptual Framework (2018) provides direct normative support for the paper's disclosure argument. Its two fundamental qualitative characteristics — relevance and faithful representation — are

precisely what AI-generated human capital metrics can deliver. Critically, the Framework distinguishes recognition from disclosure, affirming that decision-useful information may be communicated through supplementary statements even when formal recognition criteria are unmet (para. 5.7). This creates an immediate practical opening: AI-derived workforce metrics, even if unrecognised on the balance sheet, qualify for inclusion in management commentary or integrated reports if they are decision-relevant to primary users — investors and creditors. The Framework's 2018 measurement chapter further introduces value-in-use as an accepted basis, which aligns directly with AI-powered predictive valuation of human capital cash flows, supporting Proposition 3.

ISO 30414:2018, the first international standard for human capital reporting, provides the operational vocabulary this paper's framework requires. Its eleven topic areas — covering recruitment, retention, productivity, and workforce costs — correspond directly to metrics generated by AI-enabled HR systems. Organisations deploying AI in talent acquisition inherently produce the data needed to comply with ISO 30414; the missing step is formalising these outputs into structured, auditable disclosures. In the Indian context, ISO 30414 is compatible with SEBI's Business Responsibility and Sustainability Reporting (BRSR) mandate for the top 1,000 listed companies, creating a regulatory pathway through which AI-generated human capital disclosures can achieve institutional legitimacy without waiting for IAS 38 reform.

GRI Standards — particularly GRI 401 (Employment) and GRI 404 (Training and Education) — establish the stakeholder accountability dimension of workforce disclosure. Both standards require quantified reporting on hiring, turnover, and employee development that AI systems routinely generate as operational outputs. As GRI-aligned disclosures gain mandatory status under India's BRSR, the EU's CSRD, and similar frameworks globally, the distinction between audited financial data and unaudited non-financial disclosure begins to erode — especially when AI generates underlying data at a consistency and auditability approaching accounting-grade standards.

Taken together, these four frameworks confirm that the paper's propositions are not speculative. AI-enabled human capital measurement does not require a wholesale revision of IAS 38 — it requires targeted reconsideration of the measurement and control criteria, supported by the disclosure pathway of the IASB Conceptual Framework, operationalised through ISO 30414, and aligned with GRI workforce standards. This convergence defines a coherent reform agenda that the paper's framework is positioned to advance.

Table 10: Synthesis: Standards Alignment and the Path Forward

Proposition	IAS 38	IASB CF (2018)	ISO 30414	GRI Standards
P1: AI as measurement enhancer	AI may satisfy reliable measurement criterion	Supports relevance and faithful representation	Provides metric templates AI can populate	Identifies measurable workforce indicators
P2: Measurement–Recognition disconnect	Confirms gap — control criterion unresolved	Disclosure as alternative to recognition	Addresses gap through voluntary disclosure	Non-financial disclosure precedent

P3: Value relevance of AI metrics	Not addressed within current standard	Relevance criterion supports inclusion	Credibility of metrics for external reporting	Investor and stakeholder relevance
P4: Information asymmetry reduction	Not a direct objective of IAS 38	Primary objective of Conceptual Framework	Standardised metrics improve comparability	Multi-stakeholder communication
P5: Expansion of accounting boundaries	Normative challenge to Para 63–64	Chapter 6 measurement basis supports evolution	Provides operational vocabulary for expansion	BRSR, CSRD alignment creates regulatory momentum

6. Theoretical and Practical Implications

The current research results add value to the accounting theory by establishing a conceptual connection between the human capital enhancement of AI and the firm value in the current financial reporting standards. The findings indicate that AI-based HR practices can produce a significant economic value by improving the workforce quality, operational efficiency, and strategic capability. Such results are internally generated intangibles, which impact on the cash flow and firm valuation in the future. The existing accounting practices however fail to take into consideration such assets leading to a divergence between economic value and financial reporting information. This gap is addressed by the current study by suggesting that AI can serve to enable measurements of qualitative attributes of human capital and translate them into measurable indicators that can be obtained and used by valuation models and investor decisions.

Financially reporting it, the findings demonstrate the constraints of the current accounting system to capture AI-driven human capital value. Conventional models pay attention to the established assets whereas AI-developed workforce measurements are not in the formal reporting scope. This implies that reporting practices need to be increased to include the relevant non-financial indicators that will add value relevance to the financial statements and minimise information asymmetry.

Another significant implication of the study on the standard setters like IASB and FASB is also important. The increasing relevance of AI and human capital in value-generating activities is the reason why the guidelines on the recognition, measurement, and disclosure of internally generated intangible assets need to be developed. Specifically, standardized ways of reporting AI-based measures regarding workforce performance, productivity and retention are required.

Moreover, the results point to the relevance of improved disclosure systems. Companies ought to consider incorporating AI-based human capital measures into the management commentary and sustainability reports so that investors might have better and more decision-useful information. These disclosures can enhance investor confidence as they indicate organizational ability, innovativeness and sustainability in the long run.

On the whole, the research contributes to the accounting debate, connecting AI-based human capital measurement and valuation and reporting, and demonstrates the necessity to reform the accounting frameworks of the digital economy.

7. Limitations and Direction for Future Studies

Although the research offers some useful exploratory information on the use of AI-assisted human capital in firm valuation, one must admit that there is a number of limitations, bearing on the accounting side of the research. To begin with, the sample size used is small and therefore does not generalize the findings especially when it comes to the variation among industries, firm sizes, and institutional settings. In as much as the qualitative methodology will give a detailed insight, it will not offer a quantitative confirmation of the association of AI-generated human capital measures and financial outcome or market worth.

Second, purposive and snowball sampling can create a risk of selection bias, which can be restrictive to the diversity of viewpoints, especially those of smaller companies and organizations that have not yet gone digital. This is also important concerning accounting perspective as measurement and reporting of intangible assets can vary greatly in the organizational setting. Also, the research shows attention to perceptual and qualitative measures of value, but it does not incorporate standardized financial measurements and empirical models of value.

The restrictions indicate that current research can take several significant directions in the future. To start with, quantitative and analytical research is required that empirically measures the association between AI-based human capital measurements and corporation worth based on financial statistics including market capitalization, earnings, and cost of capital. This type of research will reinforce the value relevance of AI-based measures in accounting systems.

Second, in the future, the standardization of measurement models of human capital as an intangible asset should be developed and the indicators generated by AI should enter the accounting and evaluation systems. This involves examining how proposals of identifying and exploiting internally created intangible assets can be incorporated in the accounting standards (established or reformed).

Third, disclosure structures still require research, specifically, how AI-driven information on human capital can be reported in a systematic manner, whether on financial statements or management commentaries, or via integrated reporting. It is also possible to use longitudinal and cross-country studies to analyse the effect of institutional and regulatory differences on the adoption and reporting of such metrics.

In general, to promote the future development of research in this field, there should be a transition to the integration of AI-powered measurement with accounting theory, valuation models, and financial reporting practices to ensure the changing concept of firm value in the digital economy.

8. Conclusion

This paper has investigated how AI-enhanced talent acquisition and retention policies influencing the valuation and investor confidence of firms in terms of accounting. The results show that AI-based practices yield quantifiable economic value to the company by increasing operational effectiveness, the quality of workforce and strategic competency, which in turn affect the valuation of firms and investor sentiments. Nevertheless, the research notes a fundamental drawback of current accounting systems: as AI allows measuring human capital-related outcomes, including productivity, engagement, and retention, these internally produced and intangible assets have little or no individual presence in the financial statements. This creates a gap between the creation of economic value and its appearance in

financial statements and restricts the relevance and completeness of the reported information. The results also suggest that AI serves as a measurement facilitator, which allows converting qualitative workforce characteristics into measurable indicators to be used to make valuation and investor decisions. However, there are no similar recognition and disclosure systems and this limits the efficient use of such information in accounting systems. The work contributes to the accounting theory by suggesting a conceptual reconfiguration of measurement and recognition limits that may be involved in the context of AI-driven systems and the necessity to adapt accounting systems to the new type of value-generating processes in the digital economy. On the whole, the paper makes a contribution to the accounting discourse by discussing AI-enhanced human capital as one of the key, but underrepresented sources of firm value and the necessity of new reporting systems to enhance transparency and mitigating information asymmetry.

Author Contributions

Dr. Mohd. Iftikhar Baig: Conceptualization, Methodology, Writing – Original Draft, Supervision.
Dr. Smita Singh: Literature Review, Theoretical Development, Writing – Review & Editing.
Ms. Shruti Sharma: Data Curation, Visualization, Writing Support and Formatting.

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