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Artificial Intelligence vs. Human Intelligence in Interpreting the Fair Value Model: An Analytical Study

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Abstract

The research aims to identify and explore the key differences between the capabilities and potential of artificial intelligence (AI) and human intelligence (specifically accounting intelligence) in understanding the concept of accounting measurement. It also examines how this can be developed as the primary accounting dimension for evaluating accounting products' effectiveness, presence, and development in the real world. This study focuses on the fair value model, which has become the main measurement approach for most financial items after emerging as a competitor to the historical cost model. The research uses a comparative analysis between AI models (Chat-GPT) and researchers to interpret key points in the fair value. The points for comparison are illustrated by a circle surrounding the fair value. The circle begins at the center, representing the concept, then extends through the characteristics, levels, and inputs until it reaches the future. The most important conclusion is that an AI model outperforms human intelligence in response speed when explaining concepts, but lacks a philosophical understanding of ideas. Conversely, human intelligence is characterized by its ability to grasp the meaning of a concept, but requires more time to provide an optimal analytical opinion. Artificial intelligence also follows a standard structural approach to interpretation, whereas human intelligence relies on a scientific method that combines linguistics and deductive reasoning. The researcher recommends that artificial intelligence, both now and in the future, is indispensable and cannot be ignored. Despite its current presence, it has become integral to everything around us. The researcher urges others to develop their philosophical and scientific skills to meet the most challenging future obstacles.

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Introduction

The world is witnessing rapid progress in all sectors, particularly with the artificial intelligence revolution that has spread globally from the West to the East. Artificial intelligence has become an important and influential player in many fields. It has played a crucial role in analysis, reasoning, deduction, comparison, and developing solutions to challenges that scientists have struggled to solve. Artificial intelligence has played a vital role in accounting, analyzing data, drawing conclusions, and predicting performance, risks, and investment opportunities.

The problem of this study revolves around fair value as a measurement method that has not achieved an ideal interpretation and still faces challenges in understanding and application across countries. The goal is to focus on understanding the fundamental differences in the interpretive capabilities of artificial intelligence and human intelligence in the fair value approach, to arrive at a new interpretation that makes a conceptual contribution. The main question that should be addressed is the extent to which artificial intelligence can interpret the concept of fair value and whether it can bring about a fundamental change compared to human interpretations.

All studies address fair value from practical and technical perspectives, comparing it with historical cost and other measurement methods. Still, they have not addressed it conceptually and compared it with artificial intelligence. This study seeks to address a significant research gap. To bridge this gap, the study uses a comparative analysis approach between a large language processing model, represented by ChatGPT, and the researcher's interpretation, focusing on key points, including the concept of fair value, qualitative characteristics, fair value quality, methodological criteria, and the future of fair value in light of radical transformations in the business environment. These interpretations are then evaluated across six key axes: philosophical depth, application, innovation in presentation, critique and development, conceptual clarity, and coherence of ideas, to assess the two approaches systematically. The results aim to provide a conceptual contribution by clarifying whether artificial intelligence can substantially enhance the implementation of the fair value approach or whether human judgment remains superior, thus giving insight for researchers, practitioners, and standard setters.

Literature Review

Fair Value as A Measurement Approach

The first step in developing measurement concepts is establishing a clear conceptual definition of accounting measurement to identify its purpose. Paraphrasing standard dictionary definitions, measurement is the association of numbers with physical or economic characteristics. Conceptually, measurement involves applying numbers to reality. Campbell is regarded as the originator of what is now called basic and derived measurement and developed measurement theory. According to this theory, measurement is limited to assigning numbers to representative properties based on physical laws discovered through basic or derived measurement methods. Accounting measurement significantly influences corporate strategic decisions to determine the value of assets, liabilities, and equity in financial reports. Different accounting approaches can cause substantial variations in financial reporting that reflect an organization's financial position. Therefore, the accuracy of accounting measurements is especially critical. Precise accounting measurements are essential to an organization's strategic planning and decision-making. Measurement involves determining the values assigned to financial statement items and how they are presented in financial reports, such as the balance sheet and income statement. This process includes selecting a specific measurement basis to ensure that accounting measurements provide relevant, helpful, and timely information for control, planning, evaluation, and decision-making. The 2018 revised Conceptual Framework issued by the International Accounting Standards Board outlines measurement basis categories: historical cost and value in use. Value in use includes fair value, value in use (or value in completion), and current cost. The International Accounting Standards Board (IASB) has introduced a new standard, IFRS 13 Fair Value Measurement, to improve consistency and comparability in fair value measurements and related disclosures. The standard defines fair value as "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date. According to the standard, fair value is considered an exit price, meaning what you would receive for an asset when you sold it at a specific time. In this context, fair value is viewed as a market-based rather than entity-specific measure. Fair value accounting emphasizes the balance sheet and uses current market values to report certain assets and liabilities. Therefore, fair value accounting adjusts the historical cost of assets and liabilities, either upward or downward. Fair value income statements provide more relevant information to decision-makers than accrual income statements, and this approach also offers more pertinent balance sheet data than cash and accrual methods. The information derived from using fair value as a measurement basis is considered more relevant because it reflects current values, not the value at the time of purchase. Fair value also refers to the potential benefits expected from an item or its future liabilities. The International Accounting Standards Board believes that, in certain situations, fair value information is more relevant to users than historical cost. In these cases, fair value measurement provides a clearer view of a company's assets and liabilities (its financial position) and a better basis for assessing future cash flow prospects. Fair value offers better predictive value for financial reporting than historical cost because it provides up-to-date data, whereas historical cost reflects past transaction costs. Consequently, fair value is considered more relevant. One key way to enhance relevance is to. Arguments supporting the valuation of fixed assets at fair value include strengthening the financial position, decreasing the company's level of debt, and using the realized revaluation reserves to lower taxable profit upon sale [8]. The fair value measurement process involves identifying the assets and liabilities to be measured, selecting the primary or most appropriate market, and determining the suitable valuation method based on the inputs to the measurement process. Fair value is considered a more subjective and thus less precise measurement approach. However, this is not necessarily true. The accounting information provided more accurately reflects reality if an active market exists to determine fair value [11]. IFRS 13 outlines three standard valuation techniques: the market, cost, and income approaches. It also established a fair value hierarchy that categorizes the inputs of valuation techniques to measure fair value into three levels [1-16].

First, the Market Approach means organizations rely on market information and data to determine fair value. This method depends on prices and relevant details from market transactions involving entities with identical or similar assets and liabilities [14]. In theory, any share of the same type in a company is similar to the last share sold, allowing for direct valuation (assuming a liquid market). An example of a comparable market could be a car [11]. Second, the Income Approach: Valuation techniques that convert future amounts, such as cash flows or revenues and expenses, into a single present value. Fair value is based on market expectations of those future amounts [11]. The standard provides examples of this approach: (a) present value methods; (b) option pricing models; and (c) the multi-period excess earnings method. Third, the Cost Approach: This method reflects the amount currently needed to replace an asset's service capacity, often called the current replacement cost. According to the cost approach, fair value is the cost of acquiring or constructing an identical replacement asset, adjusted for obsolescence. The cost approach estimates fair value using the economic principle that a buyer will not pay more for an asset than the cost to acquire an asset of equal utility. This principle is based on substitution [17]. Level 1 fair value estimates rely on quoted prices for identical assets or liabilities in active markets. Level 2 estimates are based on quoted market prices for similar assets or liabilities and include inputs other than quoted prices, such as interest rates and yield curves. Level 3 inputs are unobservable inputs for a specific asset or liability. Unobservable inputs should be used to measure fair value when observable inputs are unavailable at the measurement date. However, the goal of estimating fair value remains the same: to determine the exit price at the measurement date from the perspective of a market participant willing to pay that price. Holds the identified asset or liability [17-20].

IFRS 13 outlines a fair value hierarchy with three levels, summarized as follows: Level 1 includes assets and liabilities with an observable market price [19]. Level 2 covers assets and liabilities where a market price can be estimated from similar items [15]. Level 3 comprises assets and liabilities without observable or inferred market price. Next, a company should use the best available information about how a market participant who owns the asset or liability would value that item [20]. Proponents of fair value see it as the most suitable measurement because it requires a comprehensive update of all items at each reporting date, providing the clearest view of performance and financial health. The key feature of fair value is relevance, with secondary features of predictability, certainty, and materiality. It offers insights into a company's financial outlook. It guides user decisions. The main advantages of this approach include increasing the relevance and transparency of financial statements by providing information that more accurately reflects an entity's economic position. It captures current market conditions and economic realities. However, criticisms persist, mainly due to significant personal bias and judgment, especially at Level 3. Many investments lack a market price and are valued based on historical costs. Variations in estimates among valuers can undermine trust and accuracy. Fair value measurements rely heavily on managerial assumptions and judgments, leading to information asymmetry. Consequently, fair value accounting can create moral hazards [21-26].

Artificial Intelligence

Artificial intelligence (AI) has advanced rapidly and significantly over the past decade. Its importance continues to grow across many fields and aspects of society. It replaces human decision-making and is used in various sectors such as business, logistics, manufacturing, transportation, healthcare, education, and more. This has increased efficiency and reduced costs. Therefore, AI will impact our personal lives and fundamentally change how businesses make decisions and interact with external stakeholders like employees and customers. The question is, which decisions are best made by AI, which by humans, and which collaboratively?. The Oxford English Dictionary defines AI as the theory and development of computer systems capable of performing tasks that usually require human intelligence. Artificial intelligence (AI) is generally described as a set of technologies that can perform cognitive tasks once limited to humans. The main goal of AI is to deepen our understanding of mental processes, reasoning, learning, linguistics, and creativity. Its core capabilities include statistics, logic, and semantics, which can be combined or enhanced in specific applications such as machine learning-based predictions, rule-based robotic process automation (RPA), semantic natural language processing, deep learning neural networks, or a combination of these Many AI techniques are used in science, the most prominent being:. First, Machine Learning: the fastest-growing AI technique in business, primarily a predictive system. Machine learning involves converting data into a process that computers can perform. It includes discovering, linking, and recognizing patterns, along with continuous regression algorithms, leading to functional predictive capabilities. It is considered a branch of artificial intelligence capable of transforming information related to product features, machinery, production lines, materials, or human resources into valuable results. It focuses on developing algorithms and models that allow computers to learn from datasets. And carry out specific tasks without pre-defined rules. Second, Deep Learning: Deep learning is a subset of machine learning that teaches computers to think using an architecture modeled after the human brain. Specifically, it involves training hierarchical artificial neural networks in an integrated manner, where flexibility at each layer helps achieve learning objectives [27-40].

Deep learning relies on creating deep neural networks with multiple hidden layers, where the layer closest to the data learns simple features, and higher layers learn more complex ones. Deep learning techniques are categorized into three main types: unsupervised, partially supervised, and semi-supervised. Third, Natural Language Processing (NLP): NLP is a core field of artificial intelligence that enables effective communication between humans and computers using natural language. It combines computer science, linguistics, and mathematics to translate human language, comprising two disciplines: natural language understanding (NLU) and natural language generation (NLG). These techniques help extract relevant information from reports and pair it with quantitative metrics to convey extensive information about current and future financial performance. Large language models (LLMs) have demonstrated unprecedented language understanding and generation capabilities, leading to breakthroughs in reasoning, mathematics, science, and many other tasks. Common approaches for applying large language models to time series forecasting generally fall into two main types: intra-modal transfer learning and cross-modal knowledge transfer [41-47].

Chat-GPT, a chatbot launched by OpenAI in November 2022, is one of the most powerful and widely used large language models (LLMs). Chat-GPT is known for generating high-quality text based on context or user-provided prompts. With its release, human writing has experienced an unprecedented transformation. For the first time, a large language model (LLM) is broadly accessible and capable of generating and proofreading text with human-like performance across many fields. Although Chat-GPT was primarily designed for human-like conversations, its capabilities extend far beyond that. It excels at creating original content such as stories, poems, and novels, and can mimic various behaviors. Chat-GPT is highly skilled in different types and levels of writing, including linguistic knowledge, language processing, information retrieval, summarization, writing tasks, and research. It can also participate in interactive conversations and follow up on previous responses. Acknowledge errors, challenge false assumptions, and reject inappropriate requests. GPT is designed for natural language processing (NLP) tasks involving two key aspects: (1) analyzing and understanding the meaning of a sentence (natural language understanding), and (2) generating new sentences based on input (natural language generation) [48-54].

The OpenAI team developed the first version of its pre-trained generative language model (GPT-1), a transformer-decoder-based model. It did not introduce new features to the model's architecture. GPT-2 included five minor improvements, expanded training data, improved generalization, and addressed the need for supervised fine-tuning when using GPT-1 for future tasks by providing more information during training. GPT-3 is a machine learning platform that allows developers to train and deploy AI models. It is also considered scalable and efficient, capable of handling large amounts of data. GPT-4 is a large multimodal model capable of processing image and text inputs and generating text outputs. These models are significant because they are helpful in many areas, such as dialogue systems, text summarization, and machine translation. Fourth: Artificial Neural Networks: An artificial neural network consists of multiple layers of interconnected nodes between input and output data. Each layer transforms the input into a more abstract representation, which the next layer then uses as input to produce that level of abstraction. An artificial neural network includes input, hidden, and output layers. The input layer receives raw data for explanatory variables, with the number of nodes matching the number of variables. It connects to hidden layers, which perform complex transformations on the data and pass it on to subsequent hidden layers. This structure forms the basic architecture of deep learning. These networks mimic the human brain because they consist of a network of information-processing nodes called neurons. Neural networks can analyze large datasets with complex features, extract distinct patterns, and help predict behaviors, detect anomalies, and recognize images, sounds, or graphics [55-62].

Methodology and Results

The study adopts a comparative analytical approach to examine the interpretation of fair value between artificial intelligence, represented by the ChatGPT-5 model, and human intelligence (accounting judgment), represented by the researcher. The study aims to determine whether artificial intelligence can provide an alternative or complementary interpretation to the human interpretation. To achieve this, the study identified five dimensions for comparative analysis: the concept of fair value, qualitative characteristics, fair value quality, fair value measurements, and the future of fair value. The interpretations generated by ChatGPT-5 were then compared with the researcher's interpretations and evaluated according to six AI-based dimensions: philosophical depth, application, innovation in presentation, critique and construction, conceptual clarity, and coherence. Each interpretation is evaluated on a 1-5 scale, with 1 representing the lowest performance and 5 representing the highest performance. The evaluation process is conducted using artificial intelligence to ensure impartiality and objectivity.

First: The Concept of Fair Value

Artificial Intelligence

Fair value isn't just a number calculated or retrieved from the market. Instead, it's a complex idea that reflects the intersection of economic worth and perceived fairness at a specific moment. It isn't the "absolute truth" of an asset's value, but rather a "consensus" among market participants, who are assumed to be rational, informed, and not forced to buy or sell. Fair value is significant for aligning information with contemporary markets, but its fundamental problem is that it is not always fair. It is fair in the market sense, but not necessarily fair from the perspective of less powerful stakeholders, because it is affected by liquidity, the dominance of market players, and supply and demand conditions.

Human Intelligence

We adopt a scientific approach to understanding any concept. We examine the term linguistically and then use deductive and inductive methods to evaluate the idea. First, what does 'value' mean in linguistic terms? It has a linguistic root (q-w-m), which means something that is valued or assessed. It is typically used to describe the worth of something in exchange for a benefit. It also means standing and stability, indicating that something remains valid and respectable, or it refers to moderation. Analyzing the linguistic root of 'value' reveals that the letter q signifies standing, w signifies moderation, and m signifies stability. Similarly, its Latin root (valere) means to be strong or worthy. We can understand 'value' as a measure used to determine the status of something within a specific context. It varies depending on the context and never refers solely to the price of something. When we say that the value of this book is excellent, we mean more than its price; we refer to its impact on knowledge, content, and overall significance. The second term is justice, which linguistically derives from the trilateral root (a-d-l), and it carries meanings related to leaning, staying away from injustice, rectitude, balance, and moderation. When we say ‘adalat’, we mean to straighten or put everything in its natural place; it signifies a measure that mediates between two sides, such as excess and deficiency. To integrate these two terms, we rely on the definition of fair value according to IFRS 13. We note that it focuses on price, implying it is purely an economic measure and neglects the social aspect, forgetting that accounting is a science meant to benefit society. Therefore, the limitation of fair value as an approach is that it reflects only the economic situation, without considering the social context. Additionally, while this approach aims to uphold justice, it may be influenced by management estimates and biases.

Second: Qualitative Characteristics

Artificial Intelligence

When discussing the "qualitative characteristics" of fair value, we don't just refer to formal traits or technical accounting details. Instead, we focus on the intrinsic qualities that make fair value understandable, meaningful, and justifiable in financial and accounting contexts. Fair value isn't only an "accurate" number; it also needs "cognitive characteristics" that make it sensible, reasonable, and acceptable to information users. Therefore, understanding the qualitative characteristics of fair value involves two perspectives: a formal and technical view. Is this value understandable, verifiable, and relevant for decision-making? A philosophical, cognitive perspective: Does this value reflect or influence reality? Does fair value mimic reality or create a new perception in the investor's mind? Here are the traits we evaluate for this approach: Relevance: How much the value impacts a decision. Faithful Representation: Does the value accurately depict what it measures? Verifiability: Can someone else produce the same value using the same method? Understandability: Is the value apparent to an average user?

Human Intelligence

By qualitative characteristics, we refer to the criteria and attributes that distinguish one thing from another and make it superior. I believe that the traits that differentiate fair value are fundamental qualities such as relevance and faithful representation. The fair value approach achieves relevance because it reflects current market prices and offers significant predictive value to users, emphasizing the present and the future. By predictive value, we mean future expectations based on current data. The characteristic of faithful representation is also well depicted by the standard value approach, as it accurately reflects the economic situation using current, not historical, data. However, we strongly criticize the characteristic of faithful representation because it only portrays an image, which limits and constrains the scope of accounting, causing the field to revolve around the same cycle and ignoring that the business environment is rapidly changing, especially with the rise of artificial intelligence. Regarding enhancing characteristics, the fair value approach, if applied effectively, achieves comparability. This trait is essential for analysis, comparison, planning, and decision-making. The comparative approach identifies similarities and differences, highlighting strengths and weaknesses. It is a scientific method fundamental to the development of all sciences. We believe that comparison leads to a decision that aims at change.

In our view, the characteristic of verifiability fails if we adopt the decision-usefulness approach because this approach requires choosing either one or zero. There is no room for debate. This approach emphasizes providing helpful information, regardless of whether the information is verifiable or provable. Therefore, we conclude that verifiability is not a crucial characteristic because most users cannot verify the source of the information, but instead focus on its usefulness.

The other characteristic is understandability. This is a reinforcing characteristic, meaning that for information to be helpful, it must be understood by the user. Ability refers to actual skill, while understanding relates to perception. We see understandability as a redundant link, implied within the relevance characteristic. How can information be relevant if it is not understandable and clear? Even if information has predictive value, it cannot be deemed appropriate. This leads us to ask an important question: how do we measure understanding among multiple levels of users? The answer depends on preparing financial statements, which target rational investors who believe in the data's validity and base their decisions on it. The other group, naive investors, is less relevant because they act randomly and lack clear objectives. The last characteristic, timeliness, according to the conceptual framework, means providing information at the right moment before it loses its ability to influence. In our view, timeliness is an essential characteristic, not just a reinforcing one. It relates to the existence or non-existence of companies in a competitive environment, serving as a criterion for success or failure. It is unreasonable to treat the criterion for a company's existence as merely a reinforcing characteristic. Expecting a company to provide timely information while struggling against the clock would be illogical. To clarify, is it rational to say that a company's characteristic is to generate profits? Is that a characteristic or an existential condition? Therefore, we conclude that timeliness cannot be a characteristic under any approach other than fair value or similar frameworks.

Third: Fair Value Quality

Artificial Intelligence

Fair value quality isn't just about numbers; it's a concept rooted in knowledge, trust, and context over time. To be considered good, a value must do more than meet standards; it should provide reliable information in practice. Fair value quality measures how well it fulfills its roles in accounting and understanding: Is it useful? Is it understandable? Can it be trusted? Does it stay stable despite changing conditions? Quality isn't only about how accurately it reflects reality and its ability to support sound decision-making. That means good value isn't always the closest to market prices; it might be the one that reduces uncertainty and presents reality with sufficient accuracy.

Human Intelligence

At this point, we will examine the quality interpretation from a linguistic and semantic perspective, then discuss the quality of the fair value approach. The word "quality" comes from the root (G-O-D), which signifies mastery, distinction, and improvement. It refers to the excellence or craftsmanship of something, making it worthy of admiration and setting it apart from others. Using this linguistic concept, we explore the quality of fair value by asking: Is the fair value approach higher quality than other measurement methods? The answer is honest and objective. The fair value approach surpasses historical cost, current value, and different measurement techniques. Its main advantage is that it relies on current market prices instead of historical ones. Additionally, it provides more relevant information and reflects economic reality more accurately. It also offers insights into future trends and helps justify decisions. Furthermore, it aligns with the decision utility approach emphasized by the conceptual framework. For example, if we presented financial statements based on fair value and those based on historical cost to a group of investors, which would they prefer? The answer isn't straightforward, as choosing one depends on analyzing all financial statement items and comparing the measurement approaches used. This comparison determines the highest quality approach and delivers the most useful financial information. Considering the qualitative characteristics gained and those sacrificed, rational logic based on decision utility and the goal of serving the user suggests that the fair value approach is the most suitable and superior method, as it offers high quality and distinguishes itself from the outdated historical cost approach.

Fourth: Fair Value Measurements

Artificial Intelligence

When we discuss fair value measures, we're referring to numerical tools or equations, cognitive systems, and philosophical ideas about what should be considered value. A value measure isn't just a calculator but a model that simplifies reality into a digital form based on specific conditions and rules. According to international standards, fair value measures are classified into three levels: Level 1 Input data from active market prices;

Level 2 Observable but indirect inputs; and Level 3 Unobservable inputs based on models and subjective estimates. However, these levels go beyond technical classifications; they represent different degrees of approximation to reality. The further we move from them, the more hypothetical and symbolic their value becomes.

Human Intelligence

The fourth point explains fair value measurements. IFRS 13 classifies fair value measurements into three levels: Level 1 includes directly observable market inputs; Level 2 covers observable but indirect inputs; and Level 3 consists of highly managed, unobservable inputs. Level 1 uses quoted prices and active markets, with no measurement issues, making it the highest quality. Level 2 involves unquoted prices and is of moderate quality because it relies on similar markets for assets and liabilities. Level 3 presents measurement challenges and depends on subjective judgment, so it is of lower quality. We recognize that Level 1 measurements are free from problems; they are verifiable, reliable, and suitable, allowing for high comparability. Level 2 is less reliable because it depends on similar market data. Management decisions can influence measurements, possibly aimed at specific objectives, which could impair financial statement quality by undermining their qualitative characteristics. Level 3 involves management-controlled estimates, leading to unreliable, unverifiable, and less comparable results due to high estimation levels, assumptions, and bias, resulting in weak neutrality. IFRS 13's three levels align with three measurement approaches: the market, income, and cost approaches. The market approach is considered the most effective because it reflects the economic reality of items on financial statements but overlooks social aspects, focusing solely on monetary measures. The income approach estimates future value by calculating the present value of expected future cash flows. It could become the best approach if applied perfectly with all conditions met and executed by automated systems, potentially replacing other measurement methods. The cost approach, in my view, is unnecessary. Its relevance is temporary and depends on the market and income approaches. If both were developed optimally, the need for the cost approach would vanish, as it makes the fair value approach less reliable and weakens the efficiency of financial markets.

Fifth: Future Fair Value

Artificial Intelligence

Suppose fair value today represents the best estimate of an asset's worth under current market conditions. Then, the question about its future becomes more complex: Will this concept still apply in a world where markets change rapidly? Will fair value still be considered "fair" under artificial intelligence? Will what we see as a measure today be regarded as a source of value creation tomorrow, rather than just a measurement? In the future digital economy and with intelligent systems, the idea of value itself becomes more fluid because it is not solely the result of human interactions in a physical market but also algorithmic interactions and self-generated forecasts. A key question arises: Will fair value continue to reflect market reality, or will it become a tool for constructing and shaping that reality? Fair value becomes more significant because it relies on predictive models that generate the future rather than merely describe it. It also becomes less transparent because it’s not created by a human who can be held accountable, but by a machine that does not think only predicts. With the rise of artificial intelligence, the traditional three metrics might be replaced by a new one: Predictive Fair Value (PFV). A value is derived not from current market data but from predictions of what the market is "expected" to be based on patterns beyond human perception.

Human Intelligence

The final element concerns the future of fair value. We expect a significant shift in the conceptual framework soon, driven by the artificial intelligence revolution. Some established concepts will be replaced, others will be eliminated, and many will be modified and expanded. The fair value approach is one of the most prominent concepts likely to be affected by this wave of change. Key predictions for its future include the following: The concept of fair value, as outlined in the framework, is a price that moves from an asset's selling price or transfer of a liability to the actual value of the asset or liability itself. We note that value includes more than just price it also encompasses quality, cognition, economic, and social dimensions. The fair value approach will influence and probably replace other measurement methods, mainly historical and current cost, as it becomes linked to artificial intelligence. The accuracy of fair value will improve significantly because it reflects current market prices at any given moment and does so continuously.

Fair value levels will be simplified, leaving only the first level, with the market approach used exclusively for measurement. We will no longer hear about the cost and income approaches. The fair value method will address the ongoing challenge of financial market efficiency. In the future, it will reduce information asymmetries and enhance market efficiency. The unification of financial statements covering all items such as assets, liabilities, revenues, and expenses will heavily depend on the role of artificial intelligence.

To objectively assess the accuracy, depth, and clarity of AI-generated and human-generated explanations, the study conducted a comprehensive evaluation across six dimensions, scoring each on a five-point scale (1 = lowest, 5 = highest) based on its quality and effectiveness. The comparative evaluation results are summarized in Table 1, which illustrates the relative strengths of the two approaches and highlights the dimensions where they appear superior.

Table 1: Evaluation Aspects between Artificial Intelligence and Human Intelligence

Comparison Side	Artificial Intelligence	Human Intelligence	Preference
Philosophical Depth	4	5	Human Intelligence
Application	4	4	Equal
Innovation In Offering	5	5	Equal
Criticism And Construction	3	4	Human Intelligence
Clarity Of Concepts	4	4	Equal
Linking Concepts	4	3	Artificial Intelligence

We conducted a purely analytical study focused on interpreting concepts represented by the fair value approach. Five items were chosen to compare artificial intelligence and human intelligence: starting with the idea of fair value, then moving to qualitative characteristics, model quality, metrics used, and finally, the model's future. Table 1 assesses these interpretations, which AI evaluates. According to the table, AI outperforms human intelligence in three areas of superiority. The first is philosophical depth, where AI is described through a logical and modern philosophical analysis that presents the concept as a consensus rather than an absolute truth, focusing on the interaction between market knowledge and predictive models. At the same time, human intelligence surpasses with its linguistic and intrinsic depth, based on the linguistic analysis of the terms "value" and "fairness," expanding into cognitive and ethical dimensions.

The second dimension focuses on qualitative characteristics. Artificial intelligence is interpreted from a complex and dual perspective, blending a normative approach with a realistic philosophical framework. Its strength lies in providing a deep understanding of the creation of reality, a very clever idea. Its weakness lies in its complexity, which makes this constructive dimension difficult for the average user to grasp. On the other hand, human intelligence provides an excellent critical analysis of the accounting conceptual framework, criticizing some features, especially accurate representation, and redefining understanding and signature. Its strength lies in its objective and intelligent critique, placing accounting reality within an evolutionary framework. Its weakness lies in using caustic phrases that criticize the conceptual framework.

The third dimension: Fair value quality. AI conceptualizes quality by linking utility to stability in decision-making, not just accuracy. Its strength reflects its understanding of what goes beyond accuracy, and thus quality as a cognitive function, while its weakness lies in how cognitive utility is measured in practice. On the other hand, human intelligence has an excellent linguistic and philosophical approach, with a clear defense of fair value against historical cost and different measurement methods. Its strength lies in an analysis based on a central question: Which do you prefer? Its weakness lies in its over-defense of fair value.

The fourth point emphasizes Fair value measurements. We observe that artificial intelligence offers a philosophical and analytical perspective on these metrics, viewing them not merely as technical categories labeled as level one, two, and three, but as varying degrees of approximation to reality that differ in their symbolic scope and proximity to market truth. The benefit of this perspective is its symbolic and philosophical approach to measurement levels, enhancing the analytical framework. However, its drawback is the absence of a direct understanding of the risks associated with each level and the lack of analysis on situations where misuse might occur such as with level three and how these could impact financial statements. In contrast, the interpretation based on human intelligence involves a detailed explanation of each of the three fair value levels, an objective comparison of the quality of their outputs, and an analysis of how each relates to concepts like neutrality and bias. Its strength resides in a structured academic method that evaluates each level by quality, verifiability, and management influence. Its weakness is that it often makes absolute judgments such as favoring one approach over another based solely on market or income considerations without considering scenarios where another approach, like cost, might be more appropriate in specific cases.

The final aspect concerns the future of fair value. AI envisions this future with an ambitious and innovative analysis that introduces a fourth level of predictive value. Its strength lies in its innovation, paving the way for academic research into models of future intelligence. However, its weaknesses include not addressing ethical issues and regulatory controls in a machine-driven future. On the other hand, human intelligence is characterized by a realistic and balanced perspective based on an evolutionary view of the conceptual framework, forecasting the integration of financial statements and moving beyond traditional measurement methods. Its strength is its solid theoretical foundation, and its predictions align with the evolution of the accounting profession. Nonetheless, its weaknesses suggest that humans will have a significantly diminished role, while the future points toward integration rather than maximization.

Discussion

The study compared the interpretive capabilities of AI and human intelligence regarding fair value as a measurement tool. The analysis focused on five key dimensions: concept of fair value, qualitative characteristics, fair value quality, fair value measurements, and the future of fair value. The results indicate that human intelligence demonstrates a superior tool for philosophical depth and critical analysis, demonstrating stronger linguistic, conceptual, and ethical reasoning. On the other hand, AI excels at connecting concepts and providing innovative and forward-looking insights, particularly about predictive models and future measurement approaches. However, both approaches demonstrate equal utility in application, conceptual clarity, and innovation, indicating that each is uniquely equivalent in interpreting fair value. These findings highlight that combining AI-based analysis with human judgment provides a more comprehensive framework for improving fair value interpretation and enhancing decision-making processes.

Conclusion

This study highlights the growing role of artificial intelligence in formulating fair value interpretation in accounting. By comparing AI-derived insights with human understanding, the study demonstrates that both approaches possess unique strengths that complement rather than compete. The results confirm that combining AI capabilities with human expertise can improve the quality and usefulness of financial information, contribute to improved decision-making processes, reduce information asymmetry, and support the ongoing transformation of accounting practices in an era of rapid technological advancement. It also allows researchers to reconsider the challenges facing measurement approaches.

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