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AI-GENERATED CONTENT AND REVENUE RECOGNITION: A CONCEPTUAL STRESS TEST OF ASC 606 AND IFRS 15

Siriyama Kanthi Herath[1] and Omolayo Ogunnoiki[1]

[1]*School of Business, Clark Atlanta University, 223 James P. Brawley Dr., S.W., Atlanta, GA 30314, USA. E-mail: sherath@cau.edu; omolayo.ogunnoiki@students.cau.edu*

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Abstract: The growing use of AI-generated content (AIGC) is creating new challenges for recognizing revenue under the accounting standards ASC 606 and IFRS 15. These rules were designed around the idea that companies can clearly identify what they are promising to deliver (their performance obligations), that there are enforceable rights and responsibilities between the parties, and that each promised item or service has a reasonably clear stand-alone selling price. However, AI-powered production settings do not fully conform to these assumptions. Generative systems operate at low to no marginal cost, are based on algorithmic and usage-based pricing models, and the intellectual property status of their outputs has not yet been legally established.

This paper presents a conceptual stress test of the five-step revenue model in AI-intensive environments. We argue that AI does not undermine the control-based structure of ASC 606 and IFRS 15; rather, it weakens the traditional evidentiary anchors that historically disciplined stand-alone selling price (SSP) estimation and transaction price allocation. As marginal cost ceases to function as an observable indicator of economic value, allocation decisions become increasingly estimation-based, expanding managerial discretion and increasing variability in reported revenues.

To overcome these tensions, we propose the AI Value Attribution Framework (AVAF), which is an interpretive clarification based on the existing Market Assessment Approach. AVAF emphasizes economic utility benchmarking because marginal

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cost is no longer a significant valuation signal. An illustrative example shows how the framework leads to improved representational faithfulness without the need to alter the existing standards. In conclusion, we suggest that additional clarification of SSP benchmarking and more AI-related disclosures would allow the maintenance of comparability and the minimization of the possible risk of economically biased reporting in AI-intensive industries.

Keywords: Artificial Intelligence; Revenue Recognition; ASC 606; IFRS 15; Stand-Alone Selling Price; Earnings Management

INTRODUCTION

Financial reporting revolves around revenue recognition. It significantly influences firm valuation, investor expectations, and executive compensation, and remains subject to recurrent regulatory review. Under ASC 606 and IFRS 15, one of the most significant steps toward harmonization was taken, and industry-specific guidance was superseded by a more unified principle-based model that places emphasis on the transfer of control (FASB, 2014). This five-step model was intended to improve comparability and reduce opportunistic timing of revenue.

There are, however, several basic assumptions in this model about value creation and measurement. It assumes that businesses are aware of what they are selling, that agreements form legally binding rights and duties, and that every product or service is sold at a stand-alone price which can be projected with reasonable reliability at a fair degree of accuracy.

The assumptions hold in a traditional business environment because organizations rely on easily identifiable costs, attributable labor efforts, and current market prices.

In Step 4 of the revenue recognition process, companies assign the transaction price to different performance obligations. This allocation is based on real-world allocation methods, such as cost-plus methods or comparing with observable market prices (FASB, 2014).

This argument is challenged by the rapid development of generative artificial intelligence. AI systems are now able to produce text, images, code, music, and other forms of digital output at scale with extraordinarily little human intervention (Wu et al., 2023). Once these systems are trained, they generate additional outputs at low marginal cost, thereby undermining the historical relationship between production inputs and economic value. With the increasing adoption rate in the media, software, finance, and marketing industries, firms' revenue models are also evolving (Yuan et al., 2025).

AI-generated content has three features that are of particular concern for revenue recognition. First, near-zero marginal cost reduces the usefulness of cost-based heuristics in determining transaction price (Wu et al., 2023). Second, uncertainty in intellectual property law--particularly regarding authorship and copyright protection--complicates the assessment of transfer of control (Voinea, 2023; U.S. Copyright Office, 2024). Third, AI services are increasingly based on dynamic, usage-based pricing schemes, thereby enhancing reliance on estimates of variable consideration (Ali & Tseng, 2025). Together, these factors do not render the control-based model obsolete, but they place substantial pressure on its application.

This paper addresses a straightforward but important question: When the cost of producing AI-generated content approaches zero, and ownership rights are difficult to clearly establish, does ASC 606 adequately capture the economic substance of these transactions?

Previous studies have already explored earnings management in revenue-based reporting (Badger et al., 2025; Stubben, 2010) and have also investigated the role of changing technology in transforming accounting practices more broadly (Herath & Herath, 2024). However, there has been inadequate focus on whether the five-step revenue recognition model continues to reflect economic reality when products or services can be produced at near-zero marginal cost.

Despite earlier studies on the earnings management topic using ASC 606 and the overall digital transformation of accounting, little focus has been directed at whether the five-step framework continues to be conceptually sound in settings where the marginal cost of production is close to zero. Specifically, the effect of the collapse of cost as supporting evidence on the estimation of stand-alone selling price (SSP) and transaction price allocation has not been clearly evaluated in the literature.

To fill this gap, this paper proposes a conceptual analysis. It adds value to accounting theory by evaluating whether the control-based revenue recognition model would be consistent in economic context with low marginal costs of production.

We frame this analysis as a robustness test of ASC 606 under conditions of marginal cost collapse. Rather than proposing structural reform, we argue that interpretive refinement within the existing framework is sufficient.

We assume that ASC 606 is internally consistent, but that its application is exacerbated by AI, particularly with respect to managerial estimation and interpretive discretion regarding the allocation of transaction prices and the timing of revenue recognition. In response to this pressure, we propose an interpretive clarification of the Market Assessment Approach under Step 4: the AI Value Attribution Framework (AVAF). Rather than applying production cost as a proxy for value, AVAF focuses on economic utility benchmarking in situations where cost is no longer a reliable indicator.

The remainder of the paper proceeds as follows. Section 2 discusses the conceptual basis of control-based revenue recognition. Section 3 analyzes the economic characteristics of AI-generated content. Section 4 undertakes a stepwise stress test of the five-step model. AVAF is developed and illustrated in Section 5. Sections 6-11 address audit implications, discretion and earnings management, regulatory considerations, limitations, future research directions, and the conclusion.

2. CONCEPTUAL BACKGROUND

2.1. The Control-Based Revenue Model

ASC 606 reflects the movement toward an asset-liability and control-based paradigm (FASB, 2014). Revenue recognition occurs when an entity fulfills a performance obligation by transferring control of a promised good or service to a customer.

The presence of control is demonstrated by the customer's ability to:

1. Direct the use of the asset,
2. Obtain substantially all of the remaining benefits, and
3. Restrict others' access.

This principle is operationalized through the five-step model:

1. Identify the contract.
2. Determine the performance obligations.
3. Establish the transaction price.
4. Allocate the transaction price and
5. Recognize revenue when or as performance obligations are satisfied.

Acceptable estimation techniques include the adjusted market assessment technique, the expected cost-plus margin technique, and the residual technique

(FASB, 2014). These techniques are useful when cost structures or market prices are available as reliable substitutes for economic value.

Evidence indicates that ASC 606 has improved interfirm comparability, although it has increased the level of managerial estimation required, particularly with respect to issues of variable consideration and stand-alone selling price estimation (Badger et al., 2025). When revenue recognition is subject to managerial judgment and increased estimation choice, incentives to manage earnings are likely to increase (Stubben, 2010; Dechow et al., 1995).

When an observable cost basis is not available, the informational underpinning for allocation decisions is weakened.

2.2. Economies and Values of Intangibles

As mentioned earlier, there is a growing tension between historical cost accounting and value creation in economies increasingly driven by intangible assets (O'Regan, 2015). Value generation in digital settings, data-driven companies, and software companies is not inherently connected to traditional asset valuation methods.

Generative AI further worsens the situation. After the training process, the AI model can generate outputs at minimum or zero marginal labor cost (Wu et al., 2023). This model reduces the usefulness of cost-based indicators traditionally used to estimate SSP of revenues to packaged services (Bouzid, 2025).

On the other hand, technological changes in accounting practices have led to an increase in the use of AI in reporting systems, in areas where revenue recognition involves interpretive judgment (Herath and Herath, 2024). With AI becoming more integrated not only in operations but also in financial reporting systems, consistency in allocation decisions and control reviews becomes increasingly important.

3. ECONOMIC FEATURES OF AI-GENERATED CONTENT

3.1. Structural Decoupling of Labor and Output

The AI system has high fixed costs of training and low marginal costs of production (Wu et al., 2023). The exact proportional relationship between labor and output is broken, and the production process is decoupled from the typical effort-output relationships.

It becomes difficult to identify the performance obligations in Step 2, particularly when customers place value on the continuous generative capability as opposed to discrete file generation. Customers, in most cases, pay for the unceasing use of the creative capacity as opposed to discrete outputs. Whether such obligations qualify as independent performance requirements, therefore, is a matter of considerable judgment, mainly in packaged or service contracts (Financial Accounting Standards Board [FASB], 2014; International Accounting Standards Board [IASB], 2022).

AI contracts may include possibilities of (i) discrete digital outputs, (ii) ongoing access to content creation, or (iii) licensing of model capabilities. Each of these has unique implications for the identification of performance obligations in Step 2.

The economic distinctiveness of generative capability, as opposed to labor, alters the information basis for the measurement of value.

3.2. Near-Zero Marginal Cost and Value Attribution

However, after the AI models are trained, additional content can be generated at a near-zero marginal labor cost (Wu et al., 2023). Under such conditions, the cost-plus analysis becomes less expressive. The absence of significant additional manufacturing costs raise questions about the relevance of cost-based rules in allocating transaction prices.

The near-zero marginal cost may result in the allocation of ratios that tend to allocate economic value to AI outputs as opposed to platform inputs. Since there is no strong relationship between labor and output, the cost ceases to be a relevant indicator of economic value.

This creates significant challenges for Step 4 of the revenue recognition standard, where the transaction price is split among different performance obligations using methods such as cost-plus analysis or comparative evaluation grounded on observable market prices (FASB, 2014).

3.3. Intellectual Property Ambiguity

Legal consideration of authorship and copyright in computer-generated works remains unsettled across jurisdictions (Voinea, 2023; U.S. Copyright Office, 2024). Professional law firms have known this as a mounting issue (New York State Bar Association, 2025).

This uncertainty in intellectual property rights has a direct impact on Step 5 of the revenue recognition process, where the transfer of control needs to be evaluated. In such situations, where ownership and exclusivity are in question, it is more demanding to determine if control has been transferred at a point in time or over a period.

3.4. Algorithmic Pricing and Variable Consideration

AI services are frequently priced using token-based consumption and tiered subscription (Hussnain & Nadeem, 2025). These pricing methods raise the likelihood of variable consideration analysis (Ali & Tseng, 2025). Table 1 shows the literature streams.

Because pricing is often based on projected usage patterns rather than fixed deliverables, firms must rely on estimation procedures that incorporate historical trends and forward-looking projections. This increases the subjectivity inherent in transaction price models under Step 3 of ASC 606.

Table 1: Literature Streams and Implications for AI Revenue Recognition

Theme	*Representative Studies*	*Implication*
Near-zero marginal cost	Wu et al. (2023)	Weakens cost-based SSP anchors
IP ownership uncertainty	Voinea (2023); U.S. Copyright Office (2024)	Complicates control transfer
Managerial discretion	Ali & Tseng (2025); (Stubben, 2010)	Expands earnings management risk
Digital audit transformation	Herath et al. (2024); Zaytoun & Elhoushy (2024)	Shifts assurance toward algorithm verification

Existing research reports technological, legal, and discretion-related dimensions separately but does not directly analyze revenue allocation under marginal cost collapse.

4. STRESS TEST OF THE FIVE-STEP MODEL

We conceptually evaluate each step of ASC 606 under AI-intensive conditions. Table 2 consolidates the primary strain points.

The stress test indicates that stress is concentrated in Steps 4 and 5. This reflects interpretive strain in allocation and control evaluation and the presence of main interpretive voids in the AI-intensive set-up, which is caused

Table 2: Stress Analysis of ASC 606 Under AI-Generated Content

Step	*Core Requirement*	*AIGC-Specific Strain*
Step 1	Identify contract	Complex contractual enforceability considerations
Step 2	Identify performance obligations	Distinguishing output vs. access rights
Step 3	Determine transaction price	Volatile variable consideration
Step 4	Allocate transaction price	Weak cost anchors; residual subjectivity
Step 5	Recognize revenue	Control ambiguous due to IP uncertainty

by allocation mechanisms and control evaluation. Even though the overall contractual framework is functional, it is becoming increasingly a matter of managerial discretion and modification, especially where marginal cost can no longer be used as a useful valuation point.

Figure 1 presents an intuitive assumption of an interdependence of AI-intensive production features with ASC 606 interpretive strain. Specifically, the

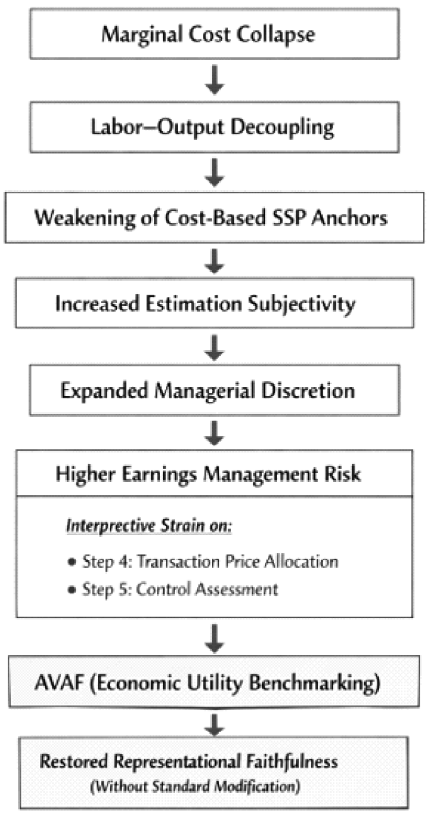

Figure 1: Conceptual Stress Pathway: AI Production and Revenue Recognition Under ASC 606

loss of the relationship between marginal cost and economic utility negatively affects classical cost-based SSP estimation proxies and imposes greater pressure on managerial judgment in allocation and recognition choices. This enhanced discretion opens the chances of variation in the reported revenues.

4.1. Why ASC 606 May Already Be Adequate

One could argue that ASC 606 is deliberately principle-based and does not rely on cost structures for revenue recognition. The standard requires allocation based on SSP, even if production cost is high or negligible. From this perspective, AI production does not modify the mechanics of revenue recognition.

However, although cost is not formally required, it traditionally served as an observable standard supporting SSP estimation. In its absence, reliance on estimation judgment rises, increasing variability in allocation outcomes among firms and reporting periods.

5. THE AI VALUE ATTRIBUTION FRAMEWORK (AVAF)

5.1. Conceptual Foundation

Importantly, AVAF functions as a disciplining mechanism rather than methodological expansion. By requiring observable or defensible economic benchmarks, it limits arbitrary residual allocation and constrains discretionary revenue attribution in AI-driven contracts.

Core principle: When production cost no longer expressively reflects the benefits delivered, benchmarking should rely on economically equivalent market outputs.

AVAF requires that economic benefits be supported by observable or defendable market indicators:

1. External comparable pricing (e.g., freelance marketplaces)
2. Replacement cost of equivalent human-created output
3. Observable willingness-to-pay surveys
4. Similar examples in related industries

5.2. Decision Logic

AVAF proposes a decision node:

Does the AI-generated output establish the primary economic value driver within the contract?

If yes → Apply economic benefit benchmarking.
If no → Traditional SSP methods remain appropriate.

5.3. Illustrative Case: SoundAI

Assume SoundAI offers AI-generated music via subscription priced $60.

Comparable human-composed track: $40

Platform subscription access: $20

Under AVAF:

- $40 allocated to AI-generated content
- $20 allocated to platform access

If subscription provides continuous generative capability, revenue is recognized over time consistent with the criteria for over-time recognition under ASC 606.

Table 3: SoundAI Allocation Comparison

Allocation Method	*Content Allocation*	*Platform Allocation*
Cost-Plus Proxy	Nominal allocation	Residual allocation
AVAF	$40	$20

AVAF aligns revenue allocation with customer economic motivation rather than marginal server expense.

6. AUDIT, ASSURANCE, AND GOVERNANCE IMPLICATIONS

The increase in AI-generated content changes the evidentiary foundation of how auditors identify revenue recognition. Customary practices of revenue audit rely on inspection (Herath et al., 2024; KPMG, 2024; Vasarhelyi et al., 2015). Digital transformation does not just happen in processing transactions but also in assurance models (Herath & Herath, 2024). The digital transformation of auditing has not occurred uniformly across jurisdictions and regulatory environments (Herath & White, 2025).

6.1. From Transaction Testing to Model Validation

Under ASC 606, auditors are obligated to assess management's judgments regarding the identification of performance obligations and the estimation of variable consideration and transaction price allocation. In domains that use artificial intelligence heavily, these evaluations are becoming increasingly based on estimation systems that are algorithm-driven as opposed to cost-driven.

Based on past research, data analytics integration makes changes to the audit methods, where sampling is performed at the transaction level and replaced by system-based, continuous, and analytics-based assessment models (Vasarhelyi et al., 2015). The role of the auditor, in this case, changes to assessing the integrity, stability, and governance of algorithmic estimation models.

When using the token-based usage pricing model, management should base its estimates on historical usage trends and predictive analytics (Ali & Tseng, 2025). These estimates rely on the stability of the underlying model and the integrity of the data. Auditors should evaluate:

- Predictive model accuracy
- Assumptions underlying usage forecasts
- Back-testing of historical estimation error

This denotes a shift from verifying delivery of goods or services toward validating the integrity of valuation methodologies (KPMG, 2024).

6.2. Algorithmic Drift and Valuation Instability

AI models are continuously trained and updated with new information, or the model setup is changed. Such recurring procedures can have a significant impact on the quality of the output, demand, and pricing strategy (Wu et al., 2023). Gradual changes in the algorithms are one of the contributing audit risks.

The auditor ought to see whether the management revises assumptions of benchmarking accordingly and that the revenue allocation methods are also consistent with the economic substance (Herath et al., 2024).

6.3. Governance Expansion: AI Literacy in Accounting Controls

The review of AI processes should be included in the internal control systems. Accounting processes are becoming more technology-focused and increasingly rely on knowledge that cuts across a variety of fields, especially when financial reporting relies on data science infrastructure (Herath & Herath, 2024).

Effective controls may include

- Documentation of SSP benchmarking methodology
- Periodic reassessment of synthetic utility benchmarks

- Oversight mechanisms for pricing algorithm modifications

Strengthening governance, therefore, requires not only traditional accounting expertise but also a foundational understanding of AI systems and analytics (Stubben, 2010).

6.4. Disclosure as Risk Mitigation

Greater transparency has the potential to mitigate the risk that is related to discretionary allocation. Simulated benchmarks and allocation strategies, as well as periodical adjustments, should be disclosed clearly to gain investor confidence (Badger et al., 2025). This can be critical to AI-driven environments, where value is ceasing to be generated mainly due to the production inputs that can be easily seen. Due to the variations in the model's performance, the individual selling price benchmark identified can be out of date.

Table 4: Audit Risks and Suggested Responses

Risk Area	*Potential Bias*	*Suggested Response*
Variable Consideration	Front-loading revenue	Historical back-testing
Control Transfer	Premature recognition	TOS & IP review
SSP Estimation	Inflated benchmarking	Third-party pricing data

7. EARNINGS MANAGEMENT AND DISCRETION IN NEAR-ZERO COST ENVIRONMENTS

The presence of near-zero marginal costs poses more than a simple challenge to revenue allocation. It also increases the degree of freedom for earnings management. With the advent of AI automation, the marginal cost of production declines significantly, and the cost structure that accounting was previously based on becomes less pertinent. In the absence of economic evidence, revenue allocation becomes more of a managerial estimate than an observable input.

7.1. The Collapse of Cost Anchors

The residual approach is normally applied when there is a portion of the packaged arrangement that has a market price, for instance, subscription access to the platform, while others, such as AI-generated content, do not. While this is permissible under the existing system, it is more subjective. This increased subjectivity may create chances to allocate revenue in ways that smooth earnings or support strategic reporting objectives (Ali & Tseng, 2025).

Prior research indicates that discretion in revenue recognition can facilitate earnings management (Stubben, 2010). When facing reporting pressures, managers may adjust accounting estimates, but they may also alter real business activities to influence reported outcomes. Such real activities manipulation, which directly affects operations, has been extensively documented (Roychowdhury, 2006).

7.2. Pricing Transparency and Market Perception

The outcomes of lower pricing transparency extend beyond procedural allocation issues. As SSP estimations become more judgment-based, it may become more difficult for outside users to analyze variations in reported revenue. In AI-intensive environments, where observable cost benchmarks are limited, the economic basis for allocation decisions may appear more challenging to interpret. This doubt can make investors uneasy and adversely affect how they understand the firm's performance.

8. REGULATORY AND STANDARD-SETTING ISSUES

While AI presents a complication in interpretation of ASC 606 and IFRS 15, both standards were intended to be principle-based and flexible (FASB, 2014). Their flexibility facilitates the adoption of new methods, but further guidance in specific areas may help to close the gap in application.

8.1. Market Assessment Clarification

In Step 4, companies are allowed to use a Market Assessment Approach to estimate SSP. In scenarios where marginal production costs cease to offer useful signals, regulators may need to provide further guidance on the practicality of benchmarking against economically sustainable items or services, as opposed to cost inputs. This may help maintain consistency among organizations and minimize deviation in application.

8.2. Intellectual Property and Transfer of Control

In contractual agreements, parties involved have extensive freedom to negotiate the transfer of property, including intellectual property and control rights (Hansen, 2000). However, in Step 5, control transfer becomes more difficult to assess when AI-generated content is involved. The current regulatory uncertainty in AI-generated content authorship and ownership creates difficulties in the appraisal of sole entitlement (Voinea, 2023; U.S. Copyright Office, 2024). When exclusivity is in doubt or is an open question of the law, a transaction may seem to be a right-of-access arrangement rather than a point-in-time transfer of control. In this case, using the licensing principle integrated in ASC 606 and IFRS 15 may be more expressive of the economic reality of the arrangement (FASB, 2014).

Questions regarding the authorship of AI and the protection of copyright complicate the evaluation of transfer of control, as existing law does not clearly accept non-human-generated works as copyrightable property. This issue has become the focus of recent professional legal reviews (New York State Bar Association, 2025).

8.3. Digital Audit Evolution

The incorporation of AI and blockchain into financial systems means the practice of auditing is evolving at a larger scale (Zaytoun and Elhoushy, 2024). The standard-setting bodies might need to give some guidance about the algorithmic benchmarking procedures and predictive revenue estimation techniques.

9. BOUNDARY CONDITIONS AND LIMITATIONS

9.1. Situational Applicability

The AI Value Attribution Framework (AVAF) is circumstantial and subjective. There are several circumstances that can reduce the relevance of this theory. AVAF can be used especially when:

1. The most important value generated is the AI output.
2. Marginal cost does not have any economic meaning.
3. There are similar analogues of the market.

Moreover, in hybrid AI-human production systems, as in architect-assisted design systems, there is still likely to be a place in conventional SSP estimation techniques, as the economic centrality of human expertise still exists (Bouzid, 2025).

9.2. Lack of Market Benchmarks

The estimation of synthetic utility can take a more speculative turn in new areas of AI where there is no similar human-made market. Other methods of valuation can be necessary in these cases (Barreto et al., 2025).

9.3. Conceptual Scope

The current paper establishes a conceptual stress test that has not yet been empirically validated. The predictive effects of the framework must be tested empirically.

10. FUTURE RESEARCH DIRECTIONS

The integration of AI into revenue-generating business models offers several research opportunities.

10.1. Earnings Volatility and Allocation Techniques

Future empirical research may examine whether AI-intensive firms are more likely to experience earnings volatility because of residual allocation procedures compared to traditional SaaS firms (Ali & Tseng, 2025). Investor perceptions may also be influenced by financial statement disclosures.

10.2. Investor Response to Disclosure

Investors may respond to disclosures made in the financial statements. Experimental studies could assess whether providing more AI-specific disclosures increases or decreases investor confidence and forecast dispersion (Badger et al., 2025).

10.3. Accounting-Legal Interaction

As intellectual property laws continue to evolve on the issue of digital copies and artificial authorship (U.S. Copyright Office, 2024), longitudinal research could be useful in establishing whether discrepancies in the definition of copyright affect revenue recognition timing practices.

10.4. Digital Audit Methodologies

Studies on the transformation of digital auditing indicate the possible need to switch to algorithmic verification, as opposed to the traditional paper-based evidentiary review (Herath et al., 2024). The estimation of AI outputs might depend on the development of standardized assurance methods.

11. CONCLUSION

The creation of AI generated-content is a major change in the economics of production. It also exerts strain on revenue recognition through algorithmic pricing, decreasing marginal costs, and persistent legal ambiguity regarding ownership, especially in allocation and control valuations. Nevertheless, ASC 606 and IFRS 15 are internally consistent and credible models (FASB, 2014). The problem lies not in a structural defect of the standards per se, but in their clarification and application. When cost information is no longer informative, automated allocation systems may generate revenue figures that do not reflect economic reality.

The AI Value Attribution Framework is based on the previous Market Assessment Approach by offering a clearer explanatory structure. Through AVAF, representational faithfulness is measured in terms of economic utility as an alternative to marginal cost. Such a method does not include any formal adjustments to existing accounting standards.

The rise of AI production does not render the control-based model obsolete but instead contests the informational premises upon which the model is founded. Disciplined allocation processes and improved disclosure practices may reduce cross-firm variability in comparability in AI-intensive reporting environments more effectively than structural modifications to the existing standards.

The marginal cost failure problem not only adds complexity to the allocation process but also extends managerial discretion in a manner that raises the possibility of earnings management. The economic properties of AI production widen the discretionary margin in earnings allocation.

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