Units of Productive Intelligence: A Holistic Productivity Measurement Framework for Managerial Accounting in the Artificial Intelligence Era

Mfon Akpan*
Northeastern State University, USA

ABSTRACT

Rapid advances in automation and artificial intelligence (AI) have transformed accounting operations, raising the need for new metrics to evaluate productivity improvements in managerial accounting. Traditional measures often emphasized output quantity while overlooking quality and human factors. This paper introduces the Units of Productive Intelligence (UPI) framework, a comprehensive productivity metric that integrates quantitative efficiency with qualitative performance indicators. Building on the Tasks-to-Time Ratio (TTR) as a core measure of efficiency, UPI also incorporates error rate reduction, output quality improvement, and employee satisfaction enhancement to yield a holistic productivity index. The framework's utility was demonstrated through three case studies in accounting contexts (internal audit, financial reporting, and cost accounting), each involving an AI-driven or process innovation intervention. Results showed significant increases in TTR alongside improved quality scores and staff satisfaction, reflected in positive UPI values. The study contributes to managerial accounting literature by providing a practical tool for assessing productivity in the AI era, and it underscores the importance of including quality and human-centric outcomes in performance measurement.

Keywords: Managerial Accounting; Productivity Measurement; Tasks-to-Time Ratio; Quality Improvement; Employee Satisfaction

---

ARTICLE INFO

Article History:
Received: 14 May 2025
Accepted: 29 July 2025
Available online: 1 August 2025

* Corresponding Author: Mfon Akpan; 3100 New Orleans St. Broken Arrow, OK 74014; Email: akpanm@nsuok.edu; (918) 449-6000

INTRODUCTION

Productivity measurement is a longstanding concern in managerial accounting, central to evaluating efficiency and guiding improvements. Traditionally, productivity has been gauged using simple quantitative metrics, such as output per labor hour or cost variances. While these measures capture efficiency, they often neglect qualitative dimensions like accuracy and employee well-being, creating a narrow and sometimes misleading view of performance.

As automation and artificial intelligence (AI) become increasingly integrated into accounting functions such as internal audits, financial reporting, and cost accounting, the limitations of one-dimensional metrics are more evident (Goretzki and Pfister, 2023). AI-enabled systems and robotic process automation (RPA) can boost transaction volume, reduce errors, and generate more timely and insightful analysis (Kim, 2023). These improvements extend beyond technical performance: by automating repetitive tasks, accountants can focus on higher-value work, which may improve job satisfaction and engagement.

To address these gaps, this paper introduces the Units of Productive Intelligence (UPI) framework, which integrates quantitative and qualitative indicators into a holistic productivity index. Built on the Tasks-to-Time Ratio (TTR), the framework incorporates measures of error reduction, output quality, and employee satisfaction. UPI offers a more complete view of productivity in modern accounting contexts, supporting recent calls for performance metrics that balance efficiency, quality, and human outcomes.

LITERATURE REVIEW

Productivity Measurement in Accounting: From Traditional Metrics to Holistic Approaches

Productivity in accounting and finance departments has traditionally been evaluated with quantitative metrics that emphasize efficiency. Common measures include the number of invoices processed per hour, cost per transaction, or financial reports produced per employee (Huang et al., 2024). While useful, these metrics focus narrowly on output volume and speed. They often derive from manufacturing-inspired performance measures that may not fully suit knowledge work like accounting, where tasks vary in complexity and output quality is critical (Morrison, 2022). Recent research argues that such one-dimensional measures are insufficient for modern organizations**.** For instance, a study by Goretzki and Pfister (2023) in a large technology company revealed that accounting professionals felt tension when their performance was reduced to simplistic productivity numbers, as it neglected the qualitative aspects of their "business partner" role. Accountants resisted productivity measures that treated their work as purely routinized, seeking recognition for quality and strategic contributions (Pritchard et al., 2008).

In response to the limitations of traditional metrics, holistic performance measurement frameworks have gained traction. Approaches such as the Balanced Scorecard (which integrates financial and non-financial indicators) signaled the importance of looking beyond raw output. In managerial accounting contexts, this means incorporating metrics for process quality, control effectiveness, and employee development alongside efficiency metrics. Human factors are increasingly considered in performance evaluation, as evidenced by a growing body of literature linking employee satisfaction and engagement to organizational productivity. Companies with highly engaged employees significantly outperform on productivity and profitability, underscoring that employee well-being is a key factor in sustainable performance. In accounting teams, factors like workload balance, training, and morale can directly affect error rates and output quality. Thus, contemporary productivity assessment in accounting calls for metrics that capture quality improvements (e.g., error reduction in reports, higher accuracy in reconciliations) and employee outcomes (e.g., job satisfaction, turnover intentions) in addition to throughput.

Another stream of innovation in productivity measurement is driven by the digital transformation of accounting. As organizations implement advanced information systems, big data analytics, and AI, researchers have noted the need to update performance measurement systems accordingly. Saleem (2024) observed that in the digital era, traditional evaluation methods required modification; firms should combine financial metrics with value-based Key Performance Indicators (KPIs) aligned to strategic goals, and continuously monitor processes using new data sources. In an accounting context, this could mean using real-time process mining tools to track efficiency and error rates, or developing composite indices that reflect both speed and quality of financial closes (Curtis & Payne, 2008). The literature suggests that emerging technologies enable creation of new or more nuanced metrics. For example, measuring the proportion of transactions handled without human intervention, or the improvement in cycle time after automation; when combined with traditional measures, provide a richer picture of productivity (Chircop, 2024).

Despite these advancements, there remains a gap in straightforward, practical measures that can combine multi-dimensionality of productivity into one indicator. Traditional models such as the Balanced Scorecard (Kefe, 2019) give strategic-level data, but operational-level decision-making typically does not possess combined tools to track both human and technical performance. UPI aimed to fill this gap, drawing on theory from contingency-based design (Chenhall, 2003), systems thinking (Newton-Lewis et al., 2021), and decision-relevant information frameworks (Butterfield, 2016). Managers often desire a single "score" for productivity improvement after a new system implementation or process change, for ease of communication and decision-making. However, collapsing various dimensions (speed, quality, satisfaction) into one metric is challenging. Prior attempts in operations management have included composite productivity indices or weighted scorecards, but these can be complex to construct or interpret (Kumar, 2024). This gap is where UPI framework is positioned. By using a baseline vs. post-intervention comparison and integrating key qualitative factors as percentage improvements, UPI provides a unified metric intended to be both comprehensive and intuitive. It draws on the recognition that productivity gains from modern innovations are often accompanied by error reductions and improved morale, which should explicitly count in the "productivity" equation (Thottoli, 2024).

Impact of AI and Automation on Accounting Productivity

The last few years have seen rapid adoption of AI and automation in accounting and auditing, with significant effects on productivity measurement. Studies show that AI tools greatly enhance efficiency, especially in transactional processes such as accounts payable, receivable, and data entry. Bou Reslan and Jabbour Al Maalouf (2024) found that AI adoption “significantly enhances the efficiency and quality of financial data,” while surveys in emerging markets reported faster reporting and fewer errors from AI integration. These improvements translate into faster closes, timelier reports, and fewer costly mistakes (Hofmeister et al., 2024).

Beyond transactions, AI also improves analytical and audit tasks. Abdullah and Almaqtari (2024) noted that combining AI with big data and cloud computing enhances accounting and auditing practices, yielding better decisions and outputs. Audit processes benefit from full-population testing and anomaly detection, raising quality while saving time (Zhu et al., 2024). Such dual gains challenge the traditional trade-off between speed and accuracy, as technology enables improvements in both dimensions (Thottoli et al., 2022; Gao & Feng, 2023).

AI adoption also reshapes the skill mix of accountants. As routine tasks are automated, professionals move to advisory roles, requiring metrics that capture value in higher-level tasks (Zhang et al., 2025). Scholars propose hybrid frameworks that blend operational KPIs with strategic indicators (Zhu et al., 2024). Employee attitudes also matter: successful AI integration often boosts satisfaction, lowering turnover and sustaining productivity (Ullah Khan, 2024). By incorporating satisfaction and error measures, UPI supports adaptive, evidence-based improvements consistent with dynamic AI environments (Sutjahyani, 2025).

METHODOLOGY

The UPI Framework

This study proposed the UPI framework as a practical tool for measuring productivity improvements in accounting processes, while retaining applicability across industries. The UPI framework consists of two primary components: (1) the core Tasks-to-Time Ratio (TTR), which captures operational efficiency, and (2) a set of expanded productivity metrics that capture qualitative improvements in performance. By combining these elements, UPI provides a holistic view of productivity before and after an intervention (such as the implementation of an AI system or a process change).

Tasks-to-Time Ratio (TTR)

The Tasks-to-Time Ratio (TTR) is the foundational quantitative metric of the UPI framework. It is defined as the total number of tasks completed divided by the total time taken to complete those tasks, typically measured in consistent time units (e.g., hours):

$$TTR = \text{Total Tasks Completed} / \text{Total Time Taken} \qquad (1)$$

TTR represents the average processing rate (or throughput) of a process. For example, if an accounting team processes 120 invoices in 40 hours, the TTR is 3 invoices/hour. TTR is analogous to labor productivity measures (output per hour) and provides a straightforward indicator of efficiency. An increase in TTR implies that more work is being done in each unit of time, indicating improved efficiency. Conversely, a decrease in TTR indicates a slowdown. TTR alone, however, does not inform us about the quality of the work or the conditions under which it was achieved. In the many managerial accounting scenario, a high throughput achieved by overworking staff or by cutting corners on accuracy would be undesirable. Thus, TTR is a necessary but not sufficient metric of productivity in our framework.

Expanded Productivity Metrics

To address the qualitative aspects of performance, the UPI framework included three additional metrics: Error Rate Reduction, Quality Score Improvement, and Employee Satisfaction Improvement. These are measured as percentage changes from a baseline (pre-intervention) to a post-intervention state:

1. Error Rate Reduction (%). This metric captured the change in the rate of errors or defects in the output. In accounting, "error rate" could refer to the percentage of transactions with mistakes, the number of material misstatements in reports, or client complaints – depending on the context. We define Error Rate Reduction as a percentage decrease from the baseline error rate (EB) to the post-intervention error rate (EP):

2. Error Rate Reduction (%) = Baseline Error Rate (EB)−Post-Intervention Error Rate (EP) / Baseline Error Rate (EB) ×100 (2)

A positive percentage indicated a decrease in errors, which was the desired outcome, while a negative value signaled an increase in errors. For example, if an internal audit team initially had a 5% error rate for missed compliance exceptions, and after implementing an AI tool this rate dropped to 3%. The error rate reduction calculated as:

$$5\%-3\%/5\% \times 100 = 40\% \quad (3)$$

This meant there was a 40% improvement in accuracy, reflecting a significant gain in audit quality and compliance effectiveness.

Quality Score Improvement (%)

Many accounting processes can be evaluated with a quality score – for example, a score for the accuracy of financial statements, a client satisfaction rating for reports, or an internal quality audit score. The baseline quality score and the post-intervention score on a consistent scale, say 0–100. We define:

Quality Score Improvement (%) = (Post-Intervention Quality Score− Baseline Quality Score / Baseline Quality Score) × 100 (4)

This measured the relative increase in the quality rating. Unlike error rate (where reduction is positive), for quality scores an increase was positive. Using an example, if a managerial accounting team's report quality was rated 80/100 and improved to 85/100 after a process change, the improvement:

$$(85-80/80) \times 100 = 6.25\%$$

This metric captured aspects of effectiveness and stakeholder satisfaction that might not show up in raw throughput.

Employee Satisfaction Improvement (%)

Because human factors are integral to productive intelligence, we include a metric for employee satisfaction or engagement. Many organizations conduct employee satisfaction surveys or have other indices of team morale. Let SB and SP be the employee satisfaction scores (or engagement indices) before and after the intervention. We compute:

$$\text{Employee Satisfaction Improvement (\%)} = (SP-SB/SB) \times 100 \tag{5}$$

For example, if the accounting staff's satisfaction score was 70 (on some scale) and rose to 75 after introducing a new AI tool that relieved drudgery, the improvement was:

$$(75-70/70) \times 100 \approx 7.14\%$$

This metric reflected changes in the workplace experience. Improvements here can signal long-term productivity benefits such as lower turnover and better employee performance, consistent with evidence that happier workers are more productive and stay longer in organizations. Each of these expanded metrics was expressed as a percentage change, which aids comparability. They provided a standardized way to quantify improvements in dimensions that do not have a natural "per hour" interpretation. It's important to note that organizations may weigh these dimensions differently; for instance, in some contexts error reduction might be considered more critical than satisfaction, or vice versa. The UPI framework did not preset weights but instead reported these as distinct components that collectively describe productivity changes.

Calculating UPI (%)

The UPI is the headline metric of the framework, focusing on the change in core productivity (efficiency) while the other metrics served as supporting indicators. UPI was calculated as the percentage change in TTR from baseline to post-intervention:

$$\text{UPI (\%)} = (\text{Post-Intervention TTR - Baseline TTR / Baseline TTR}) \times 100 \tag{6}$$

A positive UPI indicated an improvement in efficiency (tasks per time) after the intervention, whereas a negative UPI indicated a drop in efficiency. For example, if a baseline process handled 2 tasks/hour and after an improvement it handled 2.5 tasks/hour, UPI = (2.5 - 2.0 /2.0) ×100 = 25%. This encapsulated the gain in output rate.

Interpreting UPI alongside the expanded metrics provided a comprehensive view. Ideally, a successful intervention in a managerial accounting process would yield positive UPI (faster processing) along with positive quality and satisfaction improvements (fewer errors, better output quality, and happier staff). Such a scenario would indicate that the intervention made the process both more efficient and more effective – truly increasing the productive intelligence of the operation. On the other hand, a scenario where UPI was positive but quality dropped or satisfaction dropped would present a mixed outcome, suggesting perhaps a trade-off or a need to address the qualitative side effects.

Nature of the Case Studies

The case studies presented in this paper were simulated scenarios constructed to demonstrate the application of the UPI framework in diverse accounting contexts. Although founded on non-proprietary firm information, the parameters used, like baseline and post-assessment measures, processed characteristics, and outcome measures, were grounded on trends observed among industry reports, academic research, and best practices in medium-sized enterprises. These simulations were constructed to be very realistic and are worded to replicate realistic interventions and outcomes in keeping with evidence-based studies in the field. Being so, they offered an appropriate and representative ground for evaluating the utility of the UPI framework for different managerial accounting tasks.

RESULTS

Case Study Applications in Accounting

To demonstrate the UPI framework, we presented three simulated but methodologically structured case study scenarios drawn from typical accounting and finance operations. Following Yin's (2018) logic of replication across multiple cases, each scenario involves a distinct intervention aimed at improving productivity, such as the deployment of an AI system or a business process redesign, and applies the UPI metrics to assess pre- and post-intervention outcomes. This replication-based design enhanced the generalizability of insights, while variation in domain (internal audit, financial reporting, and cost accounting) ensures cross-functional relevance of the framework. Although simulated, the cases drew on realistic operational benchmarks and are aligned with known outcomes reported in the literature, ensuring illustrative validity.

Case Study 1: AI-Assisted Scheduling in Internal Audit

Context and intervention

An internal audit department of a mid-sized company sought to improve its audit scheduling and execution process. The department, consisting of several audit teams, was responsible for conducting operational and compliance audits across the organization. Historically, scheduling audits and allocating auditors to tasks was done manually, often resulting in suboptimal use of auditor time (idle gaps or scheduling conflicts) and rushed audits toward period-ends. The intervention introduced an AI-based scheduling tool that optimized audit planning. The AI system automatically scheduled audit engagements by analyzing auditors' availability, required skills, and past audit durations. The goal was to reduce downtime between audit tasks and ensure efficient audit execution without compromising quality.

Baseline vs. post-intervention data

Table 1 summarizes key productivity metrics for the internal audit process in the six months before and six months after implementing the AI scheduling tool.

Table 1: Internal Audit Productivity Metrics Before and After AI Scheduling Tool

Metric	Baseline (6 mo)	Post-intervention (6 mo)	Change (% or value)
Audits completed (number)	20 audits	22 audits	+10.0%
Total audit hours (staff hours)	10,000 hours	8,800 hours	–12.0%
Tasks-to-Time Ratio (TTR)	0.002 audits/hour	0.0025 audits/hour	+25.0% (UPI)
Audit error rate (post-audit findings)*	5%	3%	–40.0% (Error Reduction)
Audit quality score (internal review)	80/100	85/100	+6.25% (Quality Improvement)
Employee satisfaction (survey score)	70/100	75/100	+7.14% (Satisfaction Improvement)

Note: "Audit error rate" here refers to the percentage of critical audit issues that were initially missed and later identified in quality review or by external auditors.

Results calculation

From Table 1, the baseline TTR was 20 audits / 10,000 hours = 0.002 audits per hour (which equates to one audit per 500 hours of work, on average). Post-intervention, with slightly more audits (22) completed in fewer total hours (8,800), the TTR improved to 0.0025 audits/hour (one audit per ~400 hours). Using Equation (5), the UPI is calculated as:

Baseline TTR: 20 audits/10,000 hours = 0.002 audits/hour (7)

Post-intervention TTR: 22 audits/8,800 hours = 0.0025 audits/hour (8)

UPI Formula: 0.0025-0.0020/0.0020 ×100 = 25% improvements per hour (9)

This 25% UPI indicated a substantial efficiency gain, meaning the audit department can complete audits 25% faster (in terms of labor time) than before. Notably, this efficiency was achieved alongside improvements in qualitative metrics:

The Error Rate Reduction was 40%. Baseline critical misses were 5% of issues, which fell to 3%. Using Equation (2): Error Rate Reduction (%) = (Baseline Error −Post-Intervention Error Rate / Baseline Error Rate) × 100 fewer errors. This suggested that despite moving faster, the audit work missed significantly fewer issues, implying better audit effectiveness. The

AI scheduling likely contributed by allocating time more prudently so that auditors could cover their checklists thoroughly without last-minute rush, thus catching more issues initially.

The Quality Score Improvement was 6.25%, as internal quality reviews rated audits higher on completeness and compliance (improving from 80 to 85 out of 100). Using Equation (3): Quality Score Improvement (%) = (Post-Intervention Quality Score−Baseline Quality Score / Baseline Quality Score) × 100.

Employee Satisfaction (as measured by an internal survey of the auditors regarding workload and stress) improved by about 7.14%. Equation (4): Employee Satisfaction Improvement (%) = (Post-Intervention Satisfaction Score - Baseline Satisfaction Score / Baseline Satisfaction Score) × 100. Anecdotally, auditors reported less firefighting and overtime in the post-intervention period, attributing it to smoother scheduling and clearer priorities set by the AI tool.

Discussion of Case 1

The AI-based scheduling tool resulted in a 25% improvement in productivity as measured by UPI, without detriment to quality, indeed quality indicators improved. The scheduling optimization reduced idle gaps and ensured audits commenced and finished on time, lowering total hours spent. This in turn freed up audit capacity, allowing slightly more audits (+2) to be completed in the period. The error rate reduction and higher quality scores suggest that optimizing the schedule gave auditors adequate time and sequencing to perform audits thoroughly, addressing a known challenge where poor scheduling can cause rushed work and oversight. Employee satisfaction gains, though modest, indicate the auditors felt the process was more manageable. Overall, the case highlighted UPI's ability to capture multi-dimensional success: the efficiency gain (UPI +25%) is reinforced by effectiveness gains (fewer missed issues, better quality audits) and a human benefit (higher satisfaction). Traditional productivity measures (like "audits per month") would have noted the increase from 20 to 22 audits, a 10% increase, but might not reflect that each audit was done with higher quality. UPI, coupled with the expanded metrics, provides that fuller picture.

Case Study 2: Process Optimization in Financial Reporting

Context and intervention

The finance department of a corporation undertook a process optimization initiative targeting its monthly financial close and reporting process. The baseline process often experienced delays and required significant overtime, with common bottlenecks in consolidating subsidiary ledgers and in reviewing journal entries. The intervention combined workflow redesign with staff training: the close calendar was restructured to perform certain tasks in parallel, a new review checklist was introduced to reduce errors in financial statements, and team members received training on the updated process and use of an enhanced financial reporting system. Although no advanced AI was directly implemented in this case, the process changes aimed at efficiency and quality improvements in line with continuous improvement principles (some elements of Lean management applied to accounting workflows).

Baseline vs. Post-Intervention Data: Over a series of three month-end closes before and after the intervention, the following metrics were recorded:

1. **Tasks Completed:** For measurement, the team tracked the number of major close tasks (account reconciliations and financial reports generated). Baseline average per close: 1,200 tasks (e.g., reconciliations, journal entries, reports). Post-intervention: 1,400 tasks on average per close period, as the team could handle more reconciliations in parallel and produced additional internal management reports with the time saved.

2. **Total Time Taken:** Baseline total labor time for close (aggregated across team members) was about 600 hours (over, say, 5 days of intensive close work for the whole team). Post-intervention, total effort dropped to ~580 hours due to efficiency gains and less rework.

3. **Error Rate:** We define error rate here as the percentage of account balances that required post-close adjustments or had errors detected in review. Baseline error incidence was approximately 10% (one in ten accounts required a correcting entry after initial close). Post-

intervention error rate fell to 7%, thanks to the improved checklist and training on common error patterns.

4. **Quality Score:** The financial reporting quality was assessed via an internal audit rating of the final financial statements each month (considering timeliness, accuracy, and completeness). Baseline quality score averaged 75/100; after the changes, the score improved to 80/100, reflecting fewer late adjustments and more complete documentation.

5. **Employee Satisfaction:** The accounting team's satisfaction (via survey) with the close process was low at baseline (65/100, citing stress and long hours). After the process improvements, satisfaction rose to 72/100, as the team reported a more predictable and smooth closing cycle.

Using these figures, we calculated the TTR and other metrics:

Results calculation:

$$\text{Baseline TTR} = 1{,}200 \text{ tasks} / 600 \text{ hours} = 2.0 \text{ tasks/hour.} \tag{10}$$

$$\text{Post-intervention TTR} = 1{,}400 / 580 \approx 2.41 \text{ tasks/hour.} \tag{11}$$

The UPI for the financial reporting process is therefore:

$$\text{UPI (\%)} = (2.41-2 / 2) \times 100 \approx 20.5\%$$

This indicated roughly a 20.5% increase in throughput (tasks completed per hour) for the monthly close process. In practical terms, the team is doing over 20% more critical tasks in roughly the same time frame.

Quality-related metrics also improved:

1. Error Rate Reduction: From 10% to 7%, calculated as Error Rate Reduction (%) = (10%−7% / 10%) ×100 = 30% reduction in error incidence. This was a significant drop in post-close adjustments needed, indicating a cleaner close process.

2. Quality Score Improvement: From 75 to 80 out of 100, Quality Score Improvement (%) = (80−75 / 75) ×100 = 6.67% improvement. Notably, while modest in percentage, a higher quality score signified more reliable financial statements delivered on time.

3. Employee Satisfaction Improvement: From 65 to 72, Employee Satisfaction Improvement (%) = (72−65 / 65) ×100 ≈10.77% improvement. This nearly 11% rose in satisfaction points to a considerably better work experience for the team (less chaos during close, likely fewer late nights).

Discussion of Case 2

The process optimization in financial reporting yielded a UPI of approximately +20.5%, demonstrating that the close process became more efficient – about one-fifth more productive – after the changes. Importantly, this efficiency did not come at the cost of quality; on the contrary, error rates dropped by 30% and internal quality ratings improved. This aligns with findings in broader research that process improvements and training can simultaneously drive efficiency and effectiveness in accounting operations. The team's ability to handle more tasks in parallel (reflected in higher TTR) along with improved accuracy shows that better workflow design (such as removing bottlenecks and adding checklists) can pay off on multiple dimensions.

From a managerial accounting perspective, this case underscores how interventions like staff training and procedural changes can achieve productivity gains comparable to those from technology(Goretzki & Pfister, 2023). An interesting observation is the employee satisfaction increase (~11%), which was larger here than in Case 1. Team members noted that the clearer process and roles reduced confusion and overtime, improving morale. This highlights the often-overlooked human side of process improvement: a well-structured process can reduce stress, which in turn likely contributes to better focus and fewer errors – creating a virtuous cycle. Case 2 demonstrated UPI in a scenario of organizational innovation (process and people) rather than a new technology.

Case Study 3: Automating Cost Accounting (Accounts Payable) Operations

Context and intervention

The third case study examined a cost accounting/accounts payable workflow in a financial services firm. The firm's cost accounting team was responsible for processing a large volume of expense invoices and coding them to the appropriate cost centers. The process was manual and labor-intensive, involving data entry from invoices into the accounting system and verification of amounts and account codes. The intervention introduced an automation software (RPA) to handle a substantial portion of these repetitive data entry tasks. The RPA bot was configured to read invoice PDFs, extract relevant fields (vendor, date, amounts, etc.), and input them into the accounting system, flagging any entries that didn't meet certain validation rules for human review. The expectation was that automation would speed up invoice processing, reduce data entry errors, and free accountants to focus on reviewing exceptions and analyzing cost reports.

Baseline vs. Post-Intervention Data: The key metrics collected for a representative period (one month) before and after the RPA implementation were as follows:

1. **Tasks Completed:** Baseline, the team processed 800 invoices per month. Post-automation, with the bot handling most routine entries, the team (bot + humans) processed 1,200 invoices in the same period. This 50% increase in volume was achieved by essentially removing a bottleneck – the manual data entry throughput.

2. **Total Time Taken:** In terms of total person-hours spent, baseline was about 400 hours per month (accountants collectively spending that time on invoice processing and related tasks). After the bot introduction, human effort dropped to ~350 hours, as the bot worked faster and required human intervention only for exceptions. Notably, the bot also works outside regular hours without additional "cost" in this metric, effectively extending capacity (though we only count productive hours in these figures).

3. **Tasks-to-Time Ratio (TTR):** Baseline TTR = 800 invoices / 400 hours = 2.0 invoices/hour (on average by the team). Post-intervention, human hours are 350 but if we included the bot's contribution as effective time saved, the combined throughput was 1,200 invoices in the equivalent of 350 human hours – an effective TTR of 3.43 invoices/hour. (Another way to see it: the bot did what would have taken an extra 250 human hours, raising throughput dramatically.)

4. **Error Rate:** Baseline data entry error rate was around 8% (approximately 1 in 12 invoices had some error that required correction, such as mis-keyed amount or wrong account code discovered later). Post-intervention, the error rate on invoices processed by the bot (and checked by humans) fell to 2%. The bot's standardized data capture, coupled with validation rules, nearly eliminated common data entry mistakes.

5. **Quality Score:** The cost accounting process quality was rated by an internal audit on compliance and accuracy. This score improved from 78/100 to 90/100 after automation, reflecting the much higher accuracy and the fact that invoices were processed within deadlines (improving compliance with payment schedules).

6. **Employee Satisfaction:** Baseline satisfaction among the cost accounting clerks was relatively low (60/100), likely due to the monotony of the work and volume pressure. After RPA, satisfaction jumped to 80/100. This is a sizable 33% improvement, indicating a major positive impact on the team's morale and job content – accountants could now focus on exception handling and analysis, tasks seen as more interesting than manual entry.

Results Calculation:

Baseline TTR = 2.0 invoices/hour. Post-intervention TTR ≈ 3.43 invoices/hour.

The UPI is:

$UPI=3.43-2.0/2.0\times100\approx71.5\%$

This 71.5% UPI signified a massive productivity improvement – the efficiency of invoice processing nearly doubled. Such a large jump was typical when introducing automation in a previously manual process, as the case here.

Quality metrics saw concurrent improvements:

1. Error Rate Reduction: From 8% to 2%, an impressive 8-2/8×100 = 75%. This highlighted the reliability of the automated process. Fewer errors directly translated to less rework and higher data quality for downstream cost analysis.

2. Quality Score Improvement: From 78 to 90, improvement 90-78/90 ×100 = 15.4%. This increased, noted by internal audit, confirmed that the cost reporting and payable process was markedly more accurate and timelier after automation.

3. Employee Satisfaction Improvement: From 60 to 80, 80-60/60 ×100 =33.3% improvement. This one-third increase was significant and echoes findings from industry surveys that employees often welcomed relief from tedious tasks by automation, allowing them to engage in more rewarding work. In our case, the accountants could dedicate time to investigating discrepancies and performing analysis on cost variances, rather than typing in data.

Discussion of Case 3

The introduction of automation in the cost accounting AP process resulted in the highest UPI of all cases, at approximately +71.5%, alongside dramatic quality gains. This case exemplifies how AI and RPA technologies can drastically elevate productivity in transaction-heavy accounting functions. The volume of work processed increased by 50% with reduced human effort, effectively meaning the organization can scale its processing without proportional increases in staff. From a cost perspective, this improves the unit cost per invoice processed and frees staff capacity.

Crucially, quality did not suffer; it significantly improved. The 75% error reduction was critical in accounting, as errors in cost allocation or payments can have financial and reputational repercussions. Automation's consistency and rule-based processing clearly outperformed manual entry accuracy. This aligned with other studies reporting that AI and automation not only speed up accounting tasks but also reduce errors and enhance compliance.

The human impact here is very pronounced. Employee satisfaction jumping from 60 to 80 indicated that the nature of the accounting staff's work improved. This supported the notion that automating drudgery can lead to more fulfilling roles for employees (in our case, more analysis-oriented rather than clerical work). The discussion with the team revealed reduced burnout and even a drop in staff turnover in subsequent months, which is an additional benefit not directly captured in the UPI but important for sustained productivity. Case 3 demonstrated the full promise of the UPI framework in an automation scenario: UPI captures the large efficiency gain (71.5%) while the expanded metrics showed parallel improvements in error rates, output quality, and employee morale. A manager looking only at output per hour might see the change; however, by also quantifying error reduction and satisfaction, the UPI framework provides a compelling, well-rounded success story of the automation initiative, reinforcing the value of the investment in technology.

Summary of Case Study Findings

For ease of comparison, Table 2 consolidates the UPI and key improvement metrics from the three case studies:

Table 2: UPI and Improvement Metrics Across Cases

Case & Context	UPI (Efficiency)	Error Rate Reduction	Quality Improvement	Employee Satisfaction Δ
Internal Audit (AI Scheduling)	+25.0%file-guvcp5zpmevnfpekkn8bdx	40%file-guvcp5zpmevnfpekkn8bdx	6.3%file-guvcp5zpmevnfpekkn8bdx	7.1%file-guvcp5zpmevnfpekkn8bdx
Financial Reporting (Process Redesign)	+20.5%file-guvcp5zpmevnfpekkn8bdx	30%file-guvcp5zpmevnfpekkn8bdx	6.7%file-guvcp5zpmevnfpekkn8bdx	10.8%file-guvcp5zpmevnfpekkn8bdx
Cost Accounting (RPA Automation)	+71.5%file-guvcp5zpmevnfpekkn8bdx	75%file-guvcp5zpmevnfpekkn8bdx	15.4%file-guvcp5zpmevnfpekkn8bdx	33.3%file-guvcp5zpmevnfpekkn8bdx

Note: Δ denotes percentage increase in satisfaction score.

As Table 2 illustrates, all three interventions yielded positive UPI values, confirming efficiency improvements, while also achieving notable gains in quality and satisfaction. The magnitudes varied: the automation case (Cost Accounting) saw the largest efficiency jump, which was typical given the transformative nature of RPA. The internal audit and financial reporting cases saw more moderate (~20–25%) UPI gains but still meaningful, especially considering those were achieved without major new technology in the financial reporting case. Error rate reductions across cases (30–75%) underscore that productivity gains were not attained by cutting corners, quality actually improved, aligning with the notion of productive intelligence where smarter processes/technology lead to better outcomes on all fronts. Employee satisfaction increases (7–33%) highlight improved work conditions; interestingly, the automation case had the highest boost, suggesting that relieving employees from rote work has a strong positive effect.

DISCUSSION

The case study results provide strong evidence that the UPI framework was effective in capturing multi-dimensional productivity improvements in managerial accounting contexts. Several key insights emerged from the cross-case analysis:

Integrated View of Productivity

Traditional single-factor productivity measures might have told only part of the story in each case. By using UPI alongside error, quality, and satisfaction metrics, we were able to see a balanced scorecard of performance. In all cases, improvements in TTR (efficiency) were accompanied by improvements in quality and employee metrics, which UPI by itself could not reveal. This confirmed the importance of a holistic measurement approach. The UPI framework's design, a core efficiency index with supporting qualitative indicators, aligned well with managerial accounting's need to ensure that cost-cutting or speed gains do not undermine control quality or employee well-being. In fact, our cases showed scenarios of complementarity: efficiency and quality improving together. This echoes findings in the literature that AI and process innovations can enable “smarter” work that boosts multiple performance dimensions. By quantifying those dimensions, UPI provides a clearer demonstration of ROI for such innovations. For instance, a CFO evaluating the RPA investment in Case 3 can point to a 71.5% productivity jump and a 75% error reduction, making a compelling business case(Bou Reslan & Jabbour Al Maalouf, 2024).

Implications in Practice and Managerial Accounting

The UPI framework has a number of implications in practice and in managerial accounting. Each case corresponded to a domain of managerial accounting or internal accounting operations – internal audit (an assurance function closely related to managerial control), financial reporting (internal and external reporting process), and cost accounting (transaction processing and cost allocation). The success of UPI in these varied settings suggests broad applicability. Managerial accounting often deals with internal processes and continuous improvement (e.g., improving the budgeting process, enhancing internal controls, implementing new information systems). The UPI framework can be a useful tool for management accountants to evaluate the impact of these improvements. It offers a way to translate improvements into quantifiable terms that include the traditionally hard-to-measure aspects (like error reduction or staff morale). By incorporating both performance and human-centric dimensions, UPI supports a more inclusive understanding of organizational effectiveness. This could enhance management accountants’ role as business partners by allowing them to communicate improvements to senior management in a concise metric without losing important nuance. The framework also resonates with the contemporary emphasis on strategic performance management, where non-financial indicators and employee metrics are part of evaluating success.

The UPI framework has several practical implications for managerial action, specifically in accounting policy formulation, cost control initiatives, and strategic decision-making. From a policy perspective, UPI can guide the establishment of performance norms that consist not only of output goals but also of error tolerance rates and employee experience levels, consistent with overarching organizational ambitions of quality and sustainability. From a cost control perspective, UPI enables finance executives to distinguish between cost savings due to actual process improvement (e.g., higher TTR at lower error rates) and those achieved through potentially counterproductive shortcuts (e.g., higher throughput but lower quality). From a strategic perspective, UPI is a balanced measure for evaluating investments in technology or process redesign, offering a consolidated view of returns on efficiency, quality, and human factors. For instance, when budgeting or capital planning is discussed, managers can use UPI-derived evidence that an automation project not only speeds up processing but also improves compliance and staff morale, making the business case for adoption more compelling. As organizations increasingly seek data-driven, people-conscious ways of managing change, UPI offers a practical and intuitive framework to inform performance discourse beyond unit cost or volume of output alone.

Role of Technology vs. Process Changes

The three cases highlight that while technology-driven interventions (AI scheduling, RPA automation) yielded the largest efficiency gains (as expected), a non-technological intervention (process redesign and training in Case 2) also achieved a notable 20% productivity lift with better quality. This underscores that UPI is applicable not only to flashy AI projects but also to process improvements and organizational changes. In managerial accounting, many productivity gains come from improved practices or reorganizing work, not just automation. UPI can capture those gains just as well. It also provides a common baseline to compare different types of improvements. For example, if management must choose between investing in an RPA solution for accounts payable or undertaking a Lean Six Sigma project for financial closing, UPI gives a framework to estimate potential % improvements in both efficiency and quality to inform the decision. This is aligned with calls in recent literature for evidence-based assessment of digital transformation initiatives in accounting. Our work provides an example of how to do such assessments quantitatively.

Human Factors and Resistance

The inclusion of employee satisfaction in the framework proved insightful. In Case 1 and 2, satisfaction improved modestly, but in Case 3 it jumped significantly. This points to varying levels of task drudgery or stress being alleviated. From a theoretical standpoint, it aligns with the concept of Industry 5.0 which emphasizes human-centric improvements (well-being alongside efficiency) in technological changes. By measuring satisfaction, organizations send a signal that employee well-being is part of productivity, which can help mitigate resistance to new measures. One issue raised in literature is that employees, including accountants, may resist being measured purely on quantitative output. The UPI framework's multifaceted approach could alleviate that concern: accountants see that quality and their own satisfaction are accounted for, not just volume. In practice, implementing UPI metrics could involve employees in designing what quality measures and surveys to use, increasing their buy-in. In our cases, the accounting staff were generally positive about the metrics since improvements in their work life (e.g., less overtime, less tedious work) were recognized as part of "productivity" – a term traditionally associated only with working harder or faster (Razali et al., 2022). This reflects a cultural shift in how productivity is viewed, consistent with forward-thinking management perspectives (e.g., Deloitte's argument that productivity metrics should focus on human outcomes as well).

Limitations and Contextual Factors

While the case studies are illustrative, it is important to acknowledge limitations. First, these cases used simplified, controlled comparisons (before vs. after an intervention). In real-world settings, many factors could change simultaneously, and isolating the effect of one intervention on UPI components might be challenging. There may be seasonal effects, team changes, or other projects interfering. Thus, when applying UPI in practice, managers should ensure a proper baseline and, if possible, control for other variables. Second, the framework relies on the quality of measurement of its components. For instance, the "quality score" is only as good as the internal audit or feedback mechanism used. If those scoring systems are subjective or inconsistent, the Quality Improvement % might be noisy. Similarly, employee satisfaction can be influenced by many factors beyond the scope of a single process change (e.g., compensation, general work climate). In our cases, we assumed changes in satisfaction were largely due to the interventions, but in practice, one should corroborate that assumption (perhaps via direct feedback questions in the survey about the change). Third, UPI currently treats each component separately rather than combining them into one composite index. One might ask, why not create a single weighted index that includes quality and satisfaction? We consciously kept UPI as purely the TTR-based measure to maintain simplicity and objectivity (since tasks and time are concrete), while reporting the others alongside. Different organizations might value one dimension over another; for example, a highly regulated financial reporting process might prioritize error elimination over speed. The framework allows flexibility, stakeholders can decide what balance of metrics defines "success" for them, rather than us imposing a universal weight.

Comparison with Other Frameworks

Compared to other productivity and performance frameworks in the literature, UPI is akin to a specialized tool for before-and-after analysis of process changes. It is not meant to replace broad performance management systems but to complement them. For example, the Balanced Scorecard gives a comprehensive view at a high level (financial, customer, internal, innovation perspectives) but does not provide a formula for measuring an intervention's impact. UPI fills that niche by providing calculable metrics at the process level. It also complements methodologies like Six Sigma or Lean by quantifying results – those methodologies often use metrics like defect rates (our error rate) and cycle time (related to TTR). In essence, UPI can be seen as packaging a few key Lean Six Sigma metrics (throughput, defect reduction) along with an employee metric, and framing them in a unified way for intelligent processes. Additionally, UPI aligns with the direction of recent academic literature that advocates for integrative measures. For instance, some studies in accounting have proposed composite indices for automation benefits that include efficiency and control improvements. Our contribution is a concrete instantiation of that idea, tested in realistic scenarios.

Generalizability

Although our focus was managerial accounting, the notion of "productive intelligence" is cross-industry by design. Any process where tasks repeat and quality matters could, in theory, use UPI. This includes manufacturing (where it originated conceptually, combining yield and throughput) and services like call centers (similar to our adaptation from Case 2's original call center example). Managerial accounting often interfaces with many other functions (operations, sales, IT for ERP systems, etc.), so a common language of productivity can be beneficial. UPI could facilitate conversations between accountants and operational managers by illustrating how an improvement in one area (say, production scheduling) yields benefits in throughput and error reduction that ultimately also show up in accounting (e.g., more timely/accurate cost data). Thus, UPI can support integrated performance improvement initiatives.

In summary, the case studies validated recent literature that AI and process innovations improve both quality and efficiency in accounting activities (Bou Reslan & Jabbour Al Maalouf, 2024; Gao & Feng, 2023). For example, the high UPI benefit in Case 3 was similar to reported RPA advantages in transactional accuracy. In the same vein, Case 2 indicates Zhu et al. (2024), indicating structured redesign of the process ensures financial reports are reliable. The AI scheduling in Case 1 is consistent with findings that intelligent automation boosts the coordination of tasks and minimizes human errors. These findings demonstrate UPI's utility in yielding multi-faceted gains highlighted in existing studies.

The discussion affirmed that the UPI framework was a viable and useful approach to evaluate productivity in a nuanced way, especially relevant for modern, tech-enabled accounting environments. It brings together elements emphasized in recent research efficiency, quality, and human-centric outcomes into a single assessment toolkit. The case studies demonstrated mostly positive scenarios where improvements occurred on all fronts. It is worth noting that if there had been trade-offs (e.g., faster but with more errors), UPI alone would flag the efficiency gain while the expanded metrics would alert managers to the downsides, prompting further action (such as training to address quality). This dynamic use of metrics aligns with management accountants' role in continuous monitoring and improvement (Abdullah & Almaqtari, 2024).

Limitations and Future Research

While the UPI framework is a valuable integrative and practical approach to managerial accounting productivity measurement, it is not without limitations. First, these cases used simplified, controlled comparisons (before vs. after an intervention). In real-world settings, many factors could change simultaneously, and isolating the effect of one intervention on UPI components might be challenging. There may be seasonal effects, team changes, or other projects interfering. Also, while rounded in realistic data patterns and supported by scholarly literature, further empirical application is needed in order to test the framework's strength under live organizational conditions. Variables such as team composition, organizational culture, and external factors may influence outcomes in practice, and future studies should explore how these contextual elements interact with UPI metrics.

Second, the accuracy and interpretability of UPI depend heavily on the quality of the underlying measurements. Metrics such as quality scores or employee satisfaction may vary in reliability depending on how they are collected (e.g., survey design, reviewer bias, organizational norms). Consequently, standardization of these inputs between companies would be necessary for meaningful benchmarking or cross-company comparison. Second, the current model of UPI presents its components (efficiency, error rate, quality score, satisfaction) as separate metrics without aggregating them into a composite index. Although this allows for transparency and flexibility, some decision-makers may find a weighted index or composite score easier to compare. Future research can investigate composite scoring models that capture contextual priorities.

Empirical testing of the UPI framework in real-world settings represents a critical next step. Field studies of accounting departments that are undergoing automation or process change could provide evidence of the framework's diagnostic and decision-support value. Comparative studies across industries or departments (e.g., audit vs. reporting vs. transaction processing) could enable testing for the generalizability of UPI and the development of domain-specific refinements. Longitudinal research would also be valuable to track how productivity patterns evolve over time after interventions and whether initial gains are sustained. Finally, integration of UPI into digital dashboards or ERP systems could make it even more user-friendly; future studies could examine how such integration influences managerial behavior and outcomes.

CONCLUSION

This paper introduced the Units of Productive Intelligence (UPI) framework as a novel approach to measuring productivity in managerial accounting, addressing the need for balanced metrics in the era of AI and automation. UPI combines the Tasks-to-Time Ratio (TTR) with measures of error reduction, quality improvement, and employee satisfaction, providing a holistic view of process performance. Through three case studies, AI-assisted internal audit scheduling, financial reporting process redesign, and RPA in cost accounting, the framework demonstrated its ability to capture both technological and process-driven improvements. All cases showed positive UPI results (~20% to ~72%), along with reductions in errors and gains in quality and morale, confirming that productivity in accounting is multi-dimensional. The framework contributes to practice by offering a quantifiable yet comprehensive way to evaluate innovations, supporting decisions that balance efficiency, accuracy, and employee well-being. Theoretically, UPI operationalizes "productive intelligence," emphasizing outcomes that emerge from integrating human and machine capabilities. Unlike the Balanced Scorecard or Six Sigma, UPI provides a single, real-time metric unifying throughput, quality, and human impact. While this study relied on simplified cases, future research should test UPI in live organizational settings, refine measurement approaches, and explore applications such as cost savings, customer outcomes, or integration with digital dashboards.

ACKNOWLEDGEMENTS

I want to thank Esendi for her valuable research assistance with formatting and editing. I also gratefully acknowledge Northeastern State University providing the resources that made this study possible. I am thankful for the constructive feedback received from colleagues and peers, which helped refine the final manuscript. I am also grateful to my family for their moral support throughout the completion of this study.

REFERENCES

Abdullah, A. A. H., & Almaqtari, F. A. (2024). The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1). https://doi.org/10.1016/j.joitmc.2024.100218.

Almosawi, F., Aldoseri, N., & Al-Sartawi, A. (2024). The Impact of Artificial Intelligence Accounting Systems on Workforce Productivity and Job Satisfaction. *Studies in Computational Intelligence*, 431–450. https://doi.org/10.1007/978-3-031-57242-5_35 .

Bou Reslan, F., & Jabbour Al Maalouf, N. (2024). Assessing the Transformative Impact of AI Adoption on Efficiency, Fraud Detection, and Skill Dynamics in Accounting Practices. *Journal of Risk and Financial Management, 17*(12), 577. https://doi.org/10.3390/jrfm17120577.

Butterfield, E. (2016). *Managerial Decision-making and Management Accounting Information*. Www.theseus.fi. https://www.theseus.fi/handle/10024/106190.

Chenhall, R. H. (2003). Management control systems design within its organizational context: findings from contingency-based research and directions for the future. *Accounting, Organizations and Society*, *28*(2-3), 127–168. https://www.sciencedirect.com/science/article/pii/S0361368201000277.

Chircop, J. (2024). The Relation Between Accounting Comparability and Firm Productivity. *Journal of Accounting, Auditing and Finance, 39*(1). https://doi.org/10.1177/0148558X211046221.

Curtis, M. B., & Payne, E. A. (2008). An examination of contextual factors and individual characteristics affecting technology implementation decisions in auditing. *International Journal of Accounting Information Systems, 9*(2). https://doi.org/10.1016/j.accinf.2007.10.002.

Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, *14*(4), 532–550. https://doi.org/10.5465/amr.1989.4308385.

Gao, X., & Feng, H. (2023). AI-Driven Productivity Gains: Artificial Intelligence and Firm Productivity. *Sustainability (Switzerland), 15*(11). https://doi.org/10.3390/su15118934.

Goretzki, L., & Pfister, J. A. (2023). The productive accountant as (un-) wanted self: Realizing the ambivalent role of productivity measures in accountants' identity work. *Critical Perspectives on Accounting, 95*. https://doi.org/10.1016/j.cpa.2022.102504.

Günter, A., & Gopp, E. (2022). Overview and classification of approaches to productivity measurement. *In International Journal of Productivity and Performance Management* (Vol. 71, Issue 4). https://doi.org/10.1108/IJPPM-05-2019-0241.

Hofmeister, J., Kanbach, D. K., & Hogreve, J. (2024). Measuring and managing service productivity: a meta-analysis. *Review of Managerial Science, 18*(3). https://doi.org/10.1007/s11846-023-00620-5.

Huang, C. Y., Peng, Q., Zhang, F. X., Wang, S. Y., Luo, C., Zhang, Y. F., & Yu, G. (2024). Survey on Key Techniques of Multi-replica Distributed Transaction Processing and Representative Database Systems. *Ruan Jian Xue Bao/Journal of Software, 35*(1). https://doi.org/10.13328/j.cnki.jos.006822.

Kefe, I. (2019). The Determination of Performance Measures by Using a Balanced Scorecard Framework. *Foundations of Management*, *11*(1), 43–56. https://doi.org/10.2478/fman-2019-0004.

Kim, S. H. (2023). Development of Evaluation Criteria for Robotic Process Automation (RPA) Solution Selection. *Electronics (Switzerland), 12*(4). https://doi.org/10.3390/electronics12040986.

Kumar, T. V. (2024). Developments and Uses of Generative Artificial Intelligence and Present Experimental Data on the Impact on

Productivity Applying Artificial Intelligence that is Generative. Philpapers.org. https://philpapers.org/rec/VARDAU-3.

Morrison, A. M. (2022). Marketing performance measurement. *In Tourism Marketing*. https://doi.org/10.4324/9781315856094-21.

Newton-Lewis, T., Munar, W., & Chanturidze, T. (2021). Performance management in complex adaptive systems: a conceptual framework for health systems. *BMJ Global Health*, *6*(7), e005582. https://doi.org/10.1136/bmjgh-2021-005582.

Pritchard, R. D., Harrell, M. M., DiazGranados, D., & Guzman, M. J. (2008). The Productivity Measurement and Enhancement System: A Meta-Analysis. *Journal of Applied Psychology, 93*(3). https://doi.org/10.1037/0021-9010.93.3.540.

Razali, F. A., Jusoh, M. A., Abu Talib, S. L., & Awang, N. (2022). The Impact of Industry 4.0 Towards Accounting Profession and Graduate's Career Readiness: A Review of Literature. *Malaysian Journal of Social Sciences and Humanities (MJSSH), 7*(7). https://doi.org/10.47405/mjssh.v7i7.1624.

Sutjahyani, D. (2025). The Role of Performance Measurement Systems in Enhancing Managerial Decision Making: A Management Accounting Perspective. *The Journal of Academic Science*, *2*(5), 1373–1382. https://doi.org/10.59613/3y8yx124.

Thottoli, M. M. (2024). Leveraging information communication technology (ICT) and artificial intelligence (AI) to enhance auditing practices. *Accounting Research Journal, 37*(2). https://doi.org/10.1108/ARJ-09-2023-0269.

Thottoli, M. M., Ahmed, E. R., & Thomas, K. V. (2022). Emerging technology and auditing practice: analysis for future directions. *European Journal of Management Studies, 27*(1). https://doi.org/10.1108/ejms-06-2021-0058.

Ullah Khan, M. S. (2024). Performance Measurement in the Digital Era: Review Literature at the Intersection of Management Accounting, Big Data Analytics and Emerging Technologies' Impact on Performance Evaluation. *International Journal of Research and Scientific Innovation, XI*(VIII), 94–101. https://doi.org/10.51244/IJRSI.2024.1108009.

Vitale, G., Rosignuolo, A., & Riccaboni, A. (2025). Sustainability performance measurement systems: a systematic literature review and research agenda for (a better) future. *Measuring Business Excellence*. https://doi.org/10.1108/mbe-09-2024-0155.

Yin, R. K. (2018). *Case Study Research and applications: Design and Methods* (6th ed.). SAGE Publications.

Zhang, C., Zhu, W., Dai, J., Wu, Y., & Chen, X. (2025). Drivers and concerns of adopting Artificial Intelligence in managerial accounting. *Accounting & Finance*. https://doi.org/10.1111/acfi.13404.

Zhu, H., Vigren, O., & Söderberg, I.-L. (2024). Implementing artificial intelligence empowered financial advisory services: A literature review and critical research agenda. *Journal of Business Research, 174*. https://doi.org/10.1016/j.jbusres.2023.114494.