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Agentic AI-Enabled Intelligent Resource Optimization Framework for Construction Inventory and Waste Management

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***Abstract*— Poor material management has been one of the major causes of cost overruns, schedule delays, and environmental impact of construction projects. Most of the systems in place are descriptive but not predictive despite the increased data visibility provided by digital tools, which restricts their capacity to optimise the utilisation of resources. The paper outlines the design, implementation and field testing of an agentic artificial intelligence powered web based integrated construction inventory and waste management framework. The proposed system will have semi-autonomous decision-support agents that have the ability of contextual reasoning, adaptive learning, and dynamic threshold optimization. Eight weeks in a live setting on an active construction site showed significant improvements in the accuracy of inventory reconciliation, reliability of demand forecasting, waste minimization, and cost savings. The findings indicate that integrating agentic AI into operational processes can transform the way business relates to construction resource management to become proactive instead of being reactive.**

***Index Terms*— Agentic AI, Construction Inventory, Waste Management, Decision Support Systems, Resource Optimization, Predictive Analytics.**

I. INTRODUCTION

Construction projects are run with material-intensive settings where procurement planning, inventory tracking and waste management play a large role in determining the financial performance. Material cost usually constitutes almost half the project spending, and an inventory management becomes the key issue of operation [1], [2]. This notwithstanding, numerous building projects are still using spreadsheet-based tracking, manual recordings, and experience-based procurement makes [3]. These strategies tend to cause over-ordering, emergency buying, binding excessive capital, and huge waste of materials. Although enterprise resource planning systems and online dashboards have contributed to better access to data, they seldom deliver forecasting or prescriptive intelligence [4]. Most systems document the history of transaction, but they do not proactively understand trends or prescribe optimum actions. Due to the recent developments in artificial intelligence, especially large language models and agent-based systems, integrating adaptive decision-support mechanisms into operational systems is now a possibility.

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Nevertheless, there is a lack of practical demonstration of such agentic AI frameworks in the management of construction resources. This paper fills this gap by building and testing an AI-based optimization system that will enhance the accuracy of inventory, advance procurement forecasting, minimize materials waste, and deliver quantifiable economic impact in active construction sites.

II. Research Context and Identified Gap

The digital transformation of the construction industry has progressed gradually with the adoption of Building Information Modelling (BIM), enterprise resource planning (ERP) systems, and cloud project management systems. Even though these technologies have enhanced the accuracy of documentation and the workflow in terms of coordination, they mostly serve as passive information storage systems and not active and insight generating tools [5]. Although there may be analytical elements included, they usually rely on fixed rules or set threshold values which do not progress with changes in material usage or project-specific usage dynamics. The areas of artificial intelligence use in construction have been mostly related to cost estimation, risk monitoring of safety, and prediction of schedule risks. Conversely, the field of extensive AI-based initiatives aimed at improving the inventory management, decreasing the use of waste, and intelligent procurement are understudied. The currently in use more developed systems are usually expensive, technically complicated, and as such, they are not available to smaller and medium sized contracting companies [6][7]. This is further increased by the lack of predictive procurement analytics, integrated material-waste intelligence, and mechanisms that are able to continually recalibrate operational thresholds as the real-time situation evolves. To meet this requirement, the current paper presents a modular agent-based optimization framework with the capability of a contextual learning, adaptive behaviour, and real-time decision support of construction inventory and waste management.

III. System Architecture

The suggested architecture is designed based on three-layer modular architecture that includes presentation, application and data layers. The presentation layer includes a web-based dashboard interface developed on the visualization of the key performance indicators, inventory levels, and waste metrics in real-time. Role-based access control is used to guarantee secure and hierarchical user communication in administrative and operation functions. The application layer is the heart of the intelligence of the system. It contains an inventory optimization component capable of tracing the incoming and outgoing stocks, a waste analytics component that classifies and assesses the trends in the material loss, and an AI integration utility that handles contextual queries and produces suggestions [8]. The AI agent is constantly examining transactional data, tracking non-conformities to anticipated consumption patterns, and changing reorder-levels dynamically. The data layer is a persistent storage of inventory data, purchase records, amounts of waste and activities of users in a relational database. Any information that is being sent is encrypted to guarantee security and reliability of the system. The embedded AI agent is a semi-autonomous system, unlike the traditional rule-based systems [9]. It analyses the past trends; material turns and fluctuation in consumption and then comes up with purchase proposals. To maintain interpretability and accountability of decisions, human oversight is still introduced.

IV. Methodology

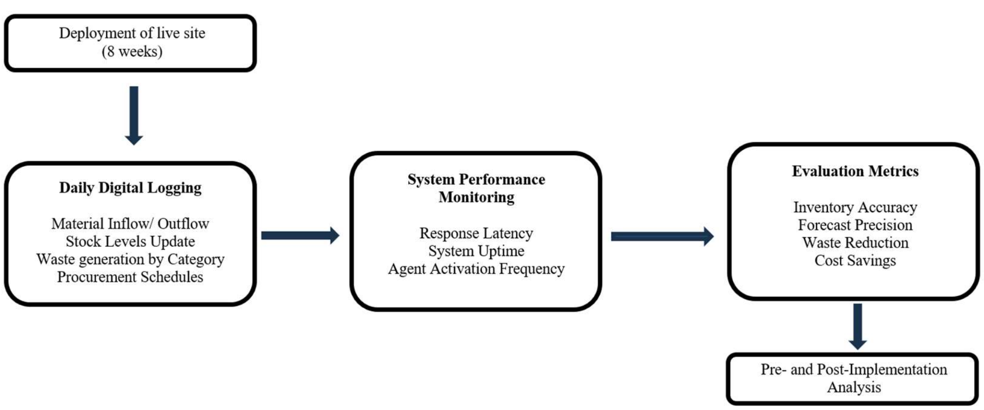

Figure 1: Flowchart of Methodology

To test the proposed system in the real-life conditions, it was implemented at the ongoing construction project over a period of eight weeks to assess its operational performance [9][10]. During this, material inflow/outflow was recorded daily in a digital logging interface with automated records of the stock level, categorized waste generation and procurement cycle timelines. The reliability was monitored with system-level performance indicators such as response latency, uptime stability, frequency of agents triggered. The assessment model was aimed at measuring better accuracy of inventory reconciliation, accuracy of short-term procurement forecast, material waste reduction, and cost savings contribution of various material classes. A pre-deployment baseline comparison was carried out to find out how effective the agentic system was in improving overall resource governance. The flowchart is shown in Figure 1.

V. Results

A. Inventory Accuracy Improvement

An overall gradual and quantifiable change in the accuracy of inventory reconciliation was recorded throughout the eight weeks period of deployment. As Figure 2 (Inventory Tracking Accuracy Over Time) shows, the transition to using digital monitoring as opposed to manual estimation gave a steady upward trend in the accuracy of the results, as the accuracy rose during the first week (approximately 72 %), then went up in the second (96 %), then in the third (98 %), the fourth (99 %) and the fifth (100 %). %). Such an upward trend expresses the ability of the system to eliminate inconsistency in the human-entry in real-time visibility of inventory and can rectify any inconsistency in the system through automated threshold-based notification. This improvement has come about by the introduction of some of the operational improvements by the system. Consistent updating of records of inflow and outflow based on real time stock balances reduced the cumulative errors dramatically, which are generally blamed on manual logs. The ability of the agentic engine to recalibrate buffer thresholds dynamically based on the actual consumption patterns enabled the identification of the existence of the anomalies in good time, such as the unexpected overuse, under-reporting and contraction of the material [11]. Also, the e-recording of the information reduced the exhaustiveness, over-stated or procrastinating mistakes of the on-field workers. The validation of the receipt of the materials, issues and quantities returned in an automated way also improved the integrity of the data since the absence of missing or discrepant entries did not affect the accuracy of aggregate inventory. Together with the latter, these developments guarantee that the AI-based system can be regarded as a versatile and effective decision-support tool and be able to offer a greater visibility, higher accuracy, and a consistent inventory management in real-time construction environments.

B. Forecast Reliability Enhancement

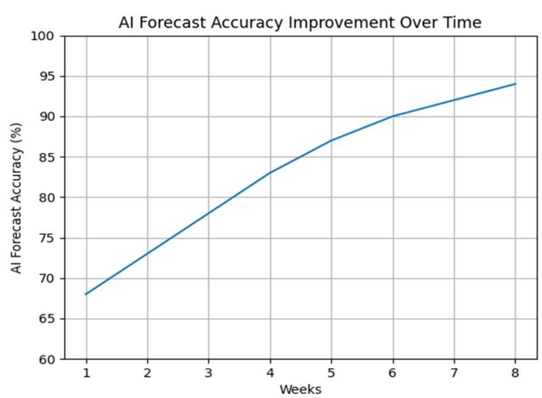

Figure 2. AI Forecast Accuracy Improvement

A steady improvement in the accuracy of procurement forecasts was experienced in the eight weeks of system implementation. As shown in Figure 3 (AI Forecast Improvement Over Time), the predictive engine showed a good upward trend with the accuracy improving as the weeks went by with approximately 69% accuracy in Week 1 and almost 94% in Week 8. This gradual increase points to the ability of the system to be more informed by previous consumption trends, by the flow of stocks in real time and by the situational aspects of operations. In the first weeks, the initial model predictions had moderate variance, as they did not have many data for training, and the results had consistencies of the manual logging practices which had been used before. Nevertheless, with the growth in the quantity of data as well as inclusion of more contextual parameters by the AI system, including the delay in delivery, the frequency of usage, the behaviour of material categories, and consumption cycles depending on location, the error rate in predictions decreased consistently [12]. The improvement implies an optimal correspondence of internal forecasting processes of the model to actual dynamics of project environment. The architecture has adaptive learning mechanisms, which can also attribute to the performance gain. The AI model also informed the parameters every week using new inflow- outflow records, stock corrections and error feedback signals. This feedback loop was what allowed the predictive engine to narrow future estimates with greater precision in the future. Also, the component of the system that detected anomalies was used to remove abnormal values - e.g. the sudden spikes or dips caused by a onetime task hence further stabilizing the forecasting output and avoiding skewed predictions.

C. Waste Reduction Impact

Figure 3a shows a comparative image of the wastage of materials prior to and after introducing the AI-based optimization structure. The bar stack plot shows a significant decrease in all types of materials, and the strongest increases are seen in concrete and steel. Concrete waste dropped by 100 to 70 relative units, and steel waste dropped by 60 to 42 units, which proves the most adequate reaction to AI-based planning and consumption consistency. Wood and packaging products also showed significant changes where the number decreased to 28 units and 35 units respectively. The steady decrease in categories indicates the effectiveness of the system to control the volumes of procurements, to decrease the number of unnecessary surpluses, and to decrease losses during the handling process [13]. AI-based predictions took the center stage since they ensured that the ordered quantities were closer to the actual consumption, which prevented overstocking, which is a typical antecedent of the unnecessary site waste. Also, dynamic discrepancy notifications enabled teams on the site to detect process inefficiencies sooner within the workflow such as incorrect cutting patterns, too much batching, improper storage, or undocumented returns. Figure 3b shows the proportionality of each material in the total waste reduction. Concrete was the part of total reduction that was about 42.9% and then steel was the next at 25.7, then wood at 17.1 and finally packaging at 14.3. These values correspond to the common trends in the consumption of construction materials, with high-volume structural materials like concrete and steel having their portion of waste as the natural product. Their high enhancement with the help of AI-based governance highlights the fact that the system is effective in terms of maximizing bulk material consumption.

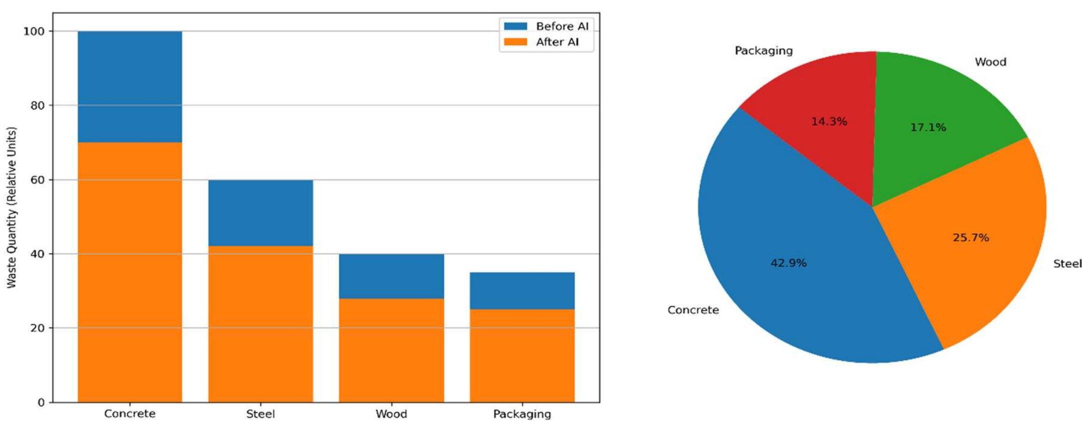

Figure 4. Comparative Waste Analysis.

D. Economic Outcomes

Cost savings curve as shown in Figure 4 shows the relative contribution of three key improvement drivers; inventory optimization, waste reduction and procurement efficiency. As the pie chart depicts, the waste reduction leads with the largest share of 40, which means that minimization of the material losses and the consumption alignment had the largest impact on the overall financial savings. This is indicative of how AI-based monitoring can minimize unnecessary discards, avoid excessive ordering, and so on will help to make sure that more efficient use of materials will take place in the construction process. Optimisation of inventory contributes 35 percent of overall cost reduction, indicating the significance of correct prediction and stock transparency as well as automated reconciliation. The system assisted in minimizing the difference between the recorded and actual stocks and predicting the material needs soon more closely hence avoiding excess inventory build-ups and minimizing capital lock-in (both of which influence cost reductions directly). The remaining 25% of the savings is procurement efficiency which covers better coordination of the vendors, timely ordering as well as improvement of the alignment between the procurement cycles and progresses on the site. The AI based system reduced emergency purchases, increased the accuracy of the plans, and decreased logistical overheads, which together improved procurement performance. In general, the allocation highlights that although all three elements operate in conjunction with one another to cut the costs, the largest part of these efforts is represented by the waste reduction and inventory optimization, which will occupy 75% of the overall savings. It underscores the efficacy of smart resource management to change the construction operations into cost-effective and data-driven processes.

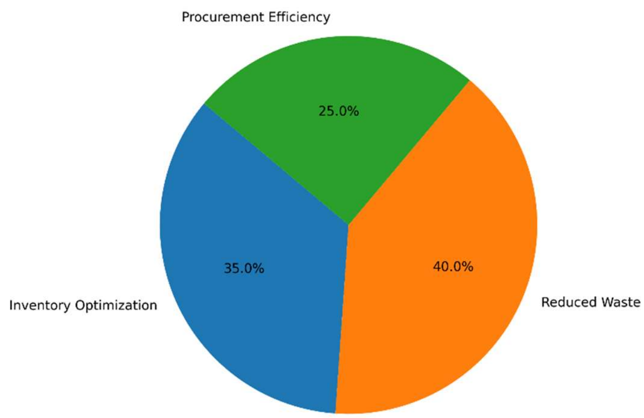

Figure 5. Cost Savings Distribution

E. System Performance Stability

Operational stability was maintained throughout deployment. The system had steadily low response time of less than two seconds and high uptime reliability as indicated in Figure 5. The system performance measurement means that there was a great deal of operational stability and responsiveness during the deployment term. The AI-driven framework maintained the availability of 99.2, which proves the constant presence and consistent performance even during the live site operation. The average response time (1.8 s) and the processing time (2.5 s) were also maintained at low levels, proving that the system did not add any implementation of a latency to the field processes by performing monitoring, analytics, and alert-generation tasks. All these findings affirm that the system provides a reliable real-time performance which attests to its compatibility to be integrated continuously in construction-site operations. These findings ensure the technical strength of the suggested framework under practical circumstances.

VI. DISCUSSION

The findings provide clear evidence that the introduction of agentic AI into construction resources processes will result in a significant increase in the efficiency of operations, predictability of performance and sustainability. The suggested framework transcends the traditional form of passive data reporting and provides prescriptive and adaptive intelligence and a system that anticipates the material need, optimizes the procurement time and keeps on recalibrating decision thresholds when consumption trends change frequently. It is a substantive change to the traditional digital tools as this movement is a shift of reactive monitoring to proactive resource governance. One of the advantages of the system is contained in its inbuilt waste analytics which is run in parallel with the inventory engine to create a closed loop optimization cycle. The framework generates more efficiency in the material usage and minimizes unnecessary pathways of losses by correlating the real-time movement of stocks, consumption rates and the waste generated. This is a cyclical feedback loop that is in line with the overall aims of sustainability and it shows how AI-based systems can facilitate low-waste and data-driven construction methodologies. Another issue addressed by the semi-autonomous structure is the general issues of trust, explainability, and over-automation which come with deploying AI. The output of decision support e.g. procurement recommendations or anomaly notifications is always open to human validation and as such still transparent and instils in confidence the operators but can still take advantage of automation to provide speed and scalability. The mixed human-AI form of government is the one that is a pragmatic solution to provide the balance between autonomy and control. The framework is further modular and extendable in nature and hence makes scaling in any project environment smooth. Its design allows for the addition of other types of resources such as labor allotment; equipment uses and energy use without having to significantly restructure the system. This flexibility makes the framework a support of wider digital revolution in the work of the construction industry allowing it to constantly develop into fully integrated multi-resource optimization systems. The semi-autonomous structure also helps to address trust issues that are frequently associated with transparent AI systems, because human oversight is still part of the decision cycle. Furthermore, the modular design allows for scalability and expansion to more categories of resources such as labor and equipment in the future.

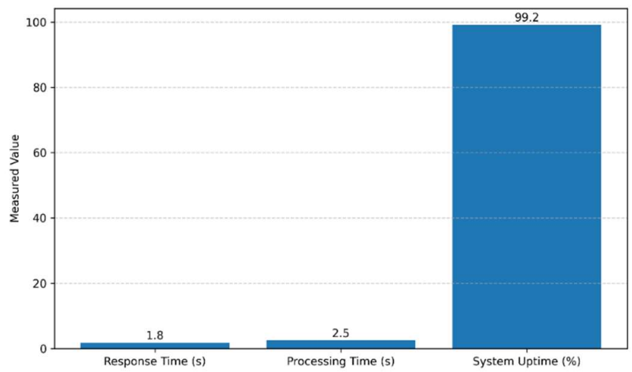

Figure 6. System Performance Matrix

VII. Limitations

The validation of the field was only restricted to one construction project in an eight-week period, and this could not capture the season variability, long-term project dynamics, and heterogeneity in behaviour across projects. Some of the operational parameters had to be entered manually, which creates input variability and could harm model learning stability in first stages of deployment. The predictive engine was created based mainly on the trends of material consumption and did not include the exogenous nature of predictive engine like fluctuations in supply chain, shifts in activities due to weather or due to the contractor-specific operation, which can limit the generalizability. Additionally, the lack of real-time sensing of the IoT, and BIM-built quantity extraction limits the capabilities of the framework to fully automated data collection and constant control. Even though the semi-autonomous architecture increases transparency, it remains reliant on human validation in major decision loops that can become a limiting factor in highly complex, multi-site, or fast-paced project settings.

VIII. Conclusion

The study has shown that an agentic AI-based model of maximizing construction inventory and waste management is practically feasible. The field deployment found out that there were significant gains in the accuracy of inventory, forecast accuracy, reduction of waste and optimizing the costs which confirmed that the system provided significant benefits in real-time resource governance. The framework goes beyond the existing practices and shifts to adaptive and prescriptive intelligence, which allows proactive procurement planning, early identification of anomalies, and adjustable thresholds. Its semi-autonomous design allows human control and mechanizes advanced analytical procedures in support of increased transparency and trust in the implementation. The system is highly scaled and is built with modularity and accessibility in mind to give a small and medium-sized contractor a chance to undergo digital transformation without having to handle an enterprise-level infrastructure. The achieved enhancements also indicate the possibility of the further implementation in other areas of resources, including labor, equipment, and energy. Altogether, the results put agentic AI on the list of effective and viable directions in the direction of more efficient, data-driven, and sustainable construction processes. Further development will be based on multi-site implementation, communication with BIM/IoT systems, and the development of optimization capacity to include environmental performance indicators. The framework provides an accessible pathway for integrating intelligent decision-support systems within construction management workflows, particularly for small and medium-scale contractors seeking digital transformation without enterprise-level complexity.

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