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DIGITAL TWIN BASED INTEGRATED DECISION SUPPORT SYSTEM FOR ENHANCED DECISION-MAKING IN THE LAST PLANNER SYSTEM

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ABSTRACT

This paper discusses the enhancement of decision-making within the Last Planner System (LPS) through digitalization, emphasizing the role of a Digital Twin-based Integrated Decision Support System (DT-IDSS) aligned with Lean Construction 4.0 principles. The proposed conceptual framework DT-IDSS aims to address the challenges in LPS decision-making in terms of autonomation, data integrity, user-centricity, and decision-making rapidness, by integrating user-centric design with advanced technologies such as Digital Twins, Internet of Things, Blockchain, and Artificial Intelligence. It features a decentralized reality capture flow for data processing and storage, and an information loop fostering collaborative stakeholder engagement. The system's user-centric development loop adopts an agile, iterative approach, meeting the dynamic needs of construction projects. The integrations of workflows and technologies in the proposed framework has a huge potential in addressing challenges in the deficiency in system integration, which are essential to effectively support information, computation, visualization, and services, thereby enabling stakeholders to make informed decisions. Future research will focus on assessing decision-making effectiveness, enhancing system scalability, improving data management security, and achieving interoperability with existing management systems. This research contributes to the digital transformation of decision-making process, aiming to provide guidance for future developments in this rapidly evolving field.

KEYWORDS

Last Planner® System (LPS), Lean Construction 4.0, Integrated Decision Support System (IDSS), Digital Twin, Smart Digital Technologies (SDTs)

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INTRODUCTION

In the field of Lean Construction, the significance of efficient and accurate decision-making cannot be overstated. The Last Planner System (LPS) is a Lean-based production planning and control system that aims to reduce variability in workflow, improve the predictability of planning, and decrease the waste of production; while acting in tandem on the social and technical aspects of planning and control in projects (Ballard, 2000). This system highlights the importance of "last planners," the individuals responsible for planning the tasks of those executing the work, such as builders and subcontractors, which empowers these planners to have a greater impact on planning and decision-making processes (Babalola et al., 2019). Hamzeh (2009) identifies key decision-making activities in the LPS are:

- **Master scheduling:** Value proposition translation, milestone setting, schedule development, and integration of master scheduling.
- **Phase scheduling:** Milestone planning, collaborative planning, reverse phase scheduling, and schedule adjustment.
- **Lookahead planning:** Lookahead filtering, constraint identification, constraint removal, and operation design.
- **Weekly work planning**: Task selection and assignment, quality criteria application, and learning from failures.

For over three decades, the LPS has become one of the most popular tools within Lean Construction, contributing a multitude of benefits to the construction industry (Sbiti et al., 2021). However, similar to various other construction project management approaches, LPS can be considered to fall under the category of the gambling paradigm. In this paradigm, decisions are made under conditions of uncertainty, where the outcomes are not certain, but the probabilities are known (Blackwell, n.d., Chapter 1). This type of decision-making often indicates that not all available information is being used effectively or in a timely manner. As a result, decision-makers may oversimplify their process, failing to gather and integrate all the relevant information (Fox et al., 2015).

This lack of comprehensive information utilization is a significant factor contributing to some of challenges that the LPS implementation faces in construction projects such as partial implementation issues (Babalola et al., 2019; Lindhard & Wandahl, 2015), the failure to involve key people in decision-making (G. Ballard et al., 2020), the inherent projects' complexity (Altan & Işık, 2023), underestimation of the social processes impact on technological adoption (Ballard, 2000; Noueihed & Hamzeh, 2022), and the limitations of applying deterministic planning in uncertain project environments (Ballard, 2000; Singh et al., 2024).

To address these challenges, digitizing the decision-making process has become one of the primary areas of focus in construction and engineering project management. Although there has been extensive research on developing digital decision support systems, challenges persist in implementing automated solutions that maintain data integrity and prioritize user-centered design (Boje et al., 2020; Rane & Narvel, 2022; Sacks et al., 2020). Previous studies have concentrated on integrating technologies such as Digital Twins (DTs) (Huang et al., 2021), Internet of Things (IoT) combined with Blockchain (Rane & Narvel, 2022), and computer vision (Mavrovounioti et al., 2015; Reja et al., 2022) to enhance decision-making in project management. However, the practical integration of these complex systems remains a major challenge (Boje et al., 2020). Therefore, a decision support system framework that facilitates the practical application of these technologies in the field is necessary.

Liu et al. (2010) investigated the effectiveness of Integrated Decision Support Systems (IDSS) in improving decision-making within the project management domain. IDSS are defined as interactive computer-based systems that aid in decision-related tasks and are essential in harmonizing data, processes, and technology to facilitate timely and accurate decisions (Liu et al., 2008; Shim et al., 2002). Their research delves into various integration aspects, including data, processes, and technology, culminating in a summarized framework depicted in Figure 1. This framework promotes a unified, interconnected, and user-friendly approach to decision-making (Ren et al., 2023).

For instance, when planning weekly tasks in the Last Planner System (LPS), decision-makers require various supports: information (e.g., progress updates, resource availability, task details), visualization (e.g., aerial site views, task flowcharts), computation (e.g., feasibility studies, cost estimation, risk management), and services (e.g., planning boards, documentation software). In an IDSS, these supports are enhanced: information support through service integration (e.g., shared drives, data management platforms) ensures data accessibility; visualization support through process integration links logical relationships; computational support through data integration converts computational data into decision-making data; and service support through presentation integration reduces cognitive load. These integrations are vital in facilitating an effective decision-making process and can be effective in addressing challenges for the decision-making process associated with the LPS. However, choosing a suitable theoretical framework to guide the IDSS development and pinpoint effective technologies and methodologies for decision-making support in the LPS, continue to be a matter that requires further investigation.

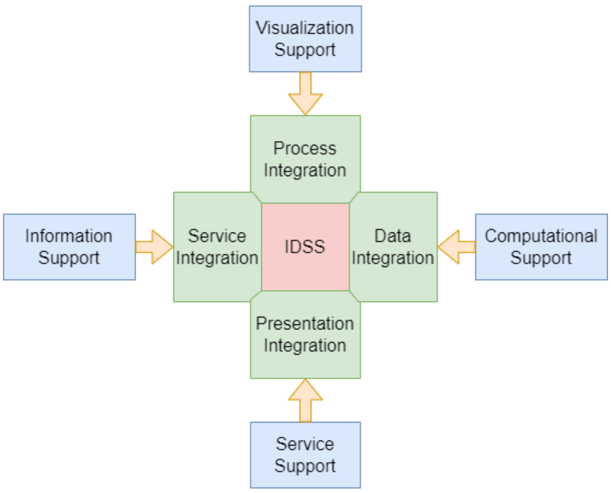

Figure 1 Integrated Decision Support Systems (IDSS) Framework, adapted from Liu et al. (2010)

Lean Construction 4.0 (González et al., 2022) presents a promising theoretical framework that reflects on some of the fundamental technology, production and people/culture shifts in the Architecture, Engineering, and Construction (AEC) sector. This framework combines the production principles of Lean Construction with Industry 4.0-inspired smart and digital technologies (SDTs), underpinned by human-centered design. This synergy aims to enhance and expedite the AEC industry's digital transformation not only by applying Lean Construction principles in tandem with SDTs, but boosting the effectiveness of decision-making processes within AEC organizations. Lean Construction 4.0 also cultivates a project management style that is both more efficient and sustainable, centered on human requirements, which leads to an effective manner to deal with the unique challenges of large-scale infrastructure projects. Through this integrated approach, Lean Construction 4.0 opens new avenues for optimizing resource utilization, mitigating risks, and accomplishing project objectives with an unparalleled level of precision and efficiency.

Building on the foundation of Lean Construction 4.0 (González et al., 2022), this paper presents a novel approach: a Digital Twin-based Integrated Decision Support System (DT-IDSS) to support the LPS implementation. The aim is to weave Lean Construction 4.0's SDTs into LPS's decision-making processes. This involves enhancing key decision-making activities in the LPS by utilizing an IDSS in crucial areas such as data collection, data analysis, decision-making application development, and information flow. The objective is to not only tackle current challenges in digital decision support systems but also to pave the way for future advancements in the development of digital IDSS in Lean Construction domain.

A BRIEF REVIEW OF DECISION SUPPORT SDTS AND INTEGRATIONS

The concept of Digital Twin (DT) has become a fundamental element in revolutionizing decision support systems among various industries. Essentially a DT serves as a digital reflection of physical entities, systems, or processes, facilitated by ongoing and timely information exchange (Sacks et al., 2020). In construction, DT goes beyond the simple digital representation of project products and processes to offer a dynamic and real-time link between the physical and digital realms. This connection enables continuous monitoring and analysis, providing deep insights and control over infrastructure projects. Creating a DT involves developing a virtual model of a physical asset, integrating real-time data from sensors and IoT devices to accurately replicate the asset's behaviour and performance (VanDerHorn & Mahadevan, 2021). Populating the DT requires continuously updating the model with live data, enabling real-time monitoring, analysis, and optimization of the asset's operation and maintenance (Boje et al., 2020). This offers a dynamic and holistic view of construction projects, integrating real-time data and predictive analytics to enhance decision-making processes (Boje et al., 2020). DT technology, known for its deep impact on data integration and visualization, has established itself as a fundamental aspect of decision support systems in diverse sectors (VanDerHorn & Mahadevan, 2021).

Based on Lean Construction 4.0, the collection of detailed data from the construction production environment is critical to generate DTs for decision-making (Bou Hatoum & Nassereddine, 2022). This ties in with the advancements in lean project management efficiency through the integration of IoT and Blockchain technologies, signaling a shift towards more secure, transparent, and instantaneous data management in construction projects (Martínez et al., 2022; Rane & Narvel, 2022; Wu et al., 2023). In this realm, IoT sensors act as crucial links between the physical and cyber worlds, capturing real-time data for subsequent modeling and analysis (Bou Hatoum & Nassereddine, 2022). Concurrently, Blockchain technology, known for its decentralized structure, immutability, and strong authentication processes, is vital for ensuring secure and reliable data distribution (Li et al., 2019). From the reality capture and data distribution perspectives, the integration of IoT and blockchain can address the dynamic challenges faced during infrastructure project management that often lead to delays, rework, and increased overhead costs (Amade & Nwakanma, 2021; Fobiri et al., 2022). By leveraging blockchain and IoT, the project management process can be transformed, offering real-time data insights, improved asset management, and enhanced security and transparency (Ghimire et al., 2016). This technologically advanced approach not only aligns with the principles of adaptive and intelligent IDSS, but also extends these principles by providing practical, real-time solutions for managing resources efficiently in large-scale infrastructure projects. The adoption of this Blockchain-IoT integrated architecture represents a significant leap in data collection and information distribution for digitalized, decentralized decision support systems.

Following the collection of data from construction sites through reality capture and IoT sensing, the timely generation of semantically enriched DTs remains a challenge (Boje et al., 2020). The integration of Artificial Intelligence (AI), via computer vision technology, into the real-time generation of DTs in construction and infrastructure projects is fundamental. It offers transformative possibilities in production management practices by providing real-time data modelling and analytics, which enables a dynamic and highly accurate representation of physical assets and revolutionize how projects are planned, monitored, and executed (Sami Ur Rehman et al., 2022; Shamsollahi et al., 2022; Soman & Molina-Solana, 2022; Xu et al., 2021). This integration is also one of the practical applications of SDTs within the Lean Construction 4.0 framework, enhancing production management practices(Stowe et al., 2020). Recent studies in this domain have underscored the value of computer vision and deep learning technologies in enhancing real-time monitoring and decision-making. For example, the application of Computer Vision-based Construction Progress Monitoring (CV-CPM) has demonstrated how real-time, accurate monitoring of project progress can be achieved (Bozorgzadeh & Umar, 2023). Also, reinforced learning with linked-data based constraint checking shows the potential of applying AI-based models to provide computational support for the decision-making in the LPS (Soman & Molina-Solana, 2022). Further, the development of regression-based deep neural networks for equipment monitoring and advanced 3D pose estimation techniques illustrates the capability of these technologies to provide detailed, real-time insights into construction operations (Cheng et al., 2023; Golparvar-Fard et al., 2013; T. H. Wang et al., 2023). These advancements in AI not only facilitate a more dynamic and holistic view of project environments but also align with the core principles of adaptive and intelligent IDSS. By enabling the continuous synchronization of physical and digital worlds, AI technologies contribute significantly to the creation of real-time, accurate DTs, which are crucial for the proactive management of safety, resource allocation, and overall operational efficiency.

Despite these technological advances, a gap remains in the form of an IDSS that cohesively combines these technologies within the decision-making workflow. This paper seeks to bridge this gap through the introduction of a User-Centric Digital Twin-Based Integrated Decision Support System conceptual framework, as illustrated in Figure 2. The proposed framework provides a vision to integrate the strengths of IoT and robotics for reality capture, blockchain for secure data distribution, and advanced AI-based data processing, all within a DT framework for IDSS. This user-centric approach aims to harness the full potential of these technologies, providing an innovative and robust solution for efficient and effective decision-making within the LPS.

THE DT-IDSS FRAMEWORK

This section offers a comprehensive overview of the proposed DT-IDSS Framework. The discussion is proceeded in the following order: system overview, decentralized reality capture flow, decision-making information loop, and user-centric development loop. Additionally, this section also presents the current research progress in applying the proposed framework.

USER-CENTRIC DIGITAL TWIN-BASED INTEGRATED DECISION SUPPORT SYSTEM OVERVIEW

The LPS decision-making process, as mentioned in the introduction section, can be considered to fall under the category of the gambling paradigm, characterized by decisions made under uncertainty. To mitigate this uncertainty, the decision support is anchored by four key pillars: information, visualization, computation, and service (Galjanić et al., 2022; Liu et al., 2010; Shim et al., 2002), which is shown in Figure 2. At the core of the system lies information support, providing essential data crucial to make informed decisions. This includes updates on project progress, availability of resources, and specific details about tasks. Key to this component is the integration of services, ensuring seamless access to important information for decision-makers. Service integration focuses on combining functions and services within the DT-IDSS, ensuring that different components of the system are compatible and accessible. This integration encompasses not just the harmonization of internal components but also the optimization of the user interface and external interactions, thus enhancing the overall utility of the system.

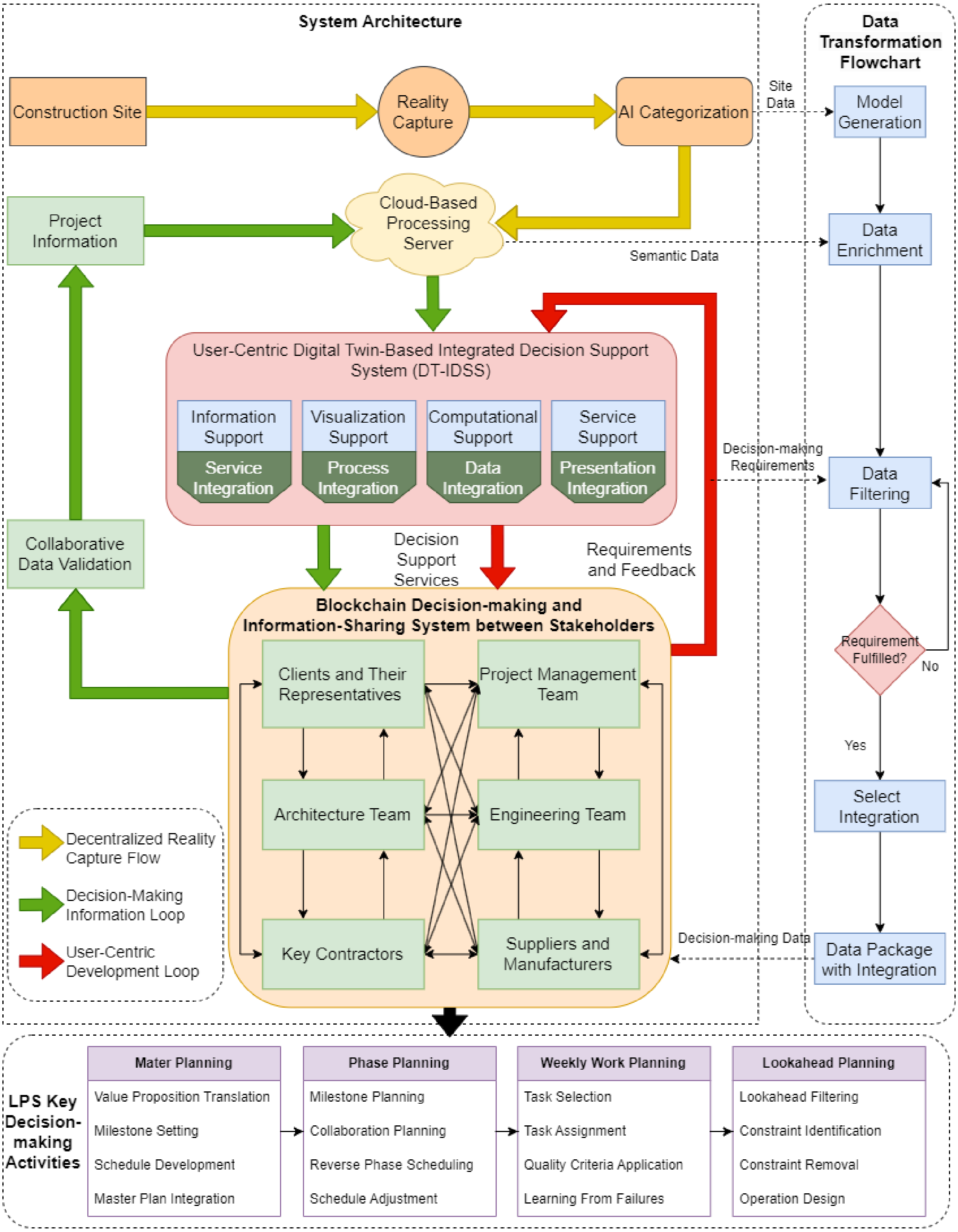

Figure 2 User-Centric Digital Twin-Based Integrated Decision Support System (DT-IDSS)

Visualization support enhances the data experience by presenting information in formats such as charts, images, videos, 2D/3D models, and Building Information Modeling (BIM) constructs. This is done in a manner that is easy to understand and user-friendly, necessitating the integration of processes to create cohesive and intuitive visual representations of data. On the other hand, computation support leverages computer systems and algorithms to streamline complex data interpretation, assisting in key areas such as planning, cost estimation, and risk analysis. This support depends on the effective integration of data, converting extensive computational outputs into practical, actionable insights.

Service support consolidates various essential tools and applications for efficient decision-making, aligned with the project's overarching objectives. This includes a range of digital planning tools, document management systems, and BIM technologies, all optimized through presentation integration for a user-centric approach. The aim here is to reduce the cognitive burden on decision-makers and make the decision-making process more efficient. Presentation integration focuses on creating a consistent user interface across the DT-IDSS, standardizing visual design and interactive elements to ease user interaction. It also involves using consistent metaphors and mental models across various components to simplify learning and minimize interference in usage.

The service support of the system offers a variety of user-focused services, like customizable interfaces for different user roles, dashboards for stakeholders. Services in presentation integration are designed to deliver a consistent and intuitive user experience across various devices and platforms, boosting stakeholder engagement and facilitating decision-making. This comprehensive approach to decision support within the DT-IDSS framework not only streamlines the management of infrastructure projects but also markedly improves the efficiency and effectiveness of the decision-making process.

Decentralized Reality Capture Flow

As illustrated in Figure 2, the primary aim of the reality capture process is to guarantee the prompt and precise transmission of data to a cloud-based processing server, ensuring the data's integrity throughout. This workflow is designed to gather the maximum amount of information feasible, tailored to meet decision-making requirements. Consequently, it is distinct from the decision-making process, a strategic separation that ensures the data remains pure and accurately represents the original information as captured and processed. In the user-centric integration development process, the data sourced from this flow undergoes only filtration without any alteration, maintaining its authenticity.

In this setup, reality capture sensors are classified into three types: photogrammetry sensors (e.g., CCTVs and stereo cameras), sensors for geometric information (e.g., location trackers and Geofencing), and Unique Identification (UID) sensors (including RFID and Bluetooth Low Energy-based beacons). The data captured by these sensors is transmitted via Narrowband Internet of Things (NB-IoT), a specialized communication technology designed for IoT sensors. Operating on cellular telecommunication bands, NB-IoT is optimized for extending wide-area connectivity to IoT devices. It offers several advantages, including low power consumption, extensive coverage, high connectivity density, and enhanced security, making it particularly suitable for infrastructure projects (Miao et al., 2018).

AI models are employed to categorize all collected data and transfer the categorized data for the model generation. For instance, computer vision models can be applied to categorize and preprocess photogrammetry data. An example using Yolov8 developed by the IHT lab in the University of Alberta (https://www.iht-lab.com/) is shown in Figure 3. Moreover, deep learning-based models with GIS data can be applied to the 3D reconstruction process, as shown in Figure 4. Depending on the computational requirements of these tasks, the AI models may be deployed either locally at the sensor level or integrated with the cloud-based processing server.

In the proposed framework, a cloud-based server is established as an independent central unit for storing, processing, and distributing IoT data within a decentralized reality capture system. This server stores both unprocessed and processed data, ensuring its availability for the

DT-IDSS as required. Importantly, it plays a vital role in creating 3D mesh models and adding semantic attributes derived from IoT sensors and project information, aiding in the creation of real-time, semantically enriched DTs. At this stage of research, the DTs are BIM models enriched with information from reality capture, sensors, and collaborative project meetings. These DTs serve as dynamic data reservoirs, aiming to improve the efficacy of real-time decision-making processes. The server is designed to manage intricate processing tasks such as action recognition, performance evaluation, quantity calculation, and the assessment of cognitive loads on workers. Its contribution to the decision-making information cycle is essential, bringing substantial value to this integrated system.

Figure 3 Example of a Computer Vision Model Detecting Excavators and Key Points

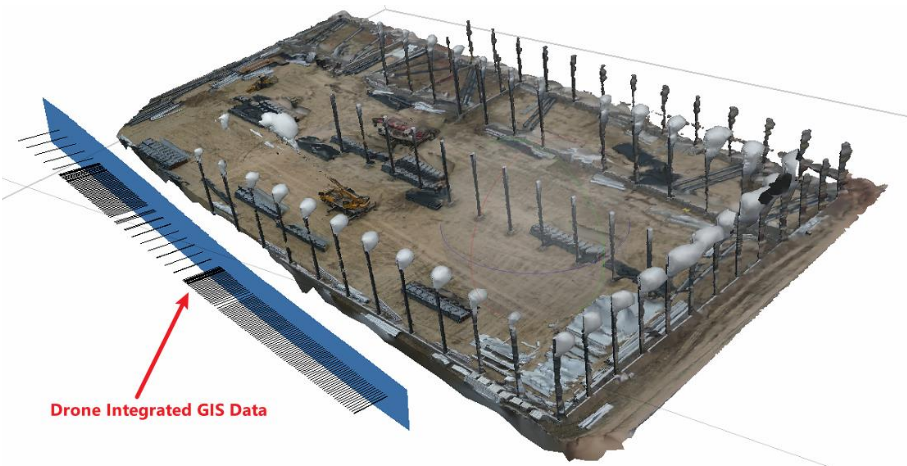

Figure 4 Example of Deep Learning Based 3D Reconstruction Using GIS Data

DECISION-MAKING INFORMATION LOOP

The decision-making information loop follows the Lean Construction 4.0 principle of *"development of human trust in the decision-making system"* (González et al., 2022). As illustrated in Figure 2, the design aims to support decentralized and collaborative interactions among stakeholders. This involves stakeholders actively participating in reviewing, validating, and updating data to ensure its accuracy and relevance to the project's needs. Stakeholders play a pivotal role in checking and refining the data within the system, while also maintaining the immutability of records, contributing their expertise, and fostering a shared understanding of project information. After the project information is validated, it is transmitted to the cloud processing server for the generation of semantically enriched DTs, which act as information conduits for the DT-IDSS. The blockchain technology here provides a decentralized approach of data management, which ensures that once data is entered, altering it requires consensus and must be transparent across all stakeholders (Wu et al., 2023). This cooperative model ensures that the system's data is current, reflective of the project status, and enriched by the varied insights and skills of all involved parties, thereby improving the quality and dependability of the decision-support framework.

Data integration within the DT-IDSS is crucial for reliable decision-making, as it ensures consistently updated and synchronized information across the system. This integration minimizes data redundancy and enables smooth data flow between system components, preserving data integrity. The establishment of clear integration standards and the maintenance of data completeness and synchronization are vital for effective decision-making. This strategy allows for quick dissemination of critical updates, such as design changes. The DT-IDSS enhances computational support by utilizing advanced techniques (e.g., data fusion, cloud computing, and blockchain) to combine and coordinate data from various sources, including architectural design software, project management tools used by the project management team, onsite reports from contractors, and inventory systems from suppliers. Leveraging decentralized blockchain technology, modifications in these data sources are instantaneously updated across all platforms accessible to stakeholders, which ensures that stakeholders receive timely, reliable, and highly integral data. As a result, they can quickly adapt their work schedules and tasks to align with evolving project requirements.

USER-CENTRIC DEVELOPMENT LOOP

The user-centric development loop in the DT-IDSS follows the Lean Construction 4.0 principle of *"consciousness about human-centered systems"* (González et al., 2022, p. 10). This method promotes an iterative and collaborative approach that is essential to agile UX design practices. It prioritizes user needs in the development of decision-making applications, ensuring that the system is not only technically proficient but also practically relevant (Wang et al., 2023). This approach is vital for successful integration of services, processes, data, and presentations, as illustrated in Figure 2, thereby improving the overall functionality and user experience within the DT-IDSS framework.

In this process, stakeholders (end-users) are actively engaged throughout the entire development cycle of DT-IDSS applications. Their crucial role involves reviewing, confirming, and enhancing system features to ensure the DT-IDSS effectively addresses practical requirements. The stakeholders' continuous involvement in validating functionalities, providing insights, and giving feedback is instrumental in the system's ongoing development. This constant loop of user engagement keeps the system in sync with the evolving needs of construction and infrastructure projects, allowing it to adapt to changes and foster a sense of ownership among all involved parties.

Agile software development principles are integrated into the design of the DT-IDSS, with a focus on sprints that address urgent needs of stakeholders. Regular meetings with interdisciplinary teams of stakeholders ensure clear communication and the swift resolution of immediate issues in the development of DT-IDSS applications. In this development cycle, backlog grooming is a continuous activity, involving regular updates to the backlog with new stakeholder requirements, feedback, and changes. At the end of each sprint, a review session is held where stakeholders can evaluate the latest version of the system and provide comprehensive feedback. Stakeholder requirements are meticulously gathered through interviews, surveys, observations, and workshops. The feasibility and impact of these requirements are analyzed, then prioritized based on the value they bring to stakeholders and the project. These consensus-based requirements are documented clearly and in detail, for instance, through user stories, to ensure they accurately reflect stakeholder needs and avoid any misunderstandings or ambiguities. An example of user-centric application designed for site surveying and progress monitoring is shown in Figure 5, applying the user-centric development framework for remote inspections adapted from Wang et al. (2023)

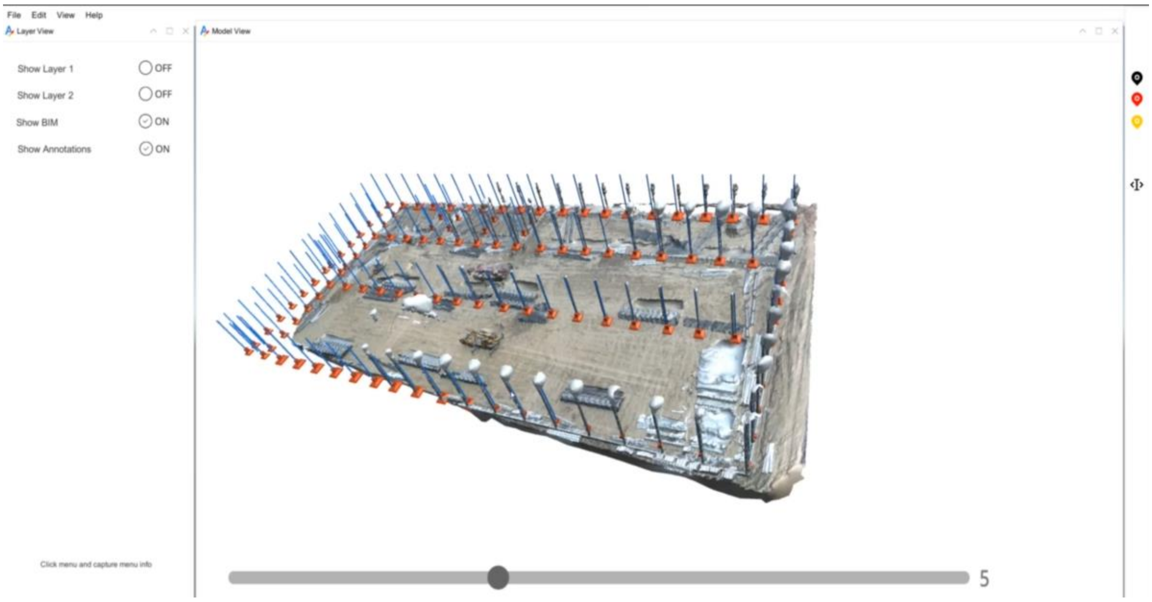

Figure 5 Application Developed for Site Surveying and Progress Monitoring

CONCLUSION AND FUTURE WORKS

This paper has highlighted the critical importance of timely and accurate decision-making in the LPS and how the digital transformation of these processes can significantly enhance project management efficacy. The proposed DT-IDSS, grounded in Lean Construction 4.0 principles, harnesses cutting-edge technologies like DT, IoT, Blockchain, and AI to tackle the complex challenges faced in LPS decision-making processes. The DT-IDSS is characterized by key elements such as a decentralized reality capture flow for accurate data processing and storage, and an information loop for decision-making that encourages collaborative involvement of stakeholders. Furthermore, the system's development loop places a strong emphasis on a user-centric, agile, and iterative approach, aligning with the dynamic needs of construction projects.

The DT-IDSS shows potential in facilitating various decision-making aspects. It assists in precise work sequencing and task allocation by utilizing real-time data on project progress and resource availability. This contributes to better forecasting, risk management, and adjustment of project schedules to accommodate changing conditions. Additionally, the DT-IDSS gives special consideration to human-centric factors, improving workforce management and safety. It offers customized work schedules to optimize team performance and well-being, while AI-driven predictive analytics help identify potential risks, creating a safer and more adaptive work environment. This comprehensive strategy is in line with Lean Construction principles, focusing on both efficiency and the human aspects of project management.

Though this framework represents an initial result of multiple ongoing research at IHT lab in the University of Alberta, it has not yet been fully developed and validated. Future research is proposed in several areas: 1) Assessing Decision-Making Effectiveness: Implement empirical studies to evaluate the impact of the DT-IDSS on decision-making and overall project results; 2) Enhancing System Scalability and Flexibility: Aim to refine the framework to cater to diverse project sizes and complexities; 3) Improving Data Management with a Focus on Security: Prioritize streamlined data management for efficient data sharing, while enhancing data security and privacy, especially regarding reality capture and data distribution in the DT-IDSS; 4) Achieving Interoperability with Existing Management Systems: Work on making the system compatible with existing project management and enterprise resource planning systems for seamless integration and data exchange.

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