Exploring the role of digital twin systems in mine safety

by Marvin Cheng, Jacob Carr, Bob Bissonette, Rebecca Knuth and Emily J. Haas

Many industries, including mining, are experiencing an increase in the use of robotic and other artificial intelligence (AI) systems to improve efficiency, productivity and precision. For example, a 2023 survey showed that mining industry executives wanted to integrate more autonomous equipment to improve productivity and alleviate workforce shortages (Haas, 2024). This feedback was coupled with an increased appetite to advance the types and uses of automation and AI in the workplace.

However, there is also an increasing concern about the ways that robotic applications may unintentionally affect worker safety. Human-machine interaction poses potential risks, especially when industrial robots operate near workers in specific environments (such as drilling, handling and transporting materials, equipment inspection and lifting heavy loads). Research has explored the unintended consequences of introducing new technologies or processes in the workplace to include incidents such as being struck by equipment and challenges around data privacy (Lööw et al., 2019; Khurram et al., 2025; Haas and DuCarme, 2015; Almeaibed et al., 2021; Zio and Miqueles, 2024). More recently, the use of digital twin technologies and simulations (hereafter referred to as digital twin systems) has been boasted as a tool that can help prevent unintended consequences around worker safety by identifying and mitigating risks before a worker completes a task in tandem with a robot or other new technology. Digital twin systems produce a virtual replica of a physical environment or process (Almeaibed et al., 2021; Zio and Miqueles, 2024; Saes, 2024).

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To this end, this article explores the potential role of digital twin systems in enhancing safety within mining and other similar environments. It will primarily focus on environments where robots and human workers may interact, although digital twin systems can be useful with other technology applications. First, we define digital twins and digital simulation as components of a system. Then, we highlight possible applications of digital twin systems in mining to replicate real-world processes, followed by potential benefits of their use and where more research may be needed.

Digital twin systems

A digital twin is a virtual model of a physical object, process or system that is created to accurately reflect an object of interest (Batty, 2018). More specifically, a digital twin uses real-time data and simulation to replicate the behavior, condition and performance of physical systems (Batty, 2018; Miskinis, 2018; TWI, n.d.). This article discusses digital twin systems as an umbrella term for digital twin technologies and simulations. The actual physical object used to create the virtual model is then equipped with sensors or other devices to gather data about the object's performance (for example, monitoring a machine's productivity) (Miskinis, 2018). By continuously syncing with sensors and control systems, digital twins provide a dynamic, data-rich environment for understanding and predicting how equipment operates under various conditions and can be used to improve aspects of the physical object or operation of the system (TWI, n.d.).

In other words, digital twin systems mirror the real-world counterpart in a digital environment, allowing for real-time analysis and monitoring. This includes the ability to simulate different scenarios, track system performance and predict outcomes based on real-time data and historical trends. For example, studies have simulated truck loader haulage systems to better understand and improve truck dispatching (Park et al., 2016; Moradi et al., 2019) whereas other research has used real-time data and trends to predict how rock fragmentation may behave during blasting processes (Nobahar et al., 2024).

The role of digital twin systems in risk and safety management

A key role of digital twin systems is to proactively identify and mitigate risks. For example, digital twin systems can help create simulations for training purposes or support workers' remote operation of equipment (Saes, 2024; Nobahar, 2024). Further discussed in this article, the literature review by Nobahar and colleagues (2024) highlighted ways in which these systems can also help to monitor workers' movements in relation to other vehicles or equipment to avoid collisions. Digital twins may also help manufacturers ensure that their technology systems are designed with the workers' safety in mind. By simulating various operating conditions and potential safety hazards, companies can certify robots and other technologies comply with industry standards and regulatory requirements before they are deployed. This proactive approach also ensures that safety standards are not only met but exceeded, safeguarding workers from the outset and minimizing the risk of costly compliance violations or shutdowns.

Other uses of digital twin systems include real-time monitoring, workflow optimization, incident investigations and continuous improvement (Nobahar et al., 2024).

Robotic applications. By creating a virtual environment that mimics the real-world mining environment or specific process, safety professionals and engineers can simulate and observe the interaction between robots and workers in their environment. Such systems may help to proactively identify hazards before they occur, supporting the reliability of robotic applications across mining.

Specifically, by continuously monitoring the performance of the robot in the virtual model, companies may more accurately predict when a component might fail or when a robot requires maintenance. For instance, engineers can simulate scenarios where sensors may malfunction, or joint movements become imprecise. This predictive capability can help fix issues early and prevent unexpected breakdowns.

Also, digital twin systems can help to identify potential failure points in the robot's operation that need to be addressed before the system is physically deployed in the real world (Cheng et al., 2024). Figure 1 shows an example of a digital twin used to model the robotic device in a virtual environment at the National Institute for Occupational Safety and Health (NIOSH) Robotics Laboratory in Morgantown, WV.

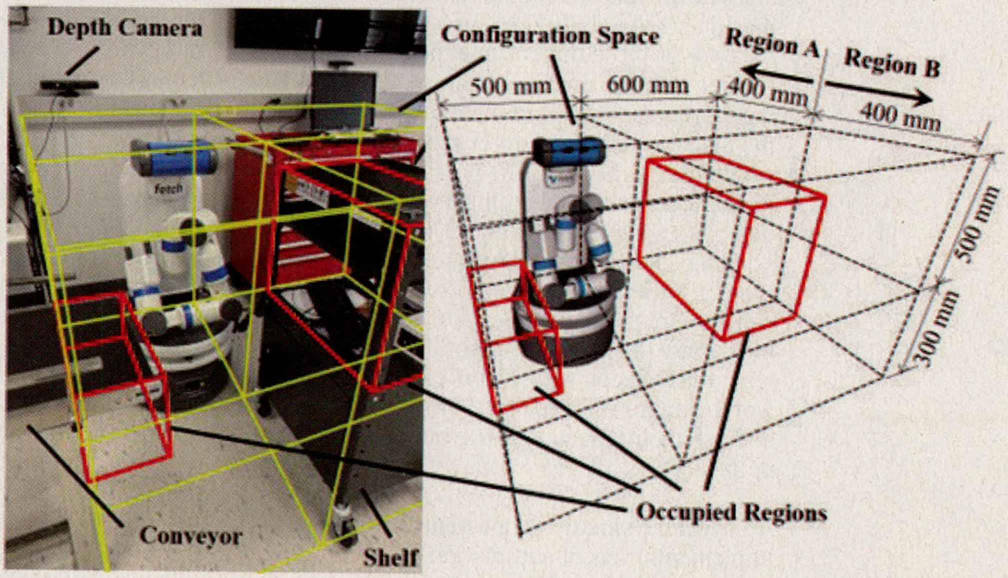
Digital twin systems provide a means to test and optimize workflows in a controlled environment. Even with well-defined zones, there is a possibility of unintended interactions with robots in the workplace (Cheng, 2024).

However, digital twin systems can simulate entire production lines, including the movements of robots and workers, to ensure smooth and efficient processes. They can also be used to identify scenarios in which a worker might unintentionally enter the robot's workspace, leading to injury. Specifically, a digital simulation can reveal if a worker's tasks are too close to a robot's range of motion, increasing the chance of unintended interaction. Adjustments can then be made to the robot's programming or the layout of the work environment to minimize risk. In some cases, companies may discover that workers need additional training to safely operate alongside robots, ensuring human errors are minimized. In other instances, companies may take other corrective actions, such as redesigning workspaces, adjusting the robot's programming or installing additional safety features like sensors and barriers.

Additionally, repetitive motion and awkward postures can cause strain injuries to workers. Digital twin systems can be used to show how robots and human workers interact to support safe ergonomic practices. There are other applications of digital twin systems specific to machine safety that can support a more effective deployment of robots in the workplace. This not only enhances productivity but also reduces the risk of human error that might lead to incidents.

Figure 1

A digital twin used to model the robotic device in a virtual environment at NIOSH.



Machine safety applications. Digital twin systems have enhanced machine safety across industrial domains. Similar to their use in robotic applications, digital twins enable continuous monitoring, simulation and predictive analysis of mobile and stationary machinery, offering the potential to mitigate hazards before they manifest. In the context of machine safety, digital twins enable a proactive approach by allowing operators and engineers to anticipate failures, assess risk scenarios and validate safety interventions before they are implemented in the field. For heavy equipment, including mining equipment, digital twins can integrate data from sensors monitoring safety-critical factors such as worker proximity or the state of machine health to identify hazardous conditions in real time. These insights can trigger automated alerts or control responses that prevent incidents, reduce exposure to dangerous machinery and support predictive maintenance strategies.

For example, in the application of proximity detection technology, digital models of not only the physical machines but also the electromagnetic fields used to determine the location of nearby workers, enable systems that can more accurately represent the worker's situation. In earlier proximity detection systems, a worker-worn receiver would measure the strength of a magnetic field produced. If the strength exceeded some preset level, alarms would be issued, or machine motion would be disabled (Haas and DuCarme, 2015).

However, by incorporating digital models into this technology, a more sophisticated system can be developed. For example, the Intelligent Proximity Detection system developed by NIOSH (Jobes et al., 2012) utilizes digital analytic models of the magnetic fields around the machine (Li et al., 2012) to precisely determine the two- or three-dimensional position of a worker near the machine (Carr et al., 2010). This digital representation of the relative positions of the machine and the worker is then combined with a digital model of the possible machine movements to create intelligent proximity detection zones (Jobes et al., 2011). Because the system includes a model of where the worker is along with how the machine can move given control inputs, the zones can be designed to block only those machine motions that could lead to a collision with a worker, allowing the worker to move more freely around the machine and use their judgement to avoid other hazards in the area.

Machine situational awareness. Future implementations of automation and autonomy will require equipment (that interacts or operates with humans) to play an active role in assuring safety. This requires that each machine — whether mobile, stationary or hybrid — has an active understanding of its environment and the objects within it (including humans) to adequately evaluate the dynamics, process risk in real time and act to keep risk at a minimum (Bissonette and Sbai, 2024; Mueller et al., 2020). Consequently, machine situational awareness (MSA) will rely heavily on robust, real-time digital twins and stochastic algorithms that can independently project interactions, calculate risk and evaluate alternate futures that mitigate existing and arising risk exposures.

To date, NIOSH researchers have identified sensor suites, software tools, mathematical models and other technologies that are needed to inform a robust, yet flexible framework for a globally applicable system (Bissonette and Sbai, 2024; Bissonette, 2023). This also includes defining what criteria must be met in a digital twin, sensor data (accounting for variance and redundancy) and real-time stochastic analysis that would not be hardware or software exclusive. To date, formative efforts have developed a 1/14th-scale openpit mine to pilot-test a framework on haul trucks, light vehicles and excavating equipment (Bissonette and Sbai, 2024; Bissonette, 2023). Applications for this technology are only limited by the number of machines at a mine.

Conclusion

Digital twin systems have revolutionized the way the mining industry addresses safety, particularly when deploying robotic and other more advanced technologies. This article discussed previous and current research underway to identify the ways that safety professionals can best leverage these technologies to better identify potential hazards, optimize workflows and ensure compliance with safety regulations prior to introducing new technologies, including robots. Moving forward, when combined with human behavior modeling, digital twin systems may also be used to improve training, simulate emergency scenarios and support human-machine collaboration, ultimately contributing to safer and more resilient mining operations. ■

Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

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