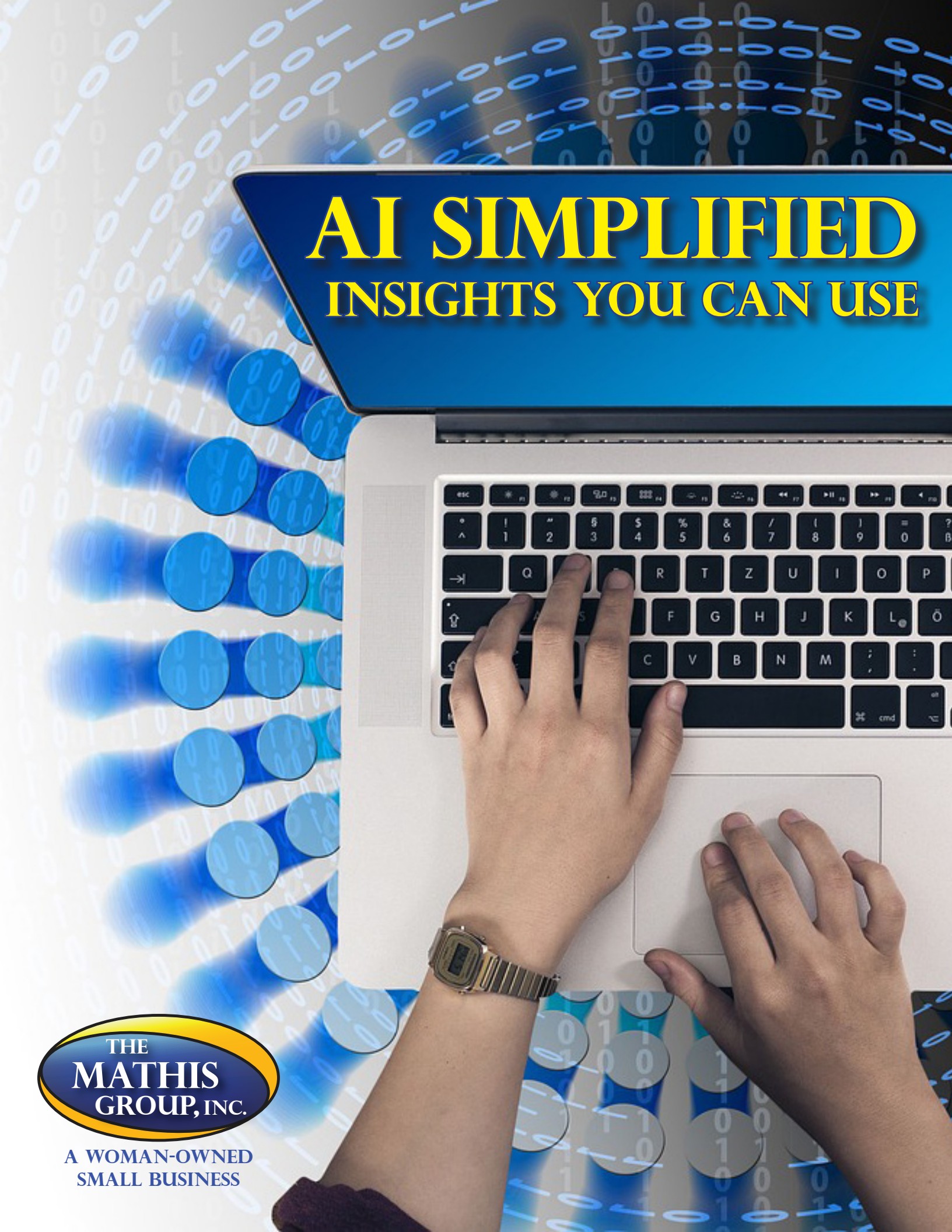
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APRIL 2026
AI CHANGES THE FIRST HOUR OF A PROJECT CRISIS

A project crisis usually does not start with one big disaster. Most of the time, it starts small. A supplier misses a few deadlines. Quality starts to drop. Customers begin to complain. One part of the project slows down, but no one yet sees the bigger problem.

This is where AI can help most. AI may not solve the crisis on its own, but it can spot warning signs earlier. It can detect small problems in scattered data before they grow into serious damage. Muralitharan et al. (2021) found that machine-learning warning systems could detect trouble earlier than simple warning tools when signs were distributed across multiple inputs. Their study was in healthcare, but the idea also fits project work, where teams must watch many things at once.

This matters because many crisis responses start too late. Teams often mistake a growing problem for a normal delay. Status reports may still look fine. People assume the schedule will recover. Leaders wait for better information. AI can help close that gap by simultaneously monitoring schedules, messages, defect logs, purchasing records, alerts, and customer feedback. No team can track all of that by hand all day long.

When AI is used well, it gives teams earlier visibility. When it is used poorly, it creates more noise. The difference often depends less on the technology itself and more on whether the organization is ready to use it. Leaders need to decide what counts as a warning sign, who reviews alerts, and what happens next. In that sense, success depends on how well the organization adapts under pressure, which aligns with Cedergren and Hassel's (2024) argument about adaptive capacity in crisis management.

CATCHING EARLY WARNING SIGNS

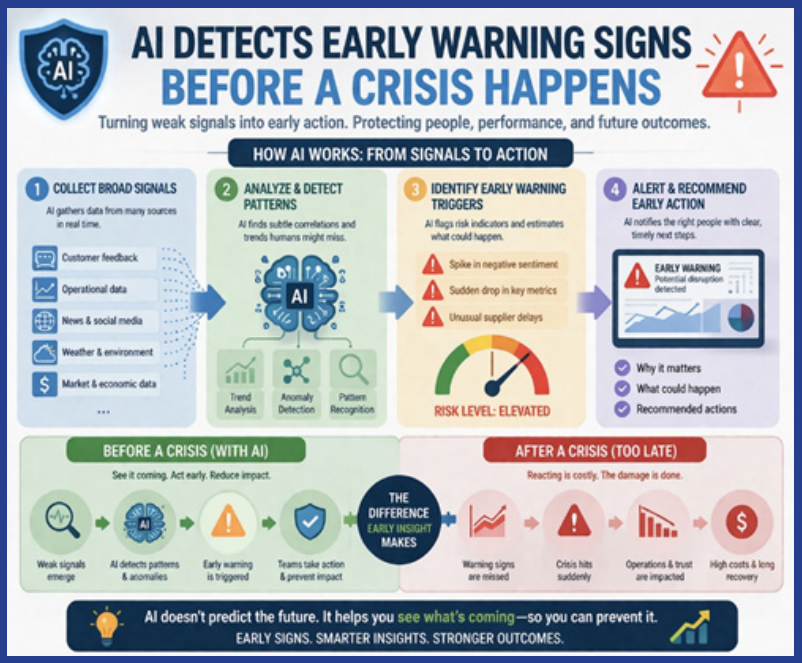
Catching early warning signs sounds easy, but it is hard in real project work. Projects generate a lot of information, but much of it arrives late, remains incomplete, or sits in different systems. Schedule data may be in one tool, risk logs in another, and email conversations somewhere else. Informal concerns may never be written down.

AI can connect patterns across these broken-up inputs, but it is only as good as the information it receives. If the data is old, incomplete, or biased, the tool may miss the correct problem or raise the wrong alarm. Ferrara (2023) explains that unfairness and error often enter through missing records, weak measurements, and uneven data, even when the final output looks neutral.

Because of this, AI should usually be used as a warning tool, not as the final answer. A strong system should flag rising risk, point out unusual patterns, and provide an estimate rather than acting as if it were fully certain. That matters because project crises do not usually move in a straight line. One delay can trigger another. A late design decision can shorten procurement time. Procurement pressure can reduce testing time. Less testing can allow defects to slip through. Those defects can then cause stakeholder conflict.

AI helps because it can identify these connected patterns more effectively than static dashboards or simple spreadsheets. Fan et al. (2021), writing about digital twins in disaster management, describe this as a way to make chain reactions easier to see.

Still, spotting a warning is only the first step. Leaders still need to interpret the alert correctly. When AI signals rising risk, leaders need to know what changed, how unusual it is, what data caused the alert, and how often the tool has been wrong before. Research on transparency shows that explainable AI can help people use automation more effectively, but it can also make them overly confident, especially under time pressure (Tatasciore & Loft, 2024a, 2024b). That is why teams need balanced trust, not blind trust.



LETTING AI HELP WITHOUT GIVING UP HUMAN JUDGMENT

Once a project enters crisis mode, time becomes very valuable. Teams must gather facts, assign tasks, notify stakeholders, update records, and find the right response plans at the exact moment people are already overloaded.

AI can help by handling some of this limited support work. It can sort incidents, route tasks, build status summaries, send preapproved alerts, draft executive messages, or begin low-risk steps that leaders already approved. This aligns with research in emergency medicine, where AI is seen as a tool to speed up triage and coordination, not to replace human decision-makers (Liu et al., 2018; Petrella, 2024).

Still, not every action should be automated. Some actions are easy to reverse, while others are serious and hard to undo. AI may be useful for sending an alert, opening a ticket, building a timeline, or starting a backup workflow. However, choices such as moving major resources, canceling a release, making public legal statements, or triggering contract penalties should usually be subject to human review.

Research on human-AI teamwork supports this idea. Fügener et al. (2021) argue that success depends on dividing work wisely, as working with AI also entails cognitive risks. Vaccaro et al. (2024) found something similar in a large review: people and AI can work better together than either one alone, but only when the work is divided in the right way.

The best path is controlled delegation. AI should handle fast coordination tasks and pattern-heavy support work. Humans should retain authority over hard trade-offs, ethical questions, and big decisions that change the project's direction. Without these boundaries, organizations may either trust AI too much or reject useful help completely.

PRACTICING BEFORE A CRISIS HAPPENS

Teams prepare better when they practice decisions before a crisis begins. Traditional drills are still useful, but they often use fixed scenarios and simple scripts. Real crises are usually more tangled than that.

AI-supported simulation can help. Digital twins, scenario tools, and agent-based models can help teams test how a schedule problem, supply disruption, cyberattack, safety issue, or stakeholder backlash might spread through a project. Fan et al. (2021) describe digital twins as practical tools that reveal interdependencies before the damage becomes too difficult to reverse. In project work, this can be very practical. A construction team can test how bad weather could make labor shortages worse. A technology team can practice what happens if a vendor outage occurs during a release freeze. A healthcare project can test the combined effect of staffing problems, regulatory delays, and product defects. These exercises move teams from vague concern to real decision-making. They also build the ability to anticipate and coordinate, which Cedergren and Hassel (2024) describe as a learned form of adaptation.

Simulation also helps in another way: it breaks false confidence. Many teams think they are ready because they have a playbook on paper. A real rehearsal tests whether that playbook actually works under pressure. Often, it shows that the organization has steps on paper but no real follow-through, clear reporting lines but no quick decisions, or roles on a chart but no shared understanding. Research on crisis learning after COVID-19 makes the same point: learning matters only when it changes daily practice, not when it merely raises awareness (Southworth et al., 2024).

THE BIGGEST PROBLEM: BAD OR MISSING DATA

During a crisis, AI cannot rise above the quality of the data it receives. This is a major issue in projects because project information is often uneven. Some workstreams are tracked closely. Others depend on late updates, messy vendor files, or human judgment. People under pressure may even soften the delivery of bad news. As a result, AI is often asked to make strong recommendations from weak information. Ferrara (2023) warns that unfairness and bias are not just abstract moral concerns. They are often built into the everyday data pipeline.

In a project crisis, bad records create two main dangers. First, the tool may miss a real problem because the needed signal never entered the system. Second, the tool may issue a false alarm because weak or distorted inputs can resemble a known risk pattern. Either result can damage trust. If users see too many weak outputs, they may stop trusting the tool even when it is right.

That is why data care should be treated as part of crisis readiness, not just paperwork. If leaders want AI to help during a disruption, they need cleaner

data before the disruption starts. They also need routines that keep the tool aligned with changing conditions (Cedergren & Hassel, 2024).

Teams also need humility. Sometimes, the most responsible output is not a firm recommendation, but an honest statement that there is not enough information to be confident.

BALANCING SPEED WITH ACCURACY

Crisis management always involves a hard tradeoff. If leaders wait for complete information, the damage may spread. If they act too fast on weak information, they may create new problems. AI does not remove this tension. In some cases, it makes it stronger.

Fast answers can create the illusion that a better answer exists now, when in truth it is only a faster guess. Tatasciore and Loft (2024a, 2024b) explain this clearly. Their work shows that transparency can help people use automation better, but it can also increase automation bias when teams are under pressure.

For project leaders, the main issue is not only how good the tool is. It is also how the decision process works. What happens when AI gives advice? Who can overrule it? How much confidence is enough before action begins? What should happen when the AI output does not fit reality?

Clear explanations can help, but they can also lead people to trust the tool too much. Strong crisis planning needs both a path for action and a path for disagreement.

One helpful way to think about this is to separate decisions into two types. Time-dominant choices require quick action even when uncertainty persists, and AI may help with them. Consequence-dominant choices have bigger downstream effects and usually need slower human review, even when the AI sounds sure.

REDUCING RESISTANCE TO AI

Resistance to AI in crisis work is often described as a training problem. That view is too simple. People do not resist only because they do not understand the tool. They also resist because they question whether it fits the work, whether it is fair, whether it is legitimate, and who will be accountable if things go wrong.

The graphic shares five ways to reduce resistance, which build trust and transparency, along with other supportive characteristics. Explaining why to as many people as possible while supporting training and empowering workers to seek help typically reduces resistance and establishes support.

Mahmud et al. (2023) found that algorithm aversion is shaped by resistance to innovation, organizational readiness, and fear that human judgment will be sidelined. That means resistance is not only a knowledge gap; it is also a leadership and design issue. This skepticism is understandable. In most organizations, human leaders remain responsible even when a machine makes the recommendation. If a crisis decision fails, a project sponsor cannot simply say, "The tool decided."

Adoption works better when AI is connected to real work, clear limits, and obvious human responsibility. Research on human-AI teamwork supports this point. Strong results come from carefully designed complementarity, not from vague talk about partnership (Fügener et al., 2021; Vaccaro et al., 2024).

Trust grows when the tool proves useful in visible ways. If it spots a supply risk two weeks earlier than current routines would have, people notice. If it speeds up triage or improves coordination during a disruption, that matters. In daily practice, resistance often wanes as AI proves itself in small, concrete, accountable tasks before leaders allow it to influence larger decisions (Mahmud et al., 2023).

EVALUATING AI AFTER THE CRISIS

When the immediate danger ends, organizations often move quickly toward closure. They want to recover the schedule, reassure stakeholders, and get tired teams back to normal work. Even so, the period after the crisis may be the best time to learn.

If AI helped with detection, triage, communication, or response, leaders should review what it actually added. That review should go beyond general opinions. Did the tool detect the problem early enough to make a difference? Which alerts helped, and which were false, late, or too vague? Did automation reduce delays? When people overruled the tool, were they right to do so?

These are not only technical questions. They are practical questions about how the tool worked in real life. Research on organizational learning in crisis settings argues that learning occurs only when experience is translated into changed practice, not when it is merely written down as "lessons identified" (Southworth et al., 2024). The point is not to prove that AI was good or bad. The point is to learn where it improved human judgment, where it distorted it, and where it needs improvement.

UPDATING CRISIS PROTOCOLS BEFORE THE NEXT PROBLEM

Reflection only matters if it changes how the organization works next time. This is where many organizations fail. They hold a lessons-learned meeting, record a few ideas, and then drift back into normal habits.

Research on crisis learning suggests that real improvement happens when lessons become routines, thresholds, communication rules, role boundaries, and better training (Southworth et al., 2024). When AI is part of crisis management, leaders need to clearly update protocols. Which alerts should now trigger escalation? Which automated steps are allowed? What evidence must come with an AI recommendation? When is a second human review required? Which inputs must be fixed before the next crisis?

These questions matter because AI tools do not work in frozen environments. Project settings change. Vendors change. Risks change. Staff turnover changes how people use the system. A tool that worked well last year may no longer fit current conditions. Cedergren and Hassel (2024) describe this as a loss of adaptive capacity.

At the same time, good protocol must still leave room for human concern outside the tool. Some of the most important warning signs begin not as measurable data, but as someone saying, “Something feels off.”

GETTING READY FOR FUTURE DISRUPTIONS

The larger lesson is simple. AI for crisis management is not just a product to buy. It is an organizational capability that must be built. Tools matter, but lasting value depends on how well an organization aligns its people, data, governance, and learning routines under pressure. Research on adaptive capacity returns to this point again and again (Cedergren & Hassel, 2024). AI can strengthen those parts of the organization, but it cannot replace them.

Preparation depends on a short list of management questions. Do teams have the right data in real time? Are alert thresholds tied to real operational risk? Do people know when to trust the tool and when to question it? Have leaders practiced the handoff between automated support and human decisions? Is there a disciplined review after every disruption?

These are management questions just as much as technical ones. When organizations answer them well, AI can help projects detect trouble sooner, coordinate faster, and learn more honestly from failure. When leaders ignore them, AI may speed up confusion.

The healthiest view is neither hype nor fear. AI works best in crisis management when it supports human judgment in a disciplined way. It is strongest when it detects weak warning signs, speeds up limited-response tasks, and makes practice scenarios more realistic (Fan et al., 2021; Liu et al., 2018). It is weakest when leaders expect it to make up for poor records, weak governance, or unclear accountability (Ferrara, 2023; Cedergren & Hassel, 2024). In the end, the projects best prepared for future disruptions will not be the ones that automate the most. They will be the ones who combine speed, caution, order, and learning under pressure.

REFERENCES

Cedergren, A., & Hassel, H. (2024). Building organizational adaptive capacity in the face of crisis: Lessons from a public sector case study. International Journal of Disaster Risk Reduction, 100, Article 104235. https://doi.org/10.1016/j.ijdrr.2023.104235

Fan, C., Zhang, C., Yahja, A., & Mostafavi, A. (2021). Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. International Journal of Information Management, 56, Article 102049. https://doi.org/10.1016/j.ijinfomgt.2019.102049

Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. Sci 2024, 6(1), 3. https://doi.org/10.3390/sci6010003

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. Information Systems Research, 33(2), 678–696. https://doi.org/10.1287/isre.2021.1079

Liu, N., Zhang, Z., Ho, A. F. W., & Ong, M. E. H. (2018). Artificial intelligence in emergency medicine. Journal of Emergency and Critical Care Medicine, 2, 82. https://doi.org/10.21037/jeccm.2018.10.08

Mahmud, H., Islam, A. K. M. N., & Mitra, R. K. (2023). What drives managers towards algorithm aversion, and how to overcome it? Mitigating the impact of innovation resistance through technology readiness. Technological Forecasting and Social Change, 193, Article 122641. https://doi.org/10.1016/j.techfore.2023.122641

Muralitharan, S., Nelson, W., Di, S., McGillion, M., Devereaux, P., Barr, N. G., & Petch, J. (2021). Machine learning–based early warning systems for clinical deterioration: Systematic scoping review. Journal of Medical Internet Research, 23(2), e25187. https://doi.org/10.2196/25187

Petrella, R. J. (2024). The AI future of emergency medicine. Annals of Emergency Medicine, 84(2), 139–153. https://doi.org/10.1016/j.annemergmed.2024.01.031

Southworth, F., Chalmers, D., Reedy, G., Amlôt, R., & Skryabina, E. (2024). Organisational learning from the public health response to the COVID-19 pandemic: Findings from a qualitative interview study. Frontiers in Public Health, 12, 1411346. https://doi.org/10.3389/fpubh.2024.1411346

Tatasciore, M., & Loft, S. (2024a). Can greater transparency into automation mitigate the effects of time pressure on automation use? Applied Ergonomics, 114, Article 104142. https://doi.org/10.1016/j.apergo.2023.104142

Tatasciore, M., Strickland, L., & Loft, S. (2024b). Transparency improves the accuracy of automation use, but automation confidence information does not. Cognitive Research: Principles and Implications, 9(1), 67. https://doi.org/10.1186/s41235-024-00599-x

Vaccaro, M., Almaatouq, A., & Malone, T. W. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. Nature Human Behavior, 8(12), 2293–2303. https://doi.org/10.1038/s41562-024-02024-1

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