

AI-ENABLED ORGANIZATIONAL ARCHITECTURE FOR STRATEGIC DECISION-MAKING AND HUMAN-MACHINE COLLABORATION

Didit Darmawan¹, Khowanas Saeed Qader²

¹Universitas Sunan Giri Surabaya, Indonesia, ²College of Administration and Economics, Lebanese French University, Kurdistan Region, Erbil, Iraq

correspondence: dr.diditdarmawan@gmail.com

Abstract - Artificial intelligence is increasingly becoming an organizational infrastructure rather than a stand-alone technological tool. This article examines how AI and data analytics reshape strategic decision-making and team effectiveness and how organizations can balance operational efficiency with human creativity and intuition. An integrative literature review was conducted across research in management, information systems, human resource management, organizational behavior, and human-AI collaboration. The synthesis indicates that AI can accelerate information processing, reduce certain forms of information asymmetry, and improve team decision quality when its capabilities are supported by reliable data, calibrated trust, digital literacy, appropriate incentives, and accountable governance. These benefits are conditional because opaque or incomplete AI systems may introduce new information asymmetries and excessive reliance. A sustainable AI-enabled organization therefore requires differentiated task allocation. Routine and structured activities can be automated, whereas complex analytical work is better augmented through human-AI collaboration. Creativity, intuition, and professional judgment remain essential for ambiguous and high-stakes tasks. The article concludes that organizational advantage depends less on maximizing automation than on designing complementary relationships between algorithmic capabilities and human agency.

Keywords: ai-enabled organization, human-ai collaboration, algorithmic decision-making, team effectiveness, artificial intelligence, human creativity, digital hrm.

INTRODUCTION

The development of artificial intelligence has shifted the position of technology in organizations from a supporting facility to a core component of the decision-making architecture. Machine learning, generative AI, predictive analytics, and recommendation systems enable organizations to process massive amounts of data and update information in a much shorter time compared to conventional analysis mechanisms (Lu et al., 2025). This change drives the emergence of the AI-enabled organization, which is an organization that places AI capabilities, data, and humans into a single interdependent working system. Jarrahi (2018) explains that the strength of AI primarily lies in its ability to process information complexity, whereas humans retain the advantage when facing ambiguity, uncertainty, intuition, and judgments that require broad comprehension (Telaumbanua et al., 2025). The relationship between the two shifts the organizational question from whether AI needs to be used to how the division of labor between computational intelligence and human judgment should be designed so that decision quality improves without eliminating the human capacity to understand the meaning and consequences of decisions.

This shift has implications for organizational design. Traditional structures rely heavily on hierarchical levels to gather information, verify reports, and provide decision authorization. When operational data can be analyzed in real time and algorithmic recommendations are available at the work unit level, some coordination functions previously embedded in the hierarchy may undergo changes (Valentine et al., 2024). Raisch and Krakowski (2021) describe the relationship between automation and augmentation as a paradox that needs to be managed simultaneously. Automation allows technology to take over specific tasks, whereas augmentation directs technology to expand human capabilities. Organizations that place too much emphasis on automation may lose tacit knowledge and judgment capacity, whereas excessive reliance on humans can reduce the benefits of large-scale data processing. The AI-enabled organization therefore needs to be designed through a division of decisions that considers task characteristics, risk levels, interpretation needs, and the value that can be added by the combination of humans and machines.

Changes in work structures are also related to job fragmentation and the emergence of increasingly flexible workforce configurations (Woolley, 2024). Mardikaningsih (2025) explains that digitalization, generational value shifts, and flexible work forms drive the reconstruction of employment relationships and demand human resource functions to move toward organizational design and worker experience management. AI accelerates this tendency because jobs can be broken down into tasks that can be automated, tasks that can be enriched by AI, and tasks that still require intensive human interaction (Oluwatoyin & Mardikaningsih, 2024). Consequently, it is not enough for organizations to adopt AI applications without reorganizing decision flows, responsibilities, skills, and team coordination forms. Job design needs

to consider who initiates decisions, who checks AI outputs, when humans can reject system recommendations, and how errors are accounted for (Hölzle et al., 2024). These questions become increasingly relevant as algorithms enter strategic areas such as workforce planning, investment, performance appraisal, innovation, and resource allocation.

Data analytics strengthens this process by providing management with a broader information base (Mardikaningsih & Darmawan, 2025). Mardikaningsih and Darmawan (2025) emphasize that big data analytics capability can strengthen organizational learning and data-driven decision making when supported by managerial readiness, data literacy, and adequate governance. High analytical capacity enables organizations to recognize patterns that are difficult to see through manual observation, test scenarios, and anticipate the consequences of alternative decisions (Altaf et al., 2025). Even so, a larger volume of information does not equal better decision quality. Data may be incomplete, unrepresentative, or tied to past patterns that are less relevant to new conditions. Decision quality also depends on the security and reliability of the employee data used in the analysis, so data management needs to be strictly safeguarded (da Costa et al., 2023). Predictive models can also give an impression of certainty that exceeds the strength of the actual evidence. The value of AI for strategic decision making depends on an organization's ability to treat predictions as input for managerial reasoning, not as an automatic replacement for the judgment process. When AI-based decisions cause harm, organizations need to ensure that responsibility is clear and that the basis of the decision can be proven (Sutanto et al., 2023).

The human dimension becomes increasingly decisive because the ability to benefit from AI differs across employees and generations (Shakil et al., 2024). Workers' ability to adapt to technological change is influenced not only by the characteristics of the technology, but also by self-efficacy, work experience, education level, and the organizational support received during the change process (Mardikaningsih & Darmawan, 2022). Work readiness and digital skills also determine how well employees make use of new technology (Darmawan, 2025). Darmawan (2024) discusses the digital readiness of the Baby Boomer generation and highlights the adaptation gap that can emerge when technological change develops faster than individual readiness. Skill retraining accompanied by social support can narrow this gap (Eddine & Darmawan, 2026). A similar problem applies to the entire workforce in an AI-enabled organization. The ability to use digital tools does not automatically produce the ability to question AI recommendations, assess model uncertainty, recognize bias, or combine machine output with job knowledge. Organizations need AI literacy that covers an understanding of the system's strengths, limits, risks, and error patterns. Without such competence, AI use can give rise to two extreme behaviors: excessive rejection or automatic acceptance of system recommendations. Both patterns reduce the benefits of human–AI collaboration because decision quality depends on judgment that can use algorithmic results critically. In addition, technology-mediated interaction changes how employees communicate, build professional identity, and assess information, so critical discussion of AI recommendations does not occur automatically (Darmawan, 2021; da Cruz et al., 2024; Evendi et al., 2025).

A scientific gap emerges because discussions of AI in organizations are often fragmented across technological productivity, HRM change, algorithmic ethics, and worker behavior. Research on AI-based decision making shows the potential for improved information processing, while studies on algorithmic management highlight the risks of lost autonomy, transparency, and trust. Not all of the literature explains in an integrated way when AI recommendations improve team decision quality and when AI instead creates new information asymmetry, automation bias, or dependence that reduces critical discussion. The same problem appears in the relationship between efficiency and creativity. Automation can free up time from routine tasks, but algorithm-based standardization can also narrow the variety of thinking if workers follow machine-generated patterns too closely. Digitalization also changes the structure of work tasks, so job design needs to be adjusted to keep the division of roles between humans and machines clear (Triono et al., 2025). Studies on the AI-enabled organization require a synthesis that brings together decision design, human competence, trust, governance, and creativity in a single explanatory framework.

This article positions the AI-enabled organization as a socio-technical system that connects computational intelligence with human judgment, experience, creativity, and accountability. This perspective avoids understanding AI as a technology that works separately from organizational structure. The value of technology is influenced by data quality, job design, the distribution of authority, user capability, communication patterns, and correction mechanisms. The article's theoretical contribution is directed at combining the literature on human–AI decision making, AI-enabled HRM, dynamic capabilities, digital literacy, organizational justice, and job redesign. At the practical level, the synthesis seeks to explain how organizations can determine which decisions are suitable for automation, which should be augmented, and which require stronger human authority. This division is needed so that AI improves productivity and team effectiveness without reducing room for creativity, intuition, and professional responsibility.

The article has two main objectives. The first objective is to analyze changes in strategic decision-making patterns after AI and data analytics are connected to work processes, including their implications for team effectiveness. The second objective is to explain the boundaries and conditions that enable organizations to achieve operational efficiency without sacrificing human creativity and intuition. On the basis of these objectives, the first research question is: How does the integration of artificial intelligence and data analytics transform strategic decision-making patterns in modern organizations, and to what extent do these changes enhance team work effectiveness? The second research

question is: To what extent does the implementation of AI within organizational structures create a balance between operational efficiency and the need for human creativity and intuition? Both questions are discussed sequentially through an examination of the relationships among data, AI, decision rights, teamwork, trust, job design, and human agency.

RESEARCH METHODS

The article uses an integrative literature review directed at building a conceptual synthesis regarding AI-enabled organizations. The integrative approach was chosen because the subject matter involves literature developing across management, information systems, human resource management, organizational behavior, and human–AI interaction. Snyder (2019) explains that a literature review can be used as a research method when the search, selection, and synthesis processes are conducted systematically according to scientific objectives. Literature evaluation uses the principles of evidence-informed management, which emphasize search transparency and the assessment of the relevance of findings to managerial problems (Tranfield et al., 2003). The synthesis process was conducted through comparative reading of research objectives, sample characteristics, units of analysis, theoretical mechanisms, and main findings. The literature was then grouped into themes of decision architecture changes, team collaboration effectiveness, trust in AI, organizational readiness, automation and augmentation, creativity, job design, and worker well-being. Torraco's (2005) integrative review principles were used to connect findings originating from different research traditions so that the analysis does not stop at individual study summaries. Interpretation was built by distinguishing empirical findings, conceptual propositions, and article inferences. Studies producing associations were not treated as causal evidence without support from appropriate research designs.

RESULTS AND DISCUSSIONS

Reconfiguration of Decision-Making and AI-Based Team Effectiveness

The integration of AI transforms decision-making from a predominantly sequential process into a more iterative system based on continuously updated information. In traditional structures, information typically moves from operational units to management via periodic reports before decisions are cascaded back down through the hierarchy. AI and analytics allow part of the information to be processed directly at the point of work, enabling individuals and teams to obtain predictions, classifications, or recommendations without waiting for the entire reporting chain (Sikhakolli et al., 2025). Li and Tian (2026) show that the quality of outcomes depends on the interaction between decision characteristics, AI capabilities, and human engagement patterns. These findings support the view that AI does not create a single universal form of decision-making. Organizations require different role allocations for routine, semi-structured, and strategic decisions that carry high uncertainty.

This change affects the locus of authority sources. Decisions previously derived their legitimacy from hierarchical positions and professional experience, whereas AI-enabled organizations introduce a new source in the form of computational evidence. This shift can enhance the quality of discussions because managerial assumptions can be compared with patterns identified from data. However, algorithmic decisions still require interpretation regarding objectives, risk boundaries, and consequences for stakeholders (Hussain et al., 2025). Del Barone et al. (2026) state that the use of AI in public administration HRM relates to the need for managerial competencies such as strategic thinking, change management, and emotional intelligence. These findings indicate that increasing machine capabilities actually raises the need for specific managerial competencies. Leaders are not sufficient simply being able to read dashboards. They must understand when information is trustworthy, how information is communicated, and how decisions retain their legitimacy.

AI can reduce some of the information asymmetry within a team when the system has access to information that was previously scattered among members (Sidor et al., 2025). Zercher et al. (2025) state that an AI configuration with centralized knowledge can improve decision accuracy compared with human teams with unevenly distributed information. The mechanism relates to reduced information imbalance and useful AI information processing. These findings are highly relevant for organizations because many group decision failures are caused not by a lack of knowledge, but by a failure to combine knowledge that is spread out. AI can act as an information integrator that reminds the team of evidence that did not surface in the discussion (da Silva et al., 2023). This benefit depends on how AI information is brought into team conversations and whether members understand the basis of its recommendations.

The same results also show the limits of AI's benefits. Zercher et al. (2025) state that when the AI itself holds incomplete information, teams may face a new form of information asymmetry and not gain the same improvement. This means AI can shift the information problem rather than remove it. Teams may assume that the system has a complete view when the model has only received certain data. Risk assessment in big data information systems helps organizations recognize data limitations before recommendations are used (Khayru & Qader, 2026). This creates the risk of epistemic overconfidence, that is, excessive confidence in machine output because the computational process appears objective. Organizations need to make data lineage, prediction confidence levels, and model limitations understandable to users.

Records of data origin and decision trails are also useful as valid evidence when a decision is challenged (Setiyono et al., 2026). Such transparency enables teams to combine AI recommendations with knowledge that did not enter the model, including changing market conditions, qualitative information, and field experience.

An organization's ability to adopt such systems is influenced by a combination of technical and organizational factors. Himanshu et al. (2026) examine internal factors affecting the adoption of AI-enabled HRM from a dynamic capabilities perspective. Their framework links HR flexibility, IT agility, dynamic capabilities, user attitudes, behavioral intention, and cognitive resistance. This finding shows that AI investment cannot be separated from system and human readiness. Organizations with strong infrastructure but a workforce that does not trust or understand the system may fail to obtain benefits. Employee resistance to technological change needs to be managed in a planned way so that adoption is not obstructed (Mardikaningsih & Wardoyo, 2024; Mardikaningsih & Wardoyo, 2026). The same applies if employees hold positive attitudes but data and technology integration are inadequate. AI-enabled decision making requires an organization's ability to detect opportunities, adjust resources, and continuously reconfigure processes. Leadership that balances the use of existing systems with trials of new ways of working helps this capability develop (Irfan & Darmawan, 2024).

The effectiveness of technology implementation in organizations depends not only on the capability of the system, but also on the leader's ability to steer change and build organizational members' readiness for new technology (Darmawan & Gardi, 2024). Digital leadership also plays a role in building employee readiness for work automation (Mardikaningsih & Darmawan, 2023). Team effectiveness is also determined by the level of trust in the system. Shukla et al. (2026) position organizational justice as an antecedent of trust in AI-enabled HRM. They show that trust develops through perceptions of fairness before, during, and after system use. This principle can be extended to team decisions. Members will be more willing to bring AI recommendations into discussion when they believe the data process, criteria, and use of the results are legitimate. Trust that is too low causes the technology to be ignored, while trust that is too high can lead to automation bias. Trust also forms easily through impressions of authenticity and closeness rather than evidence of reliability, so a source that appears convincing is not necessarily worth trusting (Hariani & Mardikaningsih, 2022). The organizational goal is not to maximize trust without limit, but to build calibrated trust, that is, a level of trust that matches the actual reliability of the system. Users need to understand the areas of strength and the failure conditions of AI so that decisions do not shift from human judgment toward algorithmic obedience.

The findings of Shil et al. (2026) show that trust and privacy concern are important conditions in the relationship between AI-enabled digital HRM and various worker outcomes. AI-DHRM has a positive relationship with job satisfaction, work engagement, job performance, and wellbeing, and a negative relationship with turnover intention. This influence runs partly through person–organization fit and psychological empowerment, while technology trust strengthens certain paths and privacy concern weakens them. These results teach that the effectiveness of AI cannot be judged by process speed alone. Measuring productivity in the digital era needs to take into account employees' creativity and innovation (Darmawan, 2023). A system can produce decisions faster but fail to improve team performance if employees feel a loss of control, do not understand how their data is used, or worry about privacy. Legal protection for employees' digital data and works helps ease these concerns (Hutama et al., 2024). Anxiety that job roles will be replaced by AI can also reduce acceptance of the system (Mardikaningsih et al., 2023). Psychological responses become part of the mechanism of technological productivity.

The relationship between AI and worker performance is also influenced by individuals' beliefs about their ability to use technology. Li and Geng (2026) examine AI use and employee performance by positioning AI self-efficacy and AI-enabled HRM as relevant mechanisms. The concept of self-efficacy is important for team effectiveness because members with low confidence may choose to stay silent, defer judgment to other members, or accept AI output without evaluation. Conversely, a sense of capability accompanied by adequate literacy can increase the courage to question the system and develop more productive ways of using it. Organizations need to develop AI competence as a cross-functional work capability, not as the exclusive expertise of the technology team. Training needs to teach prompt design or tool operation together with an understanding of data, probability, bias risk, source evaluation, and escalation procedures when AI results are doubtful.

Digital literacy strengthens the relationship between AI practices and work experience. Asif and Khan (2026) examine the relationship between AI-enabled HRM and employee work engagement and position digital literacy as a moderator. Although findings from a single group cannot be directly generalized to all organizations, the framework confirms that the same technology can produce different experiences for users with different abilities. In teams, differences in literacy can create new participation gaps. Members who are more skilled at using AI may dominate the process of compiling information, while other members become passive recipients. Inclusive communication helps all members take part even when their backgrounds and abilities differ (Mardikaningsih et al., 2024). Managers need to design the division of work so that AI does not create a new information elite. Shared access, joint training, peer learning, and review mechanisms can ensure that faster information is still accompanied by a distribution of interpretive ability.

AI also affects decision quality through incentive systems. Luong, Kumar, and Lang (2026) view human–machine collaboration as a process influenced by AI capabilities and organizational incentives. AI also affects decision

quality through incentive systems. The use of AI can optimize and speed up work that was previously done manually, thereby changing how workers complete tasks and make decisions in organizations (Maulani et al., 2023). The implication is that technological quality is not enough to guarantee good collaboration when performance targets encourage different behavior. If employees are rewarded mainly for speed, they may accept AI recommendations without checking. If failures in AI use are always punished individually, employees may avoid the technology even though the system is actually useful. Performance systems need to reward the quality of judgment, verification, and the ability to recognize when AI does not fit. Verification is important because false information spreads easily and influences judgment (Sinambela, 2022). This form of incentive encourages people to use machines as a source of information that needs to be tested, not as an authority that frees users from responsibility.

AI-enabled HRM also shows that algorithmic decisions carry an ethical dimension that is directly related to effectiveness. Qadri and Moustafa (2026) point to tensions between objectivity and embedded bias, efficiency and procedural dignity, and automation and human oversight. Bias in algorithms can produce unfair decisions if it is not checked regularly (Mardikaningsih & Oluwatoyin, 2023). The legitimacy of a decision is closely tied to explainability, contestability, auditability, and institutions that can be held accountable for decisions. The way the reasons for a decision are communicated also shapes members' views, so explanations need to be open and easy to understand (Khayru et al., 2024). This principle is relevant for teams working with AI. A decision can be fast and statistically accurate yet still hard to accept if members do not know the reasons, cannot request corrections, or do not know who is responsible. Overly strict algorithm-based management can also make workers feel treated like numbers rather than human beings (Darmawan, 2024). Team effectiveness includes the ability to maintain coordination and trust, not numerical accuracy alone.

Productive strategic decision patterns ultimately resemble a collaborative cycle. AI gathers and processes information, humans define goals and decision boundaries, the system generates alternatives, the team interprets the results, and the decision is then tested against field knowledge, organizational values, and broader consequences (Mozzarelli & Schneider, 2026). The cycle can be repeated once new data becomes available. In such a structure, hierarchy does not disappear entirely, but its function shifts from holder of information to designer of decision rights and guardian of accountability. A leadership style that integrates technology can encourage innovation and team performance (Putra & Jahroni, 2025). Teams gain faster access to information, while leaders ensure data quality, authority, review mechanisms, and risk standards. Leaks or destruction of digital data can create civil liability for organizations, so data management needs to be part of risk standards (Rasid et al., 2025). This shift gives organizations the capacity to respond to change without removing human responsibility.

AI and data analytics change strategic decisions through faster processing, a broader information base, a partial reduction of information imbalance, and a redistribution of decision rights. Team effectiveness can improve when AI provides complementary information, reduces information asymmetry, and helps members handle complexity. This improvement is conditional. Data quality, the distribution of AI literacy, organizational justice, trust, privacy, governance, and incentive design determine whether AI strengthens or instead weakens collaboration. AI that operates without transparency can create dependence and new information asymmetry. This finding leads the discussion to the second issue, namely how to gain efficiency benefits without eroding creativity, intuition, and the human capacity to form independent judgment.

Efisiensi Operasional, Kreativitas, dan Intuisi dalam Struktur Human-AI

The issue of balance stems from the distinct capabilities of AI and humans. AI is exceptionally strong in tasks with abundant data, learnable patterns, and objectives that can be formulated quite clearly. Humans possess advantages in social meaning-making, changing situations without precedent, moral judgment, empathy, and the ability to formulate new problems (Patrick et al., 2025). Puranam (2021) views human-AI collaborative decision making as an organization design problem that can be analyzed through the division of labor and learning configurations between humans and algorithms. This perspective demonstrates that the proper question is not whether humans or AI are superior in general. Organizations need to determine combinations based on task characteristics. Repetitive administrative tasks can be largely automated, whereas strategic decisions full of ambiguity require configurations where AI enriches information while humans retain interpretive authority.

Automation provides efficiency through the reduction of repetitive work, accelerated processing, and procedural consistency (Kosna & Singh, 2025). Darmawan (2025) explains that automation and AI drive job redesign and demand workforce competencies that combine digital, analytical, socio-emotional, and self-management skills. Sustainable efficiency emerges when work eliminated by technology is replaced by human activities that possess higher value. If organizations merely add AI without removing old processes, workers may run two systems simultaneously and fail to experience any workload reduction. Job redesign needs to reallocate the time freed by automation into activities such as problem solving, customer interaction, idea development, learning, or coordination. Efficiency then serves as an instrument to expand human capacity rather than merely a workforce reduction program.

Ali, Cichoń, and Abbas (2026) provide insight into the mechanisms connecting AI-driven HRM digitization with innovation. They develop a model that positions metacognitive strategies and tacit knowledge awareness as part of the relationship between HRM digitalization and innovative outcomes. In human resource development, digital innovation also holds the potential to create more efficient training systems while enhancing employee learning access (Mardikaningsih & Wardoyo, 2024). This finding is relevant because AI can generate information and alternatives rapidly, yet innovation still requires the ability of workers to understand their own thinking processes and recognize tacit knowledge gained from experience. Tacit knowledge is often difficult to encode into datasets. An experienced employee can recognize customer signals, interaction quality, or changes in the work environment that are not yet reflected in formal data. AI becomes productive when explicit knowledge resulting from analytics is combined with this kind of experience.

Creativity can also increase when AI functions as an exploration partner. Generative systems are capable of generating alternatives, varying ideas, summarizing information, and helping workers test various scenarios at a lower cost (Shoib, 2025). Saiyed et al. (2026) demonstrate how AI personalization can be linked to learning and engagement in organizational practices. The broader principle is that technology can increase exploratory capacity when systems broaden choices and provide relevant feedback. In creative work, the primary benefit of AI is not always producing final answers, but rather enlarging the idea search space. Users subsequently remain responsible for evaluating the originality, feasibility, ethics, and strategic value of those alternatives. Human responsibility remains crucial in the use of AI because excessive reliance on AI in decision-making can diminish individual responsibility when decisions are driven more by machines than by human judgment (Gani & Darmawan, 2022).

Risk arises when AI output becomes an overly strong initial anchor. Generative models produce responses from patterns in the data they have learned, so they tend to recombine forms that already exist. If people treat the initial AI result as a framework that must be followed, the variety of thinking can narrow. Research on human-AI collaboration also shows that closer collaboration does not always increase innovation. Certain forms of collaboration can lower the quality of idea selection and implementation when users depend too heavily on AI recommendations (Frich et al., 2024). The implication is that organizations need to create a phase of independent thinking before interacting with AI in work that demands originality. Individuals or teams can first formulate the problem and initial ideas, and then use AI to broaden alternatives, critique assumptions, or look for new combinations.

Worker wellbeing also determines whether technological efficiency can be sustained. Darmawan (2026) discusses psychological exhaustion caused by massive AI use and emphasizes empathetic leadership mechanisms such as authentic communication, acknowledgment of technological limitations, adjustment of performance metrics, peer support, and reduction of cognitive load. This conceptual finding is a reminder that technology that speeds up work can at the same time speed up organizational expectations. When productivity gains are immediately translated into ever-rising targets, the time freed by AI does not turn into room for creativity (Zang et al., 2025). It turns into a new production demand. Organizational effectiveness is influenced by many factors, so work speed should not be the only measure of success (Darmawan, 2024). Organizations need limits on work rhythm so that computational efficiency does not produce work intensification that erodes attention, reflection, and the ability to generate ideas (Darmawan, 2024).

Issalillah and Khayru (2025) view worker mental health as an outcome linked to organizational design, workload, formalization, culture, and the digital environment. This perspective reinforces the argument that creativity cannot be separated from psychological conditions. Individuals need sufficient cognitive capacity to explore and to step back from the pressure of routine tasks. AI can support this condition if it genuinely reduces repetitive burdens. Conversely, increasingly intensive monitoring systems can reduce the sense of autonomy and increase self-monitoring. Strict digital monitoring can suppress employees' work autonomy and sense of professional responsibility (Mardikaningsih et al., 2024). Organizations need to distinguish AI that helps people from AI that mainly extends control. Balancing efficiency and creativity requires technology design that preserves autonomy, discretion, and room for experimentation.

Individual resilience also helps determine the ability to sustain creativity during technological change. Darmawan and Mardikaningsih (2025) examine locus of control, work resilience, and coping with failure. Its relevance to the AI-enabled organization arises because working with AI creates new forms of failure. Employees may face incorrect system recommendations, inconsistent generative output, or work results that are later corrected by humans. A culture that punishes every failure can push users to follow AI defensively so that responsibility appears to be shifted to the system. In contrast, a learning culture allows members to test the technology, recognize failures, and improve processes. Knowledge sharing among members strengthens this learning and helps improve work results (Mardikaningsih et al., 2026). Resilience is not a reason to place risk on individuals, but a capacity that needs to be supported by organizational mechanisms that allow correction and learning.

Work reconfiguration also requires attention to flexibility and professional identity (Shaoshan & Yiyu, 2025). When AI takes over part of analytical activities, workers may question the value of the expertise that has long formed the basis of professional status. Mardikaningsih (2025) shows that digitalization drives changes in working relationships and demands for flexibility. In an AI-enabled organization, management needs to explain how technology transforms human contributions, rather than merely explaining application functions. Job architecture can be directed toward capabilities that are difficult for systems to replicate, such as problem framing, stakeholder communication,

ethical reasoning, integrative thinking, and creative synthesis. The balance between AI and human intuition becomes more achievable if organizations recognize that quality intuition grows from experience and domain expertise, rather than from evidence-free preferences.

The use of AI must also account for variations in worker readiness. Digital competence differs according to experience, age, job type, and access to learning. Organizations that implement AI uniformly can create new inequalities when certain groups find it easier to convert technology into productivity (Burton & Gajjar, 2024). Reskilling programs need to distinguish between operational literacy, analytical literacy, and critical AI literacy. The first level relates to device usage; the second level relates to data interpretation; the third level relates to the ability to examine assumptions, biases, and system boundaries. Human creativity is protected when users possess enough understanding not to submit blindly to AI outputs and enough competence to utilize technology as food for thought (Darmawan, 2022).

Human agency receives special attention because AI decisions can affect careers, remuneration, evaluations, and access to opportunities. Qadri and Moustafa (2026) remind us that high-stakes AI requires bias testing, accountability allocation, explainability, human-review thresholds, appeal mechanisms, audit trails, and employee voice. Although that source primarily discusses HRM, the principle applies to organizational design broadly. Human creativity and intuition cannot grow if workers feel that all activities are judged through models that cannot be questioned. Contestability gives humans the right to request reviews, present information not recorded in the system, and correct errors. Human oversight is therefore not a symbolic layer, but an organizational mechanism with real authority.

Balance can be designed through a task portfolio. Tasks with stable patterns, high volume, and easily recoverable consequences can receive greater automation. Tasks with high complexity but robust data are suitable for augmentation, with AI providing analysis and humans making decisions (Vulicevic, 2025). Tasks with radical uncertainty, high moral value, or significant creativity needs require the dominance of human judgment with AI acting as an exploration tool. This division can change as technology, data, and organizational experience evolve. Organizations need to review automation boundaries periodically rather than assume AI implementation decisions are permanent.

AI is able to create a balance between efficiency and human capacity as long as technology is used to reallocate work rather than eliminate human agency. Automation is most beneficial for repetitive and structured activities, whereas augmentation is appropriate for analytical work that still requires judgment. Creativity and intuition survive if workers have independent thinking space, learning access, the right to question the system, and protection from excessive work intensification. Job redesign, mental health, resilience, digital literacy, and ethical governance are part of the same design. Balance is not a fixed point between humans and machines. It is a continuous process of task allocation adjustment reviewed based on changes in technological capabilities and organizational needs.

CONCLUSIONS

The AI-enabled organization represents a shift in work architecture where AI and data analytics become part of decision-making processes, coordination, and job design. This integration can increase information processing speed, reduce certain information asymmetries, and strengthen team decision quality if data, competencies, trust, and governance support its use. AI does not automatically make teams more effective because opaque or excessively used systems can create new dependencies and information imbalances. Regarding the relationship between efficiency and creativity, task division is the primary determinant. Automation is appropriate for routine and structured tasks, whereas augmentation is more suitable when work requires interpretation, creativity, intuition, and ethical judgment. A productive organization is not one that maximizes AI usage across all activities, but one that is able to place AI in parts of work that produce the best complementarity with humans.

The AI-enabled organization needs to be analyzed as a socio-technical system and an organization design problem, rather than merely as a technology adoption phenomenon. AI capabilities gain value through interaction with decision rights, digital literacy, organizational justice, human agency, and job design. Research on AI and organizations needs to move from questions regarding whether technology improves performance toward identifying mechanisms, boundary conditions, and division of labor configurations that produce different outcomes. Practically, management needs to develop task classifications based on problem structure, risk, reversibility, creativity requirements, and the value of human judgment. The measurement of AI success should encompass decision quality, team effectiveness, error correction rates, employee voice, learning, and well-being alongside efficiency metrics. This framework helps organizations avoid technology investments that increase digital activity without improving the quality of organizational capacity.

REFERENCES

- Ali, A., D. Cichón, & A. Abbas. (2026). AI-driven HRM digitization in effect: Mechanisms, conditions, and employee outcomes. *Journal of Innovation & Knowledge*, 13, 100919. <https://doi.org/10.1016/j.jik.2025.100919>
- Altaf, S., D. M. Waqas, S. Altaf, & D. M. Waqas. (2025). Explorative Learning as a Pathway Linking Big Data Analytics Enabled Dynamic Capabilities to Organizational Decision Making. *Journal for Social Science Archives*, 3(4), 01–19. <https://doi.org/10.59075/jssa.v3i4.346>

- Asif, M., & M. A. Khan. (2026). The impact of AI-enabled HRM practices on employee work engagement: The moderating role of employee digital literacy. *Journal of Business Insight and Innovation*, 5(4), 91–103. <https://doi.org/10.63544/jbii.v5i4.220>
- Burton, K., & D. Gajjar. (2024). Technologies and artificial intelligence in the workforce. UK Parliament. <https://doi.org/10.58248/hs54>
- costa, S. da., Darmawan, D., & Isaac, A. de J. (2023). Safeguarding Employee Data with Blockchain in HR. *International Journal of Service Science, Management, Engineering, and Technology*, 4(3), 41–46.
- da Cruz, C., Issalillah, F., & Fariz, F. A. B. M. (2024). Alterations in Social Interaction Patterns and Identity in the Era of Social Media and Digital Culture. *International Journal of Service Science, Management, Engineering, and Technology*, 6(3), 39–47.
- da Silva, B. dos S., & D. Darmawan. (2023). Integration of Management Information Systems (MIS) in Strategic Decision Making to Improve Organization Performance. *Journal of Social Science Studies*, 3(2), 347–352.
- Darmawan, D. (2021). Social Interaction in Digital Society: Changes in Online Communication Patterns and Dynamics of Virtual Communities, *Studi Ilmu Sosial Indonesia*, 1(1), 325–350.
- Darmawan, D. (2022). Posthuman Human Resource Management in Organizations Using Generative Artificial Intelligence. *Studi Ilmu Sosial Indonesia*, 2(2), 97–124.
- Darmawan, D. (2023). Measuring Employee Productivity in the Digital Era by Considering Human Creativity and Innovation. *International Journal of Service Science, Management, Engineering, and Technology*, 4(3), 47–53.
- Darmawan, D. (2024). Algorithmic Management in Digital Platforms and Work Dehumanization in the Gig Economy. *Studi Ilmu Sosial Indonesia*, 4(2), 183–216.
- Darmawan, D. (2024). Application of Situational Leadership in Decision Making in Dynamic Organizations. *Journal of Social Science Studies*, 4(1), 499–504.
- Darmawan, D. (2024). Digital readiness of Baby Boomer generation in the workplace: A study of intergenerational gaps and organizational adaptation strategies. *Studi Ilmu Sosial Indonesia*, 4(1), 391–416.
- Darmawan, D. (2024). Distribution of Six Major Factors Enhancing Organizational Effectiveness. *Journal of Distribution Science*, 22(4), 47–58.
- Darmawan, D. (2025). Job redesign, automation, and digital workforce competencies in the twenty-first century. *Bulletin of Science, Technology and Society*, 4(3), 103–114.
- Darmawan, D. (2025). Work Readiness, Digital Skills, and Employability: a Study on the Moderating Effect of Digital Skills Among College Students. *Studi Ilmu Sosial Indonesia*, 5(2), 157–178.
- Darmawan, D. (2026). Mechanisms of Empathetic Leadership in Preventing Psychological Exhaustion from Massive AI System Use Among the Digital Native Generation. *International Journal of Service Science, Management, Engineering, and Technology*, 9(1), 7–15. <https://ejournalisse.com/index.php/isse/article/view/228>
- Darmawan, D. (2026). The Influence of Digital Human Resource Management Functions on Employee Retention: A Study of Digital Attendance, Online Performance Appraisal, and Electronic Payroll Systems. *International Journal of Service Science, Management, Engineering, and Technology*, 9(3), 11–20. <https://ejournalisse.com/index.php/isse/article/view/249>
- Darmawan, D., & B. Gardi. (2024). Digital-Oriented Leadership and Organizational Transformation: Fostering Operational Efficiency, Team Collaboration, and Innovation in the Digital. *International Journal of Service Science, Management, Engineering, and Technology*, 5(1), 37–42.
- Darmawan, D., & R. Mardikaningsih. (2025). The role of locus of control in shaping work resilience and strategies for coping with failure in the workplace. *International Journal of Service Science, Management, Engineering, and Technology*, 8(3), 18–25.
- Del Barone, L., D. De Gennaro, & F. Buonocore. (2026). AI-driven HRM and managerial competencies: Strengthening organizational resilience in Public Administration. *Management Decision*, 64(5), 1732–1751. <https://doi.org/10.1108/MD-06-2024-1252>
- Eddine, B. A. S. & D. Darmawan. (2025). The Role of Technology in the Dynamics of Social Relations and Employee Solidarity in the Workplace, *International Journal of Service Science, Management, Engineering, and Technology*, 8(1), 37–44.
- Eddine, B. A. S., & Darmawan, D. (2026). Industry 4.0 Automation Adoption and HR Upskilling Strategies with Social Reskilling for Manufacturing Workforce. *Bulletin of Science, Technology and Society*, 5(2), 89–100. <https://inti.ejournalmeta.com/index.php/inti/article/view/162>
- Evendi, W., Farid, M., Suwito, S., Khayru, R. K., & Putra, A. R. (2025). Transformation of Technology-Based Family Interaction Patterns and its Implications for Psychological Health and Early Childhood Character Building. *International Journal of Service Science, Management, Engineering, and Technology*, 7(3), 1–10.
- Frich, J., J. E. S. Grønbaek, M. Borowski, & P. Dalsgaard. (2024). Exploring the impact of AI features on collaborative creativity. 480–489. <https://doi.org/10.1145/3726986.3727015>
- Gani, A., & D. Darmawan. (2022). Ethics and Accountability in Artificial Intelligence-Based Managerial Decision Making. *Journal of Social Science Studies*, 2(1), 147–152.
- Hariani, M. & R. Mardikaningsih. (2022). The Performance of Authenticity and the Commodification of Parasocial Bonds: Twin Pillars of Influencer Culture on Social Media, *Studi Ilmu Sosial Indonesia*, 2(2), 385–412.
- Hariani, M., & Putra, A. R. (2025). Digital Communication Social Norms in the Workplace and Their Relationship with Employee Collective Solidarity. *International Journal of Service Science, Management, Engineering, and Technology*, 8(3), 26–35. <https://ejournalisse.com/index.php/isse/article/view/267>
- Himanshu, U., J. K. Jha, R. S. Kumar, S. Gupta, & P. K. Pattanaik. (2026). How Internal Organizational Enablers Influence AI-Enabled HRM Adoption: A Dynamic Capabilities Perspective. *Information Systems Frontiers*, 1–24. <https://doi.org/10.1007/s10796-026-10778-4>
- Hölzle, K., R. Rose, & V. L. Kaschub. (2024). The Interplay of Humans, Technology, and Organizations in Realizing AI's Productivity Promise. *The Economists' Voice*, 21(2), 357–362. <https://doi.org/10.1515/ev-2024-0053>
- Hussain, A., F. Yunus, D. Shaheryar Naveed, & F. Iqbal. (2025). The Influence of Artificial Intelligence on Decision-Making Processes in Modern Organizations. 4(4), 229–238. <https://doi.org/10.63056/acad.004.04.0880>
- Hutama, D. P., Hardyansah, R., & Darmawan, D. (2024). Legal Protection for Digital Content Creators: A Case Study on Social Media Platforms. *International Journal of Service Science, Management, Engineering, and Technology*, 6(2), 17–28.
- Irfan, M., & Darmawan, D. (2024). Ambidextrous Leadership as a Collective Ecosystem: Balancing Exploitation through Digital Transformation and Exploration for Long Term Growth. *Studi Ilmu Sosial Indonesia*, 4(2), 455–480.
- Issalillah, F., & R. K. Khayru. (2025). Mental health as an organizational construct: A strategic reorientation of human resource management for work environment design. *International Journal of Service Science, Management, Engineering, and Technology*, 8(3), 1–9.
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Khan, M. A., Darmawan, D., & Islam, R. (2025). Big Data Analytics as a Strategic Decision Support for Policy Direction Determination and Business Projection in Organizations. *International Journal of Service Science, Management, Engineering, and Technology*, 8(2), 66–74. <https://ejournalisse.com/index.php/isse/article/view/265>

- Khayru, R. K., & Issallillah, F. (2026). Social Media and Psychological Well-Being of Youth: Mechanisms and Protective and Risk Conditions. *International Journal of Service Science, Management, Engineering, and Technology*, 9(1), 16–26. <https://ejournalisse.com/index.php/isse/article/view/254>
- Khayru, R. K., & Qader, K. S. (2026). Role of Large-Scale Data Analytics Risk Information Systems in Addressing Social Disruptions in Infrastructure Development. *Bulletin of Science, Technology and Society*, 5(2), 101–112. <https://inti.ejournalmeta.com/index.php/inti/article/view/163>
- Khayru, R. K., Putra, A. R., & Arifin, S. (2026). Ethical Principles and Responsibility Structures in Daily Use of Artificial Intelligence. *International Journal of Service Science, Management, Engineering, and Technology*, 9(3), 1–10.
- Khayru, R. K., Rojak, J. A., & Fajar, A. S. M. (2024). The Role of Media in the Global Era in Shaping Public Opinion on Conflict and the Implications for Democracy. *Studi Ilmu Sosial Indonesia*, 4(1), 417–438.
- Kosna, S. R., & U. R. Singh. (2025). Collaborative Intelligence: Redefining Human-AI Partnerships in the Post-Automation Workplace. 1–6. <https://doi.org/10.1109/istas65609.2025.11269664>
- Li, H., & F. Tian. (2026). Advancing decision-making through AI-human collaboration: A systematic review and conceptual framework. *Group Decision and Negotiation*, 35(2), 26. <https://doi.org/10.1007/s10726-026-09980-1>
- Li, Y., & X. Geng. (2026). AI usage and employee performance: The dual roles of AI self-efficacy and AI-enabled HRM. *Systems*, 14(7), 786. <https://doi.org/10.3390/systems14070786>
- Lu, X., N. Hu, & J. Zou. (2025). Artificial intelligence in decision support systems: Impact on organizational management theory. In *Proceedings of the 9th International Conference on Electronic Information Technology and Computer Engineering*, 335–340. <https://doi.org/10.1145/3766671.3766731>
- Luong, A., N. Kumar, & K. R. Lang. (2026). Human-machine collaboration and algorithmic decision-making: The role of organizational incentives and AI capabilities. *Information & Management*, 63(6), 104384. <https://doi.org/10.1016/j.im.2026.104384>
- Mardikaningsih, R., & D. Darmawan. (2023). The Role of Digital Leadership in Building Employee Readiness for Workplace Automation, *Studi Ilmu Sosial Indonesia*, 3(1), 423–446.
- Mardikaningsih, R. (2025). The deconstruction of work and HRM reconfiguration: Flexibility and employer branding in the digital era. *International Journal of Service Science, Management, Engineering, and Technology*, 8(2), 10–17.
- Mardikaningsih, R., & D. Darmawan. (2022). The Role of Self-Efficacy in Predicting Employee Adaptability to Technological Change in the Workplace. *International Journal of Service Science, Management, Engineering, and Technology*, 2(3), 43–50.
- Mardikaningsih, R., & D. Darmawan. (2025). Utilization of big data analytics to improve corporate environmental performance in managerial and organizational dimensions. *Bulletin of Science, Technology and Society*, 4(3), 1–12.
- Mardikaningsih, R., & D. T. W. Wardoyo. (2024). The Role of Technology in Human Resource Development for Sustainability: A Literature Review on Digital Innovation. *Bulletin of Science, Technology and Society*, 3(3), 20–26.
- Mardikaningsih, R., & Hariani, M. (2025). The Implementation of Distributive Justice in Allocating Efficiency Gains Generated by Technology. *International Journal of Service Science, Management, Engineering, and Technology*, 7(3), 45–52. <https://ejournalisse.com/index.php/isse/article/view/242>
- Mardikaningsih, R., & Oluwatoyin, F. (2023). Analyzing Algorithmic Bias, Automated Justice, and Social Transformation in Artificial Intelligence Implementation. *Studi Ilmu Sosial Indonesia*, 3(1), 107–128.
- Mardikaningsih, R., & Wardoyo, D. T. W. (2025). Balancing Technological Efficiency And Employee Psychological Well-Being In Hybrid Work Systems. *International Journal of Service Science, Management, Engineering, and Technology*, 8(1), 30–36.
- Mardikaningsih, R., & Wardoyo, D. T. W. (2024). Green Technology Integration in Management for Social and Environmental Sustainability. *International Journal of Service Science, Management, Engineering, and Technology*, 6(2), 6–10.
- Mardikaningsih, R., & Wardoyo, D. T. W. (2026). Organizational Change Management Strategies in Addressing Employee Social Resistance During Green IT Transition. *Bulletin of Science, Technology and Society*, 5(2), 1–12. <https://inti.ejournalmeta.com/index.php/inti/article/view/145>
- Mardikaningsih, R., D. Darmawan, & S. N. Halizah. (2023). Worker Anxiety About Role Displacement from Artificial Intelligence Application in Human Resource Management, *Studi Ilmu Sosial Indonesia*, 3(2), 355–376.
- Mardikaningsih, R., Darmawan, D., & Hariani, M. (2024). Inclusive Public Communication in the Digital Era: A Literature Study on Multicultural Approaches in Communication Policy. *Studi Ilmu Sosial Indonesia*, 4(2), 385–402.
- Mardikaningsih, R., Hariani, M., Darmawan, D., Halizah, S. N., & Nuraini, R. (2024). The Impact of Digital Monitoring on Employee Work Autonomy and Professional Responsibility. *International Journal of Service Science, Management, Engineering, and Technology*, 5(3), 60–67. Retrieved from <https://ejournalisse.com/index.php/isse/article/view/231>
- Mardikaningsih, R., Wardoyo, D. T. W., & Haryono, N. A. (2026). Green knowledge sharing as a mediating mechanism: The effects of green HRM and environmental awareness on environmental performance with green transformational leadership as a moderator. *Journal of Intelligent Decision Making and Information Science*, 3(2), 1968–1987.
- Maulani, A., R. Hardyansah, D. Darmawan, C. N. Mendonca, & A. de J. Isaac. (2023). Juridical Analysis of the Validity of Electronic Contracts Made by Artificial Intelligence in Indonesian Law. *Journal of Social Science Studies*, 3(1), 139–144.
- Mozzarelli, M., & G. Schneider. (2026). AI and strategic decisions: Facing the incompleteness. *European Business Organization Law Review*, 1–33. <https://doi.org/10.1007/s40804-025-00356-7>
- Oluwatoyin, F., & R. Mardikaningsih. (2024). Challenges and Opportunities for Sustainability of Human Resource Development in Industry 4.0. *Bulletin of Science, Technology and Society*, 3(2), 9–16.
- Patrick, H., S. Max, K. Niklas, V. Michael, & S. Gerhard. (2025). Complementarity in human-AI collaboration: Concept, sources, and evidence. 34(6), 979–1002. <https://doi.org/10.6084/m9.figshare.29996025>
- Puranam, P. (2021). Human-AI collaborative decision-making as an organization design problem. *Journal of Organization Design*, 10, 75–80. <https://doi.org/10.1007/s41469-021-00095-2>
- Putra, A. R., & Darmawan, D. (2026). The Application of Industry 4.0 Technology in Enhancing Efficiency and Flexibility of Production Processes. *International Journal of Service Science, Management, Engineering, and Technology*, 9(2), 1–8.
- Putra, A. R., & Jahroni. (2025). Integrating Technology in Leadership Style to Improve Innovation and Team Performance. *International Journal of Service Science, Management, Engineering, and Technology*, 7(1), 7–11.
- Qadri, U. A., & A. M. A. Moustafa. (2026). AI-enabled HRM as an ethical system: A systematic review of fairness, accountability, governance and legitimacy. *International Journal of Ethics and Systems*, 1–29. <https://doi.org/10.1108/IJOES-04-2026-0308>
- Raisch, S., & S. Krakowski. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Rasid, A., Hardyansah, R., & Khayru, R. K. (2025). Civil Liability for Data Breach and Destruction of Digital Data as Corporate Assets within the Framework of Unlawful Acts. *Journal of Social Science Studies*, 5(1), 135–150. <https://jos3journals.id/index.php/jos3/article/view/427>

- Saha, S., M. Shakil, R. Yasmin, A. Chanda, & Z. Ferdous. (2024). Artificial Intelligence–Driven Decision Making and Its Impact on Strategic Performance in Organizations. *Journal of Artificial Intelligence General Science (JAIGS)*, 6(1), 649–661. . <https://doi.org/10.60087/jaigs.v6i1.444>
- Saiyed, S., A. Nimo J. R., V. Kumar, & M. Hasan. (2026). AI-enabled and gamified green HRM practices: Impacts on employee environmental engagement. *Oeconomia Copernicana*, 17(1), 181–224.
- Setiyono, B., Dirgantara, F., & Darmawan, D. (2026). Recognition of Electronic Signatures and Evidentiary Power of Digital Contracts in Indonesia. *Studi Ilmu Sosial Indonesia*, 6(1), 93–126. <https://sisijournals.id/index.php/sisi/article/view/210>
- Shaoshan, L., & S. Yiyu. (2025). Human Resilience in the AI Era – What Machines Can't Replace. 1–9. <https://doi.org/10.48550/arxiv.2510.25218>
- Shil, H. C., S. K. M. A. H. Rabby, M. M. Rahman, N. Mumtahina, M. A. Islam, F. Zafreen, A. Islam, & M. A. Fassi. (2026). AI-enabled HRM systems in business organizations: Effects on workforce outcomes and the roles of trust and privacy. *Frontiers in Artificial Intelligence*, 9, 1847241. <https://doi.org/10.3389/frai.2026.1847241>
- Shoib, E. (2025). Workforce Transformation in the Age of AI: Augmentation Over Automation. 1(2), 26–32. <https://doi.org/10.64044/x96dx491>
- Shukla, Y., J. Pandey, & V. Pereira. (2026). All's well that begins just: Organizational justice as precursor of trust in AI-enabled HRM. *Personnel Review*, 55(5), 1375–1412. <https://doi.org/10.1108/PR-05-2025-0508>
- Sidor, V. L., L. D. Cuc, D. Rad, T. F. Cilán, & G. Croitoru. (2025). Analysis of the Use and Impact of Artificial Intelligence on Managerial Decisions and Organizational Processes. *Proceedings of the International Conference on Business Excellence*, 19(1), 3896–3909. . <https://doi.org/10.2478/picbe-2025-0298>
- Sikhakolli, A. K., J. P. Joshi, A. V. Aljapurkar, S. Sikhakolli, A. Agarwal, T. Talla, A. Kumar, & S. S. Patil. (2025). The Impact Analysis of Artificial Intelligence on Decision-Making in Organizations. 1–5. <https://doi.org/10.1109/asiancon66527.2025.11280787>
- Sinambela, E. A. (2022). The Digital Public Sphere Under Threat of Disinformation a Literature Study on Hoax Dissemination Dynamic and Vulnerability Factors, *Studi Ilmu Sosial Indonesia*, 2(2), 289–306.
- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Sutanto, H., R. Saputra, & D. Darmawan. (2023). Legal Violation Patterns in Digital Technology on Liability and Proof, *Studi Ilmu Sosial Indonesia*, 3(2), 277–308.
- Telaumbanua, E., S. A. Pranidana, & R. Rustiyana. (2025). Human-Tech Symbiosis: Collaboration between Managers and AI Systems in Strategic Decision Making, 2(6), 68–78. <https://doi.org/10.62872/sw62xg16>
- Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, 4(3), 356–367. <https://doi.org/10.1177/1534484305278283>
- Tranfield, D., D. Denyer, & P. Smart. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management*, 14(3), 207–222. <https://doi.org/10.1111/1467-8551.00375>
- Triono, B., Darmawan, D., Djaelani, M., Safitri, F. S. A., & Masithoh, N. (2025). How Digitalization Reshapes Labor and Task Architecture in the Manufacturing Sector. *International Journal of Service Science, Management, Engineering, and Technology*, 7(2), 11–16.
- Valentine, M., A. L. Pratt, R. Hinds, & M. S. Bernstein. (2024). The Algorithm and the Org Chart: How Algorithms Can Conflict with Organizational Structures. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW2), 1–31. <https://doi.org/10.1145/3686903>
- Vulicevic, Z. (2025). The AI Operator: A Reference Role for Human–AI Systems an Operating-Level Framework for Human–AI Collaboration. 1–6. <https://doi.org/10.5281/zenodo.18105973>
- Woolley, A. W. (2024). Artificial Intelligence and People at Work. *Oxford Research Encyclopedia of Business and Management*. Oxford Research Encyclopedia of Business and Management <https://doi.org/10.1093/acrefore/9780190224851.013.450>
- Zahid, R. A., & Darmawan, D. (2025). Reconceptualizing Digital Literacy Dimensions as Predictors of Academic Engagement and Success in Contemporary Higher Education. *International Journal of Service Science, Management, Engineering, and Technology*, 7(3), 18–24.
- Zang, D., & M. Li. (2025). Research on the Impact of AI Introduction on Employee Creativity: The Moderating Role of Technology Overload. *Behavioral Sciences*, 15(10), 1389. <https://doi.org/10.3390/bs15101389>
- Zercher, D., et al. (2025). How can teams benefit from AI team members? Exploring the effect of generative AI on decision-making processes and decision quality in team–AI collaboration. *Journal of Organizational Behavior*, 1–28. <https://doi.org/10.1002/job.2898>