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# Artificial intelligence in manufacturing: exploring the link between waste management and factory productivity

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**Abstract**

This study examines the influence of artificial intelligence (AI) applications on waste management and factory productivity in manufacturing settings. A quantitative descriptive-analytical design was adopted, with factories in the Hashemite Kingdom of Jordan constituting the study context. A random sample of 175 employees from different managerial levels and specializations, selected based on their direct relevance to the study topic, completed a developed questionnaire. Data were analyzed using SPSS to examine the relationships among AI applications, waste management, and factory productivity. The results indicate significant positive relationships between AI and waste management, between waste management and factory productivity, and between AI and factory productivity ($p < 0.001$). These findings provide practical guidance for factory managers and decision-makers by highlighting the role of AI in supporting waste management and production efficiency. Future research should include broader industrial sectors and larger samples, examine specific AI technologies and their effects on production and waste management, and address technological gaps that may constrain effective AI adoption, particularly in small and medium-sized enterprises (SMEs).



*Keywords:* Artificial intelligence, Waste management, Factory productivity, Jordan

## 1. Introduction

Manufacturing industries increasingly face pressure to improve sustainability and resource efficiency [1]. In response to environmental challenges, manufacturers are seeking ways to raise productivity while reducing material and process waste [2]. Artificial intelligence (AI) applications offer practical tools for improving industrial performance through data-driven monitoring, prediction, and decision-making [3].

Prior research indicates that AI can enhance resource efficiency in manufacturing. Waltersmann et al. [4] highlight the growing relevance of AI applications for resource efficiency, while Andeobu et al. [5] identify continuing research gaps regarding the contribution of AI to sustainable waste management. AI can also provide timely and accurate data that support operational decisions, reduce avoidable waste, and improve productivity. Industry 4.0 provides a clear context for these developments by integrating advanced digital technologies into manufacturing operations. Javaid et al. [6] show that smart manufacturing increasingly depends on effective human-machine collaboration, while related research indicates that AI-enabled systems can improve production efficiency and reduce operating costs [7].

Hassan et al. [8] demonstrate the potential of AI to improve waste-reduction and recycling strategies in the beverage industry. Their analysis covers production optimization, demand management, and resource efficiency, illustrating how AI can support more sustainable production and logistics while reducing waste [9]. AI is also central to the development of smart factories. Cioffi et al. [10] review AI applications in smart production and show how technologies such as machine learning can support sustainable manufacturing by improving process control and decision-making. Related work also identifies AI-driven manufacturing technologies as important enablers of customized and efficient production [11].

Benotsmane et al. [12] further illustrate how Industry 4.0 technologies, including intelligent robots and AI-based systems, can improve factory productivity and agility. These technologies can streamline operations, strengthen data-driven coordination, and reduce waste across production activities [13]. Despite this progress, empirical evidence that jointly links AI, waste management, and factory productivity remains limited, particularly in manufacturing contexts where digital transformation is still developing. This gap supports further empirical investigation of how AI adoption relates to both sustainable operations and productivity. Accordingly, this study examines the relationships among AI applications, waste management, and factory productivity in Jordanian factories using a quantitative empirical design grounded in supply chain management theory.

## 2. Literature review

### 2.1. Theoretical background

Supply chain management theory is the theoretical foundation of the flow of products and information. It is one of the basic building blocks that describes how products move through different stages in production to distribution. This theory aims to achieve coherence between all entities i.e. from suppliers to final consumers [14]. The goal of supply chain management: Supply chain management wants to buy excellent economic framework products and services, reduce costs, and improve customer care services. While it is widely applied in the manufacturing sector and is essential for high productivity and low waste production. Advances in technology, such as the use of artificial intelligence, are being leveraged to improve every part of the supply chain from manufacturing to distribution [15].

Supply chain management involves many elements, which include planning and inventory management (both of which occur at the supplier), ordering, depositing from suppliers, manufacturing to order or typical manufacturing activities (in many companies, a variety of procedures occur at a single location, but the raw components vary into relatively large types and teams before that in a mix), movement, and the construction process of contributing facilities or the process of arranging for mass market production between distribution points in the design of the Model T Ford to reach customer sales except for stores (entry stage area) between retail locations [16]. All these elements are essential for the efficient functioning of any process. For example, AI tools enable better planning by forecasting demand and analyzing market data. On the procurement and supply side, use it to reduce downtime or optimize procurement-supply to reduce waste, as this means using better and more efficient labor [17]. When we have all these parts and pieces, the way they work together in harmony is how we arrive at the results [18].

By studying massive amounts of data and predicting problems before they occur, AI- powered applications will transform supply chain management. For example, with the help of AI data, sales and demand patterns are made more realistic, allowing factories to reduce or increase manufacturing volumes. Similarly, machine learning can help improve procurement and supply chain processes that reduce waste and improve product quality [19]. These technologies can also play an important role in real-time inventory management, which can save time as well as resources [20]. Thus, AI can act as a value-add with supply chain management. For example, when evaluating how AI applications can reduce waste and increase efficiency in factories, supply chain management theory can inform the research design and data analyzed [21]. But we can see how different stages of the supply chain are affected by AI applications [22]. This could include research into the impact of AI in the manufacturing stage to reduce waste due to human error or equipment failure [23]. It also explains how AI can help drive more efficient distribution processes, thus saving billions of dollars [24].

This could lead to important results in the production process and waste reduction, using supply chain management theory. We hope that the latter will lead to practical advice for factories on how best to use AI [21]. It could also help improve the overall understanding of the importance of coordination between different stages in the supply chain to achieve sustainable productivity [25]. It could provide insights that could allow companies to develop new tactics that will be able to deal with challenges in the future. Overall, combining AI and supply chain management theory could significantly improve performance and market advantage [26].

### 2.2. Research model

The research model (Figure 1) positions Artificial Intelligence as the independent variable, Factory Productivity as the dependent variable, and Waste Management as a conceptual mediating variable. H1 examines the relationship between Artificial Intelligence and Waste Management; H2 examines the relationship between Waste Management and Factory Productivity; and H3 examines the direct relationship between Artificial Intelligence and Factory Productivity. The present analysis evaluates these three constituent relationships separately rather than estimating a formal indirect-effect mediation statistic.

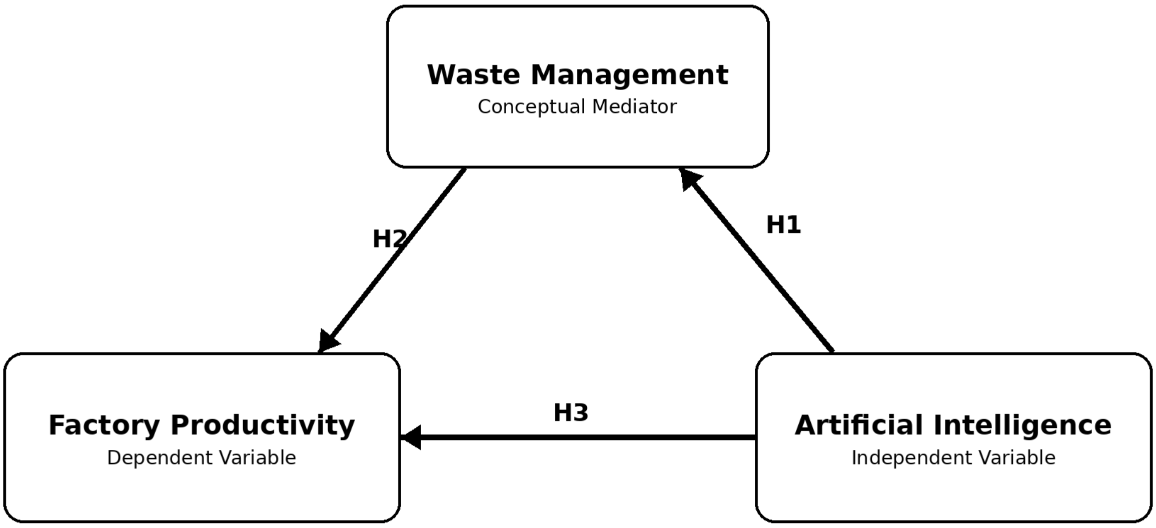


Figure 1. Research model

### 2.3. Hypotheses development

AI-powered technologies can support waste management through advanced analytics, monitoring, and decision-making [27]. AI systems can track waste generation, identify process patterns associated with excess waste, and support timely interventions [28], [29]. Machine-learning models can also use historical data to forecast waste-generation trends and help organizations plan preventive actions [30]. Accordingly:

H1: Artificial Intelligence is positively related to Waste Management.

Effective waste management can enhance factory productivity by reducing material losses, lowering operating costs, and improving resource utilization [31]. Recycling and waste-reduction practices can also support continuous improvement and environmental performance [32], while compliance-oriented waste management can reduce the risk of penalties and production interruptions [33]. Accordingly:

H2: Waste Management is positively related to Factory Productivity.

AI can improve factory productivity through predictive maintenance, production scheduling, resource allocation, and automation. Predictive analytics can help identify equipment issues before they cause unplanned downtime [34]. AI can also automate routine tasks and support higher-value decision-making, allowing employees to focus on more productive activities [35]. Accordingly:

H3: Artificial Intelligence is positively related to Factory Productivity.

## 3. Research methodology

### 3.1. Research design

This study used a quantitative descriptive-analytical survey design. Data were collected from factory employees through a structured questionnaire and analyzed to test the proposed relationships among the study variables.

### 3.2. Population and sample

The study targeted employees working in factories from different industries in Jordan. A random sample of 175 employees was selected across different managerial levels and specializations. Participants were selected because their work had a direct relation to the study topic, providing responses from employees with relevant operational or managerial exposure. The developed questionnaire was distributed to the selected employees, and the resulting dataset was used for the statistical analysis.

### 3.3. Data collection tool

A questionnaire developed specifically for this study was used to collect the data. The questionnaire consisted of two parts:

- Demographic Data: Participant characteristics, including age, gender, educational level, years of work experience, and job title.
- Research Variables: Items measuring Artificial Intelligence, Waste Management, and Factory Productivity using a 5-point Likert scale.

### 3.4. Data analysis methods

Descriptive and analytical statistical methods were used in the study, including:

- Descriptive Analysis: Frequencies, percentages, arithmetic means, and standard deviations were used to describe the sample and study variables.
- Correlational and Regression Analysis: Pearson correlations and regression-based statistics were used to examine and test the relationships among Artificial Intelligence, Waste Management, and Factory Productivity. SPSS was used for the statistical analysis.

## 4. Results and analysis

### 4.1. Descriptive statistics of research sample

Table 1 shows the descriptive statistics for the study sample.

Table 1. Descriptive statistics of the study sample (n = 175)

| Demographic | Category | N | % |
|---|---|---|---|
| Age | Below 25 | 26 | 15% |
| | 25-34 | 52 | 30% |
| | 35-44 | 45 | 25% |
| | 45-54 | 35 | 20% |
| | 55+ | 17 | 10% |
| Gender | Male | 105 | 60% |
| | Female | 70 | 40% |
| Educational Level | High School | 26 | 15% |

| Demographic | Category | N | % |
|---|---|---|---|
| | Diploma | 35 | 20% |
| | Bachelor’s | 62 | 35% |
| | Master’s | 35 | 20% |
| | PhD | 17 | 10% |
| Years of Work Experience | Less than 1 year | 17 | 10% |
| | 1-3 years | 35 | 20% |
| | 4-6 years | 44 | 25% |
| | 7-10 years | 53 | 30% |
| | More than 10 years | 26 | 15% |
| Job Title | Employee | 70 | 40% |
| | Supervisor | 44 | 25% |
| | Manager | 35 | 20% |
| | Executive Officer | 26 | 15% |

The demographic distribution of the study sample, which comprises 175 employees, is illustrated in the table. The largest percentage of participants falls within the age group of 25 to 34 years, accounting for 30%, while the subsequent age group of 35 to 44 years represents 25%. This data indicates that most employees in the sample are in their mid-career years. In terms of gender, males constitute 60% of the sample, while females constitute 40%. In terms of educational level, the largest percentage of participants hold a bachelor’s degree (35%), followed by diploma holders (20%) and master’s degree holders (20%). In terms of the number of years of work experience, the largest category has experience ranging between 7 and 10 years (30%), reflecting the presence of employees with significant professional experience in the sample. Finally, 40% of the sample holds employee positions, while supervisors and managers represent 25% and 20% respectively, reflecting the diversity of job positions in the sample studied.

### 4.2. Descriptive statistics of research variables

#### 4.2.1. Descriptive statistics of artificial intelligence variable

Table 2 shows the descriptive statistics for the Artificial Intelligence variable

Table 2. Descriptive statistics for Artificial Intelligence

| | Statement | Mean | Alpha |
|---|---|---|---|
| 1 | My company uses AI technologies to improve production processes. | 3.72 | 0.947 |
| 2 | AI provides accurate data that helps in making management decisions. | 3.92 | 0.945 |
| 3 | AI applications contribute to improving the quality of products in the factory. | 4.06 | 0.846 |
| 4 | Employees in my company are trained to use AI technologies. | 4.02 | 0.871 |
| 5 | I feel that AI helps reduce the time spent on daily tasks. | 3.81 | 0.933 |

The results of the analysis of the AI axis indicate that there is a general agreement among participants about the role of AI in improving production processes and product quality. The statement that achieved the highest average (4.06) related to the contribution of AI applications to improving product quality, indicating that workers are aware of the impact of AI on production quality. Participants also showed strong agreement that employees in the company receive training to use AI technologies, with an average of (4.02). As for the accuracy of the data provided by AI to support administrative decision-making, this statement achieved an average of (3.92). Although AI contributes to reducing the time spent on daily tasks (average 3.81), improving production processes thanks to AI came with an average of (3.72), indicating a tangible but moderate impact on some aspects of the production process.

#### 4.2.2. Descriptive statistics of waste management variable

Table 3 shows the descriptive statistics for the Waste Management variable

Table 3. Descriptive statistics for waste management

| | Statement | Mean | Alpha |
|---|---|---|---|
| 1 | My company follows effective waste management practices. | 4.08 | 0.845 |
| 2 | Employees are trained in how to reduce waste in the workplace. | 4.13 | 0.809 |
| 3 | My company uses modern technologies to recycle waste. | 4.11 | 0.799 |
| 4 | Waste management has a positive impact on the environment around the company. | 3.99 | 0.865 |
| 5 | I feel that waste management affects the image of the company to customers. | 3.89 | 0.892 |

The results of the waste management axis analysis indicate that there is strong agreement among participants about the effectiveness of waste management practices in their companies. The statement that achieved the highest average (4.13) was about training employees on how to reduce waste in the workplace, reflecting companies' interest in qualifying employees to achieve environmental goals. The use of modern technology in recycling waste also came with a high average (4.11), indicating the use of advanced technologies in this field. Moreover, the results showed that waste management practices have a positive impact on the environment surrounding the company with an average of (3.99). Finally, the results showed that participants believe that waste management affects the company's image among customers with an average of (3.89), indicating that companies are realizing the increasing importance of sustainable waste management in improving their reputation.

#### 4.2.3. Descriptive statistics of factory productivity variable

Table 4 shows the descriptive statistics for the factory productivity variable.

Table 4. Descriptive statistics for factory productivity

| | Statement | Mean | Alpha |
|---|---|---|---|
| 1 | My company provides a stimulating work environment to increase productivity. | 3.96 | 0.870 |
| 2 | Modern technology is used to increase production efficiency. | 3.88 | 0.907 |
| 3 | The necessary resources are available to achieve high productivity in my company. | 3.97 | 0.817 |
| 4 | Companies receive the necessary support to develop employee skills. | 3.95 | 0.840 |
| 5 | A culture of cooperation among employees enhances work productivity. | 4.02 | 0.824 |

The results of the analysis of the factory productivity axis indicate that participants generally agree that the work environment in their companies contributes to increasing productivity. The statement relating to the culture of cooperation among employees received the highest average (4.02), indicating that cooperation greatly enhances productivity. Participants also believe that the necessary resources to achieve high productivity are available with an average of (3.97), reflecting the availability of capabilities to achieve business goals. In terms of skills development, the results showed that companies provide the necessary support to develop employees' skills with an average of (3.95). The use of modern technology to improve production efficiency also showed a high average (3.88), reflecting the role of technology in improving performance and productivity.

### 4.3. Validity

Pearson's correlation coefficient was used to verify the internal consistency between the questionnaire items.

Table 5. Validity results

| Artificial Intelligence | | Waste Management | | Factory Productivity | |
|---|---|---|---|---|---|
| | Coefficient | # | Coefficient | # | Coefficient |
| 1 | 0.753 | 1 | 0.747 | 1 | 0.747 |
| 2 | 0.763 | 2 | 0.713 | 2 | 0.760 |
| 3 | 0.750 | 3 | 0.813 | 3 | 0.730 |

| | | | | | |
|---|---|---|---|---|---|
| 4 | 0.896 | 4 | 0.822 | 4 | 0.722 |
| 5 | 0.763 | 5 | 0.802 | 5 | 0.766 |

Table 5 indicates the Pearson correlation coefficient values for each questionnaire statement, all of which are clearly higher than 0.7, which are values indicating the existence of high internal consistency validity among the questionnaire statements.

### 4.4. Reliability

Cronbach's alpha reliability coefficient was used to ensure the reliability of the study questionnaire.

Table 6. Reliability results

| Variable | Number of phrases | Cronbach's alpha |
|---|---|---|
| Artificial Intelligence | 5 | 0.750 |
| Waste Management | 5 | 0.827 |
| Factory Productivity | 5 | 0.953 |
| Total Cronbach's alpha | 15 | 0.848 |

Table 6 shows acceptable to very strong internal consistency across the three constructs. Cronbach's alpha was 0.750 for Artificial Intelligence, 0.827 for Waste Management, and 0.953 for Factory Productivity. The overall Cronbach's alpha for the 15 items was 0.848, indicating good reliability for the questionnaire as a whole.

### 4.5. Hypothesis testing

The table below shows the results of testing the study's hypotheses.

Table 7. Hypothesis-testing results

| Hypothesis | R | R^2 | B | t | p |
|---|---|---|---|---|---|
| H1: Artificial Intelligence is positively related to Waste Management. | 0.708 | 0.513 | 1.390 | 8.463 | < 0.001 |
| H2: Waste Management is positively related to Factory Productivity. | 0.668 | 0.446 | 2.110 | 14.112 | < 0.001 |
| H3: Artificial Intelligence is positively related to Factory Productivity. | 0.764 | 0.584 | 0.394 | 1.487 | < 0.001 |

Note: B denotes the unstandardized regression coefficient. Statistical significance is reported as $p < 0.001$.

The hypothesis-testing results indicate strong positive relationships among the study variables. For H1, the relationship between Artificial Intelligence and Waste Management yielded $R = 0.708$ and $R^2 = 0.513$, indicating that Artificial Intelligence explains 51.3% of the variance in Waste Management. For H2, the relationship between Waste Management and Factory Productivity yielded $R = 0.668$ and $R^2 = 0.446$, indicating that Waste Management explains 44.6% of the variance in Factory Productivity. For H3, the relationship between Artificial Intelligence and Factory Productivity yielded $R = 0.764$ and $R^2 = 0.584$, indicating that Artificial Intelligence explains 58.4% of the variance in Factory Productivity. All three relationships were statistically significant at $p < 0.001$.

## 5. Discussion, implications, limitations, conclusions and recommendations

### 5.1. Discussion

Waste management is an important operational factor in improving productivity in industrial settings. This study therefore examined the relationships among Artificial Intelligence, Waste Management, and Factory Productivity. The results support the proposed positive relationships among the three constructs. These findings are consistent with prior work emphasizing the role of AI in operational efficiency and sustainability. Xue et al. [13] describe the contribution of AI to sustainable production, while Andeobu et al. [5] highlight the potential of AI applications to improve waste-management practices, including recycling and waste reduction. The impact of AI on productivity is further supported by previous literature. Cioffi et al. [10] found that AI applications in smart production significantly increase efficiency and decision-making capabilities. Javaid et al. [6] further illustrated the role of AI in Industry 4.0, highlighting how sophisticated technologies enhance manufacturing processes, resulting in increased productivity and optimized resource utilization. This observation is consistent with the results of the current study, which indicates that AI not only boosts productivity but also facilitates improved waste management practices.

Furthermore, the critical importance of waste management in preserving sustainability and environmental health is examined by Amritha & Kumar [33] and Fidelis et al. [32]. The implementation of effective waste management systems, enhanced by AI technologies as demonstrated in their research, exemplifies contemporary industrial practices focused on minimizing environmental impact while maximizing resource efficiency. The convergence of artificial intelligence and waste management is vital for attaining operational sustainability, as highlighted by Fang et al. [29] and Hassan et al. [8]. In summary, the research indicates that artificial intelligence serves as a crucial facilitator of improved productivity and sustainable waste management practices. These results are consistent with existing literature that highlights the transformative capabilities of AI across multiple sectors. As manufacturing facilities increasingly implement AI-driven technologies, the incorporation of these solutions will be essential for achieving future industrial sustainability and efficiency.

### 5.2. Implications

The findings of this research carry significant implications for both industrial management and sustainability initiatives. The potential for operational efficiency is evident: firms may be inclined to integrate AI-related technologies into their production processes to enhance productivity, assuming a favorable correlation between AI and productivity. This integration is likely to yield more efficient operations, more informed decision-making, and, ultimately, increased profits. Additionally, the study highlights the crucial role of AI in enhancing waste management practices. By employing AI-driven solutions, companies could effectively reduce waste, improve recycling processes, and mitigate overall environmental impact, thereby aligning with international sustainability objectives. The findings of this study indicate that management professionals should prioritize investments in AI technologies for their organizations and seek to provide their workforce with access to the best available training. Companies that adopt an AI-first approach have the potential to enhance productivity and achieve sustainability gains. Additionally, this research serves as a valuable resource for policymakers and industry leaders, encouraging them to view AI as a viable environmentally sustainable option when formulating waste management policies and corporate strategies. Moreover, the study highlights the increasing significance of AI in shaping the future of various industries, compelling companies to adopt modern technologies or face the risk of being displaced in an unpredictable market.

### 5.3. Study limitations

This study has several limitations. First, the findings are based on a survey of 175 employees in Jordanian factories and should therefore be generalized cautiously beyond this context. Second, the study relies on self-reported perceptions rather than objective operational indicators of waste management and productivity. Third, the analysis examines statistical associations among the constructs and does not establish causality or estimate a formal indirect mediation effect. Future studies can address these limitations through larger multi-industry samples, longitudinal designs, objective performance data, and formal mediation analysis.

### 5.4. Conclusions and recommendations

The study identifies significant positive relationships among Artificial Intelligence, Waste Management, and Factory Productivity in Jordanian manufacturing settings. The findings indicate that AI can support more informed operational decision-making and stronger waste-management practices, while effective waste management is associated with higher factory productivity. Together, these results reinforce the practical value of integrating AI into manufacturing operations to support both operational efficiency and sustainability objectives. Managers and policymakers should therefore consider AI adoption together with workforce training, process redesign, and waste-management capabilities rather than as a stand-alone technology investment.

Future research should broaden the industrial scope and use larger samples to improve generalizability. Longitudinal designs could evaluate the short- and long-term effects of AI adoption on Waste Management and Factory Productivity. Further work should distinguish among specific AI technologies and investigate barriers to effective adoption, particularly in small and medium-sized enterprises (SMEs). Studies should also incorporate objective operational and environmental performance indicators where possible.

## Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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