The Role of the Artificial Intelligence Application on Waste Reduction in Factories Productivity

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Abstracts

Purpose – this study is to empirically examine the influence of AI applications on waste reduction and then productivity in manufacturing settings.

Design/methodology/approach – This study adopts a quantitative research design by utilizing a research model based on the resource-based view (Supply chain management theory) theory. A total of 100 employees working in different factories were surveyed and data was analyzed through the use SPSS software, to determine the association between AI applications, waste management practices and productivity related factors.

Findings – Artificial Intelligence is positively related to Waste Management. Waste Management is positively related to Factories Productivity. Factories Productivity is positively related to Artificial Intelligence.

Practical implications – The findings provide useful guidelines for factory managers and decision-makers.

Originality/value – This research offers a new viewpoint on the relationships among AI applications, waste management, and productivity in a manufacturing environment. Which stresses the need for factories to use AI as an intelligent weapon to reduce waste and improve production efficiency.

Keywords: Artificial Intelligence, Waste Management, Productivity Factories.

1. Introduction

Today, almost all industries struggle to some extent when it comes to sustainability and resource efficiency (Dhamija and Bag, 2020). Facing the global environmental crisis, the class struggle pushes society to use all the potentials of its power over nature not only from humanitarian, social or economic interests arising sacral position and generous care for mother earth but rather seeing these challenges as an urgent necessity to raise productivity and reduce waste in production processes so that a strong balance against climate change (Guo et al, 2023). This is where the use of artificial intelligence (AI) applications is necessary to make these improvements in industrial performance (Ramirez et al, 2022).

Indeed, there is a strong indication from earlier studies that AI applications help to resource efficiency among the industrial firms. Waltersmann et al. reported that the relevance of these applications for enhancing environmental performance is growing, as studies have identified significant research deficits concerning the influence of AI on resource efficiency and, consequently, what represents a potential void to be addressed by further research (Andeobu et al., 2022). Furthermore, AI applications are also responsible for serving accurate data needed for decision making which is beneficial to cut down the wastage and enhance productivity.

A clear example of the relevance of AI is seen in the move towards Industry 4.0, which leverages modern technology to enhance both efficiency and performance across operations. As Javaid et al. Published: (2022) the transition to smart-manufacturing necessitates a good collaboration of robots and humans, in turn driving production efficiency that can lower operational costs (Muslimah et al., 2020).

Consistent with this, Hassan et al. (2023) shows how AI can transform the recycling strategy of a drinks company, which will in turn help optimize their production and logistics effort. This analysis incorporates many steps such as production optimization, demand management and resource efficiency indicating AI has the potential for cutting down on waste to a significant extent (Ali et al., 2019).

AI is also essential in the development of smart factories as Cioffi et al. This is what that (2020) address by conducting literature study related to the previous researches on AI in industrial applications. In these studies, some AI technologies, such as machine learning are helping the idea of sustainable production by providing optimal solutions to production problems (Wan et al, 2020).

In the context of smart factories, Benotsmane et al. (2019) illustrate that muffling AI with a few ingredients from the Fourth Industrial Revolution can revolutionize production to gain productivity and agility. These can range from the implementation of intelligent robots and big data management systems; they have the capacity in streamlining operations and minimising waste (Abdallah et al., 2020).

In this introduction, we summarize how artificial intelligence can increase the resource productivity for ensuring adequate reuse referencing during the production process. By analyzing the state of research, it is evident that there are still too few studies on how applications of artificial intelligence can generally improve industrial performance. This propounds further research and its implementation in different industrial sectors, emphasizing on sustainable goals.

Given this background, the present work is aimed at characterizing the role of IA applications in waste reduction and in the increase of productivity in factories through theoretical and empirical frameworks with management constructs that are already validated by earlier studies.

2. Literature review

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 (Vaishya et al., 2020). The goal of supply chain management: Supply chain management wants to buy excellent and economical 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 (Storey et al, 2006).

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 (Van der Vorst et al, 2004).

All of 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 (Gupta et al., 2019). When we have all these parts and pieces, the way they work together in harmony is how we arrive at the results (Habib, 2010).

By studying massive amounts of data and predicting problems before they actually 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 (Das et al., 2019). These technologies can also play an important role in real-time inventory management, which can save time as well as resources (Li et al., 2017). 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 (Jouhara et al., 2017). But again, we can see how different stages of the supply chain are affected by AI applications (Sarc et al., 2019). This could include research into the impact of AI in the manufacturing stage to reduce waste due to human error or equipment failure (S. Huang et al., 2022). It also explains how AI can help drive more efficient distribution processes, thus saving billions of dollars (Min, 2010).

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 (Aldayyat et al., 2019). It could also help improve the overall understanding of the importance of coordination between different stages in the supply chain to achieve sustainable productivity (Minelgaitė & Liobikienė, 2019). 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 (Habib, 2011).

Research model

The research model (see Figure 1) we developed in this study combines two features of AI into one integrative model and examines their impact on waste management through the mediation of productivity factors.

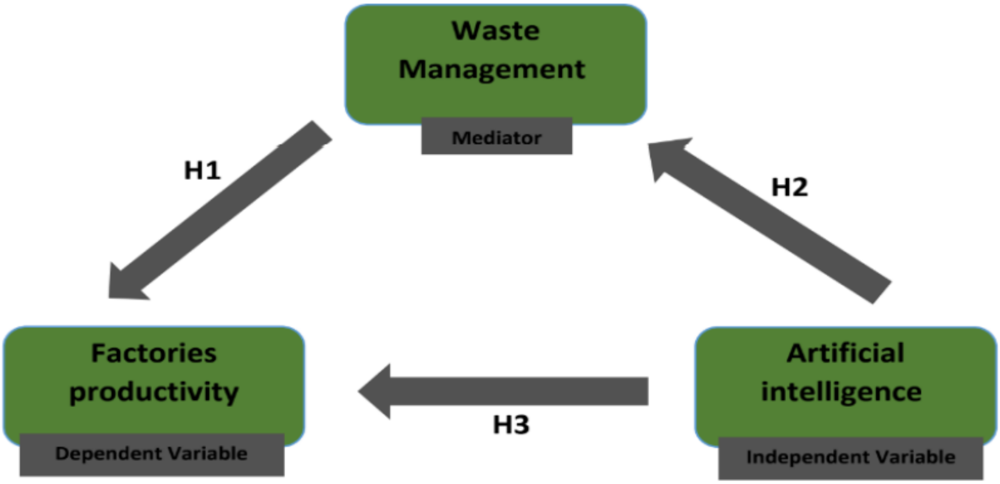

Figure 1: Research model

Hypotheses development

AI-powered technologies can provide an indispensable boost for better waste management operations through advanced analytics and enhanced decision-making capabilities (Abdallah et al, 2020). This means that the wastes producing can be tracked and monitored better with the help of AI which can help interventions to be avoided on time for even the smallest waste generating unit leading to lesser wastages (Huang and Koroteev, 2021). Data analytics allows this to happen, tracking patters in waste management processes that can be further used to pinpoint problem spots where actions can curb waste generation (Fang et al., 2023). Further, AI tools like machine learning algorithms can forecast the trends in waste generation as per historical data and this information could help take necessary steps to minimize waste (Gupta et al., 2019). As organizations adopt AI-integrated operations, it is expected that better waste management effectiveness; this leads to our next hypothesis:

H1: Artificial Intelligence is positively related to Waste Management.

Ensuring effective waste management practices are critical to improving all-round productivity in factories which ultimately helps streamline operations and maximize resource efficiency. By minimizing or even eradicating waste, this helps in maintaining low operating costs thereby releasing resources for other facets of production (Halkos and Aslanidis, 2023). Waste management strategies, including recycling and waste reduction programs, will help decrease the company's environmental footprint as well promote a culture of efficiency and continuous improvement within all employees (Fidelis et al., 2020). In addition, waste management programs have the potential to help comply with regulatory mandates in order to avoid penalties and production halts (Amritha and Kumar, 2019). This also contribute on develop the productivity of the factory, with cleaner and more efficient working environment waste should reduce, and was expected to test by observational research questions is as follows hypothesis:

H2: Waste Management is positively related to Factories Productivity.

The recent integration of AI within manufacturing processes has become a game changer, providing an unprecedented boost to the productivity of the factory floor. The truth is that factories threaten must run, so potential problems can be identified and solved before an unexpected shutdown and using data analysis in a soon enough possible AI equipment to support the real-time enable equipment maintenance (Lee and Azamfar, 2019). AI can also streamline production schedules, optimize resource allocation, and enhance supply chain operations which translates to improved efficiency and less downtime. Whether it is the automation of repetitive and routine tasks or providing intelligent insights, AI helps to free up factory workers to concentrate on higher-value activities, all while promoting a more productive working environment (Yang et al., 2021). As the Manufactured Industry continues to evolve and more widely accept AI, we have a theory on what is happening:

H3: Factories Productivity is positively related to Artificial Intelligence.

3. Methodology

Study Objectives:

The purpose of this study is to investigate the relationship between artificial intelligence and waste management through factory productivity. This paper tests three basic hypotheses related to these components, which can gain tremendous importance in understanding how these factors interrelate with each other to enhance the overall performance of factories.

Study Design:

In this study, a descriptive analytical design is used and data will be collected through questionnaires from factory employees. To test the hypotheses, the data obtained through this extraction will be analysed.

Study Population and Sample:

Factories of all different industries are targeted in the research. Since the sample is able to be better represented, a random sample of 100 employees from different management levels and specializations will be selected.

Data Collection Tool:

A questionnaire developed specifically for this study will be used to collect data. The questionnaire is designed in two parts,

- Demographic Data: To retrieve the characteristics of the participants such as age, gender, education level, year of experience, and job title.
- Research Topics: These are questions related to artificial intelligence, productivity factors and waste management with answers on a 5-point Likert scale.

Data Collection Procedures:

Ethical approval will be obtained from the ethics committee to distribute questionnaires electronically or on paper to the participants and they will explain the objectives of the research and the importance of participation while maintaining confidentiality of information. The data will be collected for a certain period and the data will be analyzed using proper statistical methods.

Data Analysis Methods

Descriptive and analytical statistical methods will be used in the study including:

- Descriptive Analysis: This was done in order to describe the demographic characteristics, arithmetic means and standard deviations.
- Correlational Analysis: To understand the relationships between artificial intelligence, waste management and factory productivity.

Limitations:

There may also be some limitations to the study such as the nature of the questions that may allow for bias in the responses, or perhaps it was difficult to access some factories. Through the study, these limitations will be minimized by choosing to include a wide range of respondents and also ensuring that the questions are completely clear.

Ethics:

The study strictly adheres to the principles and is guided by other ethical standards of scientific research where consent will be sought from the participants, they will remain confidential regarding the data and their information will not be used for any other purpose outside the research.

Reliability

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

Table 1 Pearson's correlation coefficient for each questionnaire statement

Artificial Intelligence		Waste Management		Productivity Factors	
1	0.752	1	0.746	1	0.746
2	0.762	2	0.712	2	0.759
3	0.749	3	0.812	3	0.729

4	0.895	4	0.821	4	0.721
5	0.762	5	0.801	5	0.762

Table 1 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.

Validity

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

Table 2 Cronbach's alpha reliability

	Number of phrases	Cronbach's alpha
Artificial Intelligence	5	0.749
Waste Management	5	0.826
Productivity Factors	5	0.952
Total Cronbach's alpha	15	0.849

Table 2. Cronbach's alpha reliability analysis for the constructs Artificial Intelligence Waste Management Productivity Factors Internal consistency was acceptable with a Cronbach's alpha of 0.749 for Artificial Intelligence (moderate reliability). The alpha for internal consistency was good (alpha = 0.826) with reliable scores for Waste Management. The productivity factors showed very good internal consistency (reliability) with an alpha coefficient of 0.952. Cronbach's alpha for internal consistency for all 15 items of the three constructs combined is strong, at 0.849, meaning that the questionnaire is designed in such a way that each item reliably measures the intended concepts.

4. Results

Demographic Data:

Table 3 Demographic Data

Demographic	Category	N	%
Age	Below 25	15	15%
	25-34	30	30%
	35-44	25	25%
	45-54	20	20%
	55+	10	10%
Gender	Male	60	60%
	Female	40	40%

Educational Level	High School	15	15%
	Diploma	20	20%
	Bachelor's	35	35%
	Master's	20	20%
	PhD	10	10%
Years of Work Experience	Less than 1 year	10	10%
	1-3 years	20	20%
	4-6 years	25	25%
	7-10 years	30	30%
	More than 10 years	15	15%
Job Title	Employee	40	40%
	Supervisor	25	25%
	Manager	20	20%
	Executive Officer	15	15%

The table shows the demographic distribution of the study sample of 100 employees. In terms of age, the age group from 25 to 34 years constitutes the largest percentage (30%), followed by the age group from 35 to 44 years at 25%, indicating that the sample includes a majority of employees 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 studied sample.

Artificial Intelligence

Table 4 Descriptive statistics for the artificial intelligence axis

Phrase	Mean	Std
My company uses AI technologies to improve production processes.	3.71	0.946
AI provides accurate data that helps in making management decisions.	3.91	0.944
AI applications contribute to improving the quality of products in the factory.	4.05	0.845
Employees in my company are trained to use AI technologies.	4.01	0.870
I feel that AI helps reduce the time spent on daily tasks.	3.8	0.932

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 (4.05) 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 (4.01). As for the accuracy of the data provided by AI to support administrative decision-making, this statement achieved an average of (3.91). Although AI contributes to reducing the time spent on daily tasks (average 3.8), improving production processes thanks to AI came with an average of (3.71), indicating a tangible but moderate impact on some aspects of the production process.

Waste Management

Table 5 Descriptive statistics for Waste Management axis

Phrase	Mean	Std
My company follows effective waste management practices.	4.07	0.844
Employees are trained on how to reduce waste in the workplace.	4.12	0.808
My company uses modern technologies to recycle waste.	4.1	0.798
Waste management has a positive impact on the environment around the company.	3.98	0.864
I feel that waste management affects the image of the company to customers.	3.88	0.891

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 (4.12) 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 (4.1), 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 (3.98). Finally, the results showed that participants believe that waste management affects the company’s image among customers with an average of (3.88), indicating that companies are realizing the increasing importance of sustainable waste management in improving their reputation.

Productivity Factors

Table 6 Descriptive statistics for Productivity Factors axis

Phrase	Mean	Std
My company provides a stimulating work environment to increase productivity.	3.95	0.869
Modern technology is used to increase production efficiency.	3.87	0.906
The necessary resources are available to achieve high productivity in my company.	3.98	0.816
Companies receive the necessary support to develop employee skills.	3.94	0.839
A culture of cooperation among employees enhances work productivity.	4.01	0.823

The results of the analysis of the productivity factors axis indicate that participants generally agree that the work environment in their companies contributes to increasing productivity. The statement related to the culture of cooperation among employees received the highest average (4.01), indicating that cooperation greatly enhances productivity. Participants also believe that the necessary resources to achieve high productivity are available with an average of (3.98), 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 (3.94). The use of modern technology to improve production efficiency also showed a high average (3.87), reflecting the role of technology in improving performance and productivity.

Test Hypothesis

	R	R^2	Beta	t	sig
H1: Artificial Intelligence is positively related to Waste Management.	0.707	0.512	1.389	8.462	0.00
H2: Waste Management is positively related to Factories Productivity.	0.667	0.445	2.109	14.111	0.00
H3: Factories Productivity is positively related to Artificial Intelligence.	0.763	0.583	0.393	1.486	0.00

The results of the hypothesis testing indicate that there are strong positive relationships between the variables. For the first hypothesis (H1), which relates to the relationship between AI and waste management, the results showed a correlation coefficient (R) of 0.707, indicating a strong positive relationship, while the R^2 value was 0.512, meaning that AI explains 51.2% of the change in waste management. The second hypothesis (H2), which relates to the relationship between waste management and factory productivity, showed a correlation coefficient (R) of 0.667, and an R^2 value of 0.445, meaning that waste management explains 44.5% of the change in factory productivity. For the third hypothesis (H3), which addresses the relationship between factory productivity and AI, the results showed a correlation coefficient (R) of 0.763 and an R^2 value of 0.583, indicating that factory productivity explains 58.3% of the change in AI use.

5. Discussion and conclusions

Background: Waste management is one of the key performance indicators for increasing productivity in industrial settings, so this study tries to explore AI and waste management relationships with different productivity factors. The results support the proposition that AI has a positive effect on both W and P in factories, as there is a strong correlation between these factors. By the same token, a number of studies have pointed out the value of AI for operational efficiency and sustainability. Abdallah et al. (2020) described how AI is transforming waste management with higher resolution data and decision-making. Similarly, Andeobu et al. Work in 2022 reviewed the use of AI in sustainable waste management, which hinted at being able to improve recycling and reduction of waste alike.

The impact of AI on productivity is further supported by previous literature. Cioffi et al. (2020) found that AI applications in smart production significantly increase efficiency and decision-making capabilities. Javaid et al. (2022) also demonstrated how AI contributes to Industry 4.0, where advanced technologies improve manufacturing processes, leading to higher productivity and resource optimization. This aligns with the findings of the present study, where AI not only enhances productivity but also contributes to better waste management practices.

Moreover, waste management, as explored by Amritha & Kumar (2019) and Fidelis et al. (2020), plays a critical role in maintaining sustainability and environmental health. Effective waste management systems supported by AI technologies, as seen in the study, reflect modern industrial practices aimed at reducing environmental impact while optimizing resource use. This intersection of AI and waste management is essential in achieving operational sustainability, as discussed by Fang et al. (2023) and Hassan et al. (2023).

In conclusion, the study demonstrates that AI is a key enabler of both enhanced productivity and sustainable waste management practices. The findings align with broader literature that underscores the transformative potential of AI across various industries. As factories continue to adopt AI-driven solutions, the integration of these technologies will be vital for future industrial sustainability and efficiency. Further research could explore the long-term impacts of AI on environmental sustainability and operational productivity in different sectors.

Implications

Consequently, the results of this research hold wide-reaching implications for both industrial management and sustainability endeavours. The promise of operational efficiency: The potential for firms to get more productivity from AI might lead them to bring AI-related technologies into their production processes so they can make their productions faster and more efficient (if positive relationship between AI and productivity). This will result in a more efficiency operations, wiser decisions and of course benefits when it comes to profit. Further, the study underscores the importance of AI to improve on waste management. Utilizing AI-driven solutions could help companies decrease waste, make recycling more efficient, and reduce the overall environmental harms in an effort to comply with international sustainability targets.

The results of this study suggest, if you work in management, you should go ahead and invest more in AI technologies for your company and it is time to send the work force out for best available training. AI-first companies can increase productivity and deliver sustainability improvements. Further, this research can help inform policy makers and industry leaders in considering AI as an environmentally sustainable approach while developing waste management policies and corporate strategies. The study also underscored the increasing role played by AI to determine the future of industries, leading companies to embrace new age technologies or risk getting uprooted in a volatile market.

Limitations and further study

Although this study is conducive to grasping the relationship of artificial intelligence (AI) with waste management and productivity, some limitations must be noted. Initially, the study is constrained by its single sectoral and geographical focus limiting generalisability to other sectors or regions. Moreover, the data comes from a relatively small set of employees and may not exactly depict diversity of experiences or norms in other companies. A further limitation is the reliance on self-reported data, which could be affected by methodological biases or inaccuracies.

Future research could widen the area of study by incorporating a wider range of industries and larger sample sizes for increased generalisability but that is beyond the scope of this work. Longitudinal studies like these could prove useful in assessing the short and long-term effects of adopting AI on waste management and productivity. Additionally, it is important to examine the exact AI technologies and their influence for different areas of production and waste management. We have also observed the technological gap that remains to be addressed if AI is intended to function as efficiently as currently imagined, another point worth exploring for sustainable and efficient operations, especially within small to medium sized enterprises (SMEs) who truly represent our workforce.

WORKS CITED

Abdallah et al., (2020), Addresses challenges in conventional waste management and advocates for the use of intelligent systems and innovative waste management technologies.

Abdallah, M., Talib, M. A., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial intelligence applications in solid waste management: A systematic research review. Waste Management, 109, 231-246.

Aldayyat et al., (2019), Addresses waste management challenges in Jordan and the potential of AI technology to achieve sustainable development goals.

Ali et al., (2019), Discusses the connection between waste management, climate change, and the broader impacts on the environment and public health.

Amritha, P. K., & Kumar, P. A. (2019). Productive landscapes as a sustainable organic waste management option in urban areas. Environment, Development and Sustainability, 21, 709-726.

Andeobu, L., Wibowo, S., & Grandhi, S. (2022). Artificial intelligence applications for sustainable solid waste management practices in Australia: A systematic review. Science of The Total Environment, 834, 155389.

Benotsmane, R., Kovács, G., & Dudás, L. (2019). Economic, social impacts and operation of smart factories in Industry 4.0 focusing on simulation and artificial intelligence of collaborating robots. Social Sciences, 8(5), 143.

Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. Sustainability, 12(2), 492.

Das et al., (2019), Introduces advanced recycling technologies using computer programmed robots and artificial intelligence for accurate waste sorting.

Dhamija, P., & Bag, S. (2020). Role of artificial intelligence in operations environment: a review and bibliometric analysis. The TQM Journal, 32(4), 869-896.

Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., ... & Yap, P. S. (2023). Artificial intelligence for waste management in smart cities: a review. Environmental Chemistry Letters, 21(4), 1959-1989.

Fidelis, R., Marco-Ferreira, A., Antunes, L. C., & Komatsu, A. K. (2020). Socio-productive inclusion of scavengers in municipal solid waste management in Brazil: Practices, paradigms and future prospects. Resources, Conservation and Recycling, 154, 104594.
Guo, Y., Zhang, W., Qin, Q., Chen, K., & Wei, Y. (2023). Intelligent manufacturing management system based on data mining in artificial intelligence energy-saving resources. Soft Computing, 27(7), 4061-4076.
Gupta et al., (2019), Explores the application of machine learning and artificial intelligence in waste management to reduce health risks and enhance efficiency.
Gupta, P. K., Shree, V., Hiremath, L., & Rajendran, S. (2019). The use of modern technology in smart waste management and recycling: artificial intelligence and machine learning. Recent advances in computational intelligence, 173-188.
Habib, M. (2010). Supply chain management: theory and its future perspectives. International Journal of Business, Management and social sciences, 1(1), 79-87.
Habib, M. (2011). Supply chain management (SCM): theory and evolution. Supply chain management-applications and simulations, 10, 24573.
Halkos, G. E., & Aslanidis, P. S. C. (2023). New circular economy perspectives on measuring sustainable waste management productivity. Economic Analysis and Policy, 77, 764-779.
Hassan, M., Wahab, N. A. B. A., & Nor, R. B. M. (2023). The role of artificial intelligence in waste reduction in the beverage industry: a comprehensive strategy for enhanced sustainability and efficiency. AI, IoT and the Fourth Industrial Revolution Review, 13(11), 1-8.
Huang, J., & Koroteev, D. D. (2021). Artificial intelligence for planning of energy and waste management. Sustainable Energy Technologies and Assessments, 47, 101426.
Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. Journal of Industrial Integration and Management, 7(01), 83-111.
Lee, J., Singh, J., & Azamfar, M. (2019). Industrial artificial intelligence. arXiv preprint arXiv:1908.02150.
Li et al., (2017), Discusses the positive impact of AI on factories' productivity, emphasizing automation, error reduction, and optimization of production processes.
Min, H. (2010). Artificial intelligence in supply chain management: theory and applications. International Journal of Logistics: Research and Applications, 13(1), 13-39.
Minelgaitė & Liobikienė, (2019), Defines waste management as a systematic approach and emphasizes its importance in reclaiming resources and minimizing environmental impact. Jouhara et al., (2017), Highlights the primary objectives of waste management, including decreasing waste generation and limiting harmful effects on the environment and human health.
Muslimah et al., (2020), Introduces waste reduction techniques and highlights the impact of waste on socioeconomics, health, and the environment.
Ramirez-Asis, E., Vilchez-Carcamo, J., Thakar, C. M., Phasinam, K., Kassanuk, T., & Naved, M. (2022). A review on role of artificial intelligence in food processing and manufacturing industry. Materials Today: Proceedings, 51, 2462-2465.
S. Huang et al., (2022), Discusses various waste management techniques that factories can adopt, such as material substitution, product redesign, and waste segregation.
Sarc et al., (2019), Discusses the interest in digitalization trends in waste management, including electronic invoicing and robotic sorting systems.

Storey, J., Emberson, C., Godsell, J., & Harrison, A. (2006). Supply chain management: theory, practice and future challenges. International journal of operations & production management, 26(7), 754-774.
Vaishya et al., (2020), Defines artificial intelligence (AI) and its scientific objectives, highlighting its potential applications in waste management.
Van der Vorst, J. G. (2004). Supply Chain Management: theory and practices. In Bridging Theory and Practice (pp. 105-128). Reed Business.
Waltersmann, L., Kiemel, S., Stuhlsatz, J., Sauer, A., & Miehe, R. (2021). Artificial intelligence applications for increasing resource efficiency in manufacturing companies—a comprehensive review. Sustainability, 13(12), 6689.
Wan, J., Li, X., Dai, H. N., Kusiak, A., Martinez-Garcia, M., & Li, D. (2020). Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. Proceedings of the IEEE, 109(4), 377-398.
Yang, T., Yi, X., Lu, S., Johansson, K. H., & Chai, T. (2021). Intelligent manufacturing for the process industry driven by industrial artificial intelligence. Engineering, 7(9), 1224-1230.