INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue IX September 2024

Artificial Intelligence in the Printing Industry: A Systematic Review of Industrial Applications, Challenges and Benefits

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DOI: https://dx.doi.org/10.47772/IJRISS.2024.8090141

Received: 23 September 2024; Accepted: 30 September 2024; Published: 09 October 2024

ABSTRACT

The commercial printing industry is undergoing a significant transformation with the integration of Artificial Intelligence (AI), yet there is limited literature on its specific applications and impact. This systematic review addresses two critical research questions: What are the key industrial domains where AI is applied in the printing industry, and what are the associated benefits and challenges? Our study identifies the primary AI applications across Production Planning and Control (PPC), Quality Management (QM), Maintenance Management (MM), and Supply Chain Management (SCM). PPC employs optimization algorithms to optimise scheduling and resource allocation, improving production efficiency. In QM, Machine Learning and Computer Vision detect defects and optimize print quality. MM focuses on minimizing downtime by ensuring machines operate efficiently through predictive maintenance. Despite these advancements, challenges such as high-quality data requirements, algorithmic complexity, and integration difficulties persist. This research fills a critical gap in the literature by providing a comprehensive overview of AI's role in the printing industry, offering valuable insights into its potential to drive efficiency, cost savings, and quality improvements. Our findings suggest that while AI holds substantial promise, its benefits are contingent upon overcoming significant implementation challenges. This study contributes to the ongoing discourse on digital transformation by providing a robust framework for understanding AI's current and future impact on the printing sector. Our methodology followed PRISMA guidelines, with a thorough review and thematic analysis of peer-reviewed studies. The insights gained from this review can guide future research and practical implementations, positioning AI as a crucial enabler in the evolving landscape of the printing industry.

Keywords: Artificial intelligence, Printing, Systematic review, Manufacturing

INTRODUCTION

The commercial printing industry, once dominated by traditional methods, is undergoing a transformative shift as digital technologies and artificial intelligence (AI) become increasingly integrated into its processes. With the rise of Industry 4.0, the potential for AI to revolutionize production, improve efficiency, and enhance competitiveness is more significant than ever (Politis, 2019); (Masod, 2018). As businesses face growing competition and evolving consumer demands, adopting AI technologies in the printing sector is no longer a luxury but a necessity. This shift presents opportunities and challenges, making it a critical area of study for industry stakeholders and researchers.

Despite the promising prospects of AI in the printing industry, there remains a noticeable gap in the literature regarding its specific applications and effectiveness. While Salwin et al. (2020) have highlighted the transformative potential of digital technologies, such as reducing production time and improving quality, the full impact of AI integration is not yet fully understood. Previous research has focused on broader aspects of digital transformation such as Gamprellis et al., (2021) and Tomić et al., (2022) or on the challenges faced by smaller enterprises in adopting these technologies (Politis, 2019). However, the intricacies of AI applications in areas like maintenance management, quality control, and production planning within the commercial printing sector remain underexplored. Furthermore, there are conflicts in the literature regarding the readiness of the industry to embrace AI, with some studies emphasizing the need for further innovation Cioffi et al., (2020) and Davis, R. H. (2014) highlighting the substantial hurdles, such as high costs and resistance to change (Lee et al., 2023).

Given these gaps, this study aims to systematically review the literature on implementing AI in the printing industry, focusing on the predominant AI technologies and their application domains. Specifically, this review seeks to address two key research questions: (1) What is the key industrial domain of AI and its key applications in the printing industry? Moreover, (2) What are the benefits and challenges of AI applications in the printing industry? By addressing these questions, the study will contribute to a clearer understanding of how AI is utilized and what future developments may be necessary to overcome existing barriers.

BACKGROUND

Artificial Intelligence

Artificial Intelligence (AI) refers to systems designed to perform tasks that typically require human intelligence, such as decision-making, problem-solving, and pattern recognition. It can be understood from two practical perspectives: first, as a system that simulates certain cognitive processes like learning and reasoning, enabling the automation of complex tasks, and second, as a specialized tool optimized for enhancing specific processes and improving operational efficiency. These systems learn from data, adapt over time, and deliver outputs such as predictions, recommendations, or decisions (International Organization for Standardization (ISO), 2022); (Feingold, 2023).

In industrial contexts, AI is applied with a disciplined approach to develop, validate, and maintain solutions that enhance sustainable performance. This involves the integration of various AI subfields, such as machine learning, natural language processing, optimization, robotics, and expert systems, to address complex industrial challenges (Peres et al., 2020); (Plathottam et al., (2023a); Davenport & Ronanki, (2018). Industrial AI, therefore, is both a tool for optimizing tasks like automated quality control and inventory management and a broader system that transforms business practices through advanced data analytics and adaptive learning technologies.

AI subfields, functional applications and its industry applications

Industry-specific studies, such as those by Peres et al. (2020), Wuest et al. (2016), Cioffi et al. (2020), and Bertolini et al. (2021), offer insights into AI classification within the sector, highlighting the flexibility and adaptability of AI technologies to the dynamic landscape of industrial applications. The functional applications and their application fields are in Table 1.

Table 1. AI subfields, its definitions, functional applications and its industry applications

AI Subfield	Definition	Functional Applications	Industry Applications
Computer Vision	Trains computers to interpret and understand visual data.	Image/video analysis, object detection, facial recognition, AR	Security, automotive, healthcare, retail
Machine Learning	Automates analytical model building through data-driven learning algorithms.	Predictive analytics, data mining, pattern recognition	Finance, marketing, sports
Deep Learning	A subset of machine learning involving multi-layered neural networks.	Speech recognition, natural language understanding, image classification	Telecommunications, entertainment, legal
Automated	AI systems that formulate	Logistics optimization,	Manufacturing,

Planning & Scheduling (APS)	action sequences for complex tasks.	resource allocation, workflow management	transportation, services
Robotics	Involves the design, construction, and application of robot	Assembly, packaging, material handling, surgical operations	Manufacturing, healthcare, agriculture
Knowledge-Based Systems	AI systems that apply human expertise to solve complex problems.	Expert systems, decision support, rule-based reasoning	Healthcare, finance, IT
Optimization	Enhancing efficiency and effectiveness through AI techniques.	Resource optimization, supply chain management, energy distribution	Logistics, utilities, manufacturing
Natural Language Processing (NLP)	Enables computers to understand and process human language.	Text analysis, sentiment analysis, machine translation	Customer Relationship Management

Source: Arinez et al., (2020)

METHODOLOGY

Planning and protocol development

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines by Moher et al. (2009) to ensure a transparent and rigorous approach. The review protocol, guided by Context-Interventions-Mechanisms-Outcome (CIMO) framework (Denyer & Tranfield, 2009), was designed to address our primary research question: What are the key application domains of AI and its primary applications in the printing industry? Additionally, what is the impact of these applications on the industry? This central question was further broken down into specific inquiries regarding AI technologies and the challenges associated with their adoption in this sector, as outlined in Table 2.

Table 2. Specific inquiries of about AI technologies and challenges based on CIMO

Research Questions (RQ)	**Discussion**
RQ1: What is the key industrial domain of AI and its key applications in the printing industry?	This question identifies and categorizes current AI technologies used in the commercial printing industry, focusing on their specific applications and impact on print production workflow
RQ2: What are the benefits and challenges of AI applications in the printing industry?	This question analyzes the direct and indirect benefits of AI and the challenges within technological, organizational, and environmental dimensions.

Study identification, selection and screening

A comprehensive search was conducted across Scopus, Web of Science, IEEE Xplore, Science Direct, and Google Scholar using a structured strategy with tailored search terms. The search parameters are detailed in Table 3. We applied strict inclusion criteria, focusing on peer-reviewed, English-language empirical studies that use real-life datasets related to AI in the commercial printing industry. Exclusion criteria were applied to filter out non-peer-reviewed, irrelevant, or duplicate studies. After the screening process, 325 articles were identified, and 30 were selected for detailed review. The process is illustrated in Figure 1.

Table 3. Search parameters

Search Strategy	Keywords/range	Justification
Search by range	2010 to 2022	Track the evolution and trends in AI adoption within the printing industry over the specified period.
Primary Search Parameters:	"print servic*", "printing industr*", "print service provider", and "print manufacturing"	These terms were designed to retrieve articles directly linked to the commercial printing industry.
Narrowing Parameters	"artificial intelligence", "deep learning", "machine learning", "Expert system", "Artificial neural network", "genetic algorithm", "AI algorithm", "machine vision systems", "automation", "random forest", and "robotics".	The search was narrowed to articles that specifically discuss artificial intelligence in the context of the printing industry.
Broadening Parameters	"Industry 4.0", "cognitive computing", "predictive maintenance", and "digital transformation".	To provide a more comprehensive perspective on AI adoption in the printing industry, the search was expanded to include a wider range of related concepts
AI Related Terms	"AI algorithm", "automation", "industry 4.0", "cognitive computing", "digital transformation", "machine learning", "symbolic learning", "deep learning", "Expert system", "Artificial neural network", "genetic algorithm", "machine vision systems", "Random forest", "robotics", "Industry 4.0", "cognitive computing", "predictive maintenance", "digital transformation".	The search was further refined to include specific AI-related terms. These terms encompass a range of artificial intelligence methodologies and technologies.
AI Techniques	"Convolutional neural networks", "Recurrent neural networks", "Reinforcement learning", "Transfer learning", "Generative adversarial networks", "Deep belief networks", "Support vector machines", "Decision trees", "Random forests", "Bayesian networks", "Natural language processing", "Computer vision", "Data mining".	To gain more specific insight into the AI methodologies used in the printing industry, the search included specific AI techniques

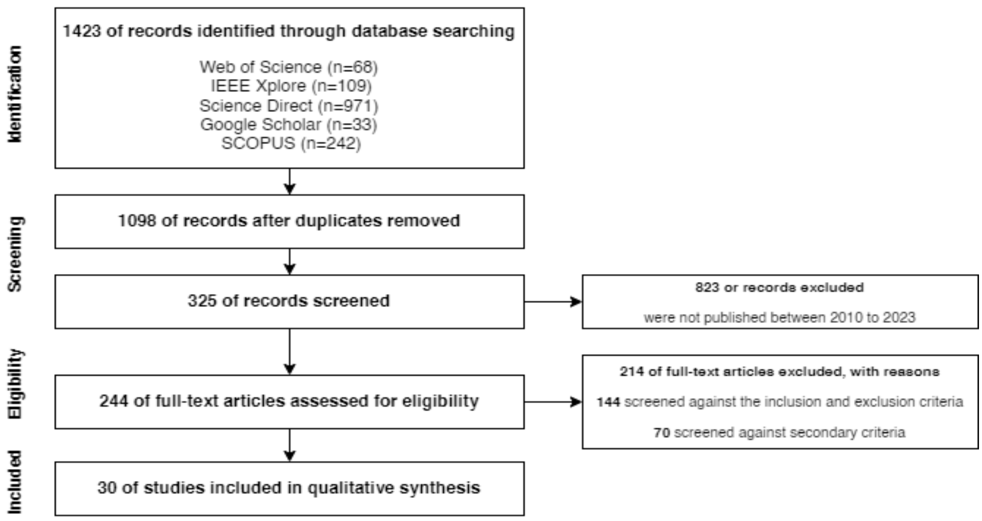

Fig. 1 PRISMA flow diagram for the systematic review

Data Extraction, Quality Assessment, and Synthesis

We conducted a quality assessment of the selected studies using a checklist adapted from Kitchenham & Charters (2007) and Hosseini et al. (2019). This checklist was tailored to evaluate the relevance of each study to our research questions, assess the risk of bias, and determine the validity of the findings. Relevance was assessed by examining how closely the study's objectives, methods, and outcomes aligned with our research focus. The risk of bias was evaluated by considering factors such as study design and data collection methods, while validity was assessed by analyzing the robustness of the findings and their applicability to the commercial printing industry.

Following the quality assessment, we synthesized the extracted data using thematic analysis, following the methodology outlined by Cruzes & Dybå, (2011). Themes were developed inductively from the data and aligned with our research questions.

RESULTS

Distribution of publication by region and year

As illustrated in Table 4, The distribution of AI research publications over the past decade reveals a clear trend of global expansion and regional diversification. Asia leads with 16 publications, highlighting its dominant role in the field. China, a major contributor, appears in the dataset every year it participated, peaking in 2022 with four contributions across China, Iran, and Japan. Europe and North America each account for 6 publications, underscoring their steady but less dominant presence. European contributions are diverse, with countries like Germany, Italy, and Sweden each making single contributions, while North America is primarily represented by the United States, contributing consistently between 2011 and 2015. Other regions, though contributing only 2 publications, show emerging interest, with Brazil and the Philippines appearing in 2020. This distribution shows the growing global interest in AI research, but also the collaborative nature of this expansion across diverse geographical regions.

Table 4 Distribution of publication by region and year

Year	Asia	Europe	North America	Other region
2010	China (1)	Sweden (1)	-	-
2011	India (1)	France (1)	United States (1)	-
2013	China (1)	-	United States (1)	-
2014	Singapore (1)	-	United States (1)	-
2015	China (1), Iran (1)	-	United States (3)	-
2019	China (2),	Germany (1), Ukraine (1)		
2020	Philippines (1)			Brazil (1)
2021	China (1), Indonesia (2)	Italy (1), Luxembourg (1)		
2022	China (2), Iran (1), Japan (1)			Canada (1)
Total	**16**	**6**	**6**	**2**

Publication by type and sources

As detailed in Table 5, Publication by Type and Table 6, Publications by Sources, reflects a balanced and impactful research output, with 30 publications split between 17 conference proceedings (56.7%) and 13 journal articles (43.3%). The conference proceedings span prestigious events such as the IEEE Winter Conference on

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue VI June 2024

Applications of Computer Vision (WACV) and the IEEE 5th International Conference on Information Technology, Information Systems, and Electrical Engineering (ICITISEE), underscoring the research's relevance across various domains. The journal articles are published in high-impact journals like IEEE Transactions on Image Processing (Q1) and the European Journal of Operational Research (Q1), indicating the research's significant influence and scholarly rigour. This distribution demonstrates a strategic approach to maximizing both immediate visibility through conferences and in-depth impact through journal publications, highlighting the research's broad applicability and contribution to the field.

Table 5 Publication by type

Publication types	**Number of publications**
Conference Proceedings	17 publications
Journal Articles	13 publications

Table 6 Publications by sources

Publication sources	**Number of publications**
2010 IEEE World Congress on Computational Intelligence, WCCI 2010	1
2013 Chinese Automation Congress	1
2013 Winter Simulations Conference (WSC)	1
2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP)	1
2020 IEEE Winter Conference on Applications of Computer Vision (WACV)	1
2020 International Conference on Applied Science and Technology (iCAST)	1
2021 9th International Conference on Information and Communication Technology (ICoICT)	1
2021 IEEE 3rd International Conference on Frontiers Technology of Information and Computer (ICFTIC)	1
2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)	1
2022 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML)	1
ACM Transactions on Design Automation of Electronic Systems	1
Advanced Materials Research	1
Applied Soft Computing	1
Computers and Industrial Engineering	1
Computers and Operations Research	1
European Journal of Operational Research	1
IEEE International Conference on Industrial Informatics (INDIN)	1
IEEE Joint International Information Technology and Artificial Intelligence	1

Conference (ITAIC)	
IEEE Transactions on Automation Science and Engineering	1
IEEE Transactions on Image Processing	2
IEEE Transactions on Industrial Electronics	1
IFIP International Conference on Advances in Production Management Systems	1
International Conference on Information and Knowledge Management	1
Journal of Coatings Technology and Research	1
Journal of Imaging Science and Technology	1
Proceedings of SPIE - The International Society for Optical Engineering	1
Proceedings of the 11th EAI International Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness, QSHINE 2015	1
Proceedings of the 2019 20th International Conference on Research and Education in Mechatronics, REM 2019	1
Sensors	1
Total	**30**

RQ1-Key Industrial domain on AI and its key applications in printing industry

To address research question one (RQ1), we explore the key industrial domains where AI is applied within the printing industry, emphasizing how various AI technologies are utilized across different operational areas. We define 'industrial domains' according to Bertolini et al. (2021). To directly respond to our inquiry about AI's key applications in the printing industry, we developed a matrix of AI applications specific to this sector. This matrix functions as a strategic tool, enabling a systematic comparison of AI subfields, datasets, algorithms, outcomes, and challenges across multiple studies. Through this matrix, we analyze AI's role in various aspects of the printing process. Table 7 details the matrix of this analysis.

Table 7 Matrix for AI application in Printing industry

Author	**Contexts of the problem**	**Industrial Domain**	**AI subfields and Algorithm**	**Datasets used**	**Outcomes**	**Challenges**
Kazmirovych & Jagiello, (2019)	Fluctuating parameters slow machine adjustments.	MM	Deep Learning: Probabilistic Neural Networks and General Regression Neural Networks	Measurements of signature thickness	8.4% prediction error.	Human oversight required.
Tarigan et al., (2021)	ERP integration issues and limited data utility.	MM	Machine Learning: Linear Regression Algorithm	Time series on power consumption and machine speed.	Reduced measurement differences: 0.33 (current), 3.2 (voltage).	Impact of extra variables and scalability concerns.
Hu &	Frequent	MM	Deep Learning:	Book	98.6%	Data

Yang, (2021)	printing equipment faults, low prediction accuracy.		Gated Recurrent Unit neural networks with Adam optimization algorithm	machine 5000 cycles of vibration, lubrication, and temperature data.	prediction accuracy	collection and the need for fine-tuning.
Hase et al., (2022)	Toner blocking due to inadequate cooling in high-speed printing.	MM	Deep Learning: Artificial Neural Networks	20 production conditions, 9 paper types, various paper and fusing parameters.	Prediction accuracy within ±5°C.	Variability in paper types and conditions.
Huang et al., (2010)	Inefficiency scheduling with varying setup requirements	PPC	Optimization: Hybrid genetic algorithm	Job times (5-2120 min) and setup times (15 or 55 min).	15.5% faster scheduling.	Complexity of print jobs.
Agrawal et al., (2011)	Optimizing print workflows under strict deadlines.	PPC	Optimization: Genetic Algorithm and Integer Linear Programming	Commercial print orders.	Effective planning: 584s vs. traditional 600s.	Efficiency drops with job complexity.
Gazeau et al., (2011)	Large-format printing on fixed, non-planar surfaces.	PPC	Robotics: Control algorithm for parallel mechanisms	Designers digital images, distance measurement data	180-360 dpi print on convex surfaces.	Limited to minimal curvature surfaces and complex real-time control adjustments.
Rai & Ettam, (2013)	Labor-intensive traditional equipment selection processes	PPC	Optimization: Modified Simulated Annealing	2,692 print jobs over 10 days.	Reduced planning from ~30 hours to 1.44-1.77 hours (90% reduction).	High computational cost and scalability issues
li et al., (2015)	Minimizing production delays and costs.	PPC	Optimization: Genetic Algorithm	Data from 38 manufacturing facilities, 12 process types, 11 subtask types.	33% delay reduction, 22% cost reduction, 85% facility utilization.	Complex implementation, reliant on high-quality data
Mokhtari, (2015)	Optimizing order scheduling on	PPC	Optimization: An Iterated Local Search enhances	Print orders with due dates,	Reduced penalty costs by 15-20%,	Requires large datasets

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS |Volume VIII Issue VI June 2024

	parallel machines with capacity limits and penalties.		the Intelligent Water Drops algorithm.	processing times, and penalties.	managed 20 orders across 3 processors.	and maintaining algorithm robustness
Qing Duan et al., (2015)	Optimizing order admission in a volatile digital print factory environment.	PPC	Machine Learning: Support Vector Machine, Decision Tree, Bayesian Probabilistic Model.	Real-life order data, factory status, historical records.	Up to 99.9% True Positive rate, 14.5% False Positive rate.	Uncertainty with new orders, needs large datasets for accuracy.
Q. Duan et al., (2015)	Real-time scheduling for mass customization and high order variability.	PPC	Optimization: Incremental genetic algorithm	Real-life order data: types, sizes, arrival times, task types, resource attributes.	On-time delivery improved from 85% to 95%, scalable for up to 400 orders.	Complex scheduling, dependent on accurate real-time data.
Lunardi et al., (2021)	Scheduling printing tasks with setup times, interruptions, and downtimes in online printing.	PPC	Planning and Scheduling: Genetic Algorithm, Differential Evolution, Iterated Local Search, Tabu Search	Real-life medium and large orders from online printing shop	30% reduction in delay for large orders, near 0% error rate.	Fixed tasks and setup times affect planning accuracy, especially in small problems.
Iori et al., (2021)	Optimizing scheduling of flexographic print jobs. Reducing delays and setup costs in the printing process	PPC	Optimization: Constructive Greedy Heuristic Algorithm	Real-world production data involving 61 to 106 jobs and 10 to 11 machines	33% reduction in delays 12% reduction in setup time 19% reduction in total costs	Managing computational complexity Ensuring scalability for larger, complex scheduling problems
Zhao et al., (2022)	Production scheduling to boost efficiency and minimize waste	PPC	Optimization: Genetic Algorithm	Production data: job routes, processing times, equipment adjustments, failure rates.	Reduced production time by 18.9% (49.6 to 37.8 hours).	Limited by chaotic systems, human decisions, and poor communication.

Mostajabdaveh et al., (2022)	Optimizing production scheduling and cutting stock by allocating print jobs	PPC	Optimization: Genetic Algorithm	Print order: size, paper type, print sides, quantity, and delivery dates.	20% reduction in paper waste, 50% faster pattern planning.	Computational complexity is limited to small job sizes.
Zhang et al., (2014)	Traditional cropping often misses key details, reducing photo impact.	QM	Machine Learning+Computer Vision: Bayesian network	6,000 high-aesthetic and 6,000 low-aesthetic photos.	90.13% accuracy in predicting gaze and enhancing aesthetics	Slow processing for complex images, crop quality reliant on training data.
Li et al., (2019)	Enhancing image quality with automated cropping, avoiding bounding box methods.	QM	Machine Learning: Fast Aesthetics-Aware Adversarial Reinforcement Learning	Professional photography (Flickr) and public image aesthetic datasets	82% IoU score, 70% faster cropping.	Cropping quality depends on input data diversity and quality.
Pang et al., (2019)	Automating textile pattern generation to reduce labor and enhance creativity	QM	Deep Learning: Reinforcement Learning and Convolutional Neural Networks	Internet images, 30,000 human-designed patterns.	2%-5% daily purchase rate of generated patterns	Needs large databases, color/style consistency issues
Lundström & Verikas, (2010)	Assessing halftone dot distortion in offset printing.	QM	Machine Learning: Fuzzy Hough Transform and k-means clustering utilize prior knowledge from Computer-To-Plate data	Real grey bar halftones from offset prints	High detection accuracy 1.0 (low noise), robust under varying noise levels 0.2-pixel radius difference.	High computational load, reduced accuracy in noisy conditions
Zhu et al., (2013)	Inaccurate and disruptive sheet counting	QM	Computer Vision: Improved Canny edge algorithm and modified Hough transform algorithm	Real images from a factory production line.	Less than 1% error rate in real-time sheet counting	Complexity of integration into high-speed production environments
Kuo, (2014)	Reducing banding and streaks in	QM	Optimization: Active digital press optimization with	Calibration and verification	Streak severity reduced from 85.6 to 65.1 at	Streak correction accuracy

	electrophotographic digital press.		noise-cancellation and deterministic optimization.	targets from digital presses	80% coverage.	depends on precise image registration.
23. Nguyen & Allebach, 2015)	Reducing print quality issues and false alarms in page uniformity.	QM	Machine Learning: Support Vector Machine	Test pages in Red, Magenta, and Cyan (acceptable and unacceptable quality)	0% false alarm rate, 25% miss rate	High computational cost, complex SVM optimization, large datasets needed.
Villalba-Diez et al., (2019)	Inefficiency in manual quality control for gravure printing cylinders.	QM	Deep Learning+Computer Vision: Deep Neural Network	26,670 labeled images of defect-free and defective gravure cylinders	98.4% defect detection accuracy, 210% productivity increase.	Variability in lighting conditions, integration with existing systems.
Valente et al., (2020)	Slow, error-prone manual defect detection; traditional methods lack accuracy.	QM	Deep Learning: Deep Convolutional Neural Network	30 real defect images, 2,949 simulated defect images.	49% detection accuracy for banding and streaks	Limited real-world datasets, high costs, and focus on specific defects.
Limchesing et al., (2020)	High spoilage in offset printing on Solid Bleached Boards (SBB), reducing profitability	QM	Deep Learning: Artificial Neural Network	80 job runs, including ink quality, machine grade, and design complexity	High spoilage prediction accuracy with error rates as low as 0.01%	Limited data quality and quantity and operator error.
Ataeefard & Tilebon, (2022)	Maximizing color gamut in electrophotographic printing	QM	Deep Learning: Artificial Neural Networks and Genetic Algorithms.	11 types of laser jet printing papers with varying properties.	Predicted maximum color gamut of 290,394.9976 with high accuracy.	Dependence on input data quality and complexity of paper properties.
Wang et al., (2022)	Inefficient manual detection; vision	QM	Machine Learning+ Computer vision: Fuzzy C-Means	Overprint identifier images from the printing process	103ms detection accuracy, meeting industry standards	Higher demands with complex prints.

	methods struggle with overlapping CMYK colors					
Govindarajalu & Kumar, (2011)	Excess scrap and inventory in printing and packaging, raising costs	SCM	Planning and Scheduling: Genetic Algorithm	Historical demand and scrap data (Feb 2010 - July 2010)	$575/month inventory cost reduction, $1,800/month scrap savings.	Complex, resource-intensive, data-dependent, scalability issues.
Kurniawan et al., (2021)	Optimizing production and preventing out-of-stock issues by forecasting stock needs	SCM	Deep Learning: Long Short-Term Memory Neural Networks	269 weekly records (Jan 2015 - Feb 2020) covering seven types of paper	21.48% average prediction error.	Prediction accuracy depends on input data quality.

Printing Industrial Domain: Quality Management (QM), Maintenance Management (MM), Production Planning and Control (PPC), Supply Chain Management (SCM)

Production Planning and Control

Production planning and control (PPC) encompasses all activities necessary to manage and enhance manufacturing processes. PPC is a major area with 12 out of 30 relevant studies focusing on AI-driven solutions to optimize various aspects of the print production workflow, particularly in production planning and scheduling.

The predominant AI subfields in PPC are Optimization, Machine Learning (ML), and Robotics. Optimization algorithms are most frequently utilized, addressing complex challenges in scheduling, resource allocation, and production efficiency. Machine Learning enhances decision-making and predictive capabilities, particularly in dynamic production environments. Robotics is applied to tasks like large-format printing, where traditional methods fall short. A significant portion of the studies (e.g., Huang et al., 2010; Agrawal et al., 2011; Rai & Ettam, 2013) focused on optimization algorithms such as Genetic Algorithms (GA), Hybrid Genetic Algorithms, and Simulated Annealing. These algorithms effectively reduce production times, costs, and waste, though they often struggle with computational complexity and scalability in more intricate or large-scale jobs. Machine Learning models, such as those employed by Qing Duan et al. (2015a) and Q. Duan et al. (2015), improved order admission planning and real-time scheduling, enhancing prediction accuracy and reliability. However, their effectiveness is heavily dependent on large, high-quality datasets. Robotics, as illustrated by Gazeau et al. (2011), was applied to large-format printing on non-planar surfaces, using control algorithms for parallel mechanisms to achieve high-resolution results. The technique, however, is limited by the complexity of the control algorithms and the need for precise real-time adjustments.

Quality management

In the printing industry, Quality Management (QM) focuses on enhancing print quality through systematic monitoring, detection, and optimization, particularly during the printing and prepress stages. Of the 30 reviewed articles, 12 focused on AI applications in this domain, with 12 addressing the printing workflow and 3 focusing on prepress processes. AI technologies such as Machine Learning (ML), Deep Learning (DL), and Computer Vision (CV) are pivotal in addressing key challenges like defect detection, print quality optimization, and process efficiency. For instance, Lundström & Verikas (2010) used Fuzzy Hough Transform and k-means clustering to detect halftone dot distortions in offset printing, achieving high accuracy despite significant computational demands. Similarly, Villalba-Diez et al. (2019) and Valente et al. (2020a) applied neural networks to detect defects in gravure cylinders with up to 98.4% accuracy, though these methods were limited by computational costs and data availability. Optimization approach, such as those by C. Kuo (2014), focused on reducing banding and streaks in electrophotographic presses, with results heavily dependent on precise conditions like image registration.

In the prepress workflow, AI enhances aesthetic quality, automates cropping, and generates design patterns, thereby reducing manual labor and increasing efficiency. Zhang et al. (2014) tackled the limitations of traditional cropping methods by using a Bayesian network to predict human gaze and enhance photo aesthetics, achieving a 90.13% accuracy rate, although processing speed remained an issue with complex images. Li et al. (2019) improved automated cropping using the Fast A3RL algorithm, achieving faster processing times and an 82% of cropping accuracy score, though the results were dependent on the diversity and quality of input data. Pang et al. (2019) automated textile pattern generation using reinforcement learning and convolutional neural networks, showing commercial potential with a 2%-5% daily purchase rate of generated patterns, despite challenges like maintaining consistency in color and style.

Maintenance management

Maintenance management (MM) aims to ensure that assets and machines operate at peak efficiency, minimizing production downtime and preventing financial losses. To achieve this, maintenance management involves the strategic assessment and planning of maintenance operations through administrative, financial, and technical approaches. Out of the 30 articles examined, only four specifically discussed the use of AI in this context, suggesting that while AI's potential in maintenance management is recognized, it still needs to be explored and may represent an emerging area of interest that warrants further research and development.

Four articles specifically focused on MM within the printing industry, highlighting the integration of AI techniques at various stages of the print production workflow, including finishing, production planning, and printing. These studies primarily utilized Deep Learning and Machine Learning to address challenges in maintenance management. Commonly used algorithms included Probabilistic Neural Networks (PNN), General Regression Neural Networks (GRNN), Linear Regression, Gated Recurrent Unit (GRU) neural networks, and Artificial Neural Networks (ANNs).

The studies employed diverse datasets, ranging from time series data on machine operations to physical measurements like signature thickness and production conditions, which were essential for training AI models to predict maintenance needs and optimize processes. All studies reported significant improvements in prediction accuracy and operational efficiency. For instance, Kazmirovych & Jagiello (2019) achieved an 8.4% error rate in adjusting parameters, while Hu & Yang (2021) reported 98.6% accuracy in fault detection. These results demonstrate AI's potential to enhance maintenance management in the printing industry.

Supply Chain management

Supply Chain Management (SCM) involves planning, controlling, and executing all logistic flows, from raw material acquisition to the delivery of end products, with a focus on efficiency and cost-effectiveness. Despite its importance, the use of AI in SCM within the commercial printing industry—particularly in print production planning and scheduling—remains underexplored. Out of the 30 articles examined, only two specifically discussed the use of AI in this context, suggesting that this is a new and developing area of study.

Govindarajalu and Kumar (2011) addressed the problem of excessive scrap and inventory in the printing and packaging industry, which resulted in increased supply chain expenses. By employing a Genetic Algorithm on historical data spanning from February to July 2010, they managed to decrease inventory expenses by $575 per month and achieve monthly savings of $1,800 by recognizing elevated scrap levels. Nevertheless, the method was intricate, requiring significant resources, and constrained by data reliance and scalability challenges. The limited applicability of the data utilized raises issues over the extent to which the conclusions may be generalized, emphasizing the necessity for more scalable alternatives. Kurniawan et al. (2021) concentrated on mitigating instances of stock depletion by predicting the future requirements for print output. The researchers utilized Long Short-Term Memory (LSTM) neural networks to examine 269 weekly data points spanning from January 2015 to February 2020. These data points encompassed the usage patterns of seven distinct paper kinds. The model demonstrated a dependable predictive ability, with an average error rate of 21.48%.

RQ2-AI application benefits in Printing

Direct Benefits

AI applications in the printing industry has yielded significant direct benefits, including cost savings, increased efficiency, error reduction, and improved accuracy in various processes. These benefits, which align with the immediate and tangible improvements described by Iacovou et al., (1995) have been demonstrated through multiple studies. AI-driven optimization of resources has led to substantial cost savings, such as an 18.9% reduction in production time through enhanced scheduling (Zhao et al., 2022) and monthly savings of up to $1,800 in inventory management (Govindarajalu & Kumar, 2011). Moreover, AI has improved operational efficiency by reducing delays by 33% and setup times by 12% through advanced scheduling algorithms (Iori et al., 2021), and it has expedited decision-making processes in complex scenarios (Agrawal et al., 2011). The integration of AI in quality control has significantly reduced production errors, with deep learning models achieving a 98.4% accuracy in defect detection in gravure printing (Villalba-Diez et al., 2019) and other quality management tasks showing similar improvements (Zhu et al., 2013). Additionally, AI has enhanced the accuracy of predictions and adjustments, such as achieving a 98.6% fault prediction accuracy for printing equipment (Hu & Yang, 2021) and optimizing color gamut in electrophotographic printing (Ataeefard & Tilebon, 2022). These advancements highlight the transformative impact of AI on the internal functions of printing organizations, leading to more efficient, accurate, and cost-effective operations.

Indirect Benefits

The indirect benefits of AI applications in the printing industry are substantial long-term advantages that enhance customer relationships, improve strategic positioning, and increase organizational flexibility. Enhanced customer relationships are achieved through AI-driven improvements in print quality and consistency, which reduce defects and, consequently, customer complaints, leading to greater product reliability and stronger customer trust (Zhu et al., 2013). Regarding strategic positioning, AI has enabled innovation in design and production processes, allowing companies to distinguish themselves in the market. For example, AI-driven textile pattern generation has reduced the need for labor, freeing designers to focus on creativity and thereby positioning their products more competitively (Pang et al., 2019). Additionally, AI has enhanced organizational flexibility by enabling better management of complex and variable production environments. This is exemplified by the use of AI in adjusting sheet delivery devices in gathering machines, which allows companies to adapt more effectively to fluctuating production parameters, ensuring continued operational efficiency in a dynamic market (Kazmirovych & Jagiello, 2019). These indirect benefits underscore the strategic value of AI in building resilient and competitive printing organizations.

RQ2- AI application challenges in the printing industry

Despite the significant benefits of AI in the printing industry, as highlighted, the technology faces challenges that hinder its broader adoption. We categorised this study under the Technological-Organizational-Environmental (TOE) framework by Tornatzky & Fleischer, (1990). The challenges identified include scalability, data dependency, algorithmic complexity, integration with existing systems, high implementation costs, and the need for skilled personnel. From technological dimension, AI adoption is hampered by the dependency on high-quality data, the difficulties of scaling AI models to real-world production environments, and the complexity of AI algorithms, which often require specific configurations and continuous optimization. Integration with existing production systems, such as Enterprise Resource Planning systems, presents additional difficulties, particularly in ensuring data consistency and real-time processing (Li et al., 2019; Lunardi et al., 2021; Zhang et al., 2014; Huang et al., 2010).

Organizational challenges include the need for more expertise to effectively implement AI technologies, resistance to change from employees concerned about job displacement or the disruption of established workflows, and the significant costs associated with AI adoption. These costs, particularly for hardware, software, and ongoing technical support, can be prohibitive, especially for organizations in less developed countries (Mokhtari, 2015; Mostajabdaveh et al., 2022a; Kinkel et al., 2022).

Environmental challenges involve navigating complex regulatory environments, particularly in sectors with strict compliance requirements like pharmaceutical packaging, and managing the environmental impact of AI technologies, especially their energy consumption. Furthermore, the rapid pace of technological change creates uncertainty and pressure on organizations to invest in new systems to remain competitive continuously, a burden that is particularly heavy on smaller companies (Villalba-Diez et al., 2019; Kazmirovych & Jagiello, 2019; Govindarajalu & Kumar, 2011). These combined challenges slow the uptake of AI in the printing industry and require strategic approaches to address them effectively.

Conceptual framework for AI application in printing industry

Based on the findings of this study, a conceptual framework for AI application in the printing industry has been developed. As illustrated in Figure 2, this framework identifies the key industrial domains where AI is identified as a critical enabler (e.g., PPC, QM, MM, and SCM). These domains are important in motivating the application of AI technologies, driving significant improvements in areas (e.g., production efficiency, print quality optimization, predictive maintenance, and cost-effectiveness in supply chain operations).

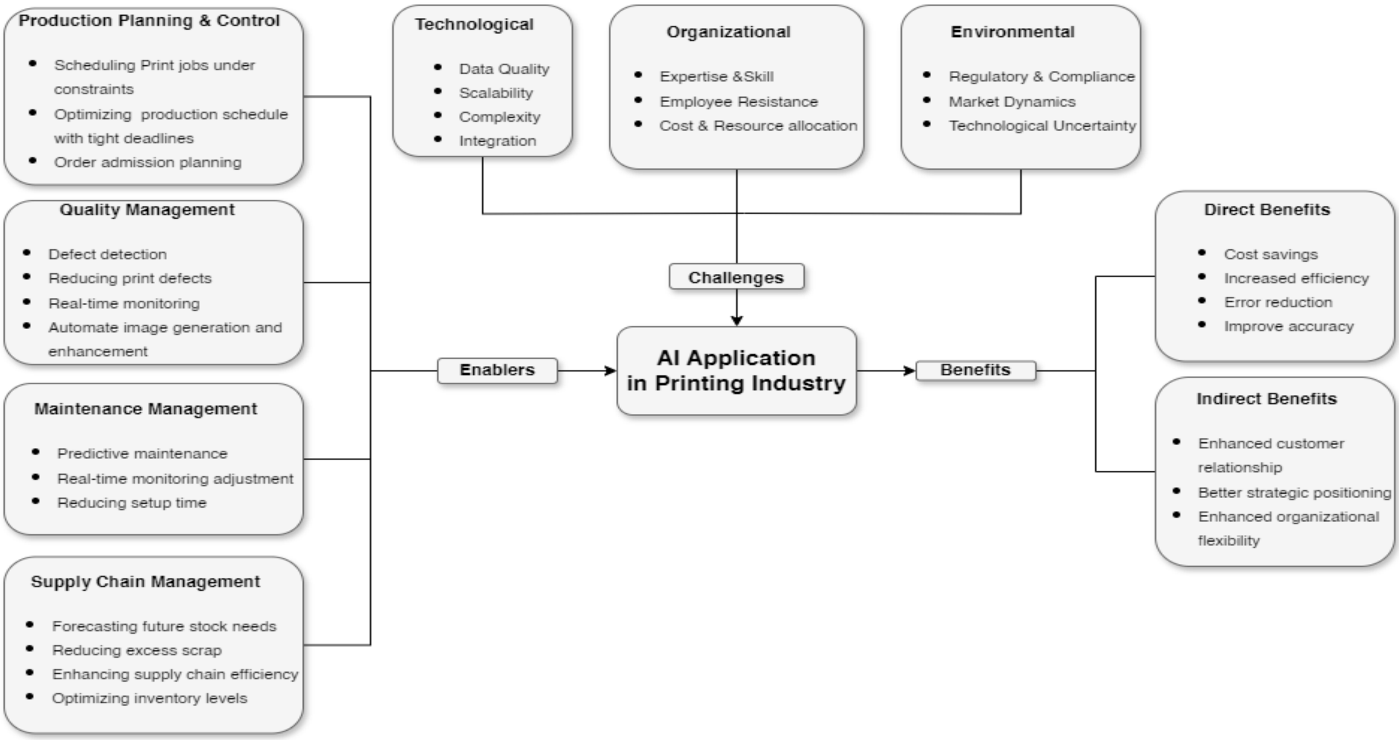

Figure 2 A conceptual framework for AI applications in the printing industry

The framework also highlighted the challenges categorized under the TOE dimensions, highlighting the significant barriers to the widespread adoption of AI. These challenges (e.g., Data quality, expertise and skill and market dynamics) must be addressed to fully harness AI's potential in printing industry. The framework presents the outcomes of AI application, distinguishing between direct benefits (e.g., increased operational efficiency and cost savings). On the other hand, the indirect benefits, (e.g., such as enhanced customer relationships and strategic positioning).

DISCUSSION

This systematic literature review aimed to explore the key industrial domains where AI is applied in the printing industry and to analyze the benefits and challenges of these applications. By reviewing 30 empirical studies, we identified that AI technologies are predominantly used in Production Planning and Control (PPC), Quality

Management (QM), Maintenance Management (MM) and Supply Chain Management (SCM). We observed improvements in efficiency, cost savings, and quality control. The research questions were addressed through thematic analysis, and a conceptual framework was developed to map AI applications and highlight the adoption challenges.

The results indicate that AI has the potential to transform the printing industry by optimizing processes, reducing errors, and enhancing decision-making. However, the findings also reveal that these benefits are contingent on overcoming several challenges, including the need for high-quality data, the complexity of AI algorithms, and the substantial implementation costs. Multiple interpretations of these results are possible, but a clear trend emerges: AI can drive significant improvements if the technological, organizational, and environmental barriers are effectively managed.

This study contributes to the existing body of research by filling a critical gap in the literature regarding the specific applications of AI in the printing sector. While previous research has focused broadly on digital transformation or on the challenges faced by smaller enterprises, our study provides a focused analysis of AI's role in key operational areas. By integrating findings from diverse sources, this research offers a comprehensive view that enhances our understanding of AI's potential in this industry and adds depth to the ongoing discourse on digital transformation (Cioffi et al., 2020; Politis, 2019).

LIMITATIONS, FUTURE DIRECTIONS AND CONCLUSION

This systematic literature review clarifies on the applications of AI in the printing industry, yet it faces several limitations. One significant limitation is the potential for selection bias due to the reliance on studies from specific databases, which may result in a narrow representation of AI advancements. This limitation may have excluded important developments, particularly those documented in less accessible or non-English sources. Future reviews should aim to address this by including a broader spectrum of literature, such as gray literature and studies from diverse databases, as well as non-English publications, to ensure a more balanced and comprehensive overview (Paez, 2017).

The review is also bounded by its focus on literature published between 2010 and 2022, which may not fully capture the rapid and ongoing advancements in AI technologies. AI has evolved significantly post-2022, with breakthroughs in techniques, hardware, and applications that could reshape its use in the printing industry. To address this limitation, periodic updates to the review are crucial to reflect the latest innovations and trends in AI and its evolving role in the industry.

Additionally, the emphasis on large-scale applications of AI in areas such as quality management, maintenance, and production planning may limit the applicability of the findings to small and medium-sized enterprises (SMEs), which often lack the resources and technical expertise to implement advanced AI solutions (Szedlak et al., 2020). Given that SMEs represent a significant portion of the printing industry, future research should focus on understanding the unique challenges and opportunities for AI adoption within these businesses. This could involve exploring more accessible AI solutions, such as cloud-based AI tools or AI-as-a-Service models, which offer SMEs cost-effective and scalable options for implementation (Schönberger, 2023).

Another limitation of this review is its correlational nature, which restricts the ability to establish definitive causal relationships between AI adoption and specific outcomes. While this review identifies key patterns and potential impacts of AI implementation, it does not determine cause-and-effect dynamics. Future studies should employ longitudinal or experimental research designs to provide more robust evidence of the causal mechanisms of AI adoption, thereby delivering more actionable insights for industry practitioners.

Finally, while this review provides valuable global insights into AI's role in the printing industry, it underscores the need for more region-specific studies. Different regions face distinct challenges and opportunities in AI adoption due to variations in cultural, economic, and technological factors. Future research should focus on exploring these regional differences to offer tailored strategies that align with the specific needs and contexts of businesses across different geographies.

In conclusion, this review highlights the transformative potential of AI to enhance efficiency, quality, and cost-effectiveness in the printing industry. However, the path to successful AI adoption is accompanied with challenges that require a strategic approach, considering both technological and organizational factors. By addressing the limitations identified, the industry can continue to evolve and adapt to the rapidly changing technological landscape. Ensuring that the benefits of AI are realized across all sectors, will be critical for the printing industry to maximize its potential, drive innovation, and maintain competitiveness (Lee et al., 2023).

ACKNOWLEDGEMENTS

The authors would like to thank the reviewers for their helpful and constructive comments and suggestions that greatly contributed to improving the final version of this paper. Special acknowledgement to College of Creative Arts, Universiti Teknologi MARA (UiTM), and individual within the organization for their time and valuable consultations

Conflict of interest statement

The authors agree that this research was conducted without any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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