IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 3, July 2025

Impact Factor: 7.67

Impact of AI and Automation Tools in SMES: A Literature Review

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Abstract: *SMEs play a pivotal role in the economic development and they usually experience difficulties in the implementation of the latest digital technologies because of their financial, technical, and organizational factors. This paper is a rigorous review of automation in SMEs that are motivated by machine learning (ML), deep learning (DL), and Industry 4.0 technology. It investigates into how supervised and unsupervised machine learning approaches may be used for enterprise resource planning, cybersecurity, risk assessment, innovation management, and decision-making. These techniques include K-means clustering, K-Nearest vilifying, Random Forest, Gradient Boosting, Autoencoders, Principal Component Analysis, and Logistic Regression. The study also compares how well deep learning models—such as Convolutional Neural Networks, LeNet, and Long Short-Term Memory Networks—perform in financial forecasting, supply chain optimization, emotion recognition, and global market analysis. Also, no-code platforms, Robotic Process Automation, and project management systems are considered as automation tools. The findings show that efficiency and decision-making gain are high and the key barriers to adoption are determined. The paper highlights that there should be scalable, explainable, and cost-effective AI solutions and capacity building and policy programs*

Keywords*:* Small and Medium Enterprises (SMEs), Artificial Intelligence, Machine Learning, Deep Learning, Automation, Industry 4.0, Digital Transformation, Predictive Analytics, AI Adoption, Big Data

I. INTRODUCTION

The process of digitization is now a vital driver of business and economy transformation in a fast-technology breakthrough and a globalized economy era. Digitalization of sectors and businesses: The use and adoption of digital technology in various fields of business to enhance productivity, competitiveness, and innovation is referred to as digitalization [1]. The Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence (AI) are a few of the technologies that make up this intricate concept [2]. The significance of digitalization, however, lies in the new technologies and the fundamental adaptations it brings to the company's plans, procedures, and models. All the results of a successful digitalization are improved consumer experiences, data-driven decision-making, increased operational efficiency, and access to new markets. Through this, the ability to fully realise the potential of digitization has become an important variable in defining competitiveness and sustainability in the present day fast-moving, interconnected world.

Small and medium-sized businesses [3] (SMEs) are vital to most economies in the world, particularly those in developing and emerging nations, and they contribute significantly to economic growth. SMEs are unlike big corporations when it comes to the level of flexibility to change in technical decisions, increased promotion of income distribution, and adaptable response to market changes and emerging customer needs. They also make decisions more quickly because to their organizational structure. But in order to engage in expansion opportunities and fulfil this potential, SMEs need a consistent flow of long-term funding. The European Commission developed a set of regulations and a contemporary, cohesive strategy for SMEs in order to promote entrepreneurship in Europe and create the circumstances necessary for the implementation of creative ideas. SMEs are regarded as an economy's cornerstone [4] because they are essential in lowering poverty, generating employment, fostering global trade, and developing novel approaches. They also greatly play a part in developing the underdeveloped countries.

In recent years, artificial intelligence (AI) [5] has proven to be a significant contributor to the revolution of various corporate processes in many industries. SMEs frequently lack technological know-how, have fewer financial and human resources than larger companies, are reluctant to change inside their organizations, and worry about data integration, security, and privacy. As a result, the strategic use of AI offers a significant potential as well as a significant challenge that might affect how SMEs adopt and utilize AI in new ways [6]. These limitations characteristically affect the implementation of AI by them. The AI technologies can increase the competitive advantage, customer relations, product development, and efficiency of the SMEs significantly. Small and medium-sized businesses frequently concentrate on solutions that pay off more quickly and require less effort to deploy, unlike larger businesses, which have the opportunity to invest in long-term, comprehensive AI programs. Small and medium-sized businesses (SMEs) need a methodical production time estimate in order to realize their full potential and maintain their market share. In the manufacturing processes, it renders effective people management, optimization of resources, and planning possible. Machine learning (ML) and data mining (DM) are highly used during the production scheduling and planning [7]. Their use in production time estimates improves scheduling and planning precision, which raises total productivity. Small and medium-sized firms (SMEs) are less likely to deploy DM and ML due to their lack of data. Rather, manufacturing time prediction is still done with imprecise and non-reproducible rough approximations.

A. Organization of the Study

The structure of the paper is as follows: Section II is a review of ML-based SME automation. Section III considers the use of DL in advanced analytics and decision-making. Section IV talks about Industry 4.0 automation tools embraced by the SMEs. Section V conducts a literature review of the current AI adoption among SMEs. Section VI is a conclusion of the study and the future research directions.

II. MACHINE LEARNING IN AUTOMATION OF SMALL AND MEDIUM ENTERPRISES (SMES)

AI has the potential to greatly boost company innovation and productivity, particularly for small and medium-sized enterprises (SMEs). Despite recent advancements in AI tools, SMEs continue to adopt AI at a relatively low rate when compared to bigger enterprises and other digital technologies. ML and AI are becoming essential due to the growth of data protection and management in the SMEs sector. SMEs in these developed countries have developed their own AI and ML-focused cyber regimes [8]. ML, a branch of artificial intelligence, enables computers to learn from data and form opinions or predictions without the need for explicit programming. According to Xia et al.'s study [9], SMEs are utilizing ML to enhance operations and support data-driven decision-making.

A. Supervised Machine Learning

Supervised learning is a kind of ML in which an algorithm uses labelled training data to learn and generate a model (function). In order for the system to effectively provide the right output to novel and unforeseen inputs, it must be able to generalize from these instances. Credit scoring and financial risk prediction are done using supervised learning methods like RF and SVM. The various supervised learning techniques are mentioned below:

Logistic Regression

A statistical approach to categorization is called logistic regression. The probability of a discrete result is modelled by this method. The primary distinction between logistic regression and linear regression is that the former represents the likelihood of the outcome using a logit (log-odds) transformation that is not linear, while the latter uses a linear combination of input characteristics. Among classification techniques, logistic regression is said to be relatively interpretable since each coefficient's sign reveals whether a predictor has a positive or negative impact on the log-odds of the result. However, because of the non-linear (logistic) transformation, it is not immediately clear how the estimated likelihood would be impacted by a unit change in an input. To put it another way, while coefficient values may be related to odds ratios, more computation is needed to convert those into absolute probability changes. Gondar, Reddy

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ISSN: 2581-9429
Volume 5, Issue 3, July 2025
Impact Factor: 7.67

and Khan [10] uses a widely used data mining method, a branch of AI, to examine the elements affecting the deployment of ERP systems in Fijian SMEs. The main factors influencing the adoption of ERP systems are determined using a logistic regression classifier. The report includes a thorough examination of several organizational, behavioural, technological, and demographic elements that offer insightful information on ERP adoption trends.

K-Nearest Neighbors

An instance-based, non-parametric ML methodology is the K-Nearest Neighbours method. Instead of creating an explicit model using the training data, K-NN makes predictions directly from the stored training examples. The technique finds the k closest data points (neighbours) in the feature space for a given instance using a distance metric, such as Euclidean distance. Among these neighbours, the class that the instance is expected to belong to is the majority class. A large number of k might lead to underfitting by over smoothing class borders, whereas a little value of k might produce overfitting because the training data's noise makes the model more susceptible. Muthu and Ace, [11] The simplicity of the K Nearest Neighbour (KNN) approach makes it one of the most popular ML algorithms. The KNN algorithm's execution speed, however, significantly drops as the dataset size increases. This study used five distinct datasets of 520, 5110, 78,096, 500,000, and 2,916,697 samples to evaluate the two parallel KNN algorithms' (GPU-based TUKNN and GPU-SME-KNN) performance in comparison to the sequential KNN approach.

Random Forest

The Random Forest classifier is an ensemble learning approach that generates a large number of decision trees and aggregates their output. Each tree in the forest is trained on a random subset of the data selected using bootstrap sampling (sampling with replacement), and each split inside a tree considers a random subset of attributes to determine the best split. This combination of data and feature randomization enhances the model's ability to generalize while also decreasing overfitting. A majority vote determines the final forecast for categorization tasks. Random Forests are resilient to noise, work well with high-dimensional datasets, and often preserve some interpretability using feature significance metrics. Liang and Zhang [12] proposes an innovation path prediction and decision model based on DT and RF algorithm for the evolution process of dual innovation in SMEs. First, the DT algorithm is used to analyze the key decision points of enterprises in the dual innovation process, revealing the key factors affecting innovation decisions and their interrelationships. Then, combined with multi-dimensional enterprise data, a multi-level and complex prediction model is constructed using the random forest algorithm to simulate the innovation evolution path of enterprises in different situations. Through simulation analysis of actual data of multiple SMEs, the model successfully predicts the choice tendency of enterprises in the dual innovation path. Karimova [13] Research looks into how a Delphi model's accuracy and precision may be increased by using a machine-learning random forest model. Since information regarding local SMEs is not publicly available, it was not possible to independently verify the facts. The research's topic is Azerbaijani SMEs, and the data was collected from the businesses by a banking institution. The study compared the two models using accuracy, precision, recall, and F-1 scores before executing the algorithms in Python.

Gradient Boosting

The additive models known as gradient boosting classifiers, to generate a forecast for a particular input, the outputs of several weak learners—in this example, decision trees—are merged. The Gradient Boosting [14] Each subsequent tree in the greedy iterative construction of the inaccuracies (residuals) caused by the earlier trees are corrected by the model during training. To minimize the loss, the model starts with a fixed value, which is the average of the objective values. The model fits a decision tree to the residuals, or the variations between the observed and expected values, at each iteration. The model is updated with the new tree's contribution once the tree is modified to minimize the loss function. For a certain number of trees (weak learners), this procedure is repeated, with each tree enhancing the model by fixing the mistakes of the ones before it. Gogas et al. [15] suggested that the Gradient Boosting technique obtains the maximum ROC AUC score and balanced accuracy. Economically, using a pertinent cost function improves these outcomes.

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B. Unsupervised Machine Learning:

In supervised learning, a data scientist provides the system with labelled data, such photos of cats that have been marked as such, so that it may learn by example. In unsupervised learning, a data scientist just provides photographs, and the system is responsible for analyzing the data and identifying whether or not the images are of cats. Unsupervised machine learning requires a lot of data.

K-Means Clustering

The practice of classifying items into groups is known as clustering or cluster analysis. Clustering [16] may be divided into several forms, including partitioning, hierarchical, overlapping, and probabilistic. Data is partitioned so that each piece of information may only belong to one cluster. Another name for it is exclusive pooling. K-means is a prime example of partitioning. In hierarchical clustering, every data point is a cluster. The number of clusters is reduced via iterative connections between the two closest clusters. It is used to organize data in overlapping fuzzy sets. Jason Subianto, Kurnianingrum and Alma Tiara [17] discusses grouping username data for Lou's Fashion Brand buyers from e-commerce using the K-means algorithm. The data source for their research was collected from the sales results of Lou's products from September 1, 2024, to March 10, 2024. The variables used were Username (Buyer), Shipping Cost Paid by Buyer, and Total Income. The data processed using the RapidMiner application with the K-means operator, which divide the data into three clusters to show which cluster has the highest total. Terttiaavini [18] suggested a hybrid strategy to assess and rank Palembang City's SME development that combines the K-Means Clustering technique with Simple Additive Weighting (SAW). SAW offers preference values ($VVii$), whereas the K-Means Clustering approach groups SMEs according to their attributes. The Palembang City Cooperative and SME Agency provided the SME statistics, which included 362 SME units. This study demonstrates the efficacy of this hybrid strategy in classifying SMEs according to their attributes and ranking them according to data-driven assessment.

Autoencoders

Autoencoders are an unsupervised learning approach that uses neural networks to do representation learning. This compression and subsequent reconstruction would be complicated if the input properties were unrelated. By passing the input through the network bottleneck, any structure present in the data—such as correlations between input attributes—may be discovered and put to use. Neloy and Turgeon [19] proposed that Auto-encoders (AEs) are a potent method that blends deep architecture with probabilistic variational modeming and generative modeming. In order to provide relevant sample data, Auto-Encoder seeks to understand the underlying data distribution. Numerous studies and modifications to Auto-Encoder design, especially in unsupervised representation learning, have given rise to this idea of data creation and the use of generative modeming. Ubaidillah et al., [20] proposed an AI-based intermediary solution that keeps an eye on any possible threats to SMEs, particularly in Malaysia. The suggested technique effectively detects potential cyberthreats by using an Autoencoder based Deep Neural Network (AEDNN) trained with the NSL-KDD dataset. AEDNN was presented in this research to identify automated cybersecurity risks; it is not meant to take the place of any current security solutions. The suggested AEDNN is made to reliably and precisely identify any potential cyberthreats in the real-time network.

Principal Component Analysis (PCA)

PCA is a dimensionality reduction approach that keeps the majority of the data information while decreasing the number of variables in the "large set" to a smaller group. It is inevitable to lose precision while reducing the number of variables in a dataset; nonetheless, the solution to reducing dimensionality is to trade some accuracy for simplicity. Because there are fewer variables to examine, smaller datasets are simpler to investigate and illustrate, data analysis is easier and faster for machine learning algorithms. Ongbali *et al.*, [21] suggested the factors were used to build a structured questionnaire, which was then given to the SME sector respondents. compiled the scores of the respondents and turned them into main data. Kendall's Coefficient of Concordance (W) and Principal Component Analytics (PCA) tools were used to analyze the data, and the findings were displayed. According to the findings of the Kendall's Coefficient of Concordance study, the judges firmly believe that the 36 factors have an impact on the growth of SMEs

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ISSN: 2581-9429 Volume 5, Issue 3, July 2025 Impact Factor: 7.67

(W) = 0.52. The PCA analysis determined the key factors influencing the expansion of SMEs Table I shows the related studies of the existing ML techniques used in SMEs Automation.

Table 1: Review of the Literature Studies of Machine Learning Techniques in Automation in SMEs

Ref.	Author(s)	Method / Algorithm	Context / Dataset	Key Findings
[15]	Gogas et al.	Gradient Boosting	SME-related dataset (not specified)	Gradient Boosting achieved balanced accuracy and the highest ROC-AUC score; performance further improved using an economically relevant cost function.
[10]	Goundar, Reddy & Khan	Logistic Regression	SMEs in Fiji	Identified the main organizational, behavioral, technological, and demographic elements affecting SMEs' adoption of ERP.
[11]	Mutlu & Aci	K-Nearest Neighbor (KNN), GPU-based Parallel KNN	Five datasets (520 to 2,916,697 samples)	Parallel KNN algorithms (GPU-based TUKNN and GPU-SME-KNN) significantly outperformed sequential KNN as dataset size increased.
[12]	Liang & Zhang	Decision Tree, Random Forest	Multiple SMEs (multi-dimensional enterprise data)	Successfully predicted SMEs' dual innovation path tendencies and identified key innovation decision factors.
[13]	Karimova	Random Forest, Delphi Model	Azerbaijani SMEs (financial institution data)	Comparing Random Forest to the Delphi model revealed a considerable improvement in accuracy, precision, recall, and F1-score.
[17]	Subianto, Kurnianingrum & Tiara	K-Means Clustering	Lou's Fashion Brand e-commerce buyers	Data clustered into three groups using RapidMiner, identifying the cluster with the highest total income.
[18]	Terttiaavini	K-Means + SAW (Hybrid Model)	362 SMEs in Palembang City	Effective grouping and prioritization of SMEs using data-driven preference values.
[19]	Neloy & Turgeon	Auto-Encoders (AEs)	Unsupervised learning context	Demonstrated the effectiveness of auto-encoders for representation learning and generative modeling.
[20]	Ubaidillah et al.	Autoencoder-based Deep Neural Network (AEDNN)	NSL-KDD Dataset (Malaysia SMEs)	AEDNN effectively detected real-time cyber threats for SMEs without replacing existing security systems.
[21]	Ongbali et al.	Kendall's W, PCA	SME sector survey data	Strong agreement (W = 0.52) on variables affecting SME growth; PCA identified critical growth determinants.

III. DEEP LEARNING IN AUTOMATION IN SMALL AND MEDIUM ENTERPRISES (SMES)

In the context of SME internationalization, deep neural networks have exceptional ability in evaluating global market data, assisting SMEs in identifying potential markets to enter. These advanced models are capable of processing intricate variables, including competitive landscapes, cultural aspects, and economic indicators, to produce data-driven market suggestions. By leveraging advanced pattern recognition techniques, DL [22] Algorithms make it possible to identify possible hazards in global markets with greater accuracy, which is essential for SMEs with limited resources to prevent expensive mistakes. DL techniques [23] can improve inventory management, forecast demand, and spot any interruptions in global networks to improve supply chain management for SMEs expanding internationally. Calheiros-Lobo, Au-Yong-Oliveira and Vasconcelos Ferreira, [24] presented DEEPEIA, a cutting-edge deep learning (DL) platform that can identify the optimal export market for any product or service that a small and medium-sized firm (SME) provides, together with the relevant foreign champion. This study tackles the main obstacles SMEs experience while expanding internationally by utilizing recent developments in generative artificial intelligence (AI) and drawing on knowledge of SME internationalization.

A. Convolutional Neural Network (CNN)

CNNs are a powerful type of neural network [25] that are widely used in image recognition tasks. These features are used before one or more fully linked layers produce a prediction, a sequence of convolutional and pooling layers collect pertinent information from the input image. Chen et al., [26] suggested GENIE, a QoS-guided dynamic scheduling framework that guarantees good system utilization and QoS for users in SME clusters. To determine the optimal locations for CNN-based tasks, a QoS-guided scheduling technique is suggested based on a prediction model obtained by lightweight profiling. They experimented with both large-scale simulations and actual SME clusters using GENIE as a Tensorflow plugin. CNNs, or convolutional neural networks, have advanced significantly in the ML services industry. In contrast to online ML services, Universities, research centers, and SMEs often employ offline machine learning services with a range of CNN workloads. Zhikang Zhang [27] proposed that to solve the problems of data distortion, non-obvious features, low feature dimension and weak feature correlation in the loans of small and medium-sized enterprises (SMEs), a convolutional neural network model based on feature transformation (FT-CNN) was proposed for the loan default prediction of SMEs. The low-order dense matrix composed of original eigenvalues were converted into high-order sparse matrix to reduce the influence of data distortion and low feature dimension on prediction. Then, the problem of unclear features and weak feature correlation was solved by the local perception virtue of CNN. Taye [28] One of the main neural network types for classification and image recognition is convolutional neural networks (CNNs). Face identification, computer vision, image processing, and object recognition are just a few of the applications for CNNs. A convolutional neural network uses images as input. Convolutional neural networks automatically learn a hierarchy of features that may be utilized for classification, as opposed to creating features by hand.

B. LENET

Yann L.C. et al. developed LeNet, one of the first CNN architectures, in 1998 to identify handwritten numbers. Two Conv_Lays and two completely linked layers make up the LeNet architecture. The fully connected layers employ a softmax activation to produce a probability distribution over the potential classes, while the Conv_Lays and Pool_Lays utilize tiny filters and Pool_Lays to extract features from the input image. Serbaya proposed utilizing the experiment's data collecting from the Geneva Multimodal Emotion Portraits (GEMEPs) corpus. Human body movements representing the archetypes of five emotions—angry, fearful, joyful, proud, and sad—are included in this data collection. The suggested Kernel Boosting LENET classifier achieved 98.5% accuracy, 94% precision, 95% sensitivity, and an F-Score of 93%, outperforming earlier emotion-detection techniques. Emotional recognition might therefore aid SME in enhancing their performance and entrepreneurial mindset [29].

C. Long Short-Term Memory (LSTM)

In order to overcome the shortcomings of conventional RNNs, Sepp Hochreiter and Jürgen Schmidhuber invented LSTM networks in 1997 [30], particularly the issues with disappearing and ballooning gradients that occur when using backpropagation through time (BPTT). Because of their special design, they can store and use data for long periods of time, which makes them appropriate for time-series prediction and dynamic system modeling. Long-term dependencies are important in anything that needs sequential data and these issues complicate the ability of normal RNNs to learn and retain them. The basic principle of LSTM is that memories are available in the form of memory cells, capable of maintaining their state with time, and some kind of a gate to control the information flow. This construct ensures that the gradients can run more effectively over longer durations of time, and LSTM models do not suffer the gradient challenge. sequences. The two steps of the proposed ODL-FCP method are Muthukumaran, Kavitha; Hariharanath [31] LSTM data categorization using the best deep convolution neural network and the Archimedes optimization algorithm-

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International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 3, July 2025
Impact Factor: 7.67

based feature selection process (AOA-FS). The CNN-LSTM method's hyperparameter optimization employs the sailfish optimization (SFO) algorithm in the ODL-FCP approach Table II shows the related studies of the existing DL techniques used in SMEs Automation

Table 2: Review of the Literature Studies of Deep Learning in Automation in SMEs

Ref.	Author	Focus Area	Methodology / Model	Dataset / Environment	Key Contributions	Key Outcomes
[26]	Chen et al.	QoS-aware scheduling for SME clusters	GENIE: QoS-guided dynamic scheduling using lightweight profiling and CNN workload prediction	Large-scale simulations and actual SME clusters	Suggested a framework for QoS-guided scheduling to maximize CNN task placement	Achieved QoS guarantees with high system utilization
[27]	Zhikang Zhang	SME loan default prediction	FT-CNN (Feature Transformation-based CNN)	SME loan datasets	Converted low-order dense features into high-order sparse matrices to mitigate data distortion and weak feature correlation	Improved prediction accuracy by leveraging CNN's local perception
[28]	Taye	CNN fundamentals and applications	Convolutional Neural Networks (CNNs)	Image-based inputs	Provided an overview of CNN architecture and applications	Demonstrated CNN effectiveness in object recognition, computer vision, and image classification
[29]	Serbaya (2022)	Emotion recognition for SMEs	Kernel Boosting LeNet classifier	GEMEP (Geneva Multimodal Emotion Portrayals) dataset	Applied CNN-based emotion detection to human gestures	Achieved 98.5% accuracy; emotion recognition shown to support SME performance
[31]	Kavitha; Hariharanath	Fault classification/ prediction	ODL-FCP using AOA-FS + CNN-LSTM with SFO hyperparameter tuning	Benchmark and real-world datasets	Combined feature selection, deep learning, and metaheuristic optimization	Improved classification accuracy and robustness

DOI: 10.48175/IJARSCT-28548

IV. AUTOMATION TOOLS IN SMALL AND MEDIUM ENTERPRISES (SMES)

In order to analyze various Industry 4.0 technologies, several European standards were reviewed, such as those put out by the Mechanical Engineering Industry Association (VDMA) and the collection of real-world examples that this association has been producing since 2019. Furthermore, benchmarking was done via online research to get a sneak peek at the best Industry 4.0 performance. Businesses like Volkswagen, Amazon, Siemens, and others have recognized best practices.

Zapier

Zapier is one of the oldest and most well-known automation platforms. It is loved by people who want to connect their apps quickly without touching a single line of code. Zapier's greatest strength is its simplicity [32]. The dashboard is neat, and all is constructed based on time-saving. The other important aspect of Zapier is its reliability.. Even if workflow has multiple steps, the platform keeps everything stable and rarely fails. Small businesses and solo entrepreneurs especially appreciate this because they can trust their automations to run smoothly in the background while they focus on growth. Padwal et al., [33] suggests a new approach to automated plant medicine recognition using highly developed computer techniques. Plant images are pre-processed using Deep Learning, Image Processing, and Natural Language Processing techniques to address typical categorization problems. In this research work, ruthless experimentation is done by evaluating different models and hyperparameter tuning to increase the accuracy of the plants' identification. Goss [34] suggested with Zapier's built-in capabilities and flexibility, users can develop simple to complex automation and link hundreds of business systems to increase productivity by cutting down on time spent on repeated chores. Discover how to fully utilize Zapier with these helpful hints and real-world examples. Organizations can link their online and cloud-based apps and automate data movement between them using Zapier, a new no-code workflow automation tool.

RPA

There isn't a single, widely recognized definition of RPA. A software robot is thought to be a computer program that executes a preset algorithm and is used to carry out commercial operations automatically, typically mimicking human labor. Applications and virtual creations known as "software robots" are designed to help and relieve people in data analysis and software operations [35]. Repetitive, monotonous, and tiresome activities can be completed by a software robot using either full automation (unsupervised mode), human involvement to some extent (participatory mode), or a hybrid mode that combines both. The entire organization is considered to be involved in the deployment of RPA. RPA is a non-traditional automation method that doesn't require database or infrastructure application integration. It can function as a computer operator's helper across programs, non-intrusively, and with the help of the current infrastructure. RPA is applicable to a wide range of business operations across several departments. However, how RPA is used in businesses differs based on organizational structure, business process flow, and internal decision-making. Erdmann and Sandkuhl [36] examined the possible applications of RPA in SMEs by attempting to pinpoint common application situations that might yield significant advantages for SMEs. The application potential is primarily addressed from a qualitative perspective, i.e., the article's contributions include (1) a systematic assessment of the literature on the current level of RPA deployment in SMEs; (2) RPA application scenarios that are evident in the literature and the capabilities of RPA platforms to facilitate these situations, and (3) experiences using commercially available RPA technologies to implement three use cases targeted at SMEs, followed by an expert review. The objective is to qualify the application fields rather than to measure the potential.

Trello

Trello is a project management tool that facilitates communication and collaboration in real time to complete tasks and objectives. Trello is perfect for small-to-medium-sized libraries because of its user-friendly layout and strong integrations, which provide teams the freedom to adapt workflows to suit their particular requirements while benefiting their user communities. Available with a free or paid subscription, this tool enhances teamwork and provides control over simple and complex projects. Syafa and Falah [37] said that project management tools are crucial for optimizing

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ISSN: 2581-9429 Volume 5, Issue 3, July 2025 Impact Factor: 7.67

project management tasks and offering a range of features to help businesses carry out projects effectively. Considering the wide range of possibilities on the market, choosing the right tool is essential. Trello works effectively for comparatively smaller projects because of its ease of use and simplicity. Through the optimization of project execution procedures to satisfy their particular objectives and specifications, this research offers businesses useful insights to match their project management tools with particular project conditions. Table III shows the Automation tools in SMEs showing their functional area, advantages and challenges.

Table 3: Review of the Literature Studies of Automation Tools in SMEs

Author(s) & Ref. No.	Automation Tool	Functional Area	Benefits for SMEs	Implementation Barriers
Padwal et al. [33]	Deep Learning–based Automated Plant Recognition System	Image-based classification and knowledge extraction	Improves accuracy in plant medicine identification; reduces manual dependency; enhances decision-making through intelligent automation	Requires large datasets; high computational cost; need for technical expertise in AI and model tuning
Goss [34]	Zapier	Workflow and process automation	Reduces repetitive manual tasks; integrates thousands of applications; increases productivity using no-code automation	Limited customization for complex workflows; dependency on third-party app integrations; cost at higher usage levels
Sandkuhl [36]	Tools for Automating Robotic Processes (RPA)	Business process automation (back-office operations)	Enhances operational efficiency; reduces human error; suitable for repetitive rule-based tasks in SMEs	Initial setup complexity; lack of RPA skills; resistance to organizational change
Syafa & Falah [37]	Trello	Project and task management	Improves task visibility and collaboration; easy to use; suitable for small-scale projects with limited resources	Limited advanced project management features; scalability issues for large or complex projects

V. LITERATURE REVIEW

An overview of the body of research on AI adoption in SMEs is given in this section, leveraging various techniques, datasets, tools and approaches. Table IV shows the automation techniques, application domain, advantages and challenges.

Vyakarnam et al. (2025) explored how these AI models can be optimally used to address significant problems in supply chain management with an emphasis on demand forecasting and logistics. These findings offer important information on the best AI options that can be used by SMBs that intend to streamline their supply chain operations at the least cost. Through a study of the tools, the research gives SMBs valuable information to improve the efficiency of their operations and competitive power in the market. The profit margins of SMBs or small and medium-sized firms are occasionally small. They might not be financially able to deploy costly Enterprise Resource Planning (ERP) or high-technology artificial intelligence (AI) solutions [38].

Arno (2025) examined two study questions: 1) how SMEs can support BPM with low-code technology; and 2) whether or not they follow the conventional BPM lifecycle. The study identifies low-code solutions to be popular in basic BPM tasks, including processes models and workflow automation, which relied on the triangulating research methodology encompassing a quick assessment of the literature combined with a survey of BPM specialists in SMEs. The more

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sophisticated functions, such as process mining and artificial intelligence are not utilized fully. Additionally, because of organizational limitations, SMEs frequently omit or modify BPM lifecycle phases [39].

Salas and Raman (2025) suggested a new Fuzzy Petri-Net (FPN)-type of risk assessment model. The model is effective to capture the uncertainty of the AI adoption situation in the form of fuzzy logic in quantifying the imprecise risk factors and using Petri Nets to model the interdependencies among the different risk components. The approach is characterized by the definition of risk factors, membership value fuzzy, creation of a Petri Net model, and the dynamic risk propagation analysis. A review of SME auto-component clusters can be viewed as the confirmation of the proposed approach, as it is rather effective to identify the regions of high risks and offer systematic information on decision-making [40].

Rana, Shanmugam and Seziyan (2025) to reduce the gap in knowledge that currently exists among Malaysian SMEs in terms of the potential of adopting AI-based ERP systems. Using the positive results that have been achieved by implementing the AI-based ERP systems and discussing the benefits and issues that accompany its use, this research aims at persuading SME owners to adopt AI-based ERP systems. This kind of implementation can contribute to the performance of SMEs in the business and can immensely help the entire economy of the country [41].

Kandeel et al. (2024) investigated how artificial intelligence (AI) applications might improve and broaden the operations of small and medium-sized businesses (SMEs), which are crucial to the growth of entrepreneurship and economic development. The goal is to ascertain how current advancements in AI have aided in the expansion of SMEs by raising profitability and productivity as well as staff productivity and efficiency. The paper concludes that AI techniques can greatly help SMEs and especially in automating administrative jobs giving the business more time to develop [42].

Shakya et al. (2023) begin with the introduction of technology, the obstacles MSMEs face in implementing MSMEs have been introduced to Industry 4.0 and its concept, along with some solutions. The study of Industry 4.0 is part of it, and robotics is a key technology that provides a variety of capacities in the industrial industry. This technology has enhanced the automation system, and high-quality products are increasingly being produced thanks to robotics. Additional discussion on human-robot partnerships in MSMEs and the growing popularity of robots in MSMEs [43].

Table 4: Review of Existing Literature on AI adoption in SMEs

Author & Year	**Automation Technology**	**Application Area**	**Benefits for SMEs**	**Adoption Barriers**
Vyakarnam et al. (2025)	AI-based analytical models	Supply Chain Management (Demand Planning & Logistics)	Improves demand forecasting and logistics efficiency; enables supply chain optimization with minimal investment; enhances competitiveness	Limited funds; unable to purchase pricey ERP or cutting-edge AI systems
Arno (2025)	Low-code automation tools	Business Process Management (BPM)	Facilitates process modeling and workflow automation; reduces development time; supports operational efficiency	Underutilization of advanced features (AI, process mining); organizational constraints; deviation from standard BPM lifecycle
Salas & Raman (2025)	Fuzzy Petri-Net (FPN)-based AI risk assessment model	AI adoption risk management	Identifies high-risk areas in AI adoption; supports structured and informed decision-making; manages uncertainty effectively	Complexity of model design; requirement of expert knowledge; limited awareness of advanced risk assessment techniques
Rana, Shanmugam & Seziyan	AI-based ERP systems	Enterprise Resource Planning	Enhances business performance; improves decision-making; contributes	Knowledge gap among SME owners; high implementation cost; resistance to adopting AI-

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 3, July 2025
Impact Factor: 7.67

(2025)			to economic growth	driven ERP solutions
Kandeel et al. (2024)	Artificial Intelligence applications	Administrative and operational processes	Increases productivity and profitability; improves employee efficiency; automates administrative tasks	Skills gap; lack of AI expertise; financial and infrastructural constraints
Shakya et al. (2023)	Industry 4.0 technologies (Robotics & Automation)	Manufacturing and production systems	Improves production quality; increases automation efficiency; supports human–robot collaboration	Lack of technical expertise, high initial cost, and opposition to technological change

VI. CONCLUSION AND FUTURE WORK

In recent years, modern SMEs rely significantly on digital transformation, which enables them to use cutting-edge technology to gain a competitive edge. In this paper, the author finds that automation made possible by ML, DL, and Industry 4.0 technologies can have a tremendous potential to revolutionize small and medium enterprises by enhancing productivity, operational efficiency, and competitiveness. The literature reviewed shows that machine learning can be successfully applied, both supervised and unsupervised, and advanced deep learning frameworks can be used to assist in decision-making, forecasting, risk management, cybersecurity, innovation planning, and supply chain optimization in SMEs. Parallel to this, simple automation tools like no-code systems, robotic process automation, and project management systems are available and offer easy avenues to SMEs to start automation with minimal resources. Nevertheless, even with such advantages, mass adoption is limited due to such factors as skills gaps, lack of data preparedness, high implementation costs and organizational reluctance to change. The paper observes that these barriers have a solution in scalable, explainable, and affordable AI solutions, personal training, improved digital infrastructure, and facilitating policy conditions. These concerns will be addressed, and it will enable SMEs to use the potential of automation technologies to their maximum abilities and achieve steady growth in an increasingly digital economy.
The next wave of research should be aimed at creating scalable and cost-effective AI solutions that can be applied to the SME context, paying attention to explainable models and real-time deployment. Applicability and adoption preparedness will be further enhanced with the involvement of empirical validation through industry case studies, sector-driven implementations, and adoption frameworks driven by the policies.

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