A Systematic Literature Review : Adopting Machine Learning (ML) Models to Measure the Financial Inclusion of Gig Workers in Malaysia

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ABSTRACT

The rapid expansion of the gig economy in Malaysia has created new employment opportunities but has also intensified challenges related to financial inclusion, particularly access to credit and formal lending services. This study aims to systematically review the financial barriers faced by gig workers and examine the role of Machine Learning (ML) in enhancing credit risk assessment and financial accessibility for individuals engaged in non-traditional employment. A systematic literature review was conducted following the PRISMA 2020 guidelines. Relevant studies published between 2020 and 2025 were retrieved from major open-access databases, including Google Scholar, ScienceDirect, DOAJ, SpringerOpen, MDPI, and PLOS. The selected studies were analysed using thematic synthesis to identify recurring patterns, machine learning applications, data features, and research gaps related to gig workers' creditworthiness. The findings reveal that gig workers experience significant difficulties in obtaining credit due to irregular income streams, limited employment documentation, and insufficient credit histories. This study contributes to the literature by proposing a conceptual framework that integrates machine learning techniques with risk identification, assessment, evaluation, mitigation, and monitoring processes to support more inclusive credit risk management. The framework offers a foundation for future empirical research and policy development aimed at improving financial inclusion among gig workers in Malaysia.

Keywords: Sistematic Literature Review, Machine Learning Models, Financial Inclusion, Gig Workers.

INTRODUCTION

The gig economy is a transformation of the labour market enabled by digital platforms, defined by short-term employment, flexible schedules, and freelancing. According to (Petkovski et al., 2022) and (Linthorst and De Waal, 2020), as cited in (Mohd Shakil, 2024), the gig economy also refers to a labour market structure in which workers are hired on a temporary or on-demand basis, without long-term employment and benefits. Mohd Shakil (2024) states that, in recent years, the gig economy has had a significant impact on both workers and firms. Consequently, gig work has been widely expanded worldwide, with higher demand in developing countries than in developed ones. The report estimates that the number of online gig workers globally ranges from 154 million to 435 million, accounting for approximately 4.4% - 12.5% of the global labour force, and highlights rapid worldwide expansion (World Bank Report, 2023).

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In Malaysia, based on the report by Department of Statistics Malaysia's Labour Force, which state that, for the third quarter of 2024, the number of own- account workers which a category that includes gig workers that increased from 2.93 million in the first quarter of 2023 to 3.09 million by the third quarter of 2024, indicating a growing participation in gig work as a source of income in Malaysia (Department of Statistics Malaysia, 2024). Furthermore, an empirical research by the Malaysian Institute of Economic Research found that around 45% of Malaysians have engaged in gig work as their main source of income, which is driven by technological advancement and digital platforms (Mohd Shakil, 2024). This research data indicates a clear increase in gig economy participation, suggesting that a significant proportion of Malaysians are turning to gig work as either their primary or an additional source of income to cope with living expenses. Besides, gig employment offers advantages, enabling individuals to diversify their income sources and engage in multiple projects simultaneously, thereby achieving financial stability. It can be concluded that gig work has proven to be a significant opportunity and offers a high chance of contributing to the future development of the digital economy.

Despite the growing presence of gig workers in Malaysia, significant gaps remain in access to formal financial institutions, particularly for credit and loan applications. This situation arises because gig workers often encounter difficulties in obtaining loans due to irregular income patterns, inadequate formal documentation, and limited credit history. Not only that, financial institutions consistently depend on solid income and employment, which places gig workers at a structural disadvantage in credit risk assessment. Therefore, this study aims to address this gap by systematically reviewing the adoption of Machine Learning- based models in measuring financial barriers faced by gig workers, with a specific focus on improving credit accessibility in non- traditional employment settings. resent introduction and background of the study.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The emergence of digital technology in Malaysia has transformed the economy by enabling individuals to generate multiple sources of income through digital devices and platforms. Digital devices have been widely used by people to stay connected with others, as well as for online shopping, social media, and flexible work. In the year prior to the COVID- 19 pandemic, when the government imposed movement restrictions, the use of digital devices and platforms became a primary focus to support the economy and gig work as a major contributor to economic stability. This phenomenon marks the rise of the gig economy, which has significant increased labour market participation among gig workers, as more businesses adopt gig-based arrangements for their flexibility and cost- effectiveness (Samsuddin et al., 2024). WSDC Team Malaysia (2025) reported that in 2023, approximately 3 million Malaysians, or over 17% of the workforce, were engaged in gig work, a significant increase from 2.4 million in 2021, and the gig economy's contribution to Malaysia's GDP increased from 18.5% in 2018 to 30% 2020. Statistics show that the gig economy has grown over time and contributes to Malaysia's GDP by reducing unemployment.

Despite the increasing participation of gig work in Malaysia. Several studies highlight significant challenges in obtaining loans from financial institutions. According to Oyeyemi (2025), gig work remains financially undetectable because the established financial system continues to assess creditworthiness based on frequent payroll deposits, official employment history, and long-term financial agreements. Consequently, gig workers do not have opportunities to obtain credit from financial institutions because bankers continue to use conventional methods to screen borrowers. The statement has supported by Uchiyama, Furuoka, and Md. Akhir (2022) found that the gig economy workers in Malaysia are typically categorized as independent contractors, lacking formal employment contracts, thereby restricting their access to conventional social protection policies and worsening their financial vulnerability. Financial vulnerability arises when individuals struggle to manage their expenses, cope with unforeseen financial constraints, and face a heightened risk of financial crises (Salignac et al.,2019, as cited in Ng et al., 2024).

To address these structural limitations, the integration of Machine Learning (ML) has emerged as a transformative approach to the primary constraints in financial systems. The broad adoption of AI in the financial sector embraced the analysis of alternative data and real-time behavioural patterns through Machine Learning (ML) techniques. As a subset of AI, Machine Learning enables predictive modelling by learning from historical and transactional data without explicit rule- based programming. In banking and credit risk management, machine learning algorithms, notably decision trees, ensemble approaches, and neural networks, improve the precision of risk prediction by identifying intricate and nonlinear correlations within borrower data. In contrast to conventional statistical models that rely heavily on formal job records, machine learning models can integrate diverse data sources, making them particularly relevant for evaluating gig workers with inconsistent income patterns.

Consequently, advances in Machine Learning models substantially enhances inclusive, data-driven credit risk assessment frameworks. According to Ekong et al. (2022), Machine Learning techniques can address challenges faced by credit analysts by automating data processing and extracting meaningful patterns from large datasets. Therefore, the adoption of Machine Learning techniques, as a subset of Artificial Intelligence, plays an important role for financial institutions in providing loan opportunities to gig workers.

Despite the rapid expansion of the gig economy in Malaysia, current findings predominantly focus on job patterns, income volatility, and worker well-being. Insufficient emphasis has been placed on the structural obstacles that gig workers encounter in obtaining official financial services, especially financing. Moreover, although Machine Learning (ML) models have been widely used in conventional credit risk assessment, there is a lack of systematic data on their application to assessing creditworthiness for gig workers in non-traditional employment contexts. Consequently, there is a deficiency in integrating existing knowledge on ML adoption to enhance financial inclusion for gig workers in Malaysia.

This systematic literature review strictly follows the 2020 recommendations of the Preferred Reporting Items for Systematic Reviews and Meta- Analyses (PRISMA) [The review followed PRISMA guidelines (Page et al., 2021; Bhandary et al., 2024, as cited in Ayari et al., 2026)]. Despite the absence of formal protocol registration (such as PROSPERO), the technique was established to ensure transparency, reproducibility, and to mitigate bias.

Research Questions

RQ 1: What are the key financial challenges faced by gig workers in accessing loans and credit?

RQ 2: How has machine learning been applied in credit scoring for gig workers?

RQ 3: What types of data and features are commonly used in machine learning models for evaluating gig workers' creditworthiness?

RQ 4: What are the gaps in current research on applying machine learning for gig workers' financial inclusion?

Research Objectives

RO 1: To identify the financial challenges and barriers faced by gig workers in obtaining credit.

RO 2: To analyse the applications of machine learning in credit scoring for gig workers.

RO 3: To examine the types of data and variables used in machine learning models for accessing for gig workers' creditworthiness.

RO 4: To highlight the research gaps and suggest areas for future studies on machine learning- based credit scoring for gig workers.

METHODOLOGY

A comprehensive and systematic search was conducted across major academic databases, such as 'Directory of Open Access Journals (DOAJ)', 'Google Scholar', 'SpringerOpen', 'MDPI', 'Public Library of Science (PLOS)', and 'ScienceDirect'. The search was performed with full open access in these databases.

	URL
Directory of Open Access Journals	https://doaj.org/
Google Scholar	https://scholar.google.com/
SpringerOpen	https://link.springer.com/brands/springer
MDPI	https://www.mdpi.com/
Public Library of Science (PLOS)	https://journals.plos.org/plosone/
ScienceDirect	https://www.sciencedirect.com/

Table 1: Database libraries

Based on the library search engines above, the researcher focuses more on open-access articles that are flexible to use as references for studies. The search strategy has been obtained by selecting specific keywords and their synonyms from identified research questions.

These keywords are then organized in a specific order using the 'AND' and 'OR' operators to construct the following query:

("financial inclusion" OR "credit access" OR 'credit scoring' OR "credit evaluation")

AND

("machine learning" OR "ML" OR "artificial intelligence" OR "AI" OR "predictive modelling" OR "data mining")

AND

("gig workers" OR "gig economy" OR "self- employed" OR "informal workers" OR "freelancers")

AND

("bank" OR "financial institution" OR "lender" OR "commercial bank" OR "fintech")

AND

(Malaysia OR "Southeast Asia" OR "Nations")

Data Inclusion and Exclusion Criteria

This paper encompasses publications from January 2020 to December 2025, highlighting a time of substantial advancements in machine learning within financial services while maintaining contemporary relevance and quality in the studies. The inclusion and exclusion criteria were established before the screening procedure was universally implemented thereafter.

Inclusion criteria

Studies were included if they met the following conditions:

i. Studies must be published between 2020 and 2025 to capture the latest advancements in machine learning for credit scoring and financial inclusion.

ii. The article or journal has to be written in English to ensure interpretability and consistency in analysis by using Mendeley.
iii. Focused on gig workers and financial services or credit scoring by implementing machine learning in artificial intelligence to support decisions and proposed new alternatives.
iv. Research papers are based on empirical results, review articles, or existing case studies.
v. Published in peer- reviewed journals or conference proceedings, to ensure academic quality.
vi. Addressed all predefined research questions outlined in section 2.1.

Exclusion criteria

Studies were included if they met the following conditions:

i. Articles that are not peer- reviewed by other researchers or reviewers, such as blogs, opinion pieces, and new articles without proper references, are excluded.
ii. Grey literature without proper data from unrecognizable institutions will be excluded.
iii. Studies published before 2020 are excluded to ensure relevance to the latest trends in the gig economy and ML adoption.
iv. Articles not related to financial inclusion, credit accessibility, gig workers, or ML applications are excluded.
v. Studies lacking empirical data, methodological details, or clear results are excluded.

Study selection process

The study is conducted by using the PRISMA 2020 guidelines. This selection process was constructed in four sequential phases.The sequential process begins with identifying records from databases, registers, and other sources, such as websites or citation searching, followed by removing duplicates and ineligible records. In the screening phase, the unique records were assessed based on titles and abstracts, after which the remaining reports were sought for retrieval. During the eligibility phase, the full texts of the retrieved reports were rigorously evaluated against predefined criteria, and any reports that did not meet these requirements were excluded with specific reasons documented. Finally, in the Inclusion phase, the new studies were combined with any previously identified studies to determine the total number of studies included in the systematic review for data synthesis.

Data Extraction

A structure data extraction form was developed and implemented the Mendeley Reference Manager to facilitate systematic management and screening of the literature. The tool was utilized to systematically collect relevant information and data from each selected study based on the defined research questions and research objectives. The extracted data focused on the following elements:

i. Gig work context: The type of gig workers examined in the study, such as e- hailing drivers, food delivery riders, or freelance workers.
ii. Financial inclusion aspects- issues related to access to financial services, credit scoring, loan eligibility, or financial accessibility for gig workers.
iii. Machine learning techniques- the algorithms or models used within artificial intelligence, such as decision trees, random forests, neural networks, or other ML approaches.
iv. Datasets or data sources- the type and origin of data used in the study.
v. Evaluation metrics- Performance measures used in the studies, such as accuracy, precision, recall, F-1 score, AUC, and specificity.

The data extraction process enabled a systematic comparison between studies and served as the foundation for the synthesis phase. The extracted information helped identify trends, research gaps, and methodological approaches related to the application of machine learning in improving financial inclusion for gig workers.

Data Analysis/Synthesis

After the screening and selection process, the relevant data from the included studies were systematically extracted and organised in a data extraction table. Key information, including author(s), year of publication, research methodology, sample characteristics, types of machine learning algorithms used, variables used for credit assessment, and main findings, was recorded. The extracted data were then analysed using thematic synthesis to identify recurring patterns, emerging trends, and gaps in the literature. The analysis focused on:

i. The financial challenges faced by gig workers,
ii. The application and performance of machine learning models in credit scoring,
iii. The relevant data features commonly used to evaluate gig workers' creditworthiness.

RESULTS AND DISCUSSION

Financial Challenges faced by gig workers

Previous studies consistently highlight that gig workers face significant financial challenges when seeking access to formal financial services. Unlike traditional employees who receive stable monthly salaries, gig workers often experience irregular income patterns, lack formal employment documentation, and face unpredictable cash flows. These characteristics make it difficult for financial institutions to evaluate their creditworthiness using conventional credit scoring methods.

Traditional banking systems tend to rely heavily on stable employment records, consistent income statements, and long- term financial histories when assessing loan eligibility. Consequently, gig workers are often classified as high- risk borrowers despite demonstrating the ability to generate income through digital platforms. This results in financial exclusion, limiting gig workers' access to loans, credit cards, and other essential financial services.

Application of Machine Learning in Credit Scoring

The results reveal that machine learning techniques have increasingly been adopted in financial institutions to improve credit risk assessment and borrower classification. Machine learning models can analyse large datasets and complex patterns in borrowers' financial behaviour, which traditional statistical models may fail to capture.

Commonly implemented algorithms identified in the reviewed literature include Decision Trees, Random Forests, Logistic Regression, Support Vector Machines (SVM), and Artificial Neural Network (ANN). Ensemble learning methods, particularly Random Forest Models are frequently reported to achieve higher predictive accuracy compared to traditional credit scoring approaches.

These findings indicate that machine learning can serve as a robust alternative to conventional methods, enabling more accurate risk classification and supporting data- driven lending decisions, especially for non- traditional borrowers such as gig workers.

Data features used in machine learning models

The studies also highlight the types of data features utilized in machine learning- based credit scoring models. These features encompass both traditional financial indicators and alternative data sources.

Traditional variables include income levels, transaction histories, repayment records, credit utilization ratios. Alternative data sources are increasingly incorporated, such as digital payment activities, platform- generated income records, mobile wallet transactions, and behavioural spending patterns.

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The integration of alternative data allows to build more comprehensive financial profiles, particularly for individuals without formal employment documentation, including gig workers. This approach enhances the predictive capacity of credit scoring models and addresses the limitations of traditional assessment methods.

Research gaps identified in the literature

Despite the growing adoption of machine learning in credit scoring, several gaps are evident in the literature. Most existing models are developed using datasets derived from traditionally employed individuals with stable financial histories. There are lack of studies focus specifically on gig workers or consider the unique characteristics of gig- based income streams. Moreover, many studies aim to optimize algorithmic performance, there is limited research of how alternative data sources can be systematically integrated to evaluate non-traditional workers. This reveals an opportunity to develop machine learning frameworks that specifically address gig workers' financial inclusion and provide equitable access to credit.

Overview of Findings

The findings from the systematic literature review highlight several critical challenges faced by gig workers in accessing formal financial services. The results indicate that gig workers are often excluded from the traditional credit system due to irregular income patterns, lack of formal employment documentation, and limited credit history.

In addition, the findings demonstrate that machine learning models can improve credit risk assessment by analysing large datasets and identifying complex financial patterns. The use of alternative data, such as digital transactions and behavioural patterns, further enhances the predictive accuracy of these models.

Despite the advances in machine learning in financial institutions, existing credit assessment frameworks remain largely dependent on traditional financial indicators. These approaches are insufficient for evaluating gig workers because existing systems are biased, as gig workers often unstable income records and formal employment. Therefore, there is a need for a structured and adaptive framework that integrates machine learning techniques with alternative data sources to better assess the creditworthiness of gig workers.

Proposed conceptual framework

Based on the findings and identified research gaps, this study proposes a conceptual framework for credit risk mitigation among gig workers in Malaysia. The framework integrates key elements, including gig workers' characteristics, risk identification, risk assessment, risk evaluation, risk mitigation, and risk monitoring. This framework aims to provide a systematic approach and data- driven approach for credit risk assessment by incorporating machine learning techniques and alternative financial data. It also addresses the limitations of traditional credit scoring systems by focusing specifically on the unique characteristics of gig workers. Therefore, the conceptual framework has been constructed as follows:

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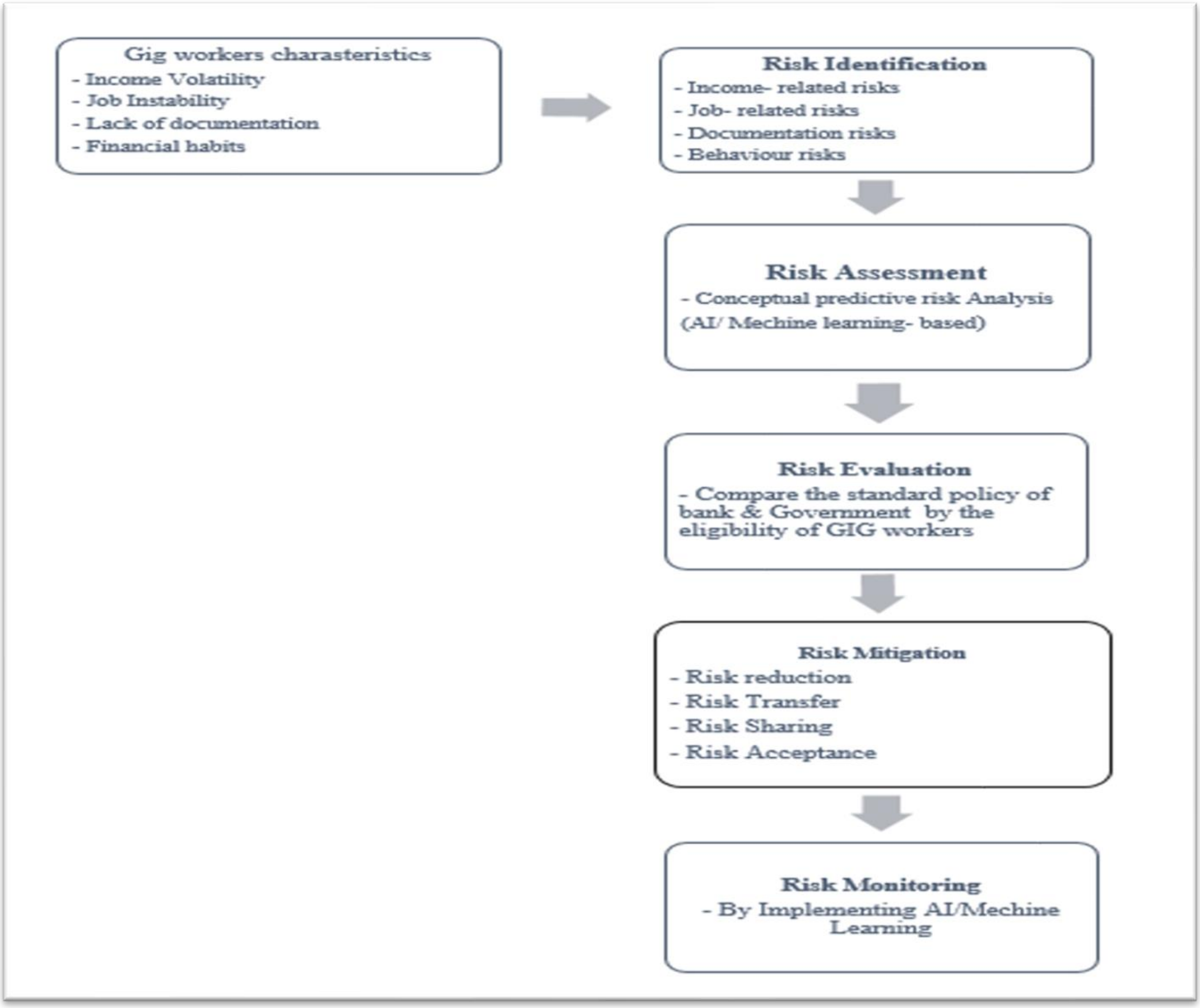

Figure 1: Conceptual Framework: Risk Mitigation of credit risk for the gig workers model

DISCUSSION

Based on the proposed conceptual framework above, this study outlines a systematic approach to understanding and mitigating credit risk among gig workers in Malaysia. The framework begins with five pillars to identify the unique characteristics of gig workers, followed by risk identification, risk assessment, risk evaluation, risk mitigation, and continuous monitoring. According to International Organization for Standardization (2018), ISO 31000 provides guidelines for organizations to manage risks systematically, aiding in strategic decision-making by integrating risk management into governance and planning. The framework enhances operational efficiency by enabling early risk identification, more effective resource allocation, and greater stakeholder confidence. It promotes a proactive approach, enabling organizations to anticipate risks and improve resilience. Thus, this model closely aligns with ISO 31000, which emphasizes the importance of integrating risk management into organizational governance and continuous improvement practices, making it highly relevant for financial institutions in Malaysia to address emerging risks to gig workers.

The conceptual framework begins with four characteristics that we can implement and monitor: income volatility, job instability, lack of documentation, and financial habits. These four primary features of gig workers are critical factors influencing credit risk. There are reasons behind four main factors that play important role to evaluate and escalate the gig workers background. De Stefano (2016) and the International Labour Organization (2021) assert that gig workers experience variable income and precarious employment situations as a result of platform-based work. The lack of official employment documentation limits their evaluation within conventional credit rating frameworks (OECD,2019). Moreover, financial behaviour influences credit risk, as erratic income often leads to unstable savings and inadequate financial planning (Lusardi & Mitchell, 2014). These factors increase financial vulnerability and the probability of default among gig workers.

Risk Identification is the first step in the risk management process, identifying potential risks that can affect any event. In this model, risk identification is a fundamental step in identifying potential risks that could influence loan approval vulnerability. At this stage, four key risks categories are assessed: income-related risk, job- related risk, documentation-related risk, and behaviour- related risk. These categories are used to systematically evaluate the financial stability and creditworthiness of gig workers, who are often exposed to higher credit risk due to the nature of non- traditional employment (De Stefano, 2016; International Labour Organization, 2021).

The second phase, risk assessment, is the process of evaluating risks to understand the probability and severity of events. During this stage, four potential risks of individuals will be assessed using Artificial Intelligence (AI) and Machine Learning (ML)- based predictive modelling to evaluate the creditworthiness of gig workers. This approach focuses on identifying potential default risks by analysing complex patterns in financial and behavioural data. The predictive model utilises structured and unstructured datasets including income history, transaction behaviour, repayment patterns, and employment stability. Machine learning algorithms are trained to learn relationships between these variables and borrower risk outcomes, enabling the systems to classify applicants into different risk categories (Bank Negara, 2023; Fuster et al., 2022; Lessman et al., 2015). Unlike traditional credit scoring methods, AI and ML models are capable of capturing nonlinear relationships and hidden risk indicators that are often overlooked in conventional statistical analysis. This improves the accuracy and consistency of risk prediction, particularly for gig workers who typically have irregular income streams and limited formal credit history.

The third phase, risk evaluation, refers to the process of analysing and comparing the results of risk assessment with predefined criteria or standards. At this stage, risk evaluation is implemented to determine the significance and severity of risks associated with gig workers in the loan approval system. After identifying key risk categories, namely income- related risk, job- related risk, documentation-related risk and behaviour- related risk, each risk is assessed based on its likelihood and the potential impact on loan repayment. The evaluation process is enhanced through the application of artificial intelligence (AI) and machine learning (ML). models, which are capable of analysing complex patterns and non- linear relationships within the data. This allows for a more accurate and consistent assessment compared to traditional methods. As a result, each applicant is assigned a risk level, such as low, medium, or high risk, which assists financial institutions in making informed and reliable lending decisions, particularly for gig workers who often have irregular income streams and limited formal credit history. This evaluation must be aligned with the standard lending guidelines established by Bank Negara Malaysia (BNM) to emphasize responsible lending practices and the assessment of a borrower's repayment capacity, financial commitments, and creditworthiness.

The fourth phase, risk mitigation, involves mplementing appropriate strategies to manage and control the risks identified and evaluated in the loan approval process for gig workers. Based on the determined level of risk, several mitigation approaches are applied, including risk reduction, risk transfer, risk sharing, and risk acceptance. Risk reduction focuses on minimizing the likelihood or impact of potential default by adjusting loan conditions, such as reducing loan amounts or applying stricter approval criteria (International Organization for Standardization, 2018). Risk transfer involves shifting the risk to a third party, for example, through guarantors or insurance mechanisms, while risk sharing distributes the risk among multiple parties, such as co-borrowers (International Organization for Standardization, 2018). Meanwhile, risk acceptance is applied when the level of risk is considered tolerable and manageable without further action (International Organization for Standardization, 2018). The integration of artificial intelligence (AI) and machine learning (ML) further enhances this process by enabling predictive analysis and recommending suitable mitigation strategies based on data patterns. This approach aligns with the responsible lending practices emphasized by Bank Negara Malaysia, ensuring a more sustainable and inclusive loan approval system for gig workers.

Lastly, risk monitoring refers to the continuous process of tracking and reviewing the effectiveness of risk management strategies applied in the loan approval system for gig workers. After the risk identification, evaluation, and mitigation stages, monitoring ensures that the risk levels of borrowers remain within acceptable limits throughout the loan lifecycle. This includes observing changes in income stability, repayment behaviour, and other financial indicators that may affect credit risk. In the risk monitoring context, AI and machine learning-based systems can be enhanced through continuous data updates, predictive analytics, and real- time risk scoring, enabling early detection potential financial distress. This enables financial institutions to take timely corrective actions and improve decision- making accuracy. The approach is aligned with responsible lending and continuous risk management practices emphasized by Bank Negara Malaysia, ensuring long- term sustainability and financial stability in the lending process.

CONCLUSION AND FUTURE RESEARCH

This systematic literature review highlighted that, this systematic literature review concludes that, despite the rapid growth of the gig economy in Malaysia and its significant contribution to the digital labor market, gig workers encounter considerable obstacles in accessing formal financial services due to irregular income patterns, absence of stable employment documentation, and insufficient credit history. These difficulties lead to financial exclusion when conventional credit rating methodologies are utilized.

This study illustrates that the amalgamation of Machine Learning (ML) and Artificial Intelligence (AI) possesses significant potential to enhance credit risk assessment by facilitating a more precise, data-driven, and inclusive evaluation of gig workers' creditworthiness via both conventional and alternative data sources. The suggested conceptual framework, which includes risk identification, assessment, evaluation, mitigation, and monitoring, offers a systematic and adaptable method for managing credit risk in accordance with responsible lending principles.

Future study should investigate the use of various, real-time alternative data sources and the advancement of hybrid and explainable AI models to improve transparency and confidence in credit decision-making systems. Subsequent research should concentrate on empirical validation within the Malaysian context, including evaluating the efficacy of AI-driven credit scoring in enhancing financial inclusion for gig workers. Furthermore, ethical problems including data privacy, algorithmic bias, and equity in automated lending systems warrant greater scrutiny to guarantee that technology progress is consistent with responsible lending practices.

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