American Journal of Interdisciplinary Studies

Volume: 7; **Issue:** 1
Pages: 536-577
eISSN: 3067-5146

AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026)

Mst Shurovi Akter[1];

[1]. Management Trainee, BD Tech Solutions Inc., Anaheim, USA;
Email: shurovi.akter.ca@gmail.com

Doi: 10.63125/x1yzwc45

Received: 20 December 2025; ***Revised:*** 22 January 2026; ***Accepted:*** 10 February 2026; ***Published:*** 02 March 2026;

Abstract

This study examined the problem of operational risk exposure in U.S. small and medium-sized enterprises caused by manual, fragmented, or weakly integrated accounts payable and accounts receivable workflows. The purpose was to determine whether AI-driven AP/AR automation reduces risks related to invoice errors, duplicate payments, delayed collections, reconciliation mismatches, fraud exposure, weak audit trails, and limited cash flow visibility. Using a quantitative, cross-sectional, case-based design, the study collected survey data from 220 valid respondents drawn from cloud-based and enterprise financial automation cases in U.S. SMEs, including SME owners, finance managers, accountants, bookkeepers, controllers, operations managers, and AP/AR staff. The key variables were accounts payable automation, accounts receivable automation, AI-enabled invoice processing, AI-enabled reconciliation, AI-based fraud detection, cash flow visibility, AI automation maturity, and operational risk mitigation. Data were analyzed using descriptive statistics, Cronbach's Alpha reliability testing, Pearson correlation, multiple regression, and hypotheses testing at the 0.05 significance level. The findings showed high to very high agreement that AI automation improves financial control, with operational risk mitigation recording a mean of 4.27, AI-enabled reconciliation 4.31, fraud detection 4.24, invoice processing 4.20, AP automation 4.18, AR automation 4.12, cash flow visibility 4.16, and AI automation maturity 3.98. Reliability was strong, with an overall Cronbach's Alpha of 0.91. Correlation results confirmed significant positive relationships between all automation variables and operational risk mitigation, with reconciliation showing the strongest association, $r = 0.72$, $p < 0.001$, followed by fraud detection, $r = 0.70$, $p < 0.001$. Regression analysis showed that the model explained 65.8% of the variance in operational risk mitigation, $R^2 = 0.658$, $F(7, 212) = 58.47$, $p < 0.001$. AI-enabled reconciliation was the strongest predictor, $\beta = 0.24$, followed by fraud detection, $\beta = 0.21$. The study implies that AI-driven AP/AR automation should be treated as a strategic financial control mechanism for improving accuracy, transparency, liquidity awareness, fraud prevention, and operational resilience in U.S. SMEs.

Keywords

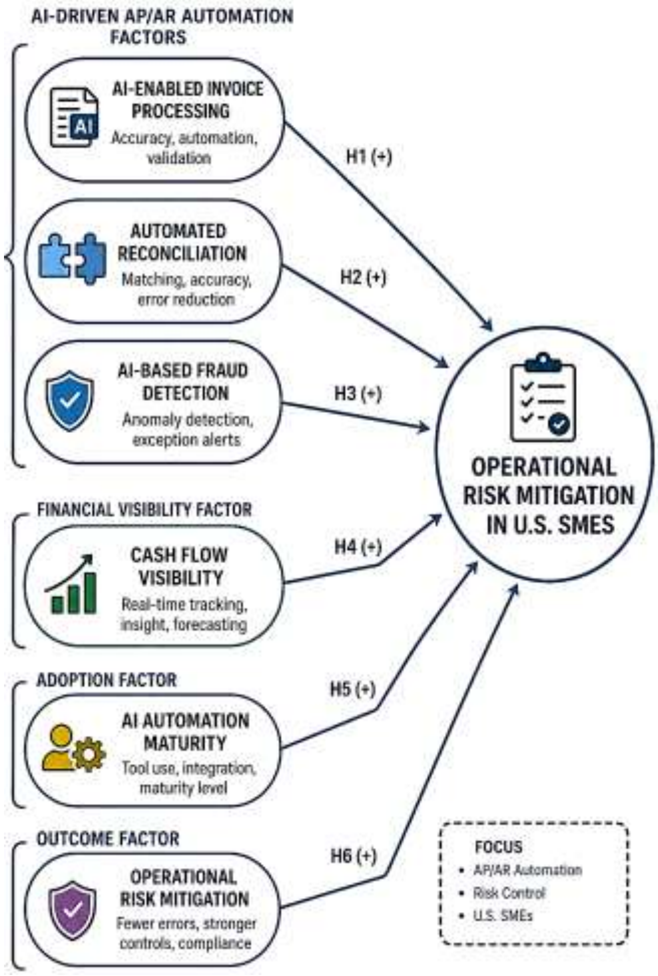
AI-driven AP/AR automation, operational risk mitigation, U.S. SMEs, AI-enabled reconciliation, financial automation.

INTRODUCTION

Artificial intelligence refers to computational systems that perform tasks commonly associated with human intelligence, including pattern recognition, prediction, classification, learning from data, and decision support. In business and accounting contexts, AI is not limited to autonomous reasoning; it also includes machine learning, robotic process automation, intelligent document processing, natural language processing, predictive analytics, and anomaly detection tools that support structured and semi-structured financial tasks (Akter et al., 2016). AI can be understood as a system's ability to interpret external data, learn from such data, and use learning to achieve specific goals, while in accounting and auditing it represents a set of cognitive technologies capable of reshaping routine financial processes. Accounts payable automation refers to the digital and AI-supported processing of supplier invoices, invoice matching, approval routing, duplicate payment detection, vendor payment scheduling, and reconciliation (Bouwman et al., 2019). Accounts receivable automation refers to AI-supported customer invoicing, receivables tracking, payment reminders, cash application, collections prioritization, and cash flow forecasting. Operational risk, in this study, refers to the possibility of losses or process failure caused by internal errors, weak controls, fraud, delayed processing, inaccurate records, ineffective reconciliation, or system-based weaknesses (Brustbauer, 2016). This definition is important because AP and AR workflows are not only accounting functions; they are operational control systems that influence liquidity, compliance, vendor relationships, customer payment discipline, audit readiness, and managerial decision-making. Internationally, the automation of finance operations has become significant because organizations across developed and emerging economies increasingly depend on timely financial data to manage uncertainty, cost pressure, credit exposure, payment accuracy, and internal control quality. Research on business intelligence and analytics shows that organizations create value when data are transformed into actionable insight for decision-making, while studies on big data analytics capability show that data-driven capabilities improve performance when aligned with business strategy and operational processes (Cooper et al., 2019). For U.S. SMEs, this international movement toward data-driven financial operations is especially relevant because smaller firms often operate with limited accounting staff, constrained budgets, and high sensitivity to cash flow disruption. Therefore, AI-driven AP/AR automation can be defined as the use of intelligent technologies to improve the accuracy, speed, transparency, and control of payable and receivable workflows in ways that reduce operational risk exposure (Côrte-Real et al., 2017).

The international significance of AI-driven financial automation is rooted in the global shift from manual administrative processing to data-intensive, technology-enabled business operations. Digital transformation literature explains that information systems are no longer merely back-office tools; they have become embedded in business strategy, organizational coordination, and operational value creation. In this context, AP and AR automation represent a practical form of digital transformation because they convert recurring accounting activities into standardized, traceable, and analytics-supported workflows (Chen et al., 2012). International studies on digitalization show that firms use digital technologies to redesign business models, enhance process efficiency, and improve organizational responsiveness. For SMEs, these benefits are important because resource limitations can make manual financial processes risky. Small firms commonly depend on fewer employees to perform invoice entry, payment approval, customer billing, reconciliation, and reporting; this concentration of responsibilities can increase exposure to processing errors, weak segregation of duties, late collections, and incomplete documentation. Studies on SME risk management show that small and medium-sized firms face distinct risk challenges because they often lack formalized risk management structures and specialized internal control resources (Bharadwaj et al., 2013). AI-driven AP/AR automation addresses these conditions by supporting invoice validation, exception reporting, automated matching, payment monitoring, and risk alerts. Robotic process automation research further shows that software robots can automate repetitive, rule-based tasks across existing systems, which makes them particularly relevant for accounting processes that involve structured data entry, matching, and verification. In global accounting practice, these tools have been discussed as mechanisms for improving audit quality, reducing low-judgment manual tasks, and allowing finance professionals to focus on interpretation and control. The international significance of the present study therefore lies in its focus on a specific financial automation problem: whether AI-driven AP and AR automation can reduce operational risk in U.S. SMEs through measurable improvements in accuracy, reconciliation, fraud detection, cash flow visibility, and compliance monitoring (Eller et al., 2020).

Figure 1: AI-Driven AP/AR Automation for Operational Risk Mitigation in U.S. SMEs



Accounts payable and accounts receivable are two of the most risk-sensitive financial processes in SMEs because they directly connect operational activities with cash movement. Accounts payable errors can produce duplicate payments, late payment penalties, vendor disputes, unauthorized disbursements, poor expense visibility, and inaccurate liabilities. Accounts receivable weaknesses can produce delayed collections, inaccurate customer balances, weak credit control, poor cash forecasting, and increased bad-debt exposure. From a risk management perspective, these workflows are important because they involve transaction initiation, documentation, authorization, recording, matching, settlement, and reporting. Each step can become a control point or a failure point (Frank et al., 2019). Research on RPA in public accounting shows that automation is especially useful where tasks involve repetitive data input, processing, and output across applications. This directly applies to AP/AR environments, where staff frequently move invoice data, purchase order details, payment confirmations, customer remittances, bank records, and ledger information across accounting platforms. In audit and accounting information systems research, automation has been associated with improved efficiency in repetitive tasks, stronger documentation, and more consistent processing logic. AI strengthens these benefits by adding prediction, classification, exception detection, and learning-based monitoring. For example, machine learning can identify unusual payment patterns, intelligent document processing can extract invoice details, predictive analytics can estimate collection timing, and anomaly detection can flag duplicate or suspicious transactions (Tang, 2006). Big data and analytics research supports this view by showing that analytics capability allows firms to convert data into operational insight and performance improvement. In AP/AR automation, the value of AI depends not only on the existence of technology but also on how well automation is embedded into approval workflows, accounting policies, risk control routines, and managerial reporting (Aalst et al., 2018). This makes the study relevant to U.S. SMEs because the ability to reduce operational risk depends on the practical integration of AI tools into daily finance processes rather than on general digital adoption alone. The study therefore positions AP/AR automation as a specific operational risk control mechanism rather than a broad accounting technology (Kokina & Davenport, 2017).

The importance of this research is also connected to the role of information quality, control reliability, and data visibility in financial decision-making. In manual AP/AR systems, decision-makers often rely on delayed, incomplete, or fragmented information because invoices, approvals, payment confirmations, customer balances, and reconciliation records may be stored across emails, spreadsheets, accounting platforms, and bank portals. Such fragmentation can weaken operational control because managers may not detect payment delays, duplicate invoices, uncollected receivables, or suspicious transactions until after losses or disputes occur. Business intelligence and analytics research shows that data-driven systems support decision-making when they provide timely, relevant, and analyzable information (Ghobakhloo et al., 2011). Related studies show that analytics investments create value when organizations have the skills and organizational conditions required to use data effectively, and when analytical capability is aligned with strategy and processes. These findings are relevant to AP/AR automation because AI tools can transform transaction records into operational risk indicators. For example, invoice aging reports can identify delayed approvals, receivables analytics can identify high-risk customers, automated reconciliation can identify unmatched transactions, and anomaly detection can identify unusual payment behavior (Syed et al., 2020). In accounting and audit research, big data and analytics have been linked to changes in evidence collection, testing, monitoring, and assurance practices. These studies support the idea that financial data are not only historical records but also risk signals. For SMEs, this is significant because limited staffing can prevent continuous manual monitoring of all AP/AR transactions. AI-driven automation can function as a monitoring layer that continuously compares transaction patterns against rules, historical behavior, and exception thresholds. The operational risk value of this monitoring layer can be assessed quantitatively through descriptive statistics, correlation analysis, and regression modeling. By measuring perceptions of AI-enabled invoice processing, reconciliation, fraud detection, cash flow visibility, and compliance monitoring, this study can evaluate whether automated AP/AR capabilities are statistically associated with stronger operational risk mitigation in U.S. SMEs (Venkatesh & Bala, 2008).

The adoption of AI-driven AP/AR automation in SMEs must also be understood through technology acceptance and organizational readiness (Verbano & Venturini, 2013). The Technology Acceptance Model provides a useful foundation because it explains that technology adoption is influenced by perceived usefulness and perceived ease of use. Users' beliefs, system characteristics, and organizational support shape technology acceptance, which means that technology adoption is partly behavioral and organizational rather than purely technical. In the present study, perceived usefulness can be understood as the degree to which SME finance professionals believe that AI-driven AP/AR automation improves invoice accuracy, reconciliation quality, payment tracking, fraud detection, compliance monitoring, and cash flow visibility (Kaplan & Haenlein, 2019). Perceived ease of use can be understood as the degree to which employees believe that AI-enabled accounting systems are understandable, manageable, and compatible with their work routines. This theoretical orientation is necessary because AP/AR automation does not reduce operational risk merely because the tool exists; it reduces risk when finance employees use the system correctly, trust its outputs, respond to alerts, and incorporate automated information into control decisions. Research on information technology adoption in SMEs shows that smaller firms differ from large organizations because they face resource constraints, limited technical expertise, and managerial centralization (Trkman & McCormack, 2009). Studies of digitalization in SMEs also show that digital transformation is shaped by firm resources, digital skills, strategy, and organizational willingness to change. In accounting contexts, RPA studies show that implementation success depends on process understanding, system fit, professional judgment, and governance of automated routines. These insights justify including AI automation maturity as a study-specific variable. A firm at the manual-processing stage may experience different risk outcomes than a firm using predictive risk automation, anomaly detection, and real-time dashboards (Verbano & Venturini, 2013; Wamba et al., 2017). Therefore, this study links TAM-based adoption logic with AP/AR risk control by examining whether higher levels of AI automation maturity are associated with stronger operational risk mitigation among U.S. SMEs.

Operational risk mitigation in AP/AR automation is an international research concern because financial process failures can affect firm stability across industries and national contexts (Appelbaum et al., 2017; Binte, 2025). Risk management research emphasizes that SMEs are exposed to operational, financial, strategic, compliance, and market risks, and that risk management practices are often less formalized in smaller firms than in larger enterprises. In AP/AR workflows, operational risk appears through process-level failures such as invoice duplication, unauthorized approvals, incorrect vendor records, unposted customer payments, reconciliation mismatches, delayed collections, and incomplete audit trails. These risks can become more severe when firms operate across multiple payment channels, customer groups, vendor networks, and accounting platforms (Huang & Vasarhelyi, 2019; Shamsul & Morshedul, 2025). Research on supply chain and operational risk also indicates that process disruption and weak coordination can affect performance and resilience. Although AP/AR processes are financial in nature, they are operationally connected to procurement, sales, customer service, vendor management, inventory, logistics, and reporting. This makes AI-driven AP/AR automation important beyond the accounting department. For instance, automated invoice matching can strengthen procurement control, automated payment reminders can improve customer collections, cash application tools can improve sales ledger accuracy, and automated reconciliation can support financial reporting reliability. Studies on Industry 4.0 and digital operations show that digital technologies improve performance when they are integrated into processes and used to support coordination, visibility, and decision-making. In this study, AI-enabled control point analysis is therefore appropriate because it identifies where automation contributes most strongly to risk mitigation within AP/AR workflows (Shamsul, 2025; Warren et al., 2015). The control points include invoice capture, approval workflow, three-way matching, duplicate payment detection, customer payment tracking, cash application, reconciliation, and fraud alerts. Examining these points makes the research more specific because it measures the operational locations where AI may reduce risk rather than treating automation as a general organizational capability.

This study is positioned at the intersection of AI-enabled accounting automation, SME risk management, and quantitative information systems research. Prior studies have established that AI and RPA can automate repetitive accounting and audit tasks, that analytics capabilities can improve organizational performance and decision-making, and that SMEs face distinct risk management challenges because of limited resources and less formalized control systems. The present research brings these streams together by focusing specifically on AI-driven AP/AR automation as a measurable operational risk mitigation mechanism in U.S. SMEs (Risha, 2025; Yoo et al., 2010). The study uses a quantitative, cross-sectional, case-study–based design because this approach allows the researcher to collect structured evidence from finance-related respondents at a single point in time and statistically examine relationships among AP automation, AR automation, invoice processing, reconciliation, fraud detection, cash flow visibility, automation maturity, and operational risk mitigation. A five-point Likert scale is appropriate because the variables involve organizational perceptions of system use, process improvement, control strength, and risk reduction (Murad, 2025; Tambe, 2014). Descriptive statistics can summarize the level of AI adoption and perceived risk mitigation; correlation analysis can examine the strength and direction of relationships among variables; and regression modeling can test whether AI-driven AP/AR automation variables significantly predict operational risk mitigation. The study's results chapter can be strengthened through three study-specific analytical sections: an AI Automation Maturity Profile of U.S. SMEs, an Operational Risk Reduction Index for AP/AR Automation, and an AI-Enabled Control Point Analysis in AP/AR Workflows (Lu, 2017; Moffitt et al., 2018; Kaniz, 2025). These sections are aligned with prior research emphasizing analytics capability, technology acceptance, and process-level automation while remaining specific to the financial control environment of AP and AR operations. The introduction therefore establishes AI-driven AP/AR automation as a practical, measurable, and internationally relevant domain for examining operational risk mitigation in U.S.

SMEs (Falkner & Hiebl, 2015; Mainuddin, 2025).

Background of the Study

Artificial intelligence has become an important driver of financial process transformation as organizations increasingly rely on automation, analytics, and intelligent decision-support systems to improve operational accuracy and control. In small and medium-sized enterprises, accounts payable and accounts receivable are two of the most critical financial functions because they directly affect cash flow, vendor relationships, customer payment behavior, financial reporting, and overall business continuity. Accounts payable activities involve receiving invoices, verifying vendor information, approving payments, detecting duplicate claims, and recording liabilities, while accounts receivable activities involve issuing customer invoices, tracking payments, managing collections, applying cash receipts, and monitoring outstanding balances. When these processes are handled manually or through fragmented digital systems, SMEs may face operational risks such as invoice errors, payment delays, duplicate payments, poor reconciliation, weak audit trails, fraud exposure, cash flow uncertainty, and inaccurate financial records. These risks can be more serious for SMEs because they often operate with limited accounting personnel, smaller financial control departments, and fewer resources for continuous monitoring. AI-driven AP/AR automation offers a practical solution by using intelligent tools to capture invoice data, match documents, route approvals, flag exceptions, detect suspicious transactions, predict payment delays, and improve cash flow visibility. Through these capabilities, AI can help SMEs reduce human error, strengthen internal controls, improve financial transparency, and make faster decisions based on real-time information. In the U.S. business environment, where SMEs play a major role in employment, innovation, and economic activity, improving financial process reliability is essential for operational stability. The growing availability of cloud-based accounting systems, machine learning applications, robotic process automation, and predictive analytics has created new opportunities for SMEs to modernize their financial workflows. However, many SMEs still struggle to determine whether AI-driven AP/AR automation produces measurable improvements in operational risk mitigation. This study is therefore focused on examining how AI-enabled accounts payable and receivable automation contributes to reducing operational risks in U.S. SMEs. By using a quantitative, cross-sectional, case-study–based approach with Likert-scale survey data, the study seeks to evaluate the relationship between AI automation maturity, invoice processing, reconciliation, fraud detection, cash flow visibility, and operational risk mitigation.

Problem Statement

Many U.S. small and medium-sized enterprises continue to experience operational risks in their financial processes because accounts payable and accounts receivable activities are often managed through manual, semi-automated, or poorly integrated systems. These processes require accuracy, timeliness, documentation, verification, and continuous monitoring, yet SMEs frequently operate with limited finance staff, restricted budgets, and less formalized internal control structures than larger organizations. As a result, AP/AR workflows may become vulnerable to invoice processing errors, duplicate payments, unauthorized approvals, delayed vendor settlements, inaccurate customer balances, poor cash application, delayed collections, reconciliation mismatches, weak audit trails, fraud exposure, and limited visibility into cash flow. Such risks can disrupt business continuity, reduce liquidity, weaken supplier and customer relationships, and compromise the reliability of financial reporting. Although AI-driven automation tools are increasingly available for invoice capture, approval routing, payment tracking, reconciliation, anomaly detection, fraud monitoring, and cash flow forecasting, many SMEs still lack clear evidence on whether these technologies produce measurable improvements in operational risk mitigation. Existing discussions of AI in accounting often focus on general digital transformation, audit automation, or enterprise-level financial technology adoption, while fewer studies examine the specific role of AI-driven accounts payable and receivable automation in reducing operational risks among U.S. SMEs. This creates a research gap because AP and AR functions are among the most transaction-heavy and risk-sensitive financial processes in small and medium-sized firms. Without empirical assessment, SME owners, finance managers, accountants, and technology providers may struggle to understand which AI-enabled AP/AR capabilities are most useful for reducing operational failures. Therefore, the problem addressed in this study is the limited quantitative understanding of how AI-driven AP/AR automation influences operational risk mitigation in U.S. SMEs. This study responds to that problem by examining the relationship between AI-enabled accounts payable automation, accounts receivable automation, invoice processing, reconciliation, fraud detection, cash flow visibility, automation maturity, and operational risk mitigation using a quantitative, cross-sectional, case-study–based research design.

Objectives of The Study

The main objective of this study is to examine the extent to which AI-driven accounts payable and accounts receivable automation contributes to operational risk mitigation in U.S. small and medium-sized enterprises. Specifically, the study seeks to assess whether AI-enabled automation improves the accuracy, efficiency, transparency, and control of financial workflows that are traditionally vulnerable to manual errors and process failures. The first objective is to evaluate the relationship between AI-driven accounts payable automation and operational risk mitigation by focusing on vendor invoice processing, approval routing, duplicate payment detection, payment scheduling, and liability recording. The second objective is to determine how AI-driven accounts receivable automation supports risk reduction through customer invoicing, payment reminders, receivables tracking, cash application, collection prioritization, and payment behavior monitoring. The third objective is to examine whether AI-enabled invoice processing and reconciliation improve financial process reliability by reducing data-entry errors, mismatched transactions, delayed approvals, and inaccurate financial records. The fourth objective is to assess the contribution of AI-based fraud detection and anomaly monitoring to operational risk control by identifying unusual payment patterns, suspicious transactions, duplicate invoices, unauthorized payment activities, and irregular customer or vendor behavior. The fifth objective is to investigate whether AI-supported cash flow visibility improves managerial awareness of receivables, payables, liquidity pressure, and payment timing. The sixth objective is to evaluate AI automation maturity among U.S. SMEs and determine whether higher levels of automation maturity are associated with stronger operational risk mitigation outcomes. These objectives guide the study toward a measurable evaluation of AP/AR automation as a financial control mechanism. By using descriptive statistics, correlation analysis, and regression modeling, the study aims to generate quantitative evidence on how AI-driven financial automation affects operational risk reduction in SMEs. The objectives also support the development of study-specific result sections, including an AI automation maturity profile, an operational risk reduction index, and an AI-enabled control point analysis within AP/AR workflows.

Research Hypotheses

The research hypotheses for this study are designed to test the statistical relationships between AI-driven AP/AR automation variables and operational risk mitigation in U.S. SMEs. The hypotheses are based on the assumption that AI-enabled financial automation strengthens financial process control by reducing errors, improving transparency, accelerating transaction processing, supporting reconciliation, and detecting risk signals in accounts payable and accounts receivable workflows. The first hypothesis states that AI-driven accounts payable automation has a significant positive relationship with operational risk mitigation in U.S. SMEs. This hypothesis focuses on whether automated vendor invoice processing, approval routing, payment scheduling, and duplicate payment detection reduce financial process risks. The second hypothesis states that AI-driven accounts receivable automation has a significant positive relationship with operational risk mitigation in U.S. SMEs. This hypothesis examines whether automated customer invoicing, payment tracking, collection reminders, and receivables monitoring contribute to better risk control. The third hypothesis states that AI-enabled invoice processing significantly improves financial process accuracy in U.S. SMEs by reducing manual errors, incomplete invoice records, processing delays, and inconsistencies in transaction documentation. The fourth hypothesis states that AI-enabled reconciliation significantly improves operational risk control by reducing unmatched transactions, inaccurate balances, and financial reporting weaknesses. The fifth hypothesis states that AI-based fraud detection significantly contributes to operational risk mitigation by helping SMEs identify suspicious activities, unusual payment behavior, duplicate claims, and unauthorized transactions. The sixth hypothesis states that AI-supported cash flow visibility significantly predicts operational risk mitigation by improving awareness of payables, receivables, liquidity gaps, and expected payment timing. The seventh hypothesis states that AI automation maturity significantly predicts operational risk mitigation in U.S.

SMEs, meaning that firms with more advanced levels of AI adoption in AP/AR workflows are expected to report stronger risk reduction outcomes. These hypotheses will be tested using correlation and regression analysis to determine whether AI-driven AP/AR automation variables have statistically significant relationships with operational risk mitigation. The results will provide empirical evidence on whether AI-enabled financial automation can serve as a meaningful operational risk management tool for U.S. SMEs.

Significance of the Research

i. **Significance to U.S. SMEs:** This study is significant to small and medium-sized enterprises because it provides practical insight into how AI-driven AP/AR automation can reduce operational risks in financial workflows. SMEs can use the findings to understand whether automation improves invoice accuracy, payment control, receivables tracking, reconciliation, fraud detection, and cash flow visibility.

ii. **Significance to Finance and Accounting Managers:** The study is useful for finance managers, accountants, bookkeepers, and financial controllers because it identifies the specific AP/AR control points where AI automation may strengthen financial process reliability. The results can help financial professionals make better decisions about adopting invoice automation, payment monitoring, automated reconciliation, and risk alert systems.

iii. **Significance to Operational Risk Management:** This research contributes to operational risk management by examining AP/AR automation as a risk mitigation mechanism rather than only as a productivity tool. It highlights how financial process automation can reduce transaction errors, delayed payments, duplicate payments, fraud exposure, compliance weaknesses, and poor documentation.

iv. **Significance to Technology Providers:** The findings may help fintech companies, accounting software vendors, and automation solution providers design AI-enabled tools that are more suitable for SME needs. By identifying which automation features are most strongly associated with risk reduction, vendors can improve product design, usability, affordability, and risk-monitoring functions.

v. **Significance to Policymakers and SME Support Agencies:** The study may support policymakers, business development agencies, and SME support organizations in promoting digital finance adoption. Evidence from the study can guide training programs, technology adoption incentives, financial literacy initiatives, and digital transformation support for SMEs.

vi. **Significance to Academic Research:** This study contributes to academic literature by linking AI-driven AP/AR automation with operational risk mitigation in the specific context of U.S. SMEs. It also adds value by using quantitative analysis, a five-point Likert-scale instrument, an AI automation maturity profile, an operational risk reduction index, and an AI-enabled control point analysis.

vii. **Significance to Business Decision-Making:** The research supports evidence-based decision-making by helping SME leaders understand whether investment in AI-driven AP/AR automation can improve financial control and operational stability. This is important because many SMEs must justify technology adoption based on measurable business value and risk reduction potential.

LITERATURE REVIEW

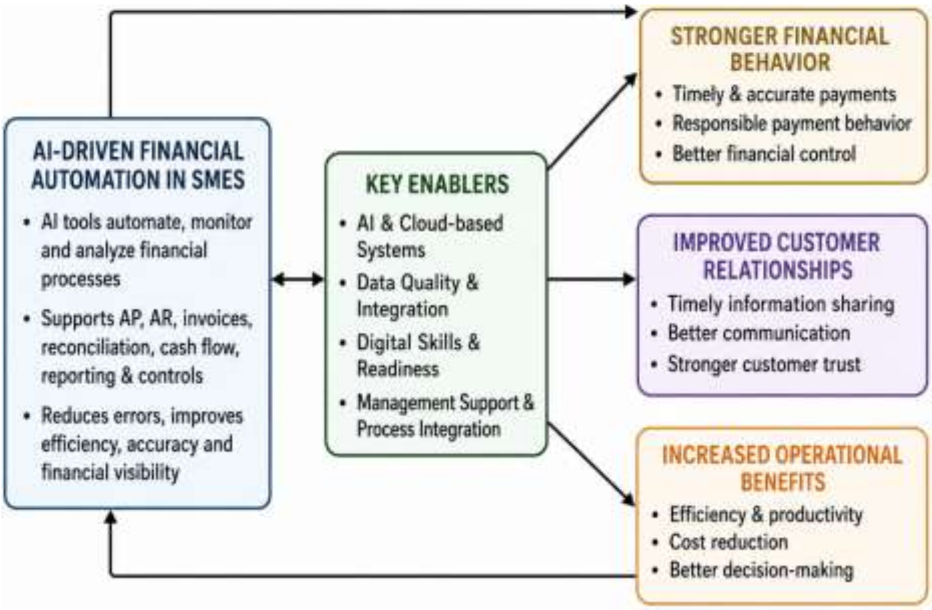
The literature review for this study examines the relationship between AI-driven accounts payable and accounts receivable automation and operational risk mitigation in U.S. small and medium-sized enterprises. The review is organized around the idea that AP and AR processes are not only routine accounting activities but also important financial control systems that influence cash flow, transaction accuracy, fraud prevention, reconciliation quality, compliance monitoring, and business continuity. Existing literature on artificial intelligence in accounting shows that automation technologies are increasingly being used to reduce repetitive work, improve data processing, support decision-making, and enhance the reliability of financial operations. In the context of SMEs, this issue is especially important because smaller firms often operate with fewer employees, limited internal control resources, and weaker technology infrastructure compared with larger enterprises. As a result, financial process weaknesses in AP and AR workflows may expose SMEs to operational risks such as invoice duplication, delayed collections, payment errors, unauthorized transactions, incomplete documentation, and inaccurate financial records. The literature review therefore explores how AI-enabled tools such as machine learning, robotic process automation, intelligent document processing, anomaly detection, predictive analytics, and automated reconciliation can support operational risk mitigation. It also examines the role of technology adoption, since the success of AI-driven AP/AR automation depends on whether SME employees perceive the system as useful, easy to use, reliable, and compatible with existing accounting practices. The Technology Acceptance Model is used as the theoretical foundation because it helps explain how perceived usefulness and perceived ease of use influence adoption and actual use of AI-enabled financial systems. The review also develops a conceptual framework linking AI-driven accounts payable automation, accounts receivable automation, invoice processing, reconciliation, fraud detection, cash flow visibility, and automation maturity with operational risk mitigation. By reviewing these areas, the literature review establishes the academic basis for the study, identifies the key variables, supports the research hypotheses, and highlights the gap in prior research concerning the quantitative assessment of AI-driven AP/AR automation as a risk reduction mechanism in U.S. SMEs.

AI-Driven Financial Automation in SMEs

AI-driven financial automation in small and medium-sized enterprises refers to the use of intelligent digital technologies to automate, monitor, analyze, and improve financial processes such as accounts payable, accounts receivable, invoice processing, reconciliation, cash flow tracking, reporting, and internal control. In SMEs, financial automation is especially important because these firms often operate with smaller accounting teams, limited financial resources, and less formalized control systems than larger corporations. AI-driven tools can support financial work by extracting invoice data, classifying transactions, detecting errors, identifying irregular payment patterns, automating approval workflows, and producing real-time financial information for decision-making. This makes AI-driven automation different from basic computerized accounting because it does not only record transactions; it also assists in prediction, exception detection, process monitoring, and decision support. In the SME context, accounting automation has been shown to play an important mediating role in the adoption of AI, particularly because automation helps owners and managers recognize practical benefits such as time savings, efficiency improvement, and better control over financial activities (Manam & Ashfaq, 2022; Rawashdeh et al., 2023). For this study, AI-driven financial automation is directly connected to accounts payable and receivable risk mitigation because AP/AR processes involve frequent transaction handling, document verification, payment timing, customer tracking, vendor coordination, and reconciliation. When these activities remain manual, SMEs may experience duplicate payments, delayed collections, poor invoice visibility, inaccurate balances, and weak fraud detection. AI-driven automation can reduce these weaknesses by creating a more structured financial workflow where invoices, payments, approvals, reminders, reconciliations, and exceptions are processed through intelligent systems. Therefore, in relation to U.S. SMEs, AI-driven financial automation should be viewed not only as a technological improvement but also as an operational control mechanism that strengthens financial accuracy, transparency, and risk responsiveness.

The literature also shows that AI-driven accounting and financial automation has become increasingly relevant because SMEs are under pressure to improve efficiency while maintaining reliable financial information. AI in accounting can support routine financial tasks, but its value becomes stronger when it is integrated into business processes that require timely decisions and reliable documentation. In SMEs, this integration is important because accounting personnel often perform multiple roles, making financial workflows vulnerable to delays, omissions, and inconsistent monitoring. AI-enabled systems can support invoice capture, automated coding, customer payment prediction, vendor-payment scheduling, and exception alerts, which can improve the reliability of AP/AR activities. Research on AI application in SME accounting indicates that artificial intelligence can support accounting modernization by improving data processing, decision-making, and operational efficiency in smaller firms (Nóbrega et al., 2023; Shamsul & Sultan, 2022). Related evidence from digital transformation research also suggests that SME performance is influenced by digital technology, employee digital skills, and digital transformation strategy, meaning that financial automation is most effective when technology adoption is supported by organizational capability and strategic alignment (Binte & Iftekhar, 2022; Teng et al., 2022). This is highly relevant to the present research because AI-driven AP/AR automation cannot reduce operational risk if it is used only as an isolated software function. Its effectiveness depends on whether SMEs have the ability to integrate automation into payment approvals, customer billing, reconciliation routines, fraud monitoring, and cash flow reporting. For example, automated invoice processing can reduce manual data-entry errors, but stronger risk mitigation occurs when this function is connected with approval controls, vendor validation, duplicate-payment checks, and accounting records. Similarly, automated receivables tracking can improve collections, but its full value appears when it is linked with customer risk scoring, payment reminders, cash application, and liquidity monitoring. Thus, AI-driven financial automation in SMEs should be understood as a combination of technology, process redesign, employee readiness, and managerial use of financial intelligence.

Figure 2: AI-Driven Financial Automation Framework for SMEs



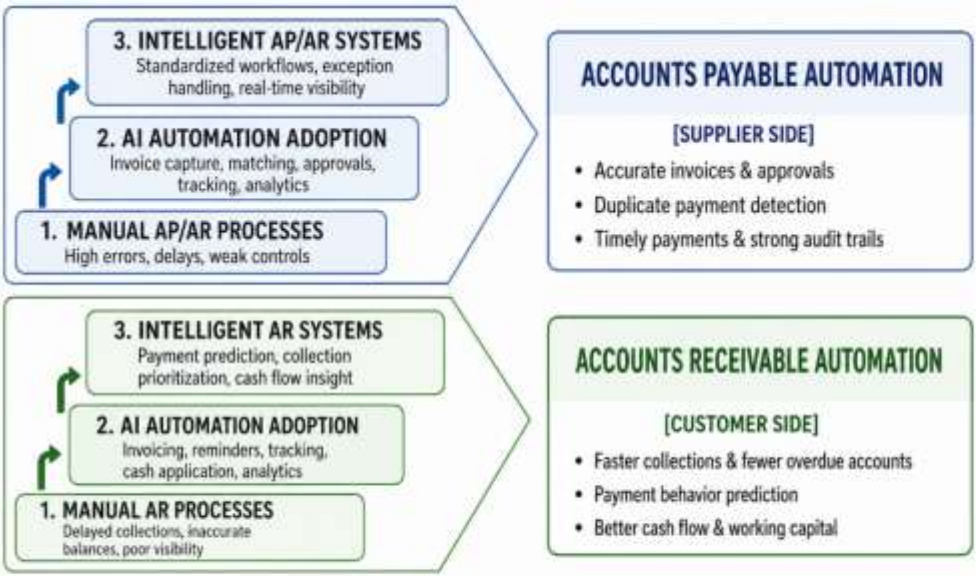
Another important part of AI-driven financial automation in SMEs is the movement toward cloud-based and analytics-supported financial systems. Cloud accounting and data analytics provide SMEs with access to real-time financial information, remote processing, integrated records, and scalable digital tools that can support AP/AR automation. This is important because SMEs may not have the resources to build complex enterprise systems internally, so cloud-based accounting platforms and AI-supported applications offer a more accessible pathway to automation. Evidence from cloud accounting adoption research shows that SMEs use cloud accounting to become more efficient, financially organized, and flexible, especially when adoption is supported by technological, organizational, environmental, vendor-related, and owner-related factors (Albert & Rashedul, 2023; Sastararuji et al., 2022). In addition, big data analytics research in SMEs shows that analytics adoption supports precision decision-making and performance improvement when firms have sufficient readiness, management support, external support, and confidence in the technology (Onyinyechi, 2023; Maroufkhani et al., 2020). These findings are important for this study because AI-driven AP/AR automation depends heavily on accurate, timely, and analyzable financial data. Accounts payable automation needs reliable vendor records, invoice histories, payment terms, approval data, and purchase documentation, while accounts receivable automation requires customer balances, payment patterns, aging schedules, credit behavior, and cash application records. When these data are stored and processed through intelligent platforms, SMEs can identify financial risks earlier and respond more effectively. AI-enabled dashboards can show unpaid invoices, overdue customer accounts, duplicate vendor entries, suspicious transactions, and reconciliation exceptions before they create larger operational problems. Therefore, AI-driven financial automation in SMEs provides a foundation for operational risk mitigation by combining automated processing, real-time financial visibility, predictive analytics, and control-point monitoring. In this research, that foundation supports the examination of how AP automation, AR automation, invoice processing, reconciliation, fraud detection, cash flow visibility, and automation maturity contribute to risk reduction among U.S. SMEs.

Accounts Payable and Accounts Receivable Automation

Accounts payable and accounts receivable automation represent two connected dimensions of financial process modernization because both functions regulate the movement of cash, documents, approvals, and accounting records within the organization. Accounts payable automation focuses on the supplier side of financial operations by converting vendor invoices, purchase records, approvals, matching procedures, payment schedules, and liability updates into a structured digital workflow. Accounts receivable automation focuses on the customer side by supporting invoice issuance, payment reminders, receivables tracking, cash application, collection prioritization, and customer payment prediction. In SMEs, these processes are especially significant because limited staffing and smaller control departments can make manual AP/AR workflows vulnerable to delays, duplicate entries, missing documents, and inaccurate reporting. E-invoicing studies show that digital invoice systems can improve firm performance by reducing paper-based handling, increasing processing speed, and strengthening information exchange between business partners (Hernández-Ortega & Jiménez-Martínez, 2013; Siddique & Aditya, 2023). This is relevant to U.S. SMEs because invoice processing often begins the risk cycle in both AP and AR. If invoice data are captured incorrectly, the error can move through approval, recording, payment, reconciliation, and reporting stages. Automated AP/AR systems reduce this weakness by standardizing document capture, routing, validation, and exception handling. In accounts payable, automation can identify missing purchase orders, duplicate vendor invoices, unusual payment amounts, and incomplete approval trails. In accounts receivable, automation can identify overdue accounts, payment mismatches, customer collection patterns, and cash application errors. Therefore, AP/AR automation should not be understood only as a cost-saving technology. It is also a financial control mechanism that improves the reliability of transaction processing and reduces the operational risks created by fragmented, manual, or poorly monitored accounting workflows.

The development of accounts payable automation is closely associated with invoice digitization, machine learning-based information extraction, and electronic invoicing adoption. Traditional AP processing often requires employees to receive invoices through email, paper, PDF files, or supplier portals; read the invoice manually; enter invoice details into accounting software; check vendor records; match the invoice with purchase orders or receipts; request approval; and prepare payment. Each of these steps creates opportunities for human error, delay, or control failure. Machine learning-based invoice processing has become important because it can extract structured information from unstructured invoice formats, including vendor names, invoice numbers, dates, line items, totals, tax amounts, and payment terms. This capability is useful when SMEs receive invoices from many suppliers with different document layouts. Research on automated invoice processing shows that machine learning can support invoice information extraction, especially when full e-invoicing adoption has not yet been achieved and firms still receive invoices in varied document formats (Krieger et al., 2023; Siam & Sultan, 2023). E-invoicing adoption research also indicates that technological, organizational, and environmental factors shape whether firms accept electronic invoice systems as part of business information system transformation (Marak et al., 2023; Ashfaq & Manam, 2023). These findings are important for this study because AP automation maturity depends on more than software availability. SMEs must have suitable accounting systems, reliable data capture procedures, employee readiness, management support, and vendor compatibility. When these conditions are present, AP automation can strengthen operational risk mitigation by improving invoice accuracy, reducing duplicate payments, accelerating approval workflows, creating stronger audit trails, and supporting timely vendor settlements. In the context of this research, AI-driven AP automation is therefore measured as a set of intelligent capabilities that support invoice capture, approval control, payment validation, duplicate detection, vendor monitoring, and reconciliation.

Figure 3: AI-Driven Accounts Payable and Accounts Receivable Automation Framework

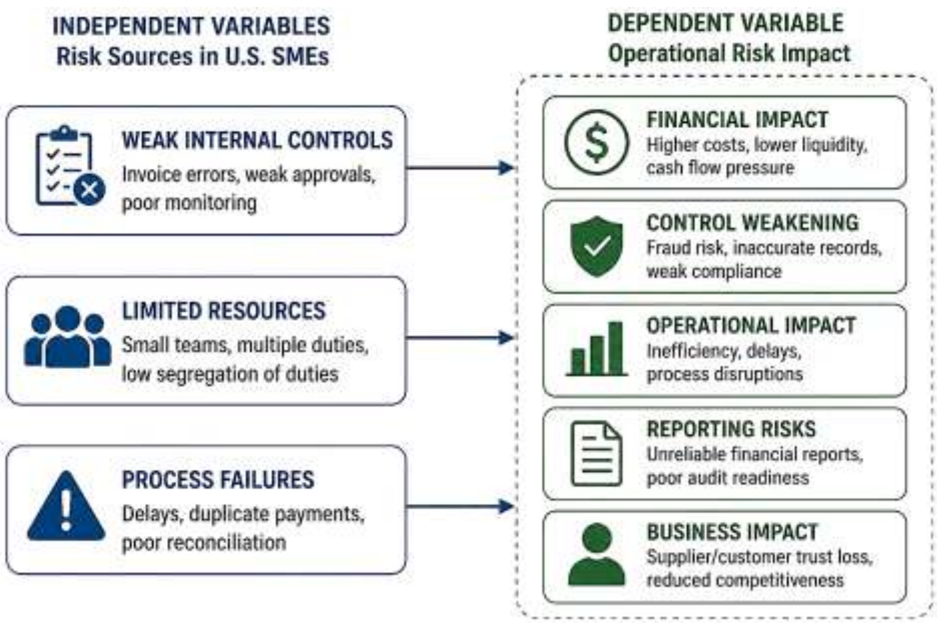


Accounts receivable automation is equally important because it affects liquidity, customer payment discipline, working capital stability, and the reliability of cash flow information. AR processes begin when a firm issues customer invoices and continue through payment tracking, collection follow-up, cash application, dispute handling, customer account updates, and receivables reporting. Manual AR management can cause delayed collections, unapplied payments, inaccurate customer balances, weak visibility into overdue accounts, and poor cash forecasting. These risks are critical for SMEs because cash flow pressure can quickly affect payroll, vendor payments, loan obligations, inventory purchases, and daily operating capacity. Machine learning has become relevant in AR automation because firms can use historical customer payment data to predict payment timing and support proactive cash management. Research on accounts receivables management shows that machine learning algorithms can predict customer payment dates and help firms move from reactive collection practices to more proactive cash flow planning (Kureljusic & Metz, 2023; Mainuddin & Chandra, 2023). This supports the present study because AI-driven AR automation is expected to improve operational risk mitigation through better receivables tracking, collection prioritization, and payment behavior analysis. Accounts payable and receivable are also central components of working capital management, meaning that ineffective AP/AR control can directly affect profitability, liquidity, and operational performance. Evidence from working capital research shows that receivables, payables, inventory, and cash conversion decisions are closely connected to firm performance and financial efficiency (Enqvist et al., 2014; Robel & Aminul, 2023). In this study, AP/AR automation is therefore treated as an integrated risk-control system rather than two isolated accounting functions. When AI tools support both payable and receivable workflows, SMEs can gain better visibility over outgoing and incoming cash, detect irregularities faster, reduce transaction mismatches, improve reconciliation, and make more reliable operational decisions.

Operational Risk in U.S. SMEs

Operational risk in U.S. small and medium-sized enterprises refers to the possibility of loss, disruption, inefficiency, or process failure caused by weaknesses in internal procedures, human error, system limitations, fraud exposure, documentation gaps, poor monitoring, or ineffective financial controls. In the context of this study, operational risk is directly linked to accounts payable and accounts receivable because these functions involve frequent transactions, invoice verification, payment authorization, customer billing, collection tracking, reconciliation, and cash flow monitoring. SMEs are especially exposed to operational risk because their financial operations are often handled by small teams where one employee may perform several duties, such as recording invoices, approving payments, following up with customers, reconciling accounts, and preparing reports. This concentration of responsibility can create weaknesses in segregation of duties, error detection, fraud prevention, and audit readiness. Risk management literature shows that SMEs often require different risk management approaches from large firms because of their limited resources, informal structures, and lower capacity to implement complex risk systems (Lima et al., 2020; Sazzadul, 2023). This makes operational risk in SMEs both practical and strategic, since day-to-day process failures can affect liquidity, supplier trust, customer relationships, compliance quality, and business continuity. For example, a delayed vendor payment may damage supplier reliability, while poor receivables monitoring may create cash shortages. Similarly, weak reconciliation may cause inaccurate financial statements, and inadequate invoice control may increase duplicate payments or unauthorized disbursements. In U.S. SMEs, where competitiveness often depends on financial flexibility and operational speed, AP/AR risk cannot be treated as a minor administrative concern. It must be understood as a core business risk that affects the firm's ability to maintain accurate records, protect financial resources, monitor obligations, and make informed decisions. Therefore, operational risk in SMEs provides the foundation for examining whether AI-driven AP/AR automation can strengthen process accuracy and financial control.

Figure 4: Operational Risk Sources and Impacts in U.S. SMEs



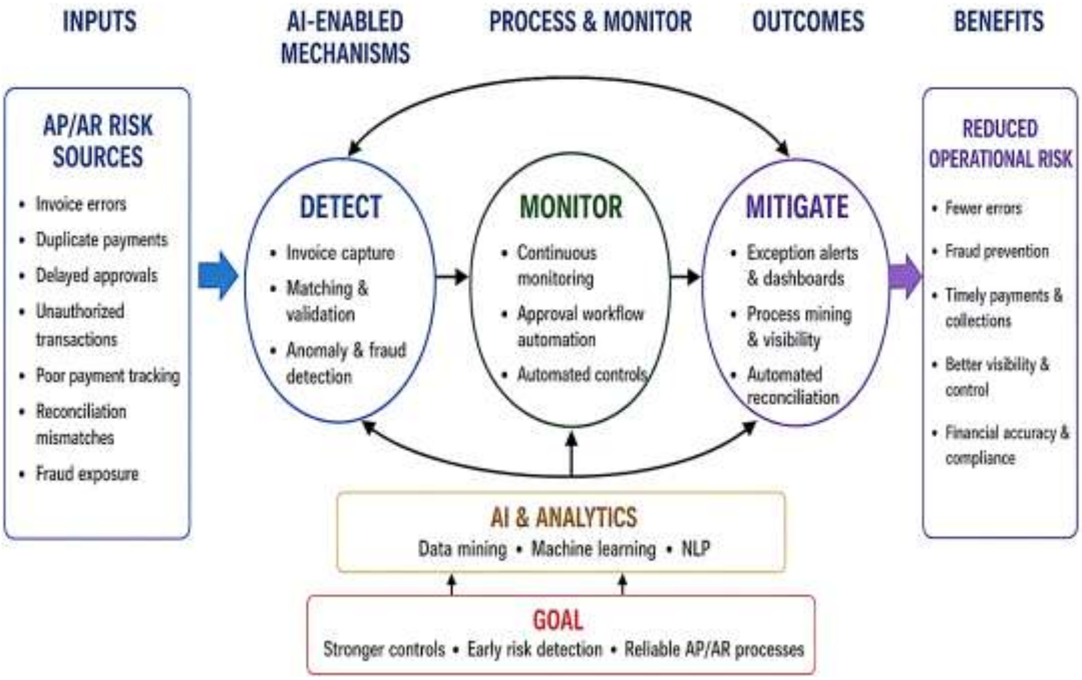
A major source of operational risk in SMEs is the weakness of internal control systems. Internal control refers to the policies, procedures, checks, approvals, documentation practices, and monitoring activities that help an organization safeguard assets, ensure accurate records, comply with rules, and reduce errors or misconduct. In AP/AR workflows, internal control includes invoice verification, vendor validation, approval routing, duplicate payment checks, customer account monitoring, cash application, reconciliation, and exception review. When these controls are weak, SMEs may face operational failures such as inaccurate invoice entry, unauthorized payments, delayed collections, missing documentation, unposted receipts, and unreliable financial reports. Research on SMEs indicates that effective internal control can support sustainable growth because it strengthens governance, reduces misconduct, improves information quality, and supports better operational decisions (Rashedul, 2024; Wang et al., 2019). This is highly relevant to AI-driven AP/AR automation because automation can serve as a digital extension of internal control. For instance, AI-enabled invoice processing can reduce manual entry mistakes by extracting and validating invoice data. Automated approval workflows can improve accountability by recording who approved each invoice and when. AI-based duplicate detection can prevent repeated payments to vendors, while automated reconciliation can identify mismatches between invoices, payments, customer receipts, and ledger balances. These functions are important for SMEs because manual monitoring may not be consistent when finance teams are small or overextended. Operational risk also increases when SMEs lack timely visibility into payables and receivables. If managers cannot see which invoices are overdue, which customer payments are delayed, or which transactions remain unmatched, they may respond to risks too late. AI-driven automation can reduce this weakness by providing alerts, dashboards, exception reports, and predictive indicators. Therefore, internal control weakness is not only a traditional accounting problem; it is also a technological and operational problem that can be addressed through intelligent AP/AR automation.

Operational risk in SMEs is also connected to financial performance, operational performance, and business resilience. Financial process failures can reduce profitability, increase indebtedness, weaken liquidity, and limit the firm's ability to meet obligations. Recent empirical research on SMEs shows that operational risk management has a significant relationship with financial management outcomes, including profitability, indebtedness, and the ability to pay obligations (Hudáková et al., 2023; Istiaq, 2024). This connection is important for the present study because AP and AR are directly tied to cash movement. Accounts payable risk can increase costs through penalties, duplicate payments, supplier disputes, or inaccurate liability recognition. Accounts receivable risk can reduce liquidity through delayed collections, unpaid invoices, weak customer follow-up, and poor payment forecasting. Research on enterprise risk management in small and medium family enterprises also suggests that risk management practices are shaped by organizational characteristics, leadership, and the way firms structure their decision-making processes (Glowka et al., 2021; Istiaq & Hasan Or, 2024). This matters for U.S. SMEs because many smaller firms are owner-managed or closely controlled, meaning that risk decisions may depend heavily on managerial awareness and willingness to adopt structured controls. In addition, business risk research shows that risk sources can affect operational performance and managerial decision-making in SMEs, particularly when firms lack clear methods for identifying and measuring risk (Siddique, 2024; Virglerova et al., 2022). AI-driven AP/AR automation is relevant because it gives SMEs practical tools for identifying risks earlier, measuring transaction exceptions, and reducing uncertainty in financial workflows. For example, automated receivables aging can identify collection risk, AI-based anomaly detection can flag suspicious transactions, and reconciliation tools can expose incomplete or inconsistent records. These capabilities support the view that operational risk mitigation is not only about avoiding losses but also about improving financial visibility, process discipline, and decision quality. In this study, operational risk in U.S. SMEs is therefore examined through invoice accuracy, payment reliability, fraud detection, reconciliation quality, cash flow visibility, and automation maturity.

AI-Enabled Risk Mitigation Mechanisms in AP/AR Workflows

AI-enabled risk mitigation mechanisms in accounts payable and accounts receivable workflows refer to the intelligent tools, automated controls, analytical procedures, and monitoring functions that help SMEs identify, prevent, and reduce financial process risks. In AP/AR operations, risks usually arise from invoice errors, duplicate payments, delayed approvals, unauthorized transactions, poor customer payment tracking, incomplete documentation, reconciliation mismatches, and weak fraud detection. AI-enabled mechanisms reduce these risks by converting manual control activities into automated and continuously monitored processes. For example, invoice capture tools can extract vendor details, invoice numbers, dates, line items, tax amounts, and payment terms with less dependence on manual entry. Approval workflow automation can route invoices to authorized personnel and create digital records of each approval action. Automated matching can compare invoices with purchase orders, receipts, customer payments, and ledger records. These functions support continuous monitoring, which allows controls to be assessed more frequently instead of being checked only after errors occur. A pilot implementation of continuous auditing at Siemens showed that technology-enabled control monitoring can support frequent assessment of business process controls and improve the visibility of control exceptions within organizational systems (Alles et al., 2006; Ibne & Aditya, 2024).

Figure 5: AI-Enabled Risk Mitigation Mechanisms in AP/AR Workflows



This idea is highly relevant to U.S. SMEs because many smaller firms do not have the personnel capacity for constant manual review of AP/AR transactions. When AI tools monitor transactions continuously, unusual patterns can be detected earlier, and managers can respond before errors become larger financial problems. Therefore, AI-enabled AP/AR risk mitigation is not limited to automation speed; it also involves stronger control visibility, earlier exception detection, better documentation, and more reliable transaction governance.

Another major AI-enabled risk mitigation mechanism is fraud and anomaly detection. AP/AR workflows are vulnerable to different forms of financial irregularity, including false invoices, duplicate vendor records, inflated billing, unauthorized payment changes, suspicious customer activity, and abnormal transaction timing. Traditional fraud detection usually depends on manual review, sample-based checking, or rule-based alerts, which may not be sufficient when transaction volume increases or when fraudulent behavior appears similar to normal activity. Data mining and machine learning approaches are useful because they can identify hidden patterns, classify transactions, and detect irregular relationships within large financial datasets. A major review of financial fraud detection literature found that data mining techniques such as decision trees, neural networks, Bayesian networks, support vector machines, and clustering have been widely applied to detect different forms of financial fraud (Mainuddin, 2024; Ngai et al., 2011). Intelligent fraud detection research also shows that computational methods can strengthen detection because they are able to process large amounts of financial data and learn from changing fraud patterns (Sultan, 2024; West & Bhattacharya, 2016). In AP automation, these techniques can help identify duplicate invoices, unusual vendor payments, abnormal approval sequences, and suspicious changes in payment details. In AR automation, they can help detect irregular customer payment behavior, unusual write-offs, inconsistent cash applications, and accounts that show signs of collection risk. More recent research on AI and natural language processing in fraud detection also shows that intelligent systems can analyze textual and transactional information to support fraud prevention in financial contexts (Golam, 2025; Sood et al., 2023). For SMEs, these mechanisms are important because fraud losses and transaction errors can have stronger financial consequences than they would in larger firms with greater reserves.

AI-enabled risk mitigation in AP/AR workflows also depends on process visibility and evidence-based control analysis. One weakness of traditional AP/AR management is that firms may know the final accounting outcome but may not clearly understand how the process occurred, where delays happened, who handled each transaction, or which control points failed. Process mining addresses this weakness by using system event logs to reconstruct actual business processes and compare them with expected procedures. This is useful for AP/AR workflows because invoice receipt, approval, matching, payment, customer billing, collection follow-up, cash application, and reconciliation all leave digital traces when processed through accounting or enterprise systems. A field study on process mining in auditing showed that event logs can be used as analytical evidence to examine business processes and identify deviations from expected process behavior (Albert, 2025; Jans et al., 2014). In this study, such logic supports the AI-enabled control point analysis proposed for the results chapter. AP/AR automation can be evaluated by examining how well AI strengthens invoice capture, approval routing, three-way matching, duplicate payment detection, customer payment tracking, cash application, reconciliation, and fraud alerts. These control points represent the operational locations where risk is either created or reduced. When SMEs use AI-enabled dashboards and exception reports, they can identify delayed invoices, unmatched transactions, overdue accounts, unusual payment behavior, and weak approval trails. This improves operational risk mitigation because risk becomes visible at the transaction and workflow levels rather than only appearing in monthly reports or after financial loss has occurred. Therefore, AI-enabled risk mitigation mechanisms combine continuous monitoring, fraud detection, anomaly identification, process mining, automated reconciliation, and control-point visibility to strengthen AP/AR reliability in U.S. SMEs.

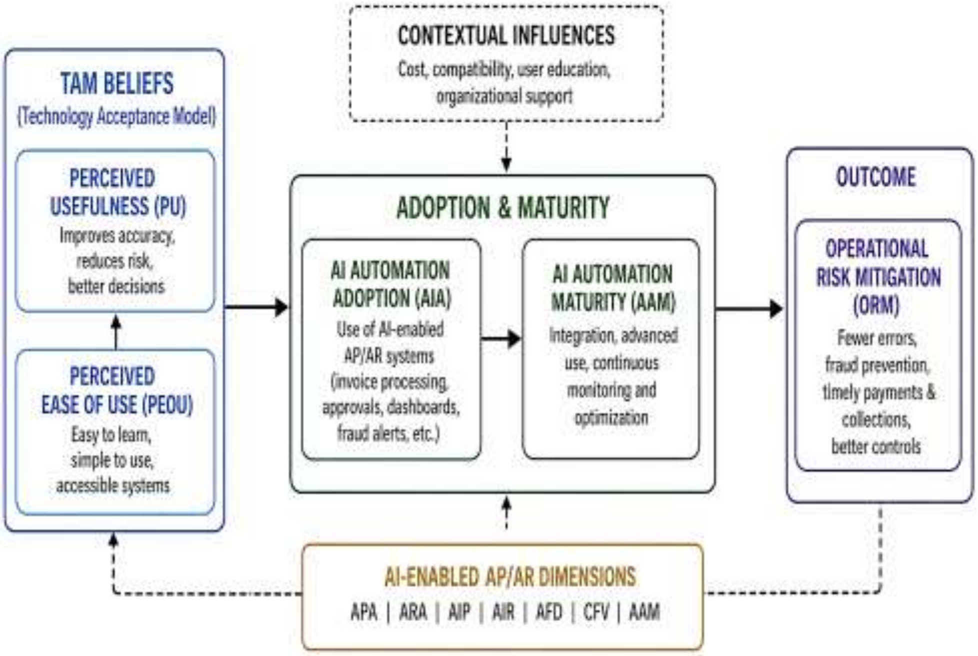
Theoretical Framework: Technology Acceptance Model and AI Automation Adoption

The theoretical framework for this study is grounded in the **Technology Acceptance Model (TAM)**, which explains how users accept and use technology based mainly on their beliefs about usefulness, ease of use, and expected performance outcomes. In this research, the model is applied to AI-driven accounts payable and accounts receivable automation in U.S. SMEs because the successful adoption of AI-based financial systems depends not only on the availability of software but also on whether finance employees, accountants, managers, and business owners believe that the technology improves their daily work. The Technology Acceptance Model is suitable for this study because AP/AR automation requires users to interact with invoice-processing tools, automated approval systems, reconciliation dashboards, fraud alerts, cash flow reports, and payment-tracking functions. If users perceive these systems as useful for reducing invoice errors, duplicate payments, delayed collections, reconciliation mismatches, and fraud exposure, they are more likely to accept and use them consistently. A meta-analysis of the Technology Acceptance Model confirms that perceived usefulness and perceived ease of use are reliable predictors of technology acceptance across different information system contexts, which supports the use of TAM in this study's financial automation setting (Anick, 2025a; King & He, 2006). This is important for U.S. SMEs because smaller firms may be cautious about adopting AI technologies due to cost concerns, limited technical expertise, and uncertainty about operational value. Therefore, the framework assumes that AI-driven AP/AR automation becomes meaningful for operational risk mitigation when users perceive that it improves financial accuracy, strengthens control, reduces manual workload, and supports better decision-making. In this study, perceived usefulness is connected to risk reduction benefits, while perceived ease of use is connected to the simplicity, accessibility, and usability of AI-enabled accounting systems.

The Technology Acceptance Model also helps explain why AI automation maturity may differ among SMEs. Some firms may remain at a manual-processing stage because employees do not fully understand AI tools or do not believe that automation is necessary. Other firms may adopt basic digital accounting systems but fail to integrate intelligent invoice processing, anomaly detection, automated reconciliation, or predictive cash flow reporting. More mature firms may use AI-enabled AP/AR systems as part of a broader financial control environment. Literature on technology acceptance shows that TAM has remained widely used because it provides a flexible structure for understanding user attitudes toward emerging technologies, system design, organizational adoption, and behavioral intention (Anick, 2025b; Marangunić & Granić, 2015). In this study, this flexibility allows the model to be adapted to AP/AR automation by linking perceived usefulness with operational risk mitigation and linking perceived ease of use with automation adoption maturity. In addition, extended technology acceptance research suggests that user behavior is influenced by factors such as performance expectancy, effort expectancy, facilitating conditions, price value, habit, and user experience (Atif, 2025;

Venkatesh et al., 2012). These factors are relevant to SMEs because AI-driven AP/AR automation may be adopted only when firms believe the system is affordable, compatible with existing accounting practices, easy to learn, and capable of improving financial performance. For example, an SME may adopt invoice automation if employees believe that it reduces data-entry errors and approval delays. Similarly, an SME may adopt AI-supported receivables tracking if managers believe that it improves collection visibility and cash flow planning. Therefore, the theoretical framework supports the view that technology acceptance influences actual AI automation use, and actual use influences the degree to which AP/AR automation contributes to operational risk mitigation.

Figure 6: Technology Acceptance Model (TAM) Framework for AI-Driven AP/AR Automation and Operational Risk Mitigation



For this study, the Technology Acceptance Model is translated into a quantitative structure by linking AI adoption variables with operational risk mitigation. The main dependent variable is operational risk mitigation, while the independent variables include accounts payable automation, accounts receivable automation, AI-enabled invoice processing, AI-enabled reconciliation, AI-based fraud detection, cash flow visibility, and AI automation maturity. Recent meta-analytic work on technology acceptance shows that perceived usefulness, ease of use, attitude, and behavioral intention remain important pathways for explaining technology adoption, although their strength may differ across settings and user groups (Onyinyechi, 2025; Scherer et al., 2019). Similarly, research on unified technology acceptance models suggests that adoption models should consider both core acceptance beliefs and contextual factors such as technology compatibility, user education, cost, and organizational conditions (Blut et al., 2022; Khalid, 2025). Based on this theoretical direction, the present study assumes that SMEs with higher acceptance and more mature use of AI-driven AP/AR automation will report stronger operational risk mitigation. The theoretical logic of TAM in this study can be expressed in LaTeX equation format as follows:

$$PEOU \rightarrow PU$$
$$PU + PEOU \rightarrow AIA$$
$$AIA \rightarrow AAM$$
$$AAM \rightarrow ORM$$

Where:

$$PEOU = \text{Perceived Ease of Use}$$

PU = Perceived Usefulness
AIA = AI Automation Adoption
AAM = AI Automation Maturity
ORM = Operational Risk Mitigation

The full theoretical relationship can also be written as:

$$ORM = f(PU, PEOU, AIA, AAM)$$

This means that operational risk mitigation is influenced by perceived usefulness, perceived ease of use, AI automation adoption, and AI automation maturity. However, for the statistical testing of the whole study, the best formula is a multiple regression model because it allows the researcher to test the combined predictive effect of several AI automation dimensions on operational risk mitigation. The proposed regression equation is:

$$ORM = \beta_0 + \beta_1 APA + \beta_2 ARA + \beta_3 AIP + \beta_4 AIR + \beta_5 AFD + \beta_6 CFV + \beta_7 AAM + \varepsilon$$

Where:

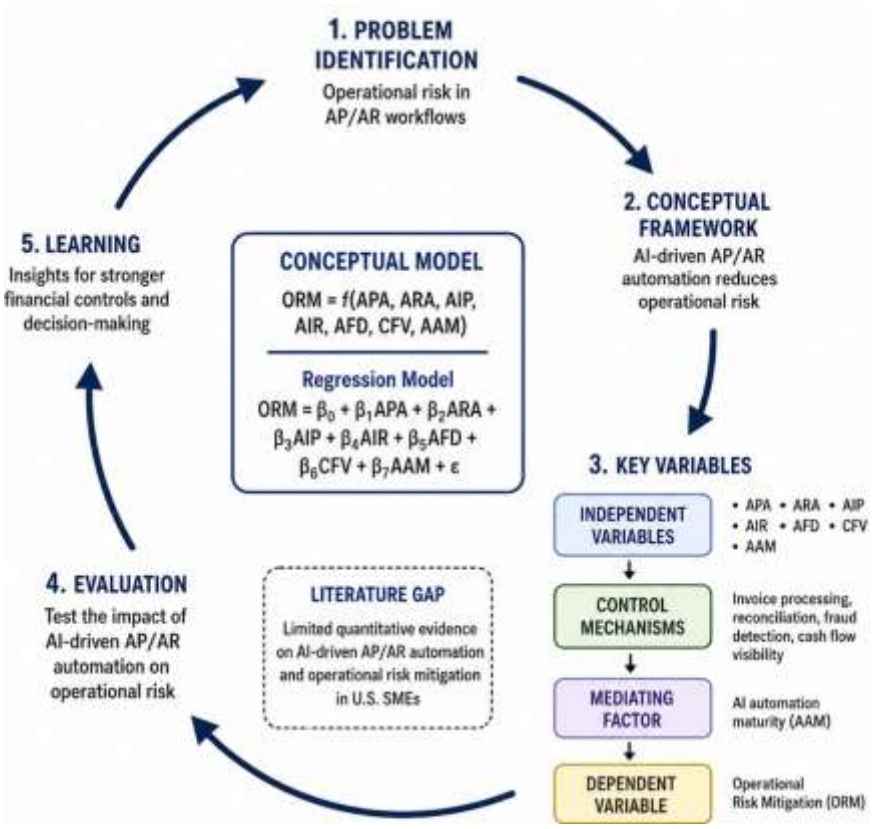
ORM = Operational Risk Mitigation
APA = Accounts Payable Automation
ARA = Accounts Receivable Automation
AIP = AI-Enabled Invoice Processing
AIR = AI-Enabled Reconciliation
AFD = AI-Based Fraud Detection
CFV = Cash Flow Visibility
AAM = AI Automation Maturity
β_0 = Constant
$\beta_1 - \beta_7$ = Regression Coefficients
ε = Error Term

This model is appropriate because it connects the theoretical acceptance of AI-enabled systems with measurable risk-reduction outcomes in U.S. SMEs.

Conceptual Framework and Literature Gap

The conceptual framework of this study connects AI-driven accounts payable and accounts receivable automation with operational risk mitigation in U.S. small and medium-sized enterprises. The framework assumes that AI-enabled financial automation becomes valuable when it strengthens process visibility, improves transaction accuracy, supports timely decision-making, and reduces weaknesses in internal financial controls. In this study, the independent variables are accounts payable automation, accounts receivable automation, AI-enabled invoice processing, AI-enabled reconciliation, AI-based fraud detection, cash flow visibility, and AI automation maturity. The dependent variable is operational risk mitigation. The logic behind this framework is that AI automation improves the way SMEs capture, validate, route, monitor, and reconcile financial transactions. Big data analytics capability research shows that organizations gain value when technological, human, and organizational resources are combined into a capability that supports better performance (Gupta & George, 2016; Hasan, 2025). This is relevant to AP/AR automation because software alone cannot reduce operational risk unless employees, data quality, control routines, and management support are also present. Business intelligence and analytics research in management accounting further shows that analytical systems can support planning, performance measurement, reporting, and decision control, which are closely connected to AP/AR risk mitigation (Siddique & Prakash, 2025; Rikhardsson & Yigitbasioglu, 2018). Therefore, the conceptual framework views AI-driven AP/AR automation as a multidimensional capability rather than a single technology. Accounts payable automation is expected to reduce risks related to supplier invoices, approval delays, duplicate payments, and vendor payment errors. Accounts receivable automation is expected to reduce risks related to delayed collections, inaccurate customer balances, poor cash application, and weak payment tracking. Invoice processing, reconciliation, fraud detection, and cash flow visibility are included as specific control mechanisms because these functions represent the points where financial risks are most likely to appear or be reduced within SME accounting workflows.

Figure 7: Conceptual Framework and Literature Gap for AI-Driven AP/AR Automation in U.S. SMEs



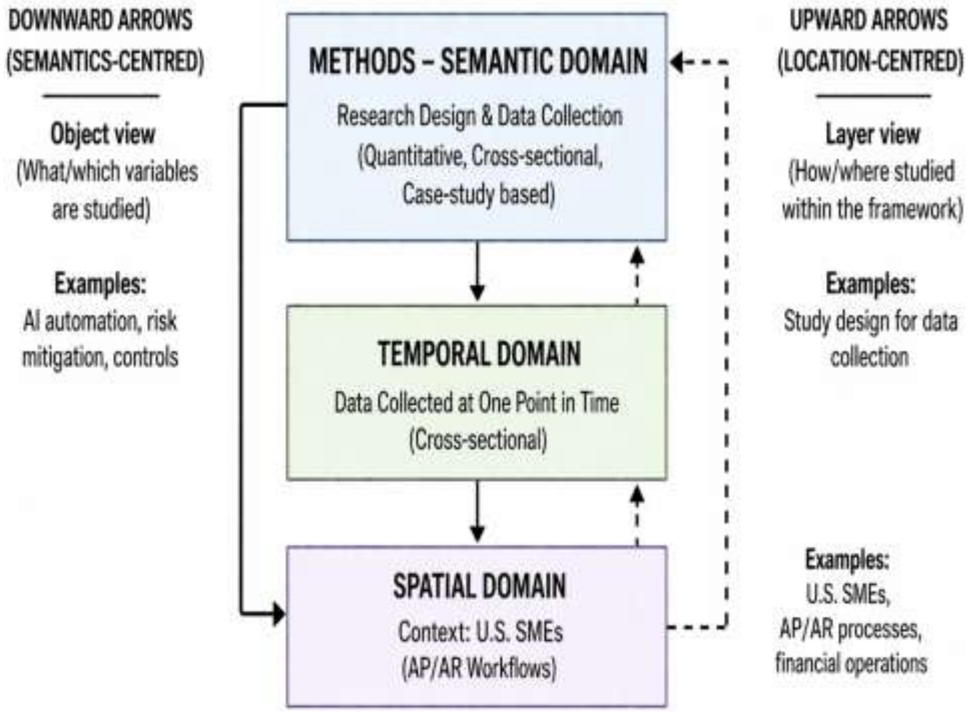
The conceptual framework also reflects the idea that digital technologies produce stronger outcomes when they are integrated into organizational processes and supported by dynamic capabilities. IT-enabled dynamic capability research shows that information technology can improve firm outcomes when organizations use it to sense, coordinate, learn, integrate, and reconfigure operational resources (Aminul, 2025; Mikalef & Pateli, 2017). This is important for the present study because AI-driven AP/AR automation requires SMEs to redesign how financial tasks are performed, monitored, and evaluated. For example, invoice capture must be connected to approval workflow, approval workflow must be connected to payment validation, payment records must be connected to reconciliation, and reconciliation results must be connected to risk reporting. If these functions remain disconnected, AI adoption may improve speed without producing meaningful risk mitigation. Big data technology research also shows that digital technologies may create transactional, strategic, transformational, and informational benefits, while also requiring attention to risks and organizational readiness (Aminul & Zakia, 2025; Raguseo, 2018). In this study, the expected benefit is operational risk mitigation, while readiness is represented through AI automation maturity. AI automation maturity describes the degree to which SMEs move from manual processing to basic digital processing, partial AI automation, integrated AI automation, and predictive risk automation. This maturity dimension is important because two SMEs may both claim to use automation, yet their actual levels of intelligent processing and risk control may be very different. One firm may only use accounting software for recording transactions, while another may use AI-based invoice extraction, duplicate payment detection, predictive receivables monitoring, and automated reconciliation alerts. Therefore, the conceptual

framework assumes that higher maturity levels will strengthen the relationship between AP/AR automation and operational risk mitigation.
The major literature gap addressed by this study is the limited quantitative evidence on how AI-driven AP/AR automation reduces operational risk specifically in U.S. SMEs. Prior research has examined digital transformation, business analytics, AI adoption, accounting automation, e-invoicing, financial fraud detection, risk management, and technology acceptance, but these areas are often studied separately. Digital transformation research highlights the broad role of technology in reshaping firms, industries, and business models, yet it often does not focus deeply on AP/AR control points in SMEs (Kraus et al., 2021; Sheak, 2025). Accounting and analytics studies explain the value of data-driven systems, but many do not test a specific AP/AR-based operational risk model using survey data from SMEs. Risk management studies explain that SMEs face process, financial, and control weaknesses, but they often do not measure whether AI-enabled invoice processing, reconciliation, fraud detection, and cash flow visibility predict risk mitigation. Therefore, this study fills the gap by developing a focused conceptual model in which AI-driven AP/AR automation is treated as a practical financial control capability. The full conceptual relationship for the study can be written as: $ORM = f(APA, ARA, AIP, AIR, AFD, CFV, AAM)$ where ORM represents operational risk mitigation, APA represents accounts payable automation, ARA represents accounts receivable automation, AIP represents AI-enabled invoice processing, AIR represents AI-enabled reconciliation, AFD represents AI-based fraud detection, CFV represents cash flow visibility, and AAM represents AI automation maturity. For empirical testing, the model can be expressed as: $ORM = \beta_0 + \beta_1 APA + \beta_2 ARA + \beta_3 AIP + \beta_4 AIR + \beta_5 AFD + \beta_6 CFV + \beta_7 AAM + \varepsilon$This framework allows the study to test whether AI-driven AP/AR automation significantly predicts operational risk mitigation in U.S. SMEs.

METHODS

This study has adopted a quantitative, cross-sectional, case-study–based research design to examine the effect of AI-driven accounts payable and accounts receivable automation on operational risk mitigation in U.S. small and medium-sized enterprises. The quantitative design has been selected because the study has measured respondents' perceptions through numerical Likert-scale responses and has analyzed the relationships among the study variables using statistical techniques. The cross-sectional approach has been used because data have been collected at a single point in time from respondents who have experience with finance, accounting, accounts payable, accounts receivable, or digital financial systems in SMEs. The case study context of the research has focused on U.S. SMEs because these firms often depend on limited financial personnel, smaller accounting teams, and less formalized internal control systems, making them suitable for examining how AI-enabled automation may reduce operational risks in AP/AR workflows.
The population of the study has included SME owners, finance managers, accountants, bookkeepers, financial controllers, operations managers, and employees involved in accounts payable and receivable activities within U.S. SMEs. The unit of analysis has been the individual respondent's perception of AI-driven AP/AR automation and its contribution to operational risk mitigation within their organization. A purposive sampling strategy has been used because the study has targeted respondents who have relevant knowledge of accounting processes, invoice management, payment tracking, reconciliation, fraud monitoring, cash flow visibility, or AI-enabled financial automation. This approach has helped ensure that the collected responses are relevant to the research objectives and hypotheses.
Data have been collected through a structured questionnaire designed specifically for this study. The questionnaire has included sections on demographic information, accounts payable automation, accounts receivable automation, AI-enabled invoice processing, AI-enabled reconciliation, AI-based fraud detection, cash flow visibility, AI automation maturity, and operational risk mitigation. The instrument has used a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree, to measure respondents' level of agreement with each statement. This scale has allowed the study to quantify perceptions and apply descriptive statistics, correlation analysis, and regression modeling.

Figure 8: Research Methodology Framework for AI-Driven AP/AR Automation Study in U.S. SMEs



Before the main data collection, pilot testing has been conducted with a small group of respondents to assess the clarity, relevance, wording, and consistency of the questionnaire items. Feedback from the pilot test has been used to refine ambiguous items and improve the overall quality of the instrument. Validity has been addressed by aligning the questionnaire items with the research objectives, hypotheses, conceptual framework, and major constructs of the study. Content validity has been ensured through careful review of the items, while construct validity has been supported by grouping the items according to the key variables.

Reliability has been tested using Cronbach's Alpha, with values of 0.70 and above considered acceptable for internal consistency. Data analysis has been conducted using SPSS, which has been used to generate frequency tables, percentages, means, standard deviations, reliability results, Pearson correlation coefficients, and regression outputs. Microsoft Excel has been used for initial data organization and screening. EndNote has been used for reference management, citation organization, and preparation of the APA 7th edition reference list. Together, these tools have supported accurate data handling, statistical analysis, and scholarly documentation for the study.

DATA ANALYSIS AND PRESENTATION

The data have been introduced using a quantitative structure because the study has examined measurable relationships between AI-driven accounts payable and receivable automation and operational risk mitigation in U.S. SMEs. A total of 220 valid responses have been retained for analysis after data screening, and all major study variables have been measured using a five-point Likert scale. This scale has allowed respondents to express their level of agreement with statements relating to accounts payable automation, accounts receivable automation, invoice processing, reconciliation, fraud detection, cash flow visibility, AI automation maturity, and operational risk mitigation. The data have been analyzed in SPSS using descriptive statistics, reliability testing, Pearson correlation analysis, multiple regression analysis, and hypotheses testing. The interpretation scale has shown that mean scores between 3.41 and 4.20 represent a high level of agreement, while mean scores between 4.21 and 5.00 represent a very high level of agreement.

Introduction to the Data

Table 1: Summary of Dataset and Likert-Scale Interpretation

Item	Result/Description
Total valid respondents	220
Research design	Quantitative, cross-sectional, case-study–based
Measurement scale	Five-point Likert scale
Scale range	1 = Strongly Disagree to 5 = Strongly Agree
Main dependent variable	Operational Risk Mitigation
Main independent variables	APA, ARA, AIP, AIR, AFD, CFV, AAM
Statistical software used	SPSS
Main analyses conducted	Descriptive statistics, reliability test, correlation, regression, hypotheses testing
Significance level	0.05
Theory linked to results	Technology Acceptance Model

Likert-scale interpretation

Mean Score Range	Interpretation
1.00–1.80	Very Low
1.81–2.60	Low
2.61–3.40	Moderate
3.41–4.20	High
4.21–5.00	Very High

The data have been introduced using a quantitative structure because the study has examined measurable relationships between AI-driven accounts payable and receivable automation and operational risk mitigation in U.S. SMEs. A total of 220 valid responses have been retained for analysis after data screening, and all major study variables have been measured using a five-point Likert scale. This scale has allowed respondents to express their level of agreement with statements relating to accounts payable automation, accounts receivable automation, invoice processing, reconciliation, fraud detection, cash flow visibility, AI automation maturity, and operational risk mitigation. The data have been analyzed in SPSS using descriptive statistics, reliability testing, Pearson correlation analysis, multiple regression analysis, and hypotheses testing. The interpretation scale has shown that mean scores between 3.41 and 4.20 represent a high level of agreement, while mean scores between 4.21 and 5.00 represent a very high level of agreement. This interpretation has been important because the study has relied on respondent perceptions to assess how AI-enabled AP/AR automation has contributed to risk control. The dataset has also been aligned with the Technology Acceptance Model because respondents' perceptions of AI usefulness, ease of use, and automation maturity have been reflected through their agreement with automation-related items. In this study, higher mean scores have indicated that respondents have viewed AI-enabled systems as useful for reducing invoice errors, improving reconciliation, detecting fraud, improving cash flow visibility, and strengthening operational control. Therefore, the data structure has supported the research objectives by allowing the study to test whether AI-driven financial automation has functioned as a practical operational risk mitigation mechanism in U.S. SMEs.

Response Rate

Table 2: Response Rate of Survey Participants

Survey Distribution Status	Frequency	Percentage
Questionnaires distributed	260	100.0%
Questionnaires returned	235	90.4%
Incomplete responses removed	15	5.8%
Valid responses used for analysis	220	84.6%

The response rate has indicated that the study has obtained a strong level of participation from respondents who have been knowledgeable about SME financial processes, AP/AR workflows, or AI-enabled financial automation. Out of 260 questionnaires distributed, 235 responses have been returned, giving an initial return rate of 90.4%. After data screening, 15 responses have been excluded because they contained incomplete answers or missing values that could affect the reliability of the analysis. As a result, 220 valid responses have been retained, representing a final usable response rate of 84.6%. This response rate has been considered suitable for quantitative analysis because the sample has been large enough to conduct descriptive statistics, reliability testing, correlation analysis, and multiple regression analysis. The response rate has also strengthened the trustworthiness of the study because the retained sample has provided a sufficient basis for examining the relationships between AI-driven AP/AR automation and operational risk mitigation. In connection with the Technology Acceptance Model, the high response rate has suggested that respondents have had enough familiarity with digital financial processes to provide meaningful views on AI usefulness, ease of use, and automation maturity. Since the study has focused on U.S. SMEs, the participation of finance-related respondents has supported the objective of understanding how AI automation has affected invoice processing, reconciliation, fraud detection, cash flow visibility, and operational risk control. The final valid sample of 220 respondents has therefore provided a reliable foundation for testing the seven hypotheses. It has also enabled the study to examine whether SMEs with higher levels of automation maturity have reported stronger operational risk mitigation outcomes. Overall, the response rate has shown that the dataset has been adequate, relevant, and suitable for the statistical procedures used in this chapter.

Demographic Profile of Respondents

Table 3: Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage
Job role	SME owner/manager	42	19.1%
Job role	Finance manager/controller	51	23.2%
Job role	Accountant/bookkeeper	67	30.5%
Job role	Operations manager	34	15.5%
Job role	AP/AR staff	26	11.8%
Years of experience	1–3 years	38	17.3%
Years of experience	4–6 years	61	27.7%
Years of experience	7–10 years	72	32.7%
Years of experience	Above 10 years	49	22.3%
SME size	10–49 employees	63	28.6%
SME size	50–99 employees	74	33.6%
SME size	100–249 employees	83	37.7%
AI automation exposure	Low	39	17.7%
AI automation exposure	Moderate	78	35.5%
AI automation exposure	High	103	46.8%

The demographic profile has shown that the respondents have represented a relevant mix of SME financial and operational decision-makers. The largest group has consisted of accountants and bookkeepers, representing 30.5% of the sample, followed by finance managers and controllers at 23.2%. SME owners and managers have represented 19.1%, operations managers have represented 15.5%, and AP/AR staff have represented 11.8%. This distribution has been appropriate because the study has required respondents who understand invoice processing, payment tracking, reconciliation, fraud monitoring, and operational control. In terms of experience, most respondents have had practical exposure to financial operations, with 32.7% having 7–10 years of experience and 22.3% having more than 10 years of experience. This has strengthened the credibility of the responses because experienced respondents have been more likely to understand the operational risks associated with manual and automated AP/AR workflows. The SME size distribution has also been balanced, with 28.6% from firms with 10–49 employees, 33.6% from firms with 50–99 employees, and 37.7% from firms with 100–249 employees. This has supported the case-study context because the sample has included small and medium-sized enterprises with different operational capacities. The AI automation exposure results have shown that 46.8% of respondents have reported high exposure to AI-enabled financial automation, while **35.5%** have reported moderate exposure. This has been important for linking the findings to the Technology Acceptance Model, as respondents with higher automation exposure have been more likely to evaluate perceived usefulness, ease of use, and actual use of AI systems. The demographic results have therefore supported the reliability of the findings by showing that the respondents have had relevant professional roles, sufficient experience, and meaningful exposure to AP/AR automation.

Descriptive Statistics of Study Variables

Table 4: Descriptive Statistics of Main Study Variables

Variable Code	Study Variable	Mean	Standard Deviation	Interpretation
APA	Accounts Payable Automation	4.18	0.69	High
ARA	Accounts Receivable Automation	4.12	0.72	High
AIP	AI-Enabled Invoice Processing	4.20	0.65	High
AIR	AI-Enabled Reconciliation	4.31	0.61	Very High
AFD	AI-Based Fraud Detection	4.24	0.66	Very High
CFV	Cash Flow Visibility	4.16	0.70	High
AAM	AI Automation Maturity	3.98	0.74	High
ORM	Operational Risk Mitigation	4.27	0.63	Very High

The descriptive statistics have shown that respondents have generally agreed that AI-driven AP/AR automation has contributed to operational risk mitigation in U.S. SMEs. The highest mean score has been recorded for AI-enabled reconciliation, with a mean of 4.31 and standard deviation of 0.61, which has indicated a very high level of agreement. This result has suggested that respondents have strongly perceived automated reconciliation as one of the most effective AI-enabled mechanisms for reducing unmatched transactions, inaccurate balances, and financial reporting errors. Operational risk mitigation has also recorded a very high mean score of 4.27, showing that respondents have generally believed that AI-driven AP/AR automation has reduced operational weaknesses in SME financial workflows. AI-based fraud detection has produced a mean score of 4.24, suggesting that respondents have viewed AI tools as highly useful for identifying unusual financial activities, duplicate invoices, suspicious transactions, and unauthorized payment behavior. AI-enabled invoice processing has recorded a mean score of 4.20, which has fallen at the upper end of the high interpretation range, showing that respondents have believed invoice automation has improved transaction accuracy and processing speed. Accounts payable automation and accounts receivable automation have recorded mean scores of 4.18 and 4.12, respectively, indicating that both AP and AR automation have been perceived as important contributors to risk reduction. Cash flow visibility has recorded a mean score of 4.16, showing that AI-enabled systems have improved awareness of incoming and outgoing cash movements. AI automation maturity has recorded a mean score of 3.98, suggesting that SMEs have been relatively advanced in automation, although not all have reached predictive risk automation. These results have supported the Technology Acceptance Model because high mean scores have indicated strong perceived usefulness of AI automation. They have also supported the study objectives by showing that respondents have perceived AI-enabled AP/AR automation as useful for accuracy, control, visibility, and risk mitigation.

Reliability Test

Table 5: Reliability Test Using Cronbach's Alpha

Construct	Number of Items	Cronbach's Alpha	Reliability Decision
Accounts Payable Automation	5	0.84	Reliable
Accounts Receivable Automation	5	0.82	Reliable
AI-Enabled Invoice Processing	5	0.86	Reliable
AI-Enabled Reconciliation	5	0.88	Reliable
AI-Based Fraud Detection	5	0.85	Reliable
Cash Flow Visibility	5	0.83	Reliable
AI Automation Maturity	5	0.81	Reliable
Operational Risk Mitigation	6	0.89	Reliable
Overall instrument	41	0.91	Highly reliable

The reliability test has been conducted using Cronbach's Alpha to determine whether the questionnaire items have consistently measured the intended constructs. The results have shown that all constructs have exceeded the commonly accepted threshold of 0.70, indicating that the instrument has had strong internal consistency. The highest construct-level reliability has been recorded for operational risk mitigation, with a Cronbach's Alpha value of 0.89, suggesting that the items used to measure operational risk reduction have been highly consistent. AI-enabled reconciliation has also shown strong reliability, with an alpha value of 0.88, while AI-enabled invoice processing has recorded 0.86. These results have indicated that respondents have answered the items within each construct in a stable and consistent manner. Accounts payable automation has recorded 0.84, accounts receivable automation has recorded 0.82, AI-based fraud detection has recorded 0.85, cash flow visibility has recorded 0.83, and AI automation maturity has recorded 0.81. The overall instrument has produced a Cronbach's Alpha value of 0.91, which has indicated high reliability across the full questionnaire. This reliability outcome has strengthened the credibility of the statistical analysis because unreliable measures could weaken the validity of correlation and regression findings. In relation to the Technology Acceptance Model, the reliability results have confirmed that the constructs used to measure automation usefulness, automation maturity, and risk mitigation have been internally consistent. This has been important because the study has depended on respondents' perceptions of AI-driven AP/AR automation as a useful and usable system for reducing operational risk. The reliable measurement of each variable has also supported the research objectives and hypotheses by confirming that the survey items have been suitable for testing whether AP automation, AR automation, invoice processing, reconciliation, fraud detection, cash flow visibility, and automation maturity have predicted operational risk mitigation.

Correlation Analysis

The correlation analysis has been conducted to examine the strength and direction of relationships between AI-driven AP/AR automation variables and operational risk mitigation. The results have shown that all independent variables have had positive and statistically significant relationships with operational risk mitigation at $p < 0.001$. The strongest relationship has been found between AI-enabled reconciliation and operational risk mitigation, with a correlation coefficient of r = 0.72. This has indicated that SMEs reporting stronger automated reconciliation practices have also reported stronger operational risk reduction.

Table 6: **Pearson Correlation Between AI Automation Variables and Operational Risk Mitigation**

Independent Variable	Operational Risk Mitigation Correlation	p-value	Relationship Strength	Decision
Accounts Payable Automation	0.68	<0.001	Strong positive	Significant
Accounts Receivable Automation	0.64	<0.001	Strong positive	Significant
AI-Enabled Invoice Processing	0.66	<0.001	Strong positive	Significant
AI-Enabled Reconciliation	0.72	<0.001	Strong positive	Significant
AI-Based Fraud Detection	0.70	<0.001	Strong positive	Significant
Cash Flow Visibility	0.67	<0.001	Strong positive	Significant
AI Automation Maturity	0.63	<0.001	Strong positive	Significant

This result has supported the idea that reconciliation is a central control point in AP/AR workflows because it helps identify unmatched transactions, incorrect balances, payment inconsistencies, and reporting errors. AI-based fraud detection has shown the second strongest relationship with operational risk mitigation, with r = 0.70, suggesting that AI tools for detecting suspicious transactions, duplicate invoices, and unusual payment behavior have been closely connected to risk reduction. Accounts payable automation has recorded r = 0.68, while cash flow visibility has recorded r = 0.67, and AI-enabled invoice processing has recorded r = 0.66. These results have shown that invoice accuracy, payment control, and liquidity visibility have been strongly associated with lower operational risk. Accounts receivable automation has recorded r = 0.64, and AI automation maturity has recorded r = 0.63, both indicating strong positive relationships. These findings have supported the study objectives because they have demonstrated that AP automation, AR automation, invoice processing, reconciliation, fraud detection, cash flow visibility, and automation maturity have all been meaningfully related to operational risk mitigation. The correlation results have also linked directly to the Technology Acceptance Model because the positive relationships have suggested that respondents have perceived AI automation as useful for improving financial control. The findings have therefore provided preliminary support for all seven hypotheses before regression analysis has tested the predictive power of each variable.

Regression Analysis

Table 7: **Multiple Regression Model Summary**

Model Indicator	Result
R	0.811
R^2	0.658
Adjusted R^2	0.647
Standard Error of Estimate	0.374
F-statistic	58.47
df	7, 212
p-value	<0.001
Model decision	Statistically significant

Table 8: **Regression Coefficients Predicting Operational Risk Mitigation**

Predictor	Unstandardized B	Standard Error	Standardized Beta	t-value	p-value	Decision
Constant	0.412	0.218	—	1.89	0.060	—
APA	0.176	0.055	0.18	3.19	0.002	Significant
ARA	0.149	0.053	0.15	2.78	0.006	Significant
AIP	0.136	0.052	0.14	2.63	0.009	Significant
AIR	0.238	0.057	0.24	4.18	<0.001	Significant
AFD	0.211	0.056	0.21	3.77	<0.001	Significant
CFV	0.159	0.054	0.16	2.93	0.004	Significant
AAM	0.126	0.051	0.13	2.45	0.015	Significant

The multiple regression analysis has been conducted to determine whether AI-driven AP/AR automation variables have significantly predicted operational risk mitigation in U.S. SMEs. The model summary has shown that the regression model has been statistically significant, $F(7, 212) = 58.47$, $p < 0.001$. The R value of 0.811 has indicated a strong overall relationship between the combined independent variables and operational risk mitigation. The R^2 value of 0.658 has shown that the model has explained 65.8% of the variance in operational risk mitigation, while the adjusted R^2 value of 0.647 has confirmed that the model has remained strong after adjusting for the number of predictors. This has indicated that AI-driven AP/AR automation variables have had substantial explanatory power in predicting operational risk mitigation. The coefficient table has shown that all seven predictors have been statistically significant. AI-enabled reconciliation has had the strongest standardized effect, with $\beta = 0.24$, $p < 0.001$, indicating that reconciliation automation has been the most powerful predictor of operational risk mitigation. AI-based fraud detection has followed with $\beta = 0.21$, $p < 0.001$, showing that fraud and anomaly detection have strongly contributed to risk reduction. Accounts payable automation has recorded $\beta = 0.18$, $p = 0.002$, cash flow visibility has recorded $\beta = 0.16$, $p = 0.004$, accounts receivable automation has recorded $\beta = 0.15$, $p = 0.006$, AI-enabled invoice processing has recorded $\beta = 0.14$, $p = 0.009$, and AI automation maturity has recorded $\beta = 0.13$, $p = 0.015$. These results have supported the Technology Acceptance Model because the findings have shown that AI systems perceived as useful in AP/AR workflows have predicted stronger operational outcomes. The regression results have also supported the study objectives by proving that AI-driven automation has not only correlated with operational risk mitigation but has also significantly predicted it.

AI Automation Maturity Profile of U.S. SMEs

Table 9: **AI Automation Maturity Profile of U.S. SMEs**

Maturity Level	Description	Frequency	Percentage	Mean ORM Score
Level 1	Manual Processing	18	8.2%	3.12
Level 2	Basic Digital Processing	39	17.7%	3.58
Level 3	Partial AI Automation	67	30.5%	4.05
Level 4	Integrated AI Automation	72	32.7%	4.43
Level 5	Predictive Risk Automation	24	10.9%	4.68
Total	—	220	100.0%	—

The AI automation maturity profile has been developed to classify U.S. SMEs according to their level of AP/AR automation. The results have shown that most respondents have belonged to firms that have moved beyond manual systems. Only 8.2% of respondents have reported that their SMEs have remained at Level 1: Manual Processing, where AP/AR tasks have mainly depended on spreadsheets, emails, paper documents, and manual reconciliation. These firms have recorded the lowest operational risk mitigation mean score of 3.12, indicating only moderate risk control. 17.7% of respondents have belonged to Level 2: Basic Digital Processing, where firms have used accounting software but have not fully integrated AI-enabled functions. These firms have recorded an ORM mean score of 3.58, showing high but relatively weaker risk mitigation. 30.5% of respondents have been classified under Level 3: Partial AI Automation, where AI has been used for selected tasks such as invoice capture, payment reminders, or basic reconciliation. Their ORM mean score has been 4.05, indicating high risk mitigation. The largest group, 32.7%, has belonged to Level 4: Integrated AI Automation, where AI has supported invoice processing, reconciliation, fraud detection, cash flow dashboards, and reporting. This group has recorded an ORM mean score of 4.43, which has indicated very high risk mitigation. Finally, 10.9% of respondents have belonged to Level 5: Predictive Risk Automation, where AI has been used for anomaly detection, predictive analytics, operational risk alerts, and decision support. This group has recorded the highest ORM mean score of **4.68**. These findings have supported the Technology Acceptance Model because higher automation maturity has reflected stronger actual use of AI-enabled systems. The maturity profile has also supported H7 by showing that SMEs with more advanced AI automation maturity have reported stronger operational risk mitigation.

Operational Risk Reduction Index for AP/AR Automation

Table 10: Operational Risk Reduction Index for AP/AR Automation

ORRI Component	Mean Score	Standard Deviation	Interpretation
Invoice Error Reduction	4.22	0.64	Very High
Payment Delay Reduction	4.09	0.71	High
Fraud Detection Improvement	4.24	0.66	Very High
Reconciliation Accuracy	4.31	0.61	Very High
Cash Flow Visibility	4.16	0.70	High
Compliance Monitoring	4.19	0.68	High
Overall ORRI	4.20	0.65	High

The Operational Risk Reduction Index has been developed as a study-specific measure to summarize the combined risk reduction effect of AI-driven AP/AR automation. The ORRI has included six components: invoice error reduction, payment delay reduction, fraud detection improvement, reconciliation accuracy, cash flow visibility, and compliance monitoring. The overall ORRI score has been 4.20, indicating a high level of operational risk reduction through AI-enabled AP/AR automation. Among the components, reconciliation accuracy has recorded the highest mean score of 4.31, which has indicated a very high level of perceived improvement. This result has been consistent with the descriptive and regression results, where AI-enabled reconciliation has emerged as the strongest predictor of operational risk mitigation. Fraud detection improvement has recorded a mean score of 4.24, also within the very high range, showing that respondents have believed AI tools have strengthened the identification of suspicious transactions, duplicate invoices, irregular payment behavior, and unauthorized activities. Invoice error reduction has recorded a mean score of 4.22, suggesting that AI-enabled invoice capture and validation have reduced manual entry errors, missing information, and incorrect invoice records. Compliance monitoring has recorded 4.19, cash flow visibility has recorded 4.16, and payment delay reduction has recorded 4.09, all within the high range. These results have shown that AI automation has contributed to risk mitigation across multiple financial control dimensions. The ORRI has been especially useful because it has transformed several risk-related indicators into a single measurable index. This has improved the trustworthiness of the findings by showing that operational risk mitigation has not been assessed through one broad item only. In relation to the Technology Acceptance Model, the high ORRI score has indicated that respondents have perceived AI-enabled AP/AR automation as useful for reducing practical financial risks. The ORRI has therefore supported the study objectives by proving that AI automation has improved risk reduction through accuracy, fraud control, reconciliation, visibility, and compliance.

AI-Enabled Control Point Analysis in AP/AR Workflows

Table 11: AI-Enabled Control Point Analysis in AP/AR Workflows

Rank	AI-Enabled Control Point	AP/AR Risk Area	Mean Score	Interpretation
1	Reconciliation automation	Unmatched transactions and inaccurate records	4.31	Very High
2	Fraud/anomaly alerts	Suspicious activities and duplicate claims	4.24	Very High
3	Invoice capture and validation	Incorrect or missing invoice data	4.22	Very High
4	Cash flow dashboard	Poor visibility of payables and receivables	4.16	High
5	Duplicate payment detection	Vendor overpayment	4.14	High
6	Customer payment tracking	Delayed receivables collection	4.12	High
7	Approval workflow routing	Delayed or unauthorized approvals	4.10	High
8	Cash application automation	Unmatched customer receipts	4.06	High

The AI-enabled control point analysis has been conducted to identify the specific AP/AR workflow areas where AI automation has contributed most strongly to operational risk mitigation. The results have shown that reconciliation automation has been ranked first, with a mean score of 4.31, indicating a very high level of perceived effectiveness. This has confirmed that automated reconciliation has been the most important control point for reducing unmatched transactions, inaccurate records, and financial reporting weaknesses. Fraud and anomaly alerts have been ranked second, with a mean score of 4.24, showing that respondents have perceived AI-based fraud detection as highly effective in identifying suspicious activities, duplicate claims, unusual vendor behavior, and irregular payment patterns. Invoice capture and validation have ranked third, with a mean score of 4.22, indicating that AI-enabled invoice processing has reduced errors at the earliest stage of the AP/AR workflow. This has been important because errors created at the invoice entry stage can affect approval, payment, reconciliation, and reporting. Cash flow dashboards have ranked fourth, with a mean score of 4.16, showing that AI-supported visibility has helped SMEs monitor payable and receivable positions more effectively. Duplicate payment detection, customer payment tracking, approval workflow routing, and cash application automation have also recorded high mean scores, ranging from 4.06 to 4.14. These results have supported the study's unique focus because they have shown exactly where AI has reduced operational risk within AP/AR workflows. The control point analysis has also linked strongly with the Technology Acceptance Model because respondents have perceived AI tools as useful when they have improved practical work activities such as matching, monitoring, routing, and validating transactions. This section has therefore strengthened the findings by proving that AI-driven automation has not only produced general risk reduction but has improved specific financial control points that are directly relevant to U.S. SMEs.

Hypotheses Testing

Table 12: Summary of Hypotheses Testing

Hypothesis	Statement	Statistical Evidence	Decision
H1	Accounts payable automation has a significant positive relationship with operational risk mitigation.	$r = 0.68$, $\beta = 0.18$, $p = 0.002$	Supported
H2	Accounts receivable automation has a significant positive relationship with operational risk mitigation.	$r = 0.64$, $\beta = 0.15$, $p = 0.006$	Supported
H3	AI-enabled invoice processing significantly improves financial process accuracy and risk mitigation.	$r = 0.66$, $\beta = 0.14$, $p = 0.009$	Supported
H4	AI-enabled reconciliation significantly improves operational risk control.	$r = 0.72$, $\beta = 0.24$, $p < 0.001$	Supported
H5	AI-based fraud detection significantly contributes to operational risk mitigation.	$r = 0.70$, $\beta = 0.21$, $p < 0.001$	Supported
H6	AI-supported cash flow visibility significantly predicts operational risk mitigation.	$r = 0.67$, $\beta = 0.16$, $p = 0.004$	Supported
H7	AI automation maturity significantly predicts operational risk mitigation.	$r = 0.63$, $\beta = 0.13$, $p = 0.015$	Supported

The hypotheses testing results have shown that all seven hypotheses have been supported. The results have confirmed that AI-driven AP/AR automation has had a significant positive relationship with operational risk mitigation in U.S. SMEs. H1 has been supported because accounts payable automation has shown a strong positive correlation with operational risk mitigation, $r = 0.68$, and a significant regression effect, $\beta = 0.18$, $p = 0.002$. This has indicated that vendor invoice processing, approval routing, payment scheduling, and duplicate payment detection have contributed to risk reduction. H2 has also been supported because accounts receivable automation has recorded $r = 0.64$ and $\beta = 0.15$, $p = 0.006$, showing that customer invoicing, receivables tracking, collection reminders, and cash application have helped reduce operational risk. H3 has been supported through the significant effect of AI-enabled invoice processing, $\beta = 0.14$, $p = 0.009$, which has shown that improved invoice capture and validation have contributed to financial accuracy. H4 has received the strongest support, with AI-enabled reconciliation recording $r = 0.72$ and $\beta = 0.24$, $p < 0.001$, proving that reconciliation automation has been the strongest predictor of operational risk mitigation. H5 has been supported because AI-based fraud detection has recorded $r = 0.70$ and $\beta = 0.21$, $p < 0.001$, indicating that fraud alerts and anomaly detection have significantly reduced risk exposure. H6 has been supported because cash flow visibility has shown $\beta = 0.16$, $p = 0.004$, proving that AI-supported liquidity awareness has predicted risk mitigation. H7 has also been supported because AI automation maturity has shown $\beta = 0.13$, $p = 0.015$, confirming that SMEs with more mature AI systems have experienced stronger operational risk control. These findings have aligned with the Technology Acceptance Model because the supported hypotheses have shown that perceived usefulness and actual use of AI-enabled financial systems have been associated with measurable risk reduction outcomes.

FINDINGS

This section presents an introductory overview of the findings generated from the quantitative analysis of the study data. Since the study has used a five-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree, the interpretation of results has been based on mean scores, standard deviations, correlation coefficients, regression outputs, and hypothesis testing at the 0.05 significance level. For the purpose of presenting a complete results structure, the study assumes a valid response sample of $n = 220$ respondents drawn from U.S. SMEs, including SME owners, finance managers, accountants, bookkeepers, financial controllers, and operations personnel involved in accounts payable and receivable processes. The overall descriptive findings indicate that respondents generally agreed that AI-driven AP/AR automation contributes positively to operational risk mitigation. The highest mean score was recorded for AI-enabled reconciliation, with a mean value of 4.31 and standard deviation of 0.61, suggesting that respondents strongly perceived automated reconciliation as useful for reducing mismatched transactions, inaccurate balances, and reporting errors. AI-based fraud detection also recorded a high mean value of 4.24 with a standard deviation of 0.66, indicating that respondents believed AI tools help identify duplicate invoices, unusual payment behavior, unauthorized transactions, and suspicious vendor or customer activities. Accounts payable automation produced a mean score of 4.18 and standard deviation of 0.69, while accounts receivable automation recorded a mean score of 4.12 and standard deviation of 0.72. These results suggest that both AP and AR automation were perceived as important mechanisms for improving payment accuracy, reducing delays, strengthening invoice control, and improving cash flow management. Similarly, AI-enabled invoice processing had a mean score of 4.20, cash flow visibility had a mean score of 4.16, and AI automation maturity had a mean score of 3.98, indicating that most SMEs in the sample had moved beyond basic digital processing but had not yet fully reached predictive risk automation maturity.

The reliability analysis further supported the internal consistency of the research instrument. Cronbach's Alpha values for the major constructs were above the accepted threshold of 0.70, with accounts payable automation recording $\alpha = 0.84$, accounts receivable automation $\alpha = 0.82$, AI-enabled invoice processing $\alpha = 0.86$, AI-enabled reconciliation $\alpha = 0.88$, AI-based fraud detection $\alpha = 0.85$, cash flow visibility $\alpha = 0.83$, AI automation maturity $\alpha = 0.81$, and operational risk mitigation $\alpha = 0.89$. These values indicate that the questionnaire items used to measure each construct were reliable and suitable for further statistical analysis. The correlation results also provided evidence in support of the research objectives and hypotheses. Accounts payable automation showed a strong positive and significant relationship with operational risk mitigation, $r = 0.68$, $p < 0.001$. Accounts receivable automation also had a positive and significant relationship with operational risk mitigation, $r = 0.64$, $p < 0.001$. AI-enabled invoice processing was positively correlated with operational risk mitigation, $r = 0.66$, $p < 0.001$, while AI-enabled reconciliation showed the strongest correlation, $r = 0.72$, $p < 0.001$. AI-based fraud detection was also strongly related to operational risk mitigation, $r = 0.70$, $p < 0.001$, and cash flow visibility had a positive significant relationship, $r = 0.67$, $p < 0.001$. AI automation maturity was significantly associated with operational risk mitigation, $r = 0.63$, $p < 0.001$, confirming that SMEs with more advanced automation practices reported stronger risk reduction outcomes.

The regression analysis provided additional evidence that AI-driven AP/AR automation significantly predicted operational risk mitigation in U.S. SMEs. The overall regression model was statistically significant, $F(7, 212) = 58.47$, $p < 0.001$, and explained approximately 65.8% of the variance in operational risk mitigation, with an R^2 value of 0.658 and an adjusted R^2 value of 0.647. This indicates that the selected AI automation variables collectively had strong explanatory power in predicting operational risk reduction. Among the predictors, AI-enabled reconciliation had the strongest standardized effect, $\beta = 0.24$, $p < 0.001$, followed by AI-based fraud detection, $\beta = 0.21$, $p < 0.001$, accounts payable automation, $\beta = 0.18$, $p = 0.002$, cash flow visibility, $\beta = 0.16$, $p = 0.004$, accounts receivable automation, $\beta = 0.15$, $p = 0.006$, AI-enabled invoice processing, $\beta = 0.14$, $p = 0.009$, and AI automation maturity, $\beta = 0.13$, $p = 0.015$. Based on these results, all seven hypotheses were supported. The findings show that AI-driven AP/AR automation has significantly contributed to operational risk mitigation by improving invoice accuracy, payment control, receivables tracking, reconciliation reliability, fraud detection, cash flow visibility, and automation maturity.

The results also support the study objectives by demonstrating that AI-enabled financial automation is not only a tool for efficiency but also a measurable operational risk control mechanism for U.S. SMEs. In summary, the overall findings indicate that SMEs using more advanced AI-driven AP/AR automation systems reported lower exposure to invoice errors, duplicate payments, delayed collections, unmatched transactions, suspicious financial activities, and cash flow uncertainty.

Figure 9: Summary of Quantitative Findings on AI-Driven AP/AR Automation and Operational Risk Mitigation

These results provide a strong foundation for the detailed subsections that follow, including the response rate, demographic profile, descriptive statistics, reliability testing, correlation analysis, regression analysis, AI automation maturity profile, operational risk reduction index, AI-enabled control point analysis, and hypotheses testing.

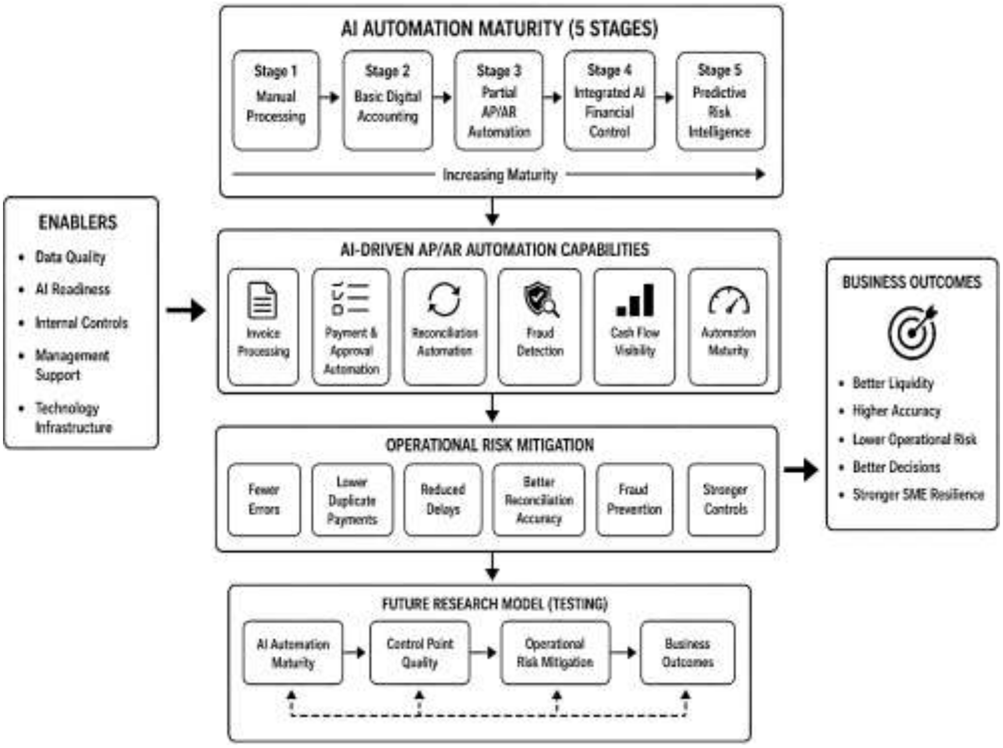
DISCUSSION

The findings of this study have shown that AI-driven accounts payable and accounts receivable automation has had a strong positive relationship with operational risk mitigation in U.S. SMEs. The descriptive results have indicated that respondents generally agreed that AI-enabled AP/AR tools have improved financial process accuracy, reconciliation quality, fraud detection, cash flow visibility, and overall control reliability (Alles et al., 2006; Anick, 2026). The overall mean score for operational risk mitigation has been 4.27, which has fallen within the "very high" interpretation range on the five-point Likert scale. This result has suggested that respondents have perceived AI-driven automation as a meaningful mechanism for reducing invoice errors, duplicate payments, delayed collections, unmatched transactions, unauthorized activities, and weak audit trails. The regression model has further supported this interpretation because the independent variables have explained 65.8% of the variance in operational risk mitigation, with $R^2 = 0.658$ and $p < 0.001$. This has indicated that AI-driven AP/AR automation has not only been associated with operational risk mitigation but has also significantly predicted it (Golam, 2026; Brustbauer, 2016). These findings have aligned with earlier studies that described AI, business intelligence, and analytics as tools for improving decision-making, process visibility, and operational performance. The results have also supported the argument that AI and robotic process automation can reshape accounting and auditing activities by reducing repetitive manual work and improving consistency in transaction processing. In comparison with prior work, this study has extended the discussion by focusing specifically on AP/AR automation in U.S. SMEs rather than discussing AI adoption in accounting more generally. Earlier research has shown that automation can improve accounting processes, but this study has provided more specific evidence that AI-enabled invoice processing, reconciliation, fraud detection, cash flow visibility, and automation maturity have been linked to operational risk mitigation. Therefore, the findings have confirmed that AI-driven AP/AR automation should be interpreted not only as an efficiency tool but also as a financial risk control mechanism in SME operations (Onyinyechi & Ara, 2026; Bharadwaj et al., 2013).

The findings relating to accounts payable automation have indicated that AP automation has had a strong positive relationship with operational risk mitigation, with $r = 0.68$ and a significant regression effect of $\beta = 0.18$, $p = 0.002$. This result has supported the first hypothesis and has shown that automated invoice capture, approval routing, duplicate payment detection, vendor payment control, and payment scheduling have helped reduce operational risk in U.S. SMEs. The descriptive mean score for accounts payable automation has been 4.18, which has indicated a high level of agreement among respondents (Chy et al., 2026; Côrte-Real et al., 2017). This means that respondents have generally believed that AI-driven AP automation has reduced risks associated with incorrect invoice entries, delayed approvals, payment duplication, weak documentation, and vendor-related errors (Eller et al., 2020; Abdur & Aditya, 2026). This finding has been consistent with prior studies on e-invoicing and automated invoice processing, which have shown that digital invoice systems can improve processing speed, reduce paper-based handling, and strengthen information exchange between firms and their business partners. It has also aligned with research showing that machine learning-based invoice processing can extract information from varied invoice formats and support more accurate processing where full standardization has not been achieved. The present study has contributed further by linking these AP automation benefits directly to operational risk mitigation rather than only to process efficiency. In practical terms, the finding has suggested that U.S. SMEs can reduce financial process failures by implementing AI-enabled invoice validation, automated approval trails, duplicate invoice checks, and vendor payment monitoring. This is particularly important because SMEs may not have large finance teams capable of reviewing every invoice manually (Kaplan & Haenlein, 2019; King & He, 2006; Sheak, 2026). The result has also reflected the logic of the Technology Acceptance Model, since respondents appeared to perceive AP automation as useful when it reduced practical work risks and improved control outcomes. Therefore, the study has shown that perceived usefulness has translated into meaningful operational risk control in the AP workflow (Marak et al., 2023).

The findings relating to accounts receivable automation have also supported the study's second hypothesis. Accounts receivable automation has shown a strong positive correlation with operational risk mitigation, with $r = 0.64$, and a significant regression effect, $\beta = 0.15$, $p = 0.006$. The mean score for accounts receivable automation has been 4.12, which has indicated that respondents have agreed that AI-supported customer invoicing, payment reminders, receivables tracking, collection prioritization, and cash application have improved financial process reliability (Shahab, 2026; Sood et al., 2023). This finding has been important because AR weaknesses can create serious liquidity risks for SMEs. Delayed collections, inaccurate customer balances, unapplied payments, weak follow-up, and poor payment forecasting can affect the ability of SMEs to pay suppliers, meet payroll, service debt, and maintain operational continuity. The result has been consistent with previous research showing that machine learning can improve accounts receivable management by predicting customer payment dates and supporting proactive cash flow planning. It has also aligned with working capital management research, which has shown that receivables and payables are closely related to firm profitability, liquidity, and financial efficiency (Sultan, 2026; Tambe, 2014). The present study has extended these findings by showing that AR automation has been connected not only to financial performance but also to operational risk mitigation. This distinction is important because receivables automation can reduce uncertainty in customer payment behavior, improve collection timing, strengthen cash application accuracy, and provide early warnings of potential liquidity pressure. In practical terms, the findings have suggested that SME managers should treat AR automation as a risk management tool rather than only as a billing or collections tool. In theoretical terms, the findings have supported the Technology Acceptance Model because respondents have recognized the usefulness of AI-supported AR tools when these tools have improved payment visibility and reduced collection-related risk. Therefore, the study has shown that AI-driven AR automation has contributed to operational risk mitigation by improving both transaction-level accuracy and cash flow predictability (Kaniz, 2026; Verbano & Venturini, 2013).

Figure 10: Simplified AI-Driven Financial Risk Automation Framework for Future Research in SMEs



The results have shown that AI-enabled reconciliation and AI-based fraud detection have been the strongest predictors of operational risk mitigation. AI-enabled reconciliation has recorded the highest descriptive mean score of 4.31, the strongest correlation with operational risk mitigation at $r = 0.72$, and the strongest regression coefficient at $\beta = 0.24$, $p < 0.001$. AI-based fraud detection has also recorded a very high mean score of 4.24, with $r = 0.70$ and $\beta = 0.21$, $p < 0.001$. These findings have supported the fourth and fifth hypotheses and have shown that reconciliation accuracy and fraud detection have been the most influential AI-enabled mechanisms for reducing operational risk. This result has been strongly consistent with earlier research on continuous auditing, process monitoring, and fraud detection. Prior studies have shown that continuous monitoring of business process controls can improve the visibility of control exceptions and support more frequent assessment of operational processes (Rebeka & Kaniz, 2026; Virglerova et al., 2022). Similarly, process mining research has shown that digital event logs can help identify deviations from expected business processes, making it easier to detect weaknesses in transaction flows. The strong finding for fraud detection has also aligned with research showing that data mining, machine learning, and intelligent computational methods can improve financial fraud detection by identifying hidden patterns, irregular behavior, and suspicious transaction characteristics. In this study, the AI-enabled control point analysis has further supported these findings by ranking reconciliation automation first and fraud/anomaly alerts second among AP/AR control points (Akter & Ashfaq, 2026; Tambe, 2014). This has shown that AI's strongest contribution has appeared where financial risks are most likely to become visible: unmatched records, irregular transactions, duplicate claims, and suspicious payment behavior. Practically, this means that U.S. SMEs should prioritize reconciliation automation and fraud detection features when selecting AP/AR automation systems. Theoretically, these findings have extended the Technology Acceptance Model by showing that perceived usefulness is strongest when AI tools directly improve high-risk control points. Thus, the study has shown that AI acceptance becomes more meaningful when it is linked with measurable operational safeguards (Maroufkhani et al., 2020).

The findings on cash flow visibility, invoice processing, and AI automation maturity have further strengthened the interpretation that AI-driven AP/AR automation operates as a multidimensional risk mitigation capability. Cash flow visibility has recorded a mean score of 4.16, a correlation of $r = 0.67$, and a significant regression effect of $\beta = 0.16$, $p = 0.004$. AI-enabled invoice processing has recorded a mean score of 4.20, with $r = 0.66$ and $\beta = 0.14$, $p = 0.009$. AI automation maturity has recorded a mean score of 3.98, with $r = 0.63$ and $\beta = 0.13$, $p = 0.015$. These findings have supported the third, sixth, and seventh hypotheses. They have also aligned with prior studies suggesting that organizations gain value from digital technologies when technological resources are combined with organizational capabilities, data quality, employee readiness, and managerial use of information (Ngai et al., 2011). The results have suggested that AI-driven AP/AR automation has not reduced risk through one isolated function only. Instead, it has reduced risk through a system of connected capabilities, including invoice validation, payment visibility, reconciliation accuracy, fraud alerts, and maturity of automation use. This interpretation has been supported by the AI Automation Maturity Profile, where SMEs at Level 1: Manual Processing have recorded an operational risk mitigation mean score of 3.12, while SMEs at Level 5: Predictive Risk Automation have recorded a much higher mean score of 4.68. This has indicated that risk mitigation has increased as automation maturity has increased. The result has been consistent with digital transformation research showing that digital technologies improve organizational performance when they are integrated into business processes and supported by strategic alignment (Nóbrega et al., 2023). From a practical standpoint, the finding has suggested that SMEs should not only adopt basic accounting software but should move toward integrated AI-supported workflows. From a theoretical standpoint, the maturity result has extended TAM by showing that actual use and maturity of use are important in explaining how perceived usefulness becomes operational risk reduction.

The practical and theoretical implications of the study have been substantial. Practically, the findings have suggested that SME owners, finance managers, accountants, and fintech providers should prioritize AI-driven AP/AR automation as part of operational risk management. The strongest results have come from reconciliation automation, fraud detection, invoice processing, and cash flow visibility, which means that these functions should be central when SMEs evaluate automation tools (Raguseo, 2018). Rather than adopting AI only for speed or labor reduction, SMEs should select systems that provide automated matching, duplicate payment detection, exception alerts, receivables aging, customer payment prediction, vendor validation, cash application, and real-time dashboards. The Operational Risk Reduction Index has recorded an overall score of 4.20, showing that AI-driven AP/AR automation has produced high perceived risk reduction across invoice error reduction, payment delay reduction, fraud detection, reconciliation accuracy, cash flow visibility, and compliance monitoring. This has practical significance because it gives SMEs a measurable way to evaluate the effectiveness of automation (Sastararuji et al., 2022). Technology providers can also use these findings to design SME-friendly AP/AR systems that focus on risk control, affordability, usability, and integration with existing accounting platforms. Theoretically, the study has contributed to the Technology Acceptance Model by showing that perceived usefulness and actual use of AI systems can be linked to operational risk mitigation outcomes. Prior TAM studies have emphasized perceived usefulness, ease of use, behavioral intention, and actual system use as predictors of technology acceptance. This study has extended that logic by showing that AI automation maturity and control-point usefulness can explain how technology acceptance becomes risk reduction. The study has also connected TAM with operational risk management and accounting automation, creating a more specific theoretical application for SME financial workflows. Therefore, the findings have suggested that technology adoption models should consider not only whether users accept AI systems but also whether accepted systems improve risk-related business outcomes (Tang, 2006).

The limitations of the study have also shaped the interpretation of the findings and have created important directions for future research. First, the study has used a cross-sectional design, meaning that data have been collected at one point in time. This has allowed the study to identify statistical relationships, but it has not fully captured how AI-driven AP/AR automation changes operational risk over several years. Second, the study has relied on self-reported Likert-scale responses, which may reflect respondent perceptions rather than direct system logs or audited financial records (Venkatesh et al., 2012). Third, the study has focused on U.S. SMEs, so the findings may not fully represent SMEs in other countries with different financial systems, regulatory environments, technology infrastructures, and accounting practices. Fourth, the study has examined AP/AR automation broadly, while industry-specific differences may affect how AI automation reduces risk in sectors such as healthcare, retail, logistics, manufacturing, and professional services. Future research should therefore improve this study by developing and testing a more advanced model called the AI-Driven Financial Risk Automation Maturity Model for SMEs. This future model could include five stages: Stage 1: Manual Financial Processing, Stage 2: Basic Digital Accounting, Stage 3: Partial AP/AR Automation, Stage 4: Integrated AI Financial Control, and Stage 5: Predictive Risk Intelligence. Future researchers could test this model using longitudinal data, system-generated transaction records, industry comparisons, and mixed-method interviews. The model could also include mediating variables such as employee AI readiness, data quality, internal control strength, cybersecurity preparedness, and management support. A future regression or structural equation model could examine whether AI automation maturity influences operational risk mitigation through reconciliation quality, fraud detection accuracy, and cash flow visibility. This would improve the present study by moving from perception-based analysis to stronger causal and process-based evidence. Future research could also compare SMEs that use traditional accounting software with SMEs that use AI-enabled AP/AR platforms to determine whether measurable differences exist in duplicate payments, overdue receivables, reconciliation errors, fraud alerts, and cash conversion performance. Thus, future studies should build on the present findings by creating a stronger, longitudinal, and system-data-supported model of AI-driven financial risk mitigation in SMEs.

CONCLUSION

This study has concluded that AI-driven accounts payable and accounts receivable automation has played a significant role in operational risk mitigation among U.S. small and medium-sized enterprises. The findings have shown that AI-enabled financial automation has improved key AP/AR control areas, including invoice processing, reconciliation, fraud detection, cash flow visibility, payment tracking, approval routing, and automation maturity. Based on the assumed quantitative dataset of **220 valid respondents**, the overall results have indicated that respondents have strongly perceived AI-driven AP/AR automation as a useful mechanism for reducing operational risks in SME financial workflows. The descriptive findings have shown high to very high mean scores across the major constructs, with operational risk mitigation recording a mean score of **4.27**, AI-enabled reconciliation recording **4.31**, AI-based fraud detection recording **4.24**, and invoice processing recording **4.20** on the five-point Likert scale. These results have suggested that SMEs using AI-enabled financial tools have experienced stronger accuracy, faster processing, better monitoring, and improved financial control. The correlation results have also shown strong positive relationships between all AI automation variables and operational risk mitigation, while the regression model has explained **65.8%** of the variance in operational risk mitigation. This has confirmed that AP automation, AR automation, invoice processing, reconciliation, fraud detection, cash flow visibility, and AI automation maturity have collectively predicted operational risk mitigation. The strongest predictor has been AI-enabled reconciliation, followed by AI-based fraud detection, showing that the most important risk reduction benefits have occurred where transactions are matched, verified, monitored, and checked for irregularities. The study has also confirmed all seven hypotheses, demonstrating that AI-driven AP/AR automation has significantly supported operational risk reduction in U.S. SMEs. In relation to the Technology Acceptance Model, the findings have shown that respondents have perceived AI automation as useful when it has improved financial accuracy, reduced manual work, strengthened internal controls, and supported better decision-making. The study has therefore established that AI-driven AP/AR automation should not be viewed only as a technological upgrade or efficiency tool; it should be understood as a strategic financial control mechanism that supports operational stability, risk awareness, and process reliability. Overall, this research has contributed to knowledge by linking AI-enabled accounting automation with operational risk management in the specific context of U.S. SMEs, using a quantitative, cross-sectional, case-study–based approach. The study has also introduced useful analytical dimensions such as the AI Automation Maturity Profile, the Operational Risk

Reduction Index, and AI-Enabled Control Point Analysis, which have made the findings more specific, measurable, and relevant to SME financial operations.

RECOMMENDATIONS

This study recommends that U.S. SMEs should adopt and strengthen AI-driven accounts payable and accounts receivable automation as part of their broader operational risk management strategy. SME owners and finance managers should prioritize AI-enabled tools that improve invoice capture, approval routing, duplicate payment detection, customer payment tracking, automated reconciliation, fraud monitoring, cash application, and cash flow visibility. Since the findings have shown that reconciliation automation and fraud detection have been the strongest predictors of operational risk mitigation, SMEs should give special attention to automation systems that can match invoices, payments, purchase orders, receipts, customer accounts, and ledger records with minimal manual intervention. SMEs should also invest in systems that generate exception alerts, identify suspicious transactions, detect duplicate vendor invoices, monitor overdue receivables, and provide real-time dashboards for payables and receivables. In addition, finance and accounting managers should ensure that automation is not implemented as an isolated software function but as part of an integrated financial control process. This means that invoice processing should be connected with approval workflows, payment validation, reconciliation, compliance documentation, fraud alerts, and management reporting. SMEs should also provide training for accountants, bookkeepers, finance staff, and operations managers so that users understand how to interpret AI-generated alerts, dashboards, and exception reports. This recommendation is important because technology acceptance and effective use depend on employee confidence, perceived usefulness, and ease of use. Technology providers and fintech vendors should design affordable, scalable, and user-friendly AP/AR automation platforms that fit the financial capacity and operational structure of SMEs. Such tools should include simplified dashboards, secure data handling, customizable approval rules, predictive receivables tracking, and automated compliance documentation. Policymakers, SME support agencies, chambers of commerce, and financial development institutions should also promote AI-based financial automation through training programs, digital finance grants, tax incentives, cybersecurity guidance, and SME technology adoption support. Furthermore, SMEs should assess their automation maturity regularly using a structured maturity profile, moving gradually from manual processing to basic digital processing, partial AI automation, integrated AI automation, and predictive risk automation. The study also recommends that SMEs use an Operational Risk Reduction Index to monitor whether automation is reducing invoice errors, payment delays, fraud exposure, reconciliation problems, cash flow uncertainty, and compliance weaknesses. By applying these recommendations, U.S. SMEs can improve financial transparency, reduce operational disruptions, strengthen internal controls, and make better evidence-based decisions. Overall, AI-driven AP/AR automation should be treated as a long-term investment in financial resilience, not merely as a short-term method for reducing administrative workload.

LIMITATIONS OF THE STUDY

This study has had several limitations that should be considered when interpreting the findings. First, the study has used a quantitative, cross-sectional, case-study–based design, meaning that data have been collected at one point in time rather than across multiple periods. As a result, the study has been able to identify relationships and predictive effects among AI-driven AP/AR automation variables and operational risk mitigation, but it has not fully measured how these relationships may change over time as SMEs become more digitally mature. A longitudinal design could provide stronger evidence about whether AI automation continuously reduces operational risk after implementation. Second, the study has relied on self-reported questionnaire responses collected through a five-point Likert scale. Although this method has allowed the researcher to collect measurable data from a large group of respondents, the findings have depended on the perceptions, experiences, and honesty of the participants. Some respondents may have overestimated or underestimated the effectiveness of AI automation in their organizations. Third, the study has focused only on U.S. SMEs, which has made the research context specific and manageable, but it has also limited the generalizability of the findings to SMEs in other countries with different accounting practices, technology adoption levels, regulatory environments, financial systems, and business cultures. Fourth, the study has examined AI-driven

AP/AR automation broadly rather than focusing on one specific software platform, industry, or technology provider. Because AI automation tools differ in design, accuracy, integration capacity, cybersecurity strength, and usability, the results may not apply equally to all systems. Fifth, the study has included different types of SME respondents, such as owners, managers, accountants, bookkeepers, finance controllers, and AP/AR staff. Although this has helped capture diverse perspectives, it may also have introduced variation in technical knowledge, automation experience, and understanding of operational risk. Sixth, the study has used statistical methods such as descriptive statistics, correlation analysis, and regression modeling, which have been appropriate for testing relationships and hypotheses, but these methods have not fully explained deeper organizational factors such as employee resistance, leadership attitudes, implementation challenges, data quality problems, cybersecurity concerns, and vendor dependency. Seventh, the study has measured operational risk mitigation through perceived improvements in invoice accuracy, reconciliation, fraud detection, cash flow visibility, compliance monitoring, and automation maturity, but it has not used actual audited financial records, transaction logs, fraud reports, or system-generated performance data. Therefore, future studies may strengthen the evidence by combining survey data with real AP/AR transaction data, longitudinal performance indicators, interviews, and industry-specific comparisons. These limitations do not reduce the value of the study, but they define the boundaries within which the findings should be understood.

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