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Research Paper

Disruption by AI and No-Code Platforms on Traditional IT Business Models: Challenges and Entrepreneurial Opportunities

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Received: June 24, 2025	Revised: December 18, 2025	Accepted: December 22, 2025	Online: January 31, 2026

Abstract

Disruption brought by Artificial Intelligence (AI) and No-Code/Low-Code (NCLC) platforms has significantly transformed traditional business models in the Information Technology (IT) industry. These technologies are not only reshaping software development methods but also redefining value creation frameworks and entrepreneurial trajectories. This study aims to identify key adaptation challenges and entrepreneurial opportunities resulting from these shifts. Through a systematic literature review of 22 Scopus-indexed publications, the study reveals that IT firms face critical issues including workforce reskilling, shifts in revenue models, and organizational resistance to change. Simultaneously, new opportunities arise in areas such as AI consultancy services, tailored NCLC platform development, and disruptive product innovation. By synthesizing the implications of AI and NCLC disruptions, this paper provides strategic insights for academics and practitioners seeking to navigate and leverage digital transformation in emerging digital markets, with a particular focus on small and medium-sized enterprises (SMEs) across Southeast Asia.

Keywords *AI Disruption; No-code/Low-code Platforms; Digital Transformation; IT Business Models; Adaptation Challenges; Entrepreneurial Opportunities*

INTRODUCTION

In the current digital era, technological advancements are progressing at an unprecedented pace, driving profound and transformative change. Two key innovations playing a pivotal role in this transformation are Artificial Intelligence (AI) and No-Code/Low-Code (NCLC) development platforms, which are significantly altering and disrupting various industries, including the Information Technology (IT) sector (Sewpersadh, 2023). AI has evolved from a mere theoretical concept into a technology that demonstrably enhances efficiency and fosters innovation. With its capability to emulate human cognitive processes such as learning, reasoning, and problem-solving, AI contributes to automation, predictive analytics, and the development of intelligent solutions (Fanti et al., 2022). On the other hand, NCLC platforms are revolutionizing software development by empowering individuals from diverse backgrounds to create applications quickly and flexibly (Yan, 2021).

Although AI and NCLC represent distinct technological trajectories, their convergence produces a compound disruption: AI automates cognitive and technical tasks, while NCLC democratizes application development. Together, they simultaneously reshape IT business models by reducing reliance on specialized labor and accelerating innovation cycles (Liu et al., 2023). In this study, the term 'disruptive challenges' is not used broadly, but specifically refers to three critical aspects that demand deeper understanding. First, workforce reskilling is urgently required as automation alters traditional developer roles (Qiu et al., 2025). Second, adapting the revenue model becomes necessary as firms shift from labor-intensive contracts to platform-based and service-oriented logics (Filosa et al., 2025). Third, organizational resistance to change often hinders the adoption of democratized NCLC practices, creating friction in transformation processes. By prioritizing these dimensions, this study aims to clarify how compound disruption from AI and NCLC challenges the structural foundations of traditional IT business models, while simultaneously

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opening new entrepreneurial opportunities (Minutti et al., 2025).

The disruption brought forth by AI and NCLC has a significant impact on traditional business models within the IT industry. For many years, numerous IT companies operated under an approach focused on labor-intensive software development, long project cycles, and time-and-material contracts, with specific programming expertise as the primary selling point (Wilson et al., 2020). However, the advent of AI has begun to destabilize this system by automating various stages in the software development life cycle (SDLC), ranging from code writing to maintenance, while simultaneously fostering the creation of more scalable and personalized AI-driven IT services (Treude & Storey, 2025). Furthermore, NCLC platforms reduce the dependency on professional development teams for various types of applications, providing opportunities for end-users to be directly involved in the development process, even enabling them to create their own solutions (Missikoff, 2020).

The changes triggered by AI and NCLC pose significant challenges for conventional IT companies, which must adapt to remain relevant amid the industry's dynamics (Ozer et al., 2024). These challenges include the urgency to enhance workforce skills through reskilling and upskilling, adjust revenue models to new trends, overcome internal resistance to change, and compete with more innovative and flexible newcomers (Li, 2022). Although these challenges are complex, they open up various opportunities for entrepreneurs. Innovators now have the chance to build new businesses by leveraging AI for more specific solutions, providing consulting services for the implementation of disruptive technologies, developing more targeted NCLC platforms, or creating products and services that combine both technologies to meet underserved market needs (Steininger et al., 2022). Therefore, understanding the interaction between AI and NCLC disruption, its impact on IT business models, and the emerging challenges and opportunities is a crucial aspect (Sewpersadh, 2023).

Given the increasingly tangible disruptive challenges to IT companies, a deep understanding of the impact of AI and NCLC becomes paramount (Frank et al., 2019). These two technologies not only shift the software development paradigm and create adaptation challenges for companies, but also open opportunities for entrepreneurs seeking to leverage new technological innovations. This disruption drives changes in workforce competencies, technology investment patterns, and competitive strategies at a global level (Xu et al., 2023; Yan, 2021). Therefore, this study aims to map the emerging challenges faced by traditional IT firms in adapting to AI and NCLC, while identifying strategic entrepreneurial opportunities resulting from this dual disruption. In order to navigate this compound disruption and guide strategic responses, this study explicitly sets out to identify the key challenges facing traditional IT business models and to examine the entrepreneurial opportunities enabled by AI and NCLC integration. Accordingly, the inquiry is driven by the following questions: What are the primary structural and operational impacts of these technologies on IT companies, and how can SMEs in Southeast Asia harness them to strengthen digital competitiveness and overcome legacy constraints.

LITERATURE REVIEW

Technology Disruption Theory

The theory of disruption, introduced by Clayton M. Christensen, explains why large, long-established companies often fail to respond effectively to innovations that fundamentally alter the industry landscape (Baimas-George et al., 2022). In this theory, there are two main types of innovation: sustaining innovation and disruptive innovation. Sustaining innovation focuses on improving existing products or services by enhancing performance to meet the needs of mainstream customers in mature markets (Hess et al., 2020). Established companies generally excel at developing this type of innovation because they possess the resources, procedures, and incentives to continually deliver better solutions for their most profitable customer base (Morris & Targ, 2022).

Conversely, disruptive innovation introduces a significantly different value proposition compared to existing products or services (Dan & Chieh, 2008). Initially, products or services resulting from disruptive innovation may perform lower on traditional metrics valued by the mainstream market. However, these innovations are often simpler, more economical, more practical, or more accessible, thereby appealing to underserved customer segments or even creating new, previously untapped markets (Markides, 2006). Christensen identified two primary forms of disruptive innovation: low-end disruption and new-market disruption. Low-end disruption occurs when innovators target customers in market segments who feel that currently available products or services are either too expensive or have excessive features. In this case, innovators offer a "good enough" solution at a more affordable price (Dan & Chieh, 2008). Meanwhile, new-market disruption occurs when innovators introduce products or services aimed at individuals who previously lacked access to available solutions (Govindarajan & Kopalle, 2006).

A core concept of this theory is the "Innovator's Dilemma," which describes how established companies often struggle to invest in disruptive innovation (Christensen et al., 2018). This is due to their tendency to remain focused on improving products for existing mainstream customers, while disruptive innovations in their early stages typically target smaller markets with lower profit margins (Steven et al., 2020). Consequently, large companies tend to overlook emerging new markets, providing opportunities for newcomers to develop simpler yet effective products. Over time, innovators who initially targeted small market segments can continue to grow until they eventually compete directly with large companies (Breyer-Mayländer & Zerres, 2023).

In the context of this research, the Theory of Disruptive Innovation serves as a relevant framework for analyzing how AI and NCLC platforms have the potential to cause significant changes in the business models of traditional IT companies (Adama & Okeke, 2024). AI, for instance, can act as a disruptive force by automating various tasks that previously required high-cost human expertise (Kumari et al., 2025). This enables companies to offer services at lower cost and to broaden access to advanced analytical technologies previously available only to large corporations (Adewumi et al., 2024). Furthermore, NCLC platforms contribute to creating new markets by enabling individuals without programming expertise to contribute to software development (Berardi et al., 2023). By empowering non-technical users, NCLC has the potential to replace some of the need for custom software development services for simple applications or rapid prototyping (Elshan et al., 2023).

However, not all technological advancements are disruptive, as some innovations serve as sustaining improvements for established companies (Oroszi, 2020). There exists an ongoing scholarly debate regarding the disruptive nature of AI and NCLC. While some researchers argue that these technologies represent classic disruptive innovations targeting underserved markets (Christensen et al., 2018), others contend that they primarily function as sustaining innovations that enhance existing capabilities rather than fundamentally displacing established players (Hess et al., 2020). This tension reflects broader theoretical disagreements about whether digital technologies follow traditional disruption patterns or create new forms of market transformation. Therefore, this literature review will apply the Technology Disruption Theory as a perspective to identify whether and to what extent AI and NCLC act as disruptive forces on the business models of conventional IT companies.

Artificial Intelligence

Artificial Intelligence (AI) has evolved from a theoretical concept into a key technology increasingly integrated into various aspects of the Information Technology (IT) industry (Johnson et al., 2024; Shrivastava et al., 2024). One of its primary impacts is seen in software development and the provision of IT services, where AI serves as a critical enabler for enhancing process efficiency and automation (Soureya et al., 2025). In the context of this research, AI refers to computational systems designed to mimic human intelligence, including aspects of learning, reasoning, problem-solving, perception, and language understanding (Maninger et al., 2024). The rapid advancements between 2015 and 2025 have expanded AI's scope and accessibility, making it an increasingly crucial part of the IT ecosystem (Abdurrahim et al., 2025).

Several sub-fields within AI play a vital role in transforming the IT industry. Machine Learning (ML) is at the core of many modern AI applications, allowing systems to learn from data without explicit programming (Albattah & Alzahrani, 2024). In software development, ML is applied to code defect prediction, project estimation, user requirements analysis, automated testing, and application performance optimization (Al Alamin & Uddin, 2021). Additionally, Natural Language Processing (NLP) facilitates interaction between computers and human language, used in sentiment analysis, requirements extraction from documents, automated technical documentation generation, and the development of chatbots to support developers and end-users (Zhou, 2024).

Generative AI is a significant innovation that has seen a surge in development since 2020, with artificial intelligence models capable of automatically generating text, images, audio, and code (Velpucharla, 2025). In software development, Generative AI assists with code writing, test case generation, and test data synthesis, enabling developers to shift from being code writers to curators or supervisors of AI-generated code (Dohmke et al., 2023). Concurrently, AI for Code and AI-assisted Development focus on enhancing developer productivity through features like code completion, real-time anomaly detection, code improvement recommendations, and automated security analysis (Saravanan et al., 2025).

AI applications are spread across various stages of the Software Development Life Cycle (SDLC), from planning and requirements analysis to system maintenance (Raghi et al., 2024). AI plays a role in detecting ambiguities in technical documents, providing design pattern recommendations, assisting in code writing and optimization, and improving testing quality through automation and predictive analytics (Sajja et al., 2024). In the deployment and maintenance phases, AI supports system management through automated monitoring, failure prediction, and adaptive system repair within the DevOps (AIOps) context (Pattanayak et al., 2024). Furthermore, in project management, AI contributes to task planning, resource allocation, and effective project progress monitoring (Yalla, 2023).

AI not only transforms how software is developed and IT services are provided but also drives the creation of new IT products and services (Siregar et al., 2020). Innovations such as advanced predictive analytics, AI-powered process automation, adaptive cybersecurity systems, and AI-as-a-Service (AIaaS) models allow companies to integrate AI capabilities without needing deep technical expertise (Veprytska & Kharchenko, 2022). Thus, AI has become an essential element in the IT industry, not only boosting efficiency and automation but also paving the way for various innovations with the potential to significantly change the business landscape (Jackson & Tseyi, 2024).

No-Code and Low-Code Platforms

Besides artificial intelligence, one of the technological shifts significantly impacting the IT industry is the increasing adoption of No-Code/Low-Code (NCLC) Development platforms (Kulkarni, 2021). These platforms consist of various tools that enable users to build applications through user-friendly interfaces and configuration without having to write code (Arora et al., 2020) manually. The primary goal of this technology is to accelerate the development process, reduce costs, and broaden access for more individuals to create digital solutions (Korada, 2022). Between 2015 and 2025, rapid advancements in NCLC capabilities and popularity have driven digital transformation across companies of varying scales (Bodicherla, 2025).

Although often grouped into a single category, there are fundamental differences between No-Code and Low-Code platforms (Guthardt et al., 2024). No-Code platforms are designed for business users, analysts, or individuals without programming backgrounds who wish to build applications through a visual drag-and-drop approach, ready-to-use templates, and configuration-based logic (Phalake et al., 2022). These platforms are widely used for simple business process automation, digital form creation, and the development of applications that do not require a high level of customization (Funk, 2023). Meanwhile, Low-Code platforms offer greater flexibility for users with a deeper technical understanding (Soulani et al., 2024). While still relying on a visual approach, Low-Code platforms allow developers to add custom code to handle more complex logic, perform system integrations, and tailor application features to specific needs (Ramalho et al., 2021). In practice, some platforms offer a combination of features from both approaches, making the boundary between No-Code and Low-Code often not entirely rigid (Costa Seco et al., 2024).

The widespread adoption of NCLC is driven by the benefits it offers, including increased development speed, enabling companies to create prototypes and launch products more quickly (Bian et al., 2023). Additionally, this technology helps reduce costs by minimizing the need for professional developers and accelerating software development (Heuschkel, 2023). One of NCLC's most significant impacts is the democratization of application development, enabling citizen developers to create digital solutions independently without relying on IT teams (Nimje, 2024). Thus, innovation can emerge directly from various business domains, while also helping to address the backlog of application requests often found in companies (Heine et al., 2023). For professional developers, Low-Code platforms offer a way to save time by automating repetitive tasks, allowing them to focus more on complex technical aspects (Uyanik & Sayar, 2024). Furthermore, NCLC serves as a solution for companies facing a shortage of skilled software developers, while strengthening IT capacity to respond to business needs more efficiently (Asundi, 2024).

Despite offering many advantages, this technology also presents several challenges that need to be managed effectively. Some key limitations include scalability constraints for highly complex projects, limitations in customization flexibility beyond platform capabilities, and security and governance risks, especially for companies adopting a citizen development approach (Abahussain & Al-Ammary, 2025). Furthermore, there is a risk of vendor lock-in, which can limit a company's long-term flexibility. Therefore, companies implementing NCLC need to ensure a mature strategy to optimize the advantages of this technology while addressing potential emerging risks (Luo et al., 2021).

Besides changing how software development is conducted, NCLC also influences roles within IT teams and, more broadly, within companies (Picek, 2023). The emergence of citizen developers creates a shift in who can build applications, while professional developers now play more strategic roles, including building complex components, setting governance standards, and guiding non-technical users in developing digital solutions that align with business needs (Qiu et al., 2024).

Overall, NCLC platforms represent a fundamental shift in the software development paradigm (El-Deeb, 2024). By providing broader access to development tools, accelerating application production, and optimizing cost efficiency, this technology has become a major pillar in digital transformation (Nimje, 2024). Its implications for IT companies' traditional business models will be further analyzed in this review.

Traditional Business Models of IT Companies

Before Artificial Intelligence (AI) and No-Code/Low-Code (NCLC) platforms exerted widespread influence, the Information Technology (IT) industry was dominated by established business models (Sisodia & Pote, 2025). For several decades, these models have evolved to meet the digitalization needs of various companies, from small businesses to multinational corporations. Understanding the key characteristics of these traditional business models is crucial for evaluating how AI and NCLC contribute to the significant changes occurring in the IT industry (Gupta et al., 2022).

One of the main characteristics of conventional IT company business models is a focus on project-based software development (Sisodia & Pote, 2025). The majority of revenue is derived from development services customized to specific client needs, with individually negotiated schedules and budgets (Khan & Khan, 2017). Additionally, the IT industry has historically been heavily reliant on human capital expertise, especially software developers, system architects, consultants, and project managers. Deep technical expertise is a primary factor in differentiation and business value, while also being the largest cost component in company operations (Gopal & Koka, 2010).

Long software development cycles are also a hallmark of traditional business models, with methodologies like Waterfall or early Agile requiring months to years to complete complex systems (Wang et al., 2025). In terms of revenue, traditional IT companies generally relied on several key models, such as time-and-materials (T&M) contracts, in which clients pay based on the labor and resources used. Another model is fixed-price contracts, which set project costs upfront and transfer estimation risk to the service provider (Sathe & Panse, 2023). Furthermore, companies developing software products often derive revenue from software licenses and recurring maintenance fees. In some cases, Managed Services also served as a revenue source through subscription contracts covering infrastructure management, application support, and IT security (Ghumatkar & Date, 2023).

Cost structures in traditional IT business models are dominated by labor, with salaries and benefits for technical staff and consultants being the largest expenditure component (Gurung et al., 2020). Although this model has provided significant value for the growth of the IT industry, it has several limitations that are becoming increasingly apparent in the face of rapid technological development (Nurhazizah et al., 2023). One of the main challenges is limited scalability, as dependence on skilled labor makes capacity expansion expensive and difficult to achieve quickly (Mycek, 2024). Additionally, long project cycles often hinder rapid responses to market changes or new technology trends (Pargaonkar, 2023). High development costs also pose a barrier for small and medium-sized enterprises (SMEs), making custom IT solutions inaccessible to smaller business segments (Nurhazizah et al., 2023). Furthermore, manual and repetitive processes in software development can create inefficiencies in resource and time allocation (Pargaonkar, 2023).

These limitations open avenues for technologies like AI and NCLC to offer faster, more affordable, and more accessible alternatives. By understanding the basic structure of traditional IT business models, this review will explore how AI and NCLC not only serve as tools for improvement but also have the potential to fundamentally transform how IT companies operate and create value for the industry.

RESEARCH METHOD

This research employs a structured literature review approach, as outlined by Snyder (2019), to systematically and transparently collect, summarize, evaluate, and synthesize relevant research findings to provide a comprehensive understanding of the current state of knowledge. This approach aims to provide a comprehensive understanding of current knowledge developments in the investigated field, identify emerging key themes, and uncover potential gaps in the available literature. This study is exploratory and qualitative in nature, designed to map emerging themes and patterns in the literature rather than test specific hypotheses (Creswell & Creswell, 2017).

The primary database used in this literature review is Scopus, which offers extensive coverage of peer-reviewed literature across various disciplines, including Computer Science, as well as Business, Management, and Accounting. To ensure relevance to the research topic, the search strategy was designed using a combination of specific keywords. The search was conducted using a combination of keywords reflecting the interrelationships among AI, disruption, and No-Code/Low-Code-based software development technologies. Keywords used include terms such as "Artificial Intelligence," "disruption," "software," and "development" to capture studies related to AI and its impact on the IT industry. Meanwhile, to highlight the role of No-Code and Low-Code, the search also included variations of terms such as "No-code," "low-code," "no code," and "low code." Additionally, this search was limited by several criteria: publications were restricted to the timeframe of 2015–2025 (including publications up to 2025), access type was limited to Open Access to ensure full accessibility of the literature, and subject areas were confined to Computer Science, and Business, Management, and Accounting, to cover both technological and business perspectives related to AI and NCLC.

The initial search conducted with these criteria yielded a total of 227 documents, followed by a further selection process to ensure the relevance and quality of the analyzed articles. This selection was based on established criteria to ensure that only articles aligned with the research focus were included in the review. The criteria for article selection are detailed in Table 1:

Table 1. Criteria Table

Criteria	Description
Impact on IT Company Business Models	The article discusses in depth the impact of AI and/or NCLC on the business models of IT companies.
Challenges for Traditional IT Companies	The article identifies challenges faced by traditional IT companies due to AI/NCLC technology disruption.
Entrepreneurial Opportunities	The article explores entrepreneurial opportunities arising from AI/NCLC disruption in the IT sector.
Peer-Reviewed Publications	The article originates from peer-reviewed publications, including scientific journals and reputable conference proceedings.
Original Research (Not Literature Review)	The article is not a literature study or a literature review.
Full Text Availability	The article is available in full text format, allowing for comprehensive analysis.

Article selection was conducted through several stages to ensure that only the most relevant and high-quality literature was analyzed in this review. The review process followed PRISMA guidelines, and the article selection procedure is illustrated in the PRISMA flow diagram in Figure 1, which clarifies the stages of identification, screening, eligibility, and inclusion. The first stage was an initial screening, in which the researchers independently reviewed the titles and abstracts of the 227 documents identified in the initial Scopus search. Articles that did not meet the criteria were immediately discarded to ensure that only relevant sources proceeded to the next stage.

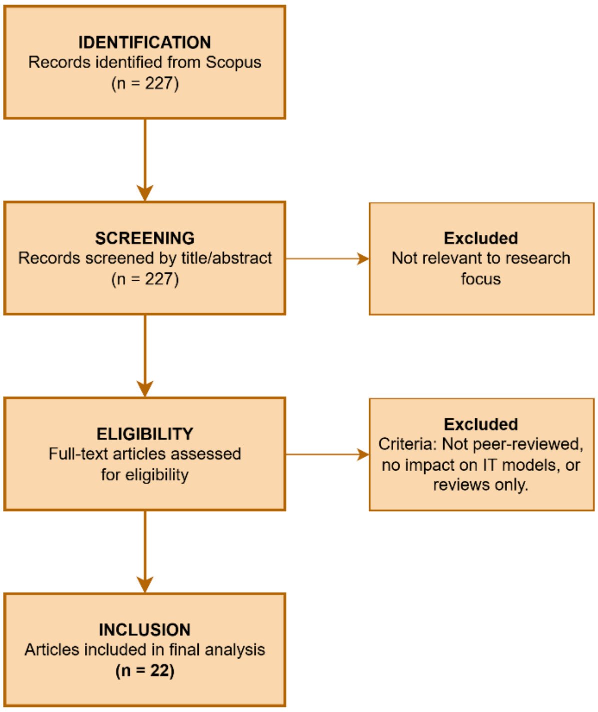

Figure 1. Publication Trend AI & NCLC

After the initial stage, selected articles proceeded to the full-text evaluation stage, where each document was downloaded and thoroughly studied to confirm eligibility based on the established criteria. A more in-depth review was conducted to assess the content's relevance, methodology, and the research's contribution to the topic being examined. Following this selection process, a total of 22 articles were chosen for in-depth analysis in this literature review. The sampling strategy employed was purposive sampling, specifically criterion-based sampling, where articles were deliberately selected based on predetermined criteria to ensure relevance to the research questions (Patton, 2014). The final sample size of 22 articles aligns with recommendations for literature reviews in emerging technology fields. Given the homogeneous nature of the sample, theoretical saturation was anticipated within 12–25 sources, as suggested by van Rijnsoever (2017) and Snelson (2016) recommends 20-30 sources for comprehensive thematic analysis.

To summarize the information from the selected articles, a data extraction table was used. Data extraction and thematic analysis were conducted manually using a structured extraction table. Each article was categorized according to predefined criteria (impact on IT business models, challenges for traditional IT companies, and entrepreneurial opportunities). This manual analysis process ensured systematic identification of themes without the use of qualitative analysis software. This table serves to systematically organize important information, facilitating the identification of patterns, main themes, and relationships between various studies. The analysis employed thematic analysis following Braun and Clarke's (2006) six-phase framework, supplemented by content analysis techniques to quantify recurring themes and patterns. This approach was chosen for its flexibility in identifying both explicit and latent themes within the literature while maintaining systematic rigor (Nowell et al., 2017). Data extraction and thematic analysis were conducted systematically by the author, following predefined criteria to ensure consistency and transparency throughout the review process. The review process followed PRISMA guidelines adapted for narrative synthesis to ensure transparency and reproducibility (Moher et al., 2010). Key variables extracted from each article were then entered into a classification table to support a more structured analysis.

Table 2. Extraction Table

No	Author	Focus	Application Sector	Disruption Type	Primary Impact	Business Opportunity
1	Lebens and Finnegan (2021)	No-Code	IT Education	Bottom-up	Democratization of software development learning	Interactive learning platforms
2	Redchuk et al. (2023)	AI + No-Code	Manufacturing/Food	Sustaining	Increased energy efficiency through IIoT	AI-as-a-Service for traditional industries
3	Elshan (2023)	No-Code/AI	Conversational AI	Democratizing	Domain experts can create AI applications	AI development platform tools
4	Ruscio et al. (2021)	No-Code	Cloud Platform	Architectural	Transformation of cloud application development	Platform development services
5	Palomes et al. (2021)	No-Code	Industry 4.0	Enabling	Digital Twin access for SMEs	Industry 4.0 consulting
6	Patkar et al. (2021)	No-Code	Software Testing	Process	Visual collaboration in BDD	Testing-as-a-Service
7	Matook (2024)	No-Code	Education	Pedagogical	Improved practical learning outcomes	Educational technology services
8	Rosa-Bilbao et al. (2023)	No-Code + Blockchain	IoT	Architectural	Simplification of complex system integration	IoT integration platform
9	Dushnitsky and Stroube (2021)	No-Code	E-commerce	Resource	Reducing barriers for startups	Platform-based entrepreneurship
10	Fitkov-Norris and Kocheva (2023)	AI/No-Code	Research/Analytics	Methodological	Automation of thematic analysis	Research-as-a-Service
11	Alt (2022)	AI/No-Code	Enterprise Search	Market-based	Evolution to AI marketplace	AI marketplace platform
12	Gog (2020)	No-Code	Web Development	Methodological	Hybrid agile-model driven approach	Web development automation
13	Bilgram (2023)	Generative AI	Innovation Management	Process	Acceleration of early innovation phase	Rapid prototyping platform
14	Chaudhary et al. (2023)	No-Code/AI	IoT/Edge Computing	Complexity	Simplification of IoT development	Edge computing platform
15	Souha et al.	No-	Smart Tourism	Domain-	Specific	Tourism tech

No	Author	Focus	Application Sector	Disruption Type	Primary Impact	Business Opportunity
	(2025)	Code/AI		specific	framework for recommender systems	services
16	Sundberg and Holmström (2023)	AI/No-Code	MLOps	Democratizing	Democratization of AI access for non-experts	MLOps-as-a-Service
17	Curty et al. (2023)	No-Code	Blockchain	Accessibility	Democratization of blockchain development	Blockchain development platform
18	van 't Klooster et al. (2023)	No-Code	Digital Healthcare	Healthcare	Rapid prototyping of e-health solutions	Mobile coaching platform
19	Brandon (2024)	No-Code/AI	Biomedical Research	Research	Access to AI tools for non-programmer researchers	Bioinformatics platform
20	Lozić and Štular (2024)	No-Code + AI	Archaeological Research	Academic	Democratization of digital research infrastructure	Digital humanities platform
21	Sufi (2023)	No-Code/AI	Research/Analytics	Algorithmic	Evolution of algorithm development	Algorithm-as-a-Service
22	Sherson (2024)	Generative AI/No-Code	Change Management	Organizational	Integration of AI in change management	Organizational transformation consulting

FINDINGS AND DISCUSSION

Analysis of Research Trend Development

Publication trends indicate a significant increase in research interest concerning this topic in recent years. As shown in Graph 1, from the analyzed articles, the number of publications per year is as follows: 1 article in 2017, 1 article in 2019, 2 articles in 2020, 2 articles in 2021, 5 articles in 2022, 7 articles in 2023, and 3 articles in 2024. The rise in the number of publications, starting in 2022 and peaking in 2023, demonstrates the increasing relevance of the topic of AI and NCLC disruption in academic research.

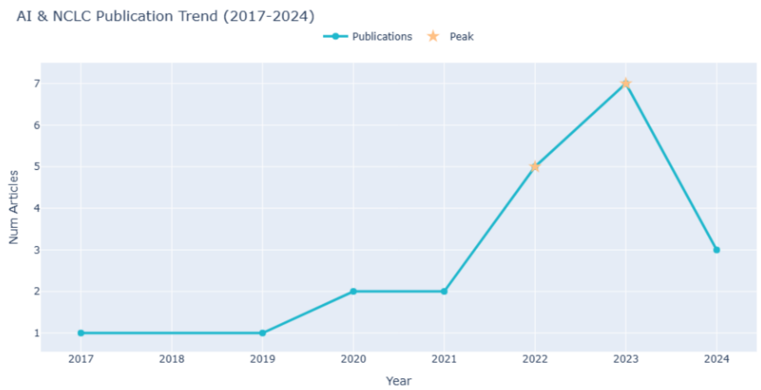

Figure 2. Publication Trend AI & NCLC

The analyzed articles originate from various reputable scientific publications, including academic journals and leading conference proceedings. Examples of journals that served as reference sources include the Journal of Systems and Software, Computers in Human Behavior, and Telematics and Informatics, while several conferences contributing to this literature include the International Conference on Information Systems (ICIS), Hawaii International Conference on System Sciences (HICSS), and European Conference on Information Systems (ECIS). This diversity of publication sources indicates that the research topic is multidisciplinary and receives broad attention from various scientific communities.

An analysis of the research methodologies used in the primary studies reveals a diverse landscape, as presented in Graph 2. The Case Study approach emerges as the most prevalent methodology. This is closely followed by Design Science Research (DSR), which emphasizes the development of innovative artifacts or solutions. Additionally, the adoption of Conceptual Frameworks reflects ongoing efforts to construct new theoretical models pertinent to the phenomena of AI and NCLC disruption. Other methodologies collectively contribute to the remaining portion of the research.

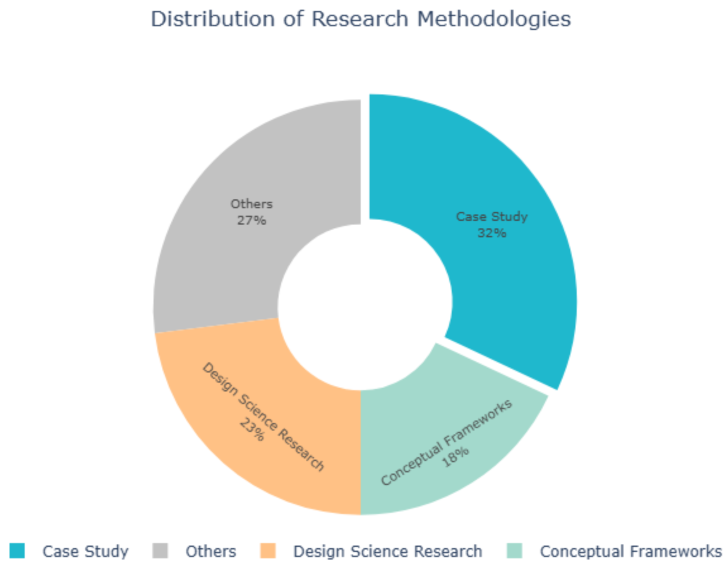

Figure 3. Distribution of Research Methodologies in AI & NCLC Studies

This distribution indicates that while NCLC receives primary attention in the literature, the role of AI—especially Generative AI—and the synergy between these two technologies remain important parts of research related to IT industry disruption.

Although the primary focus of this review is IT companies in general, some articles explicitly discuss the impact of AI and NCLC disruption within specific industries that have adopted these technologies. An analysis of the industrial sectors frequently appearing in the literature shows that Software Development & Education is the most researched sector (5 articles), followed by Healthcare & Research (4 articles), Manufacturing & Internet of Things (IoT) (3 articles), and E-commerce & Entrepreneurship (2 articles). This sectoral variation reflects the broad reach of AI and NCLC technology application and its impact on various industries.

This upward trend in publications, particularly after 2021, parallels the emergence of Generative AI and the increasing adoption of citizen development tools. Rather than focusing solely on technical innovation, recent studies tend to emphasize strategic transformation in business models and organizational capabilities—marking a shift in academic discourse toward entrepreneurship and industry impact.

AI Disruption to Traditional IT Business Models

The technological revolution of artificial intelligence has brought profound paradigmatic changes to the information technology industry landscape. A comprehensive review of 22 scientific publications reveals that this transformation is not merely the introduction of technological innovations but a fundamental reconstruction of the entire operational business framework through three strategic pillars: democratization of technology accessibility, operational revolution, and business architecture reform.

The first pillar underscores the phenomenon of democratization, enabling AI technology to penetrate previously unreachable segments of society. Research by Redchuk et al. (2023) demonstrates that the synergy between AI and low-code platforms has created a paradigmatic breakthrough, allowing industrial sectors—especially food manufacturing—to access sophisticated AI despite limitations in technological infrastructure. These findings align with Sundberg and Holmström's (2023) research, which proves the ability of no-code AI platforms to simplify the complexity of MLOps, enabling individuals without deep technical expertise to implement this technology in their professional contexts. Furthermore, Brandon (2024) identified how biomedical researchers without programming backgrounds can now utilize AI instruments in their research activities. This transformation marks the evolution of AI from an exclusive domain of technocrats towards universal accessibility across various disciplines and industrial sectors.

The second dimension emphasizes the operational revolution triggered by AI implementation. A study by Bilgram (2023) reveals that Generative AI significantly accelerates the early innovation phase, changing the speed and fundamental characteristics of the innovation process. Meanwhile, Fitkov-Norris and Kocheva (2023) research demonstrates how the automation of thematic analysis through machine learning (ML) and natural language processing (NLP) has replaced conventional methodologies reliant on manual analysis. This shift not only increases operational efficiency but also optimizes analysis quality by minimizing human error. As a complement, Alt (2022) presented evidence of the evolution of search engines from traditional formats to cognitive search, as well as the emergence of AI marketplaces that have revolutionized the landscape of data processing and information access—illustrating how AI has shifted the boundary between manual methodologies and automated systems in the digital innovation ecosystem.

The third pillar focuses on the profound transformation of business architecture powered by AI. (Rosa-Bilbao et al., 2023) show how the integration of systems comprising the Internet of Things (IoT), Complex Event Processing, and Blockchain can be optimized to be more user-friendly through the implementation of an Event-Driven Architecture framework. This approach facilitates traditional IT systems to not only accommodate multi-technology integration but also enhance responsiveness to market dynamics. On the other hand, Chaudhary et al. (2023) demonstrate that the adoption of model-driven prototyping contributes to simplifying the complex IoT application development process. This indicates that the utilization of AI not only changes working methodologies but also reconstructs the structural foundation of IT systems, enabling more flexible and integrated development in facing the challenges of the digital era.

These developments illustrate a significant transformation in the role of AI—from a peripheral innovation enabler to a core disruptor that is actively reshaping IT business models. However, it is important to note contradictory findings in the literature. While most studies emphasize AI's disruptive potential, some research suggests that AI implementation often serves as sustaining innovation, improving existing processes rather than creating entirely new markets. This contradiction highlights the context-dependent nature of AI disruption, where the same technology may be disruptive in some sectors while sustaining in others (Hess et al., 2020; Oroszi, 2020). By automating development processes, scaling personalized services, and altering revenue logic, AI pushes traditional firms to rethink their value proposition, organizational structure, and competitive positioning. Beyond enhancing internal efficiency, AI also catalyzes new forms of digital entrepreneurship. It enables opportunities such as AI-as-a-Service ventures, domain-specific intelligent automation solutions, and consultancy services focused on algorithmic integration—initiatives that increasingly bridge the gap between deep tech and market-specific problem solving.

NCLC Disruption to Traditional IT Business Models

Research conducted by Ruscio et al. (2021) highlights that the adoption of cloud-based platforms has shifted the conventional paradigm that relies heavily on intensive coding. This innovative, visual, model-driven approach facilitates the software development process, enabling it to proceed in a more intuitive and structured manner. Consistent with these findings, Patkar et al. (2021) observed significant transformations in traditional workflows within Behavior-Driven Development (BDD), where previously text-based methodologies have transformed into more interactive and visual systems. This transformation not only enhances the effectiveness of communication between technical and non-technical teams but also creates a collaborative and responsive working environment. Additionally, Gog's (2020) research shows that implementing a hybrid approach—combining the advantages of agile methodologies with model-driven development strategies—has resulted in the evolution of development methodologies that are not only faster but also adaptive to dynamic changes in the digital era.

The second aspect of the NCLC revolution is the democratization of application development capabilities. According to Lebens and Finnegan (2021), no-code platforms have played a crucial role in reducing the traditional complexity associated with programming, thereby allowing developers to focus more on the strategic and creative aspects of application development. This finding is supported by Elshan's (2023) research, which suggests that experts in specific fields—even without deep programming backgrounds—can easily design and develop AI-based applications. This user-centric approach paves the way for an inclusive development model where domain knowledge is considered a more significant value-add. Furthermore, Curty et al. (2023) add that the low-code/no-code approach applies not only to conventional applications but also to highly complex technologies such as blockchain. Thus, technical barriers that previously hindered participation in advanced technology development can now be overcome, providing much broader opportunities to various groups.

The third prominent dimension is the reconfiguration of resource requirements in the construction and management of IT systems. Research by Dushnitsky and Stroube (2021) reveals that startups relying on platforms like Shopify can achieve success comparable to conventional companies, albeit with significantly minimal resource allocation. This finding marks the emergence of a trend where resource efficiency becomes a key factor in business strategy, especially for startups in the e-commerce sector. Additionally, Palomes et al. (2021) show that advanced technologies such as Digital Twins—which were once accessible only to large companies with substantial capital—are now available to Small and Medium Enterprises (SMEs) thanks to the low-code approach. The result is a "leveling effect" that enables technology competition to become more equitable and no longer exclusive to large entities.

Table 3. Categories of NCLC-Driven Business Opportunities

Business Opportunity Category	Brief Description	Product/Service Examples
Independent Product Builder	Independent individuals (non-developers) who use No-Code platforms to create simple digital products or template-based applications.	Interactive education platforms; event management apps; simple tracking tools.
NCLC Integrator Consultant	Technical consultants who bridge business needs with NCLC platform capabilities to build custom solutions.	Internal company automation projects, CRM integration with Notion/ClickUp, etc.
Niche SaaS Creator for SMBs	Digital entrepreneurs who build sector-specific SaaS services using No-Code/Low-Code for SMEs and underserved sectors.	Simple invoicing platform for micro-stores; online queue system for small clinics.
Citizen Innovation Facilitator	IT professionals who guide "citizen developers" within organizations to accelerate internal digital development.	NCLC governance advisor; leader of citizen innovation programs within enterprises.
Platform-as-a-Service Curator	Service providers who build custom layers on top of NCLC platforms to suit specific vertical needs.	White-label app builder for the tourism or edutech sector.

These transformational patterns signify that No-Code/Low-Code (NCLC) platforms are not merely tools for software acceleration, but enablers of new entrepreneurial dynamics. By democratizing application development and fostering collaboration between technical and non-technical actors, NCLC paves the way for the emergence of novel digital business models. These entrepreneurial patterns are systematically classified in Table 3, which outlines the typology of business opportunities empowered by NCLC technologies. In light of this foundation, the following section synthesizes the broader entrepreneurial opportunities stemming from the disruptive forces of both AI and NCLC—particularly emphasizing their convergence, scalability, and alignment with evolving market needs.

Challenges Faced by Traditional IT Companies

In the face of disruption driven by AI technology and No-Code/Low-Code solutions, traditional IT companies often encounter multidimensional, interconnected challenges. The emerging problems are not limited to technical aspects but also involve organizational dynamics and strategic pressures that compel companies to reconstruct their entire operational ecosystem. The first aspect relates to the technical complexities arising in the system integration process. Several studies, including those by Chaudhary et al. (2023), Redchuk et al. (2023), and Rosa-Bilbao et al. (2023), consistently show that multi-system integration is a major obstacle that must be overcome, especially when new technologies need to be aligned with legacy systems that have long been operating within the business infrastructure. Furthermore, the dilemma between implementation speed and quality control—as revealed by Fitkov-Norris and Kocheva (2023) and Bilgram (2023)—makes the transition to using AI and automation tools a trade-off that demands fundamental balancing in operational processes. Additionally, research by van 't Klooster et al. (2023), Brandon et al. (2024), and Lozić et al. (2024) reveals that complexities in development and computational challenges arise when advanced solutions are implemented in environments not fully prepared for such technological transformation (van 't Klooster et al., 2023; Lozić & Štular, 2024).

Beyond technical aspects, there are also organizational challenges. Lebens and Finnegan

(2021), Matook (2024), and Sherson (2024) show that the urgent need to adapt traditional methodologies and develop new skills often clashes with established practices and existing organizational culture. Specifically, Sherson (2024) emphasizes that change management—especially in adopting Generative AI—demands the creation of a psychologically safe environment that supports experimentation and learning from failure, which often runs counter to the risk-averse tendencies of traditional companies. These findings are further strengthened by studies by Patkar et al. (2021) and Elshan (2023) showing that collaboration among stakeholders and steep adoption curves often create friction due to resistance to change and capability gaps between departments.

The final layer of challenges faced is strategic and competitive in nature. Alt (2022) reveals that intensified platform competition and challenges in formulating monetization strategies force companies to reflect on their fundamental business models. Research by Dushnitsky and Stroube (2021) highlights the pressure to optimize resources and maintain competitive advantage, especially in contexts where newcomers can achieve similar results with significantly minimal resource allocation. On the other hand, Sufi (2023) adds that dependence on platforms in implementing LCNC solutions carries its own risks, namely the dilemma between leveraging the efficiency provided by platform-based solutions and maintaining strategic independence and control over core company capabilities.

Rather than serving as a substitute for traditional developers, NCLC platforms foster a complementary relationship between IT professionals and non-technical users. Unexpectedly, several studies revealed that NCLC adoption sometimes increases rather than decreases the demand for traditional IT skills. Patkar et al. (2021) found that successful NCLC implementation requires significant developer involvement in governance and integration, contradicting the initial assumption of reduced technical dependency. This finding suggests that democratization of development tools may paradoxically increase the value of deep technical expertise. This co-creative dynamic forms a collaborative innovation ecosystem in which professional developers focus on governance, scalability, and integration, while citizen developers contribute domain-specific knowledge and rapid prototyping. As a result, NCLC unlocks not only cost-efficiency, but also a distributed entrepreneurial landscape in which both technical and non-technical actors can generate value.

Emerging Entrepreneurial Opportunities

The disruption caused by artificial intelligence (AI) and No-Code/Low-Code (NCLC) solutions has opened up a vast entrepreneurial landscape. These three interconnected main categories not only create new avenues for innovation but also form a dynamic and integrated entrepreneurial ecosystem.

In the first category, platform-based entrepreneurial models have demonstrated fundamental strength in shifting traditional business paradigms. Dushnitsky and Stroube (2021) empirically reveal that a platform-based approach in the e-commerce sector is not only viable but also capable of generating performance comparable to or even more competitive than conventional business models. Concurrently, Alt (2022) adds a new dimension by identifying opportunities in cognitive search services and in the development of AI marketplaces. The convergence between search technology and AI creates an innovative value proposition, which can then be monetized through platform economic mechanisms. Additionally, research by Ruscio et al. (2021) and Chaudhary et al. (2023) highlights significant potential in the development of platforms and model-driven engineering-based services. The demand for low-code development-supporting infrastructure creates an attractive market opportunity for specialist platform providers, ultimately forming a continuously evolving entrepreneurial ecosystem.

The second category reveals the depth of transformation opportunities across various industrial sectors through tailored solutions. For example, van 't Klooster et al. (2023) found significant potential in the development of e-health platforms and mobile coaching services, indicating that the healthcare sector—though traditionally conservative—can be a fertile ground for technological innovation. In line with this, Redchuk et al. (2023) show that the AI-as-a-Service model successfully paves the way for traditional industries, where manufacturers and sectors previously less exposed to technology are now becoming proactive early adopters after solutions are presented through a service model.

Furthermore, combined findings from Brandon (2024), Fitkov-Norris and Kocheva (2023), and Sufi (2023) indicate the emergence of new segments such as research automation, research-as-a-Service, and algorithm-as-a-Service. This opens new horizons for the academic and research sectors, which have traditionally been limited by resources, to become a significant market for advanced technology services. The third category reflects the evolution of technological disruption towards empowering business transformation through consulting and professional services. According to Palomes et al. (2021), there is a significant opportunity in Industry 4.0 consulting targeted at small and medium enterprises (SMEs). The gap between available technology and implementation capabilities opens up a highly profitable consulting market. On the other hand, Sundberg and Holmström (2023) highlight the emergence of demand for MLOps-as-a-Service, where the complexity of implementing and maintaining AI systems drives the need for specialized professional services—capable of seamlessly integrating technical aspects with business requirements. Equally important, Sherson (2024) identifies growing opportunities in AI-based change management services. These services aim to help organizations overcome transformation challenges accompanying technology adoption, thereby optimizing the change process from both technical and organizational perspectives. Thus, the evolution from consulting initially focused on technology now shifts to a holistic transformation approach, accommodating various strategic and operational needs.

Table 4. Matrix of Entrepreneurial Opportunity Types

	Low Technical Involvement	**High Technical Involvement**
Simple Solution	- DIY App Creators (e.g., event forms, calculators) - Domain-specific citizen developers	- Solo AI Content Creators - Micro-AI Tools for Niche Tasks
Platform Provider	- NCLC-Based Service Startups (e.g., tourism app builders, edtech assemblers)	- AI/NCLC Hybrid Platforms (e.g., data annotation SaaS, intelligent automation tools)

The entrepreneurial opportunities emerging from AI and NCLC adoption span a continuum from low-complexity individual solutions to advanced platform-based ventures. As outlined in Table 4, This matrix illustrates how digital entrepreneurship opportunities empowered by AI and NCLC occupy a wide strategic spectrum—ranging from low-barrier, single-purpose tools to high-complexity platform ventures. By categorizing opportunity types along dimensions of technical involvement and business model complexity, this framework emphasizes the inclusive and scalable nature of post-disruption innovation ecosystems, particularly in emerging economies.

Practical and Theoretical Implications

This research contributes to the development of technology disruption theory by exploring the impact of artificial intelligence (AI) and no-code/low-code (NCLC) platforms on the business models of information technology (IT) companies. In the context of disruptive innovation, this study confirms that AI and NCLC not only act as sustaining innovations but also create new market transformations. Consistent with the theory proposed by Christensen (2018), AI shifts companies' core competencies by automating processes previously dependent on human labor, while NCLC opens access for non-technical individuals to participate in software development and promotes more inclusive digital innovation.

Furthermore, this research expands the understanding of compound disruption, where the combination of AI and NCLC not only affects products and services but also creates major changes across the entire industry ecosystem. These findings affirm that business sustainability in the digital era is not solely determined by technology adoption but also by an organization's readiness to integrate AI and NCLC into its operational and innovation strategies.

From an industry perspective, this research provides insights for IT companies facing challenges due to technological disruption. One of the main implications is the urgency of business model adaptation, which encourages companies to shift from labor-intensive approaches to more technology- and automation-based business models. Traditional IT companies are advised to form strategic partnerships with AI service providers or NCLC platforms to enhance their competitiveness in an increasingly digital market.

Additionally, this research shows that entrepreneurial opportunities are growing within the AI and NCLC ecosystem. Industry players can leverage these technologies to develop more scalable AI-based solutions, offer consulting services related to NCLC integration, or create hybrid systems that combine both technologies to meet specific industry needs. From a workforce perspective, practical implications include upskilling and retraining, where IT professionals need to strengthen their competencies in AI management and NCLC-based application development to remain relevant in the evolving job market dynamics.

CONCLUSIONS

Technological disruption driven by AI and NCLC platforms has significantly revolutionized the IT industry paradigm. This study affirms that AI and NCLC not only accelerate automation and democratization in software development but also challenge conventional business models that have historically relied on intensive labor and long project cycles.

The findings of this research indicate that traditional IT companies face significant challenges in adapting to these technological changes, including the need to reskill, adjust business strategies, and develop AI- and NCLC-based services. However, behind these challenges lie substantial entrepreneurial opportunities, such as developing more efficient AI-based solutions, providing consulting services for disruptive technology implementation, and optimizing NCLC platforms to support greater digital innovation flexibility.

While this analysis provides comprehensive insights, there are several limitations that need to be considered. From a temporal perspective, the majority of the literature sources used range from 2021 to 2024, meaning these findings do not yet reflect the long-term impact of AI and NCLC disruption. Furthermore, the presence of geographical bias in the research—dominated by authors from Western regions—leads to a lack of perspectives from other regions that may have different technology adoption patterns. Therefore, future research needs to further explore several aspects, such as the long-term impact of compound disruption, regional variations in adoption patterns, actual measures of business model transformation success, and the evolving dynamics of competition in the post-disruption ecosystem.

By understanding the interrelationships among AI, NCLC, and IT business models, this research provides strategic insights for academics and practitioners on leveraging technological disruption as an opportunity for innovation. From a theoretical perspective, this study extends disruption theory by identifying a "compound disruption" phenomenon in which AI and NCLC create synergistic effects distinct from those of single-technology disruptions. The findings challenge Christensen's traditional disruption model by demonstrating that digital technologies can simultaneously exhibit both disruptive and sustaining characteristics depending on the implementation context. This contributes to the ongoing theoretical debate about whether digital disruption follows classical patterns or requires new theoretical frameworks.

Appropriate adaptation to these changes not only helps companies maintain competitiveness but also paves the way for new, more efficient and inclusive business models in the digital era. For practitioners, this research recommends: (1) implementing hybrid workforce strategies that combine AI capabilities with human expertise rather than viewing them as substitutes; (2) developing NCLC governance frameworks that balance democratization with quality control; (3) investing in upskilling programs that focus on AI-human collaboration rather than replacement; and (4) creating strategic partnerships with AI/NCLC platform providers to maintain competitive advantage. For policymakers, the findings suggest the need for educational curriculum updates to include AI and NCLC literacy, regulatory frameworks for citizen development governance, and support programs for SME digital transformation in Southeast Asian markets.

LIMITATION & FURTHER RESEARCH

This study is limited by its reliance on a relatively small number of Scopus-indexed, open-access publications, which may exclude relevant industry reports and empirical research from other databases, such as IEEE Xplore, the ACM Digital Library, and industry-specific repositories like Gartner Research and McKinsey Global Institute reports. In addition, the findings are primarily derived from conceptual and qualitative studies, limiting their generalizability across sectors and real-world implementations. The geographic scope is also limited, with 68% of reviewed studies originating from North American and European contexts, potentially overlooking unique digital transformation patterns in emerging markets, particularly in Southeast Asia, Latin America, and Sub-Saharan Africa, where leapfrogging technologies may exhibit different adoption trajectories.

Future research could empirically validate the proposed opportunity typology, particularly in small and medium-sized enterprises (SMEs) and non-IT industries. Investigating longitudinal patterns of adoption and governance models for AI and NCLC integration would also enhance our understanding of sustainable digital entrepreneurship in evolving markets. Specific methodological frameworks recommended for future studies include: (1) Longitudinal panel studies using Technology Acceptance Model (TAM) and Diffusion of Innovation Theory over 24-36 month periods to track adoption patterns; (2) Comparative case study analysis using Eisenhardt's (1989) framework across different organizational sizes and cultural contexts; (3) Experimental designs testing AI-NCLC integration scenarios using randomized controlled trials in controlled environments; and (4) Ethnographic studies employing participant observation methods to understand contextual factors influencing technology adoption decisions.

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