Liabilities of Newness and Smallness in the Age of Artificial Intelligence: What Liabilities?

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The most significant improvement in productivity is the division of labor powered by technology. The speed at which businesses adopt, assimilate, and disseminate these technologies impacts their survival. Size has been identified as a major factor that affects the speed and rate of technology adoption. Despite the contribution of small businesses to the world's economy, access to resources has constrained their growth, making them appear small, less legitimate, and more prone to failure. Artificial intelligence is helping small businesses gain legitimacy and overcome some of the liabilities of smallness and newness. Artificial Intelligence is a system created to analyze data and perform specific tasks through human-like decision-making processes and has significantly impacted organizations, societies, and individuals. AI adoption and benefits are not fully understood since existing literature is in its infancy and fragmented. Multiple or recurring Gartner's Hype Cycles makes AI technology adoption different from general technology adoption. Moreover, with AI technology adoption, size and incumbency may not be advantageous to large businesses. Implications and future research directions are discussed.

Keywords: incumbency, size, AI technology adoption, Gartner Hype Cycle

INTRODUCTION

Scholars, business practitioners, and government and political leaders have recognized small businesses as the backbone of national economies. The Small Business Administration (SBA) defines a small business as one that is independently owned and operated and is not dominant in its field of operation, while the European Union (EU) defines it by staff headcount, turnover, or balance sheet total: Micro business (less than 10 employees, equal or less than 2 million euros in turnover or balance sheet), small business (less than 50 employees, equal or less than 10 million euros in turnover and balance sheet, and medium-sized (less than 250 employees, equal or less than 50 million euros in turnover and equal or less than 43 million euros in the balance sheet). Across the globe, small and medium-sized enterprises (SMEs) constitute 90% of the world's economy, accounting for a robust 55% of the world's GDP and providing between 60% and 70% of employment (World Trade Report, 2016). In the United States, Small businesses drive the U.S. economy, creating two out of every three new jobs and accounting for 44% of national economic activity (Rowinski, 2022). Beyond these important facts, small businesses serve as supply conduits for raw materials and distributors for finished products of large corporations. According to the SBA, small innovative businesses are 16 times more productive than larger innovative firms in terms of patents per employee (Barringer & Ireland, 2019). SMEs account for approximately one-third of patents in solar energy and smart grids (Barringer & Ireland, 2019). Despite their significant contribution to the world's economy, access to capital has constrained the growth of these small businesses (Abubakar, 2015; Rao, Kumar, Chavan, & Lim, 2021), resulting in their remaining small, appearing less legitimate, and therefore, more prone to failure. However, virtually embedded technologies (Morse, Fowler, & Lawrence, 2007), such as electronic data interchange, e-commerce, social media, and, most recently, artificial intelligence (AI), are helping small businesses overcome some of the liabilities of smallness and newness.

The speed at which small businesses adopt, assimilate, and disseminate these technologies impacts their survival. Generally, small businesses that adopt technology more quickly tend to survive and thrive. Size is a significant factor that affects the speed and rate of technology adoption, assimilation, and dissemination. The relationship between the size of an organization and its adoption and use of technology has received much attention from economists, organizational theorists, and other researchers (e.g., Ein-Dor & Segev, 1982; Foster, & Rosenzweig, 2010; Granic, 2022; Kimberly & Evanisko, 1981; Lai, 2017).

Although size may have a positive relationship with general technology adoption, AI technology adoption does not seem to have a linear positive relationship with size, as the U.S. Census Bureau reports that although large businesses tend to adopt technology faster than small businesses, that trend is changing with advances in generative AI, as small businesses are closing the gap by adopting AI technology at a much faster rate (U.S Census Bureau, 2024). Introducing new technology or innovation is often accompanied by “ups and downs,” known as the Gartner Hype Cycle. Gartner Inc. Dedehayir and Steinert (2016), King and Prasety (2023), Linden and Fenn (2003), and Prasad and Choudhary (2021) defined this as a hype cycle, characterized by technology trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and plateau of productivity. Artificial Intelligence (AI) advancements enable AI-based Information Systems (IS) to perform activities that humans traditionally perform. However, their adoption and benefits are not well understood, as existing literature on AI adoption is still in its infancy and thus fragmented. There are major theories aimed at addressing technology adoption and acceptance such as Technology Acceptance Model (Davis, Bagozzi, & Warshaw,1989; Marangunić & Granić, 2015; Venkatesh & Bala,2008) and Unified Theory of Acceptance and Use of Technology (Baptista & Oliveira, 2015; Venkatesh, Thong, & Xu, 2012, 2016; Williams, Rana, & Dwivedi, 2015). Although these theories are helpful in understanding technology acceptance, adoption, and assimilation by businesses, they are not specific to small businesses and AI.

This exploratory paper focuses on the asset or strength view of small businesses and AI adoption rather than the more common deficiency approach of identifying barriers and problems that small businesses face regarding AI technology adoption. Thus, the paper aims to (1) illuminate the strides made by small businesses in closing the AI technology adoption gap, (2) explain how the capabilities of larger firms (around size and incumbency) have become their liabilities, and (3) add to the growing body of literature that views small businesses from a strength perspective rather than a deficiency perspective.

LITERATURE REVIEW

The most significant productivity improvement is the division of labor powered by the invention of machines by workers, philosophers, and manufacturers (Smith, 1776). Early researchers focused their study of technology on specific aspects, which has led to the current conflicting and ambiguous understanding of technology and its influence on organizations (Ogbolu, 2009). Some researchers, for example, Hulin and Roznowski (1985), defined technology as the physical combined with the intellectual or knowledge by which materials are transformed into outputs, and Berniker (1987) defined technology as a body of knowledge about how we interact with our world. Technology has always been a central variable in organizational theory; however, despite decades of research, there is little agreement on the definition and measurement of technology (Orlikowski, 1992). The divergent definitions and opposing perspectives of technological research have stifled our understanding of the impact of technology on organizations.

Technological change brings about a fundamental shift in the knowledge base, for example, the change from steam to diesel and electric technology in locomotives (Cooper & Smith, 1992). These authors examined how managers of incumbent organizations respond to changing technology. Technological changes often create capability gaps for incumbent organizations, as a firm’s capabilities can also define its limitations (Christensen, 2000). This gap arises due to the discrepancy between an incumbent organization's existing capabilities and the capabilities that will emerge successfully after technological change (Lavie, 2006). These technological discontinuities signal the era of ferment, characterized by high uncertainty and product innovation among both old and new competitors, after which a new technological standard emerges (Anderson & Tushman, 1990). This period is usually short for new technology arising from already established technology and longer for relatively new technology like AI.

One of the most transformative forms of innovation comes from the steam engine. The steam engine is a groundbreaking innovation that has fundamentally reshaped society, driving economic growth, industrial advancement, and profound societal transformation (Bragg, 2016; Bruland & Smith, 2013; Musson & Robinson, 1959; Nuvolari, 2006). As a result, the steam engine became the driving force behind the expansion of industries such as textiles, iron production, and manufacturing, transforming the economic landscape and setting new standards for innovation. Previously, industrial operations were constrained by geography and limited to locations near rivers or areas with steady wind conditions. The steam engine revolutionized the industry by freeing factories from reliance on traditional power sources, such as water and wind. The introduction of the power loom (1780-1840) to the textile industry in Manchester, England, was met with sabotage and vandalism by workers who believed that machines were replacing them. Once the power loom was fully established and accepted, the number of weavers increased exponentially. The fear and apprehension surrounding AI are like those experienced by weavers in Manchester, England, regarding the power loom**.** Some labor unions are beginning to include specific clauses in their agreements that limit organizations from using AI technology to replace employees' functions (Kelley, 2023). Because, despite AI's potential to liberate workers from tedious tasks, AI is used to replace workers and undermine their bargaining power (Press, 2024).

Artificial Intelligence

Artificial intelligence may seem relatively new, but its origins date back to the mid-20th century. Turing (1950) published a paper titled "Computing Machinery and Intelligence," in which he asked, "Can machines think?" His central inquiry was whether machines could use information and reason to solve problems like humans, proposing the Imitation Game, also known as the Turing Test, to define machine intelligence (see Turing, 1950). The term "artificial intelligence" was coined by computer scientist John McCarthy six years later. Over recent decades, AI's capabilities have surpassed those of human intelligence in many fields (Anyoha, 2017). Various forms of AI differ in their characteristics, uses, and applications. AI is a system created to analyze data and perform specific tasks through human-like decision-making processes (Brock & Von Wangenheim, 2019). There are many definitions of Artificial intelligence. Some of the definitions are discipline-based. For instance, the study of AI in communication utilizes broad descriptions from computer science and engineering, sociology, and legal studies as "learning algorithm used to approximate some form of intelligence operating within computing machines" (Ninness & Ninness, 2020, p. 100) and Simmons and Chappell (1988) defined the term artificial intelligence as behavior of a machine which, if a human behaves in the same way, is considered intelligent (Simmons & Chappell, 1988). Gartner (2023) defined AI in terms of applied analytical and logic-based techniques, including machine learning and automated decision-making and performance (Gartner, 2023). Others define AI as a subfield of computer science that develops and manages technologies capable of autonomously making decisions and performing actions on behalf of humans (Rouse, 2023). Technically, AI is defined as the application of advanced analytics and logic-based techniques, including machine learning, to interpret events, support and automate decisions and perform actions (Gartner, 2023). Artificial Intelligence has significantly impacted organizations, societies, and individuals by offering systematic capabilities of human-like reasoning based on external inputs and learning through the differences in expected outcomes. As it predicts and adapts to changes in its ecosystem and the stimuli it receives from its external environment, it enables organizations to make informed decisions (Dwivedi et al., 2023). AI technology is pervasive and used in almost every industry, including education (Fox, Pittaway, & Uzuegbunam, 2024), accounting (Hasan, 2021), and medicine (Briganti & Le Moine, 2020). As mentioned earlier, new technology or innovation is often accompanied by "ups and downs," known as the Gartner Hype Cycle.

The Gartner Hype Cycle is a visual representation of technology adoption, implementation, and dissemination, illustrating how businesses address challenges by leveraging emerging opportunities (King & Prasteyo, 2023). Gartner's Hype Cycle mode can forecast technological development, which is critical for organizations in formulating marketing and other organizational strategies (Dedehayir & Steinert, 2016). Gartner's Hype Cycle begins with an innovative trigger, attracting early adopters, and then gains momentum with mainstream adopters (See Gartner, 2023). According to (Gartner, 2023), there are five key phases in the life cycle of a given technology, namely, (a) Innovation Trigger, (b) Peak of Inflated Expectations, (c) Trough of Disillusionment, (d) Slope of Enlightenment, (e) Plateau of Productivity: Characterized by mainstream adoption and is usually the final phase of Gartner's Hype cycle of technology adoption, implementation, and dissemination. However, with AI technology, several authors have reported multiple or recurring Gartner's Hype Cycles (e.g., Dedehayir & Steinert, 2016; Jun, Yeom, & Son, 2014; Linden & Fenn, 2003).

Having multiple Gartner's Hype Cycles makes AI technology adoption different from technology adoption in general. The nature of each hype cycle (disruptive or incremental) poses an advantage or a disadvantage for large incumbent organizations. For example, if a new version of AI technology is disruptive and, therefore, competence-destroying, it will require a radical redesign of the existing structures, processes, and capabilities of large incumbent organizations. Inertial forces tend to predispose large incumbent firms to adapt to new versions quickly, whereas the newness and agility of smaller firms enable them to adapt speedily (Nascimento & Meirelles, 2022). Unlike larger incumbent firms that have been through earlier versions of AI technology, smaller and newer firms have no history of peak of inflated expectations and subsequent disillusionment from a previous cycle; therefore, they are more likely to adopt new versions of AI technology more quickly. Therefore, factors such as size and incumbency, once regarded as strengths for larger businesses can become their weakness, while newness becomes an asset for small and new businesses instead of a liability.

New businesses must overcome the liabilities of newness (Stinchcombe, 1965) that arise due to the lack of specific sets of resources and capacities possessed by more established businesses. Therefore, new ventures experience higher rates of failure than more established ones (Hannan & Freeman, 1984). Hannan and Freeman (1984) observed that new organizations have weak claims to sources of support and are highly vulnerable to environmental shocks, making them more prone to fail than established ones. Morse, Fowler, and Lawrence (2007) explained the issues of liabilities of newness and their effects on new ventures in general. The authors stated that new ventures must develop extant routines because they lack established roles and systems, which can result in issues of trust and legitimacy. Aldrich and Fiol (1994) suggested that trust is a critical first-level determinant of business success and an important factor in most social transactions, including business transactions where there is uncertainty about actions and outcomes.

Like trust, legitimacy is critical for diminishing the effects of the liabilities of newness. An entrepreneur's success ultimately depends on the entrepreneur's ability to gain customer support by achieving high levels of legitimacy (Zarkada-Fraser & Fraser, 2002). Aldrich and Fiol (1994) described two legitimacy processes: cognitive and sociopolitical legitimation. Cognitive legitimation refers to the point at which an activity, type of business, or business owner's ethnicity becomes so familiar that consumers believe they are knowledgeable users of the product or service. Sociopolitical legitimation refers to the process by which a venture is accepted by the public as appropriate, given the existing norms. Businesses can mitigate the liabilities of newness by enhancing consumers' perceptions of business legitimacy, which in turn increases business patronage (Aldrich & Fiol, 1994; Morse et al., 2007). However, due to undercapitalization and low growth potential, small businesses continue to fail at a higher rate than bigger businesses. Higher failure rates negatively impact consumer perceptions of business legitimacy, leading to lower patronage and increased failure rates. Small businesses must explore alternative avenues to establish their legitimacy. One such avenue is virtual embeddedness through technology adoption, more specifically, AI technology adoption.

Several factors influence technology adoption. Size as a variable in the study of technology adoption has been studied extensively. However, there are conflicting findings among researchers regarding the relationship between a firm's size and its adoption of technology. Coria and Kyriakopoulou (2018) and

Mathauer and Hofmann (2019) have, through empirical research, demonstrated that large firms tend to adopt more technological innovations. While Reynolds, Cotrino, Ifedi, and Donthu (2020) believe that smaller organizations adopt technology more than larger organizations.

Another factor that the author examined was incumbency. Incumbent firms tend to develop structural inertia. Structural inertia, as defined by Hannan and Freeman (1977), refers to a firm's inability or reluctance to adapt to changes in its environment. Structural inertia is a critical issue that incumbent firms face. A firm's ability to respond to environmental changes is crucial and can determine its viability.

Leadership is yet another factor that the author examined. Leadership and successful technological innovation are positively related. The successful adoption of technology by an organization depends on the availability of a leader or leaders who will champion it. These leaders risk both prestige and position because they have to assume ownership of the innovation idea for it to succeed (Schon, 1963).

Competition was the last variable examined by the author in the context of technology adoption by organizations. New entrants and other challengers can compete against dominant organizations through technological innovation. Technological discontinuities, as described by Anderson and Tushman (1990), provide the opportunity for new firms to enter the marketplace due to incumbent firms' sluggishness in adopting new technology. In general, larger and more established organizations adopted technology more readily due to their access to resources, capabilities, and existing processes. Kurup and Gupta (2022) found that organizational size, structure, leadership, availability of resources, compatibility of machine learning technology with existing technology, and change management capabilities were key factors influencing the adoption of AI technology. Structure, machine compatibility, and change management compatibility speak to structural inertia and incumbency, while organizational size and resource availability relate to the ability to bear the cost of new technology. Of these factors, the most critical for small businesses are size and incumbency due to their close association with an organization's newness and smallness.

Organizational Size

There is no consensus on the relationship between a firm's size and its adoption of technology. While some researchers believe that larger organizations adopt technology more, others disagree. Christensen (2000) attempted to explain this apparent conundrum regarding the size and adoption of disruptive technology. The author posited that (a) Technology must meet customers' and investors' needs to be supported, (b) Large businesses' growth needs are not usually met by small markets (advantage small businesses), (c) An organization's capabilities will define its disabilities, (d) Non-existent markets cannot be analyzed, (e), Technology supply may surpass market demand resulting in performance oversupply. Burton and Obel (1998) also attempted to clarify the differing effects of technology on organizational structure by considering organizational size and number of employees, the routineness of technology, technology type (informational or automated), and industry type (see Burton & Obel, 1998).

Some empirical studies have shown that large firms tend to adopt more technological innovations (Aiken & Hage, 1971; Coria & Kyriakopoulou, 2018; Damampour, 1987; Mathauer & Hofmann, 2019). Schumpeter (1942) characterized size as the single most important variable in technology adoption because large firms seem to have more resources than small firms and are better able to absorb losses that may arise from technology adoption than small firms (Damapour, 1987; Mathauer & Hofmann, 2019). Large organizations have the leverage to capture significant market share and have greater access to low-cost capital required to acquire new technology than smaller firms. In contrast, researchers claim that smaller firms adopt technology more rapidly than larger firms. Julian and Raymond (1994) demonstrated that small manufacturing enterprises have been implementing new computerized technologies at an ever-increasing rate to differentiate themselves from their competitors. Reynolds, Cotrino, Ifedi, and Donthu (2020) believe that the speed of technology adoption among small businesses depends heavily on the willingness and desire of their top executives. Drydakis (2022) described the ability of small businesses to transform through the digital integration of AI technologies facilitated by their precise business operations (Drydakis, 2022).

Globally, disruptive innovations, such as artificial intelligence (AI), are altering the competitive landscape within all industries (Reim, Åström, & Eriksson, 2020). AI's competitive advantage potential makes it the most important technological development (Brock & Von Wangenheim, 2019). Advancements in AI enable AI-based Information Systems to perform activities that were previously executed solely by skilled humans. AI can also help increase productivity, reduce costs, and enhance decision-making, which is a significant advantage for SMEs that may not have the resources to hire the type and number of skilled employees they need. Employees of SMEs view AI as a co-worker (Einola & Khoreva, 2023; Loof, Spinks, & Gagnon, 2024; Ötting, 2020), as AI helps small firms automate processes, analyze data, and enhance consumer experiences (Loureiro, Guerreiro, & Tussyadiah, 2021; Tishtykbayeva, Gelashvili, & Turusbekov, 2023). Customer inquiries and complaints, marketing initiatives, inventory management, employee scheduling, and shipping, among other tasks, are areas where AI can automate processes, thereby freeing up employee time for other activities (Tishtykbayeva, Gelashvili, & Turusbekov, 2023). This is also an advantage for SMEs, as AI has lowered the barriers to accessing technological tools that were previously only accessible to larger firms (Dapp & Slomka, 2015). Thus, small firms can leverage AI technologies and potentially create competitive advantages through their speed of adaptation and ease of incorporating change (Nascimento & Meirelles, 2022). Thus, the author offers propositions that represent a departure from Aiken and Hage (1971), Coria and Kyriakopoulou (2018), Damapour (1987), and Mathauer and Hofmann (2019) who believe that larger firms are better able to adopt more technology because of their resources and ability to absorb shocks from losses due to technology absorption. These propositions align more closely with Nascimento and Meirelles (2022), who stated that although inertial forces predispose large incumbent firms to adapt quickly to the new version, smaller firms' newness and agility enable them to adapt speedily. This finding is also in direct agreement with Pan, Froese, Liu, Hu, and Ye (2023), who found that organizational size, which represents organizational richness, has no significant impact on AI technology adoption. The author of this paper believes that size may hurt AI technology. Thus, the author proposes the following:

Proposition 1: *The size of an organization is negatively related to the speed of AI adoption, dissemination, and implementation.*

Incumbency

Incumbent firms are those that manufacture and sell products belonging to the product generation preceding a radical product innovation (Chandy & Tellis, 2000). Incumbency in an innovation context reflects a firm's participation in the previous generation of products. While it is easy to argue that larger firms have the resources to adopt technology, they are also more prone to structural inertia (Hannan & Freeman, 1977). Incumbent and usually larger organizations often suffer from structural inertia, defined as a firm's inability or reluctance to adapt to change (Hannan & Freeman, 1977). Ecology theorists postulate that a firm's inability or unwillingness to adapt to its environment will negatively impact its viability (Burns & Stalker, 1961; Stinchcombe, 1965). Incumbent organizations may possess internal and external inertial components (Hannan & Freeman, 1977). Internal inertial components include an organization's investments in plants, equipment, personnel, power dynamics, and other routines (Ogbolu, 2009). Organizational routines must change for organizations to develop new knowledge and capabilities (Anyoha, 2017; Benner & Tushman, 2002; Cohen & Levinthal, 1990; Henderson & Clark, 1990; Leonard-Berton, 1992).

Even in the process of acquiring new technology, incumbent organizations tend to apply knowledge and skills that are associated with old technology. Hammer and Champy (1993) believed that incumbent organizations must engage in reengineering, which they believed was a path to change that organizations must take to reinvent themselves in dynamic environments. The authors defined reengineering as " the fundamental rethinking and radical redesign of business processes to achieve dramatic improvement in critical, contemporary performance measures, such as cost, quality, service, and speed" (Hammer & Champy, 1993, p. 401). Incumbent organizations maintain their basic structures and routines while attempting to change. The result is a patchwork of fixes for emerging technologies, such as AI. Competence-destroying technologies, such as AI, necessitate a radical redesign rather than incremental changes within existing structures, processes, and capabilities. Thus, newer organizations, even those without a history of technology adoption or innovation investments, can leverage AI technologies to mitigate their disadvantages compared to large companies and potentially create competitive advantages through their speed of adoption, implementation, and dissemination (Nascimento & Meirelles, 2022). Structures, internal capabilities, and processes acquired during founding periods and periods of incremental change tend to persist within the organization for an extended period, a phenomenon known as imprinting. These structures and processes are usually unsuitable for technological changes (Benner, 2007; Hammer & Champy, 1993). Overcoming these inertial forces requires incumbent organizations to develop dynamic capabilities or research new domains to adapt successfully (Benner, 2007). External barriers include legal and fiscal constraints, as well as legitimacy constraints imposed by the environment. Incumbent organizations are slow to adopt new technology and are often replaced by ones better adapted to the environment (Hannan & Freeman, 1977).

Additionally, institutionalization affects the ability of incumbent organizations to adopt technology. Even though organizations may be able to adapt to technological changes by developing new capabilities, institutional pressure can still constrain an organization's response (DiMaggio & Powell, 1983; Meyer & Rowan, 1977). Organizations face institutional pressure from customers, suppliers, and competitors to conform to strategies and forms of like organizations. For these reasons, even when incumbent organizations adopt AI technology, they are slower to adapt to new versions of AI technology because of its multiple iterations.

However, incumbency can also have a positive relationship with the adoption of technology. For firms to attain incumbency status, they must have encountered and adapted to specific technological changes in the past to remain in business. Due to technological discontinuities, when technological change is incremental, incumbent firms are generally better suited to adopt new technology than non-incumbents (Anderson & Tushman, 1990). Anderson and Tushman (1990) described this phenomenon in their cyclical model of technological change, where they observed that if a new technology builds upon existing technology (competence-enhancing), the performance of an incumbent firm improves. Incumbents have more advantages if the new technology builds upon an existing form. However, AI is different. Even when AI technology appears incremental due to newer versions building on older versions and, therefore, enhancing competency, it still favors newer organizations with no history of using the older versions. Given that disruptive AI technology favors non-incumbent firms because inertial forces and incremental AI technology do not burden them, it is also not a disadvantage to non-incumbent firms because AI characteristic multiple Gartner Hype Cycles, the author proposes that:

Proposition 2a: *Incumbency is negatively related to AI technology if AI technology is competency-destroying.*

Proposition 2b: *Incumbent and newer organizations have an even advantage when AI technological change is incremental.*

Discussion and Conclusion

The most important reason any firm adopts new technology is to gain a competitive advantage (Dwivedi, Alabdooli, & Dwivedi, 2021; Majumdar & Venkataraman, 1993; Skare & Soriano, 2021).). Technology ranked among the top ten most important issues organization top managers face (Niederman, Brachchuer, & Wetherbee (1991). Research indicates that the higher the level of competition, the greater the likelihood that organizations will adopt technology (Ferguson & Olfert, 2016; Wang, Cho, & Scheller-Wolf, 2021). Thus, organizations must determine the competitive advantage of adopting new technology, as they will not adopt new technology unless it offers an increased competitive advantage over existing technology. Despite the importance of small businesses, they face significant challenges to technology adoption, including a lack of technical expertise and limited access to external networks and knowledge, primarily due to limited financial resources (Govori & Sejdija, 2023). As mentioned earlier, limited financial resources constrain small businesses from engaging in research and development, employing experts, and acquiring new technologies. Governmental policies that foster supportive ecosystems and offer financial incentives can help mitigate these challenges (Iyelolu, Agu, Idemudia, & Ijomah, 2024).

However, AI is unlike any other new technology that has emerged in the last few decades due to its affordability, accessibility, and widespread use across all industries. AI technology is the new electricity (Ng, 2018). Artificial Intelligence advancements enable AI-based Information Systems to perform tasks that were previously executed solely by skilled and well-trained professionals. AI is fast becoming the employees that small businesses need but could not afford in the past, as AI-based solutions can substitute a team of experts for specific tasks (Lacity & Willcocks, 2021). Researchers claim this will result in a significant shift in work and unemployment (see Susskind & Susskind, 2022).

Regarding AI, small businesses can overcome some of the advantages that larger businesses had in the past with general technology adoption, such as size and incumbency (especially with incremental technology). Because AI technology is available and affordable, small businesses are using AI technology more thereby nullifying the argument that larger firms adopt technology faster and more frequently due to cost. Compared to technology adoption in general, small businesses have been adopting and using AI more rapidly in recent years. According to the U.S. Chamber of Commerce Technology Engagement Center (2024) report, 40% of small businesses use generative AI in 2024 compared to 23% in 2023 (17% increase). Around the same period, general technology adoption increased by 4%. About 91% of these businesses believe it will help grow their businesses (U.S. Chamber of Commerce, 2024). Although, in general, incumbent firms tend to adopt new technology when the new technology is incremental because of their existing capabilities, smaller and newer firms tend to adopt AI technology just as much, even when AI technology appears to be incremental, because of AI's unique multiple Gartner hype cycle; newer firms are introduced to the current version for the first time at the point of adoption; therefore, they usually have no history of the different phases of the hypes of previous versions, including disappointment of the technology not meeting expectations.

In addition, small businesses do not have the alienation problems that employees of larger firms experience due to adoption of technology, such as feelings of powerlessness, job meaninglessness, isolation, and self-estrangement. Employees often feel powerless when they are manipulated and dominated by impersonal systems, such as technology (Blauner, 1964). Powerlessness occurs when employees are unable to self-direct or exert control; they believe they should have control over their work process, decision-making, or the final product. AI technology has exacerbated the feeling of powerlessness among employees of large firms, as AI is now performing some work tasks that were previously under their control. In contrast, smaller firms can fill skill gaps with AI technology, and their employees feel more empowered as they can utilize AI to perform tasks that were previously impossible.

Technology adoption can lead to a sense of meaninglessness of work within larger organizations, as it erodes the connection with the overall structure of roles and results in a lack of sense of purpose (Blauner, 1964). The meaninglessness of work is particularly evident in large firms, where employees are increasingly dominated by AI technology in their jobs. Some researchers believe that soon, AI technology will lead to job losses in large organizations (Bessen, 2018; Rawashdeh, 2023). In addition, due to bureaucracy and a lack of connection to the overall structure, there will be a heightened sense of job insecurity among the remaining employees of these organizations, as only top management is privy to whether more employees will lose their jobs to AI. Smaller firms with few or no employees are embracing AI technology, as it makes previously impossible or difficult tasks possible and more manageable. Einola and Khoreva (2023), Loof, Spinks, and Gagnon (2024), and Ötting (2020) report that AI technology enables small businesses to perform tasks that would have previously required employees.

Finally, technology adoption in organizations can result in isolation and self-estrangement due to a loss of sense of belonging and membership in a given community, as well as what employees have come to believe is the norm. Since organizations employ new technology to be more productive and to offer them a competitive edge, there is a feeling among employees of large organizations that they and their jobs are mere means to an end, and will result in lower self-expression and self-actualization and damaged self-esteem, since these employees view themselves simply as objects (things) or cogs in the organization's machine (Blauner, 1964). However, for smaller organizations with few or no employees, the adoption of AI technology brings about ease of work and increased employee empowerment, as employees can utilize AI technology to perform tasks they could not previously do. Put together, these alienation problems dispose large businesses to extreme structural inertia and motivate their employees to resist adopting AI technology as enthusiastically as small businesses.

Implications

This research examines the significance of AI technology adoption among small businesses. More importantly, it illuminates how increased AI technology adoption helps small businesses to overcome the liabilities of newness and the liabilities of smallness that have kept them small and more prone to failure than larger businesses. It also reemphasizes the need to refocus on the importance of small businesses by contextualizing some of the reasons for failure and how AI technology can mitigate these for small enterprises. One such reason is size. Large businesses have traditionally had an advantage over small businesses in terms of survival and success due to their ability to adopt technology; however, with AI technology, those advantages are dissipating, as small businesses are adopting AI technology at rates similar or higher than those of larger businesses. In addition to size, the cost of adopting technology historically has been prohibitive for smaller businesses. AI technology is relatively affordable. Therefore, smaller firms are adopting AI technology without the heavy cost burden that was previously associated with technology adoption. AI has become the employees that small businesses need but could not afford in the past. Small businesses now employ AI-based solutions as substitutes for a team of experts.

The U.S. Census Bureau 2024 report (Business Trends and Outlook Survey between September 2023 and August 2024) shows that although large businesses tend to adopt technology faster than small businesses, that trend is changing with advances in generative AI, which may have a disproportionate impact on small firms' adoption and use of AI (U.S Census Bureau, 2024). This report argues that AI can help close the technology and performance gap between small and large businesses and can enable small businesses to take on tasks that would have required costly specialized workers or outsourcing, thereby giving small businesses a competitive edge, boosting their productivity, in turn resulting in higher adoption of AI among small businesses, especially very small businesses. Although large businesses have been leading the way in AI adoption, very small businesses have also had relatively high AI adoption rates in recent times, and this trend is likely to continue into the near future. Advances in AI could have a significant impact on small businesses, especially minority-owned businesses, which are often small. Given the importance of small businesses to the U.S. and global economies, government policies and programs should be aimed at encouraging the adoption of AI technology by more small businesses. These policies would be necessary to help mitigate the costs of hiring human and technical experts to manage change and provide management oversight to enable more small businesses adopt AI technology more quickly.

Limitations

There are a few limitations that must be acknowledged. First, this study is exploratory and will require further analytical inquiry. The author acknowledges that there are many definitions of small business. As such, there may be some overlap in how different entities, such as the Small Business Administration (SBA) and other bodies, as well as country-specific definitions of small business, define what constitutes a small business or a large business. Finally, this paper is by no means exhaustive. One of its aims is to highlight strides small businesses have made toward AI technology adoption. The author admits that apart from incumbency and size, there are other factors that influence AI technology adoption beyond those mentioned herein.

Future Research Direction

Much future research, particularly longitudinal studies, is needed further to develop the theory of AI adoption in small businesses. For instance, studies focusing on the role of ethics in small business AI adoption will be necessary, as small businesses, due to their limited resources, often struggle to understand and address ethical issues and regulatory frameworks surrounding AI technology adoption. Furthermore, it will be fruitful to engage in longitudinal studies examining AI-driven SME transformation over time. Additionally, there are potential opportunities and approaches to test and measure the impact of AI technology on small businesses, particularly those owned by racial and ethnic minorities and women, given that these minority-owned businesses are founded at a high rate (Brush & Cooper, 2012; Patil & Deshpande, 2018). In addition, research focusing on Black business AI embeddedness could provide solutions to some unique challenges faced by Black entrepreneurs, such as low legitimacy perceptions (Ogbolu, Singh, & Wilbon, 2015) and higher failure rates (Fairlie & Robb, 2007). Since Black-owned businesses are often small and undercapitalized, embracing AI technology and its advantages may help reduce the failure rates of Black-owned businesses by mitigating the size and financial resource disadvantages they face. Therefore, focusing on the advantages of increasing AI technology use by Black-owned businesses is important for several reasons. Virtual embeddedness enables new and small businesses to establish roles and systems and access trust-based relationships, social capital, and economic capital (Morse, Fowler, & Lawrence, 2007), thereby gaining legitimacy (Aldrich & Fiol, 1994). More research in this direction would significantly enhance the development of theory surrounding Black entrepreneurial ecosystems, increase Black new venture creation and successful entrepreneurship, and steer the nation toward a more sustainable path toward economic and social justice by addressing racial wealth disparities (Singh & Nurse, 2024).

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