The good and the dark side of integration and dependence for IT adoption

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Abstract:

In the digitally evolving manufacturing sector, IT adoption and data is critical for operational efficiency and competitive edge. This research explores how systems integration, IT dependence, and Interdependence with other plants influence IT adoption, drawing on Resource Dependence Theory (RDT). It features a survey of 286 UK manufacturing plants and uses Partial Least Squares Structural Equation Modelling (PLS-SEM) and ANOVA for analysis. Results show that while systems integration boosts IT adoption, its impact is mediated by IT dependence. Interdependence with other plants also promotes IT adoption but does not significantly mediate it. Large plants tend to have higher IT adoption rates due to better resources and IT governance, unlike smaller plants which struggle with financial and technical limitations. The study underscores the dual impact of IT dependence and plant interdependence in manufacturing, suggesting that effective IT governance and tailored support for SMEs are vital for enhancing IT system adoption.

Keywords: IT adoption; Dependence; Systems integration; Plant interdependence; Resource dependence theory

Wordcount: 6907

1. Introduction

In the contemporary manufacturing landscape, information technology (IT) is indispensable. In the UK, 85% of businesses handle digital data, with 66% sharing data with other businesses (GOV.UK, 2022). The integration and sharing of data are pivotal for maintaining competitive advantage and enhancing operational efficiency (Sohal et al., 2001; Offodile and Abdel-Malek, 2002; Alcácer and Cruz-Machado, 2019). However, many organisations, particularly SMEs, still use rudimentary IT systems while struggling or in some cases avoid adopting more advanced IT systems. The necessity for more diverse IT in plants, specifically technologies such as IoT, augmented reality, big data analytics, cyber security, simulation technologies, cloud computing, and horizontal and vertical integration technologies (e.g., ERP and SCADA), is increasingly critical in a digital era ever more dependent on data and information (Abdollahzadegan et al., 2013). These technologies facilitate enhanced connectivity within the supply chain and support the implementation of more advanced systems like digital twins and AI, which are becoming essential for competitive differentiation and operational efficiency (Krakowski et al., 2023). This inherent technological advancement and connectivity introduce significant dependence on data and IT resources. The question therefore arises whether the integration of systems and growing dependence on data and information strengthens a plant's position to adopt more advanced IT or potentially hinders this adoption.

The concept of dependence in organisational contexts refers to the extent to which a business relies on external resources, including data and information, to conduct its operations. Such resource dependence can manifest as interdependence among plants within a network and dependence on IT resources (Barua et al., 2004). This reliance warrants scrutiny because it impacts how organisations function and adapt to new challenges or opportunities. Examining dependence helps identify potential vulnerabilities, such as over-reliance on outdated systems or a single supplier, and opportunities, such as improving efficiency through integrated technologies (Tarifa Fernández, 2022). This understanding is critical as it affects strategic decisions around investing in and deploying more advanced IT solutions that support business goals while managing risks associated with dependence on technology and data. It is also currently not well understood how contextual factors such as plant size influence the mediating effect of resource dependence on IT adoption (Kearns and Lederer, 2004).

Studies specifically addressing the adoption and integration of these advanced IT technologies at the manufacturing plant level are scant, highlighting a significant gap in both academic and practical applications. This is particularly true when considering the roles of strategic resource dependence inherent in sharing information and data both internally among various business functions and externally across partner plants and organisations (Straub et al., 2008). This gap persists despite the broad recognition of systems integration's impact across various organisational levels (Chen and Fu, 2001; Chuang et al., 2009). According to a KPMG technology report, investments in cloud computing, AI/automation, cybersecurity, and edge computing remain top priorities for UK organisations (KPMG, 2024). Nonetheless, technical debt remains a significant barrier to seamless IT adoption for many UK firms, requiring investment in both new technology and legacy system upgrades.

Given the above, the primary aim of this study is to empirically measure and investigate how systems integration, IT dependence, and interdependence with other plants influence IT adoption in UK-based manufacturing plants. Employing Resource Dependence Theory (RDT) as the theoretical lens, this study frames its hypotheses around how organisations manage and strategise around external dependencies and resources, which is crucial in understanding the integration and interdependence of IT across plants (Hillman et al., 2009). The focus on the UK manufacturing sector is justified by its significant contribution to the national economy and its ongoing drive towards digital transformation. While experiencing short-term volatility, the manufacturing sector's 8.6% share of the UK's economic output highlights its substantial role in the nation's economy.

Our research is structured as follows. Section 2 introduces the relevant literature on IT adoption, integration, and inherent dependencies, highlighting the limitations of the current research at the plant level. Section 3 presents the theoretical research framework and hypotheses development, grounded in Resource Dependence Theory. Sections 4 and 5 detail the methodology and results, respectively. Lastly, Sections 6 and 7 discuss the findings, their implications for theory and practice, and conclusion.

2. Literature review

The integration of Information Technology (IT) in plant operations is crucial for competitive advantage and efficiency in manufacturing. Whilst extensive research covers IT adoption and systems integration, there remains a gap in understanding their impact at the plant level. Specifically, how IT dependence and interdependence with other plants influence these processes (Simon and Yaya, 2012).

IT systems rarely operate in isolation, requiring integration across departments, partners, and other plants. Despite individual studies, the intersection and mutual influence of these factors are often overlooked, especially in smaller, plant-specific environments (see Table 1) (Bose et al., 2008; Almeida et al., 2014). Systems integration is vital for enhancing operational capabilities (Bhatt, 2000) and is influenced by technological readiness (Hasa, 2024; Chen et al., 2025). Notably, smaller plants face significant integration challenges (Chapman and Kihn, 2009). Research indicates higher system integration can lead to higher office information system success rates and impacts manufacturing performance based on environmental uncertainty (Liao and Tu, 2008). System integration is also key for enterprise information systems in construction (Tatari and Skibniewski, 2011), analysing AI big data (Lin and Liu, 2024), and addressing cybersecurity threats while offering business value (Mai-Inji et al., 2024). These technologies collectively form the digital backbone enabling increased automation, including advanced robotics and AI-driven processes, within contemporary manufacturing plants. Challenges in systems integration, including technical factors, persist across sectors.

The adoption of IT in manufacturing is shaped by internal and external factors like management support and technological readiness (Nguyen, 2009; Henri and Wouters, 2020). Smaller plants struggle due to limited resources (Kannabiran, 2012), reinforcing the need for research on contextual influences. The impact of Dependence on IT systems remains debated; whilst some studies suggest efficiency gains (Chen and Fu, 2001; Chuang et al., 2009), others caution that increasing dependence can lead to negative effects from technology disruptions (Klumpp and

Loske, 2021). Strategic governance can mitigate risks associated with Dependence on IT (Nguyen, 2009; Héroux and Fortin, 2014; Henri and Wouters, 2020). Recent empirical analysis confirms that the technological context, particularly technology readiness and compatibility, is a predominant catalyst for IT adoption in small and medium enterprises (SMEs), and that smaller and younger firms exhibit greater agility in adopting new technologies (Hasa, 2024). Challenges persist in small business IT adoption, with internal factors influencing implementation despite customer driving forces (Nguyen, Newby and Macaulay, 2015).

Table 1 Literature Landscape on IT Adoption

Citation	*Unit-of-Analysis*	*Information Technologies*							*Conditions*		
		AR	IoT	BDA	Cyber Security	Cloud Computing	Simulation	Integration Technology	Systems Integration	Dependence on IT	Interdependence with other plants
Bose et al. (2008)	Firm/Organisation	X	X	X	X	X	X	✓	✓	X	X
Chapman and Kihn (2009)	Plant level	X	X	X	X	X	X	✓	✓	X	X
Liao and Tu (2008)	Firm/Organisation	X	X	X	X	X	✓	✓	✓	X	X
Henri and Wouters (2020)	Firm/Organisation	X	X	X	X	X	X	X	X	X	✓
Klumpp and Loske (2021)	Operations/Logistics	X	X	✓	X	✓	X	✓	✓	✓	X
Kim et al. (2006)	Firm/Relationship	X	X	X	X	✓	X	X	✓	X	✓
Nguyen et al. (2015)	Firm/Organisation	X	X	X	X	✓	X	X	X	X	X
Gattiker and Goodhue (2005)	Plant level	X	X	X	X	X	X	✓	✓	X	✓
Flynn et al. (2016)	Plant level/Supply Chain	X	X	X	X	✓	X	X	✓	X	✓
Davies et al. (2009)	Project	X	X	X	X	X	✓	X	✓	X	X
Chang and Ho (2006)	Organisation	X	X	X	X	✓	X	X	X	✓	X
Lyu et al. (2022)	Enterprise/Supply Chain	X	X	X	X	✓	X	X	✓	X	✓
Klein et al. (2007)	Relationship/Supply Chain	X	X	X	X	✓	X	X	✓	X	✓
Cheng et al. (2016)	Plant/Network	X	X	X	X	X	X	X	✓	X	✓

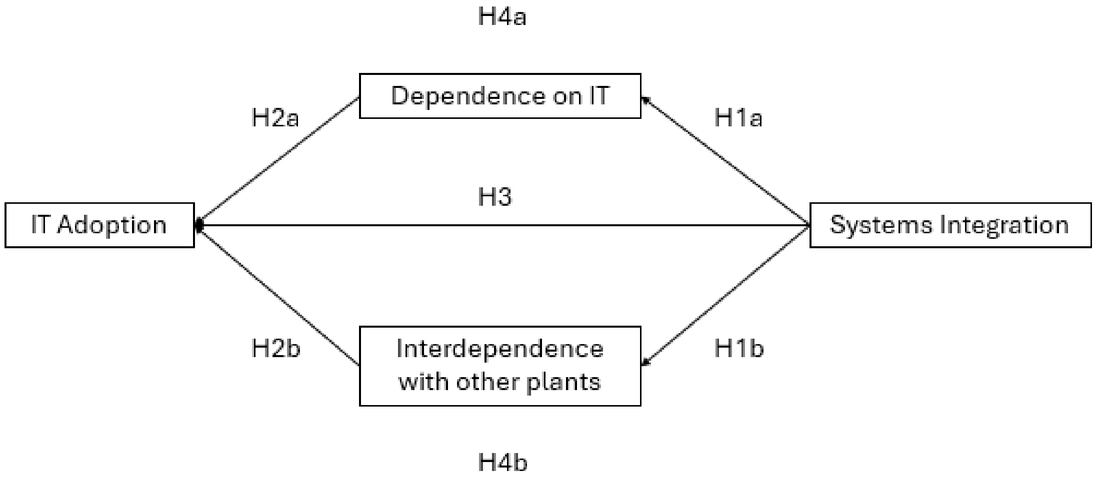
Similarly, interdependence with other plants fosters synergies, resource sharing, and operational efficiency (Gattiker and Goodhue, 2005; Flynn et al., 2016). Effective IT integration depends on aligning business processes with technological structures. Studies have shown how interdependence can lead to enhanced supply chain management and operational flexibility (Casciaro and Piskorski, 2005; Davies et al., 2009). However, increased interdependence can also create coordination challenges and heighten costs and complexity (Chang and Ho, 2006). More research is needed to identify when interdependence enhances IT adoption versus when it creates inefficiencies. Studies show that mutual dependence and partner substitutability influence the survival of cross-border alliances (Xia, 2011), and supply chain relationships' interdependence structure and environmental uncertainty affect interfirm governance (Ryu, 2006; Ryu et al., 2007). Recent studies find green supply chain information integration promotes information sharing (Lyu et al., 2022) and integrated IT improves supply chain integration, flexibility, and competitive advantage in manufacturing. Reliance on external entities is also relevant to understanding compliance in sustainable supply chains (Touboulic et al., 2014). Interdependence in supply chain logistics requires information sharing via integrated systems (Klein et al., 2007), and interplant coordination, supply chain integration, and operational performance in manufacturing networks are key (Cheng et al., 2016).

Despite the recognised role of IT dependence and interdependence, the current literature fails to capture their full impact on IT adoption specifically within manufacturing plants (Simon and Yaya, 2012). Existing studies, as shown in Table 1, often focus on broad organisational and technological outcomes, missing the nuances of plant-level integration. Specifically, the literature falls short in capturing the nuanced mechanisms through which such interdependence can directly influence IT adoption across different plants of varying sizes. Furthermore, while the importance of systems integration is widely acknowledged across various organisational levels (Bhatt, 2000; Chapman and Kihn, 2009), its interplay with the inherent dependence and interdependence created by increased connectivity remains underexplored at the plant level. This study aims to bridge this significant gap by examining how systems integration, IT dependence, and interdependence with other plants collectively shape IT adoption within manufacturing settings. By addressing these limitations in the current body of knowledge, the findings can contribute to more effective IT adoption strategies tailored to the specific context of manufacturing plant operations.

3. Theoretical framework and hypotheses development

Our theoretical research framework employs Resource Dependence Theory (RDT) to investigate how systems integration influences IT adoption, mediated by IT dependence and interdependence with other plants (Casciaro and Piskorski, 2005; Hillman et al., 2009). RDT posits that organisational behaviour is shaped by the need to acquire essential external resources and mitigate the uncertainties and constraints associated with dependencies on other entities. In the context of IT adoption in manufacturing plants, this theory provides a powerful lens to examine how strategic actions related to systems integration are influenced by and, in turn, influence a plant's reliance on IT resources and its interconnectedness with other plants. Managing these dependencies is crucial for maintaining operational autonomy and achieving strategic goals, including the successful adoption of advanced IT (Hillman et al., 2009). RDT helps in understanding these strategic dependencies and how plants can effectively navigate them to improve IT adoption outcomes (Xia, 2011). The theory is also pertinent in exploring how dependencies on specific IT systems and integration partners can drive strategic decisions and operational practices in plants.

Figure 1 Theoretical Research Framework



Based on RDT, we propose a theoretical framework (Figure 1) and test seven hypotheses exploring the relationships between systems integration, IT dependence, interdependence with other plants, and IT adoption. Below we explore and justify the reasoning behind each hypothesis in more detail, grounding each relationship within the principles of Resource Dependence Theory.

3.1 Linking systems integration to dependence on IT and interdependence with other plants

In contemporary business environments, the integration of various systems constitutes a core aspect of organisational strategy, influencing operational efficiency and competitive advantage. The intricate relationship between systems integration and IT dependency is increasingly evident, as organisations that consolidate their systems inevitably centralise critical functions that are crucial to their daily operations (Chang and Ho, 2006; Tarifa Fernández, 2022). Therefore, the question arises if increasing integration leads to dependence on external resources as defined by the resource dependence theory. For instance, in the telecommunications sector integration of IT systems leads to growing strategic dependency on IT to exploit this value fully (Barua et al., 2004). Likewise, practical implementation of systems integration through ERP and SCM systems can streamline operations and necessitate a high level of dependency on these integrated systems for efficient operation (Davies et al., 2007; Bose et al., 2008). In this vein, systems integration facilitates improved decision-making and operational effectiveness, leading to an inherent reliance on IT to maintain these improvements (Sahin and Robinson Jr, 2005; Chapman and Kihn, 2009). Also, systems integration in the context of mergers and acquisitions could dramatically alter the information systems landscape, increasing dependence on robust IT infrastructures to harmonise disparate systems (Giacomazzi et al., 1997; Robbins and Stylianou, 1999). This integration also creates dependencies on IT infrastructures that require meticulous management and oversight (Zhuang and Zhou, 2004). Notably, centralising IT systems streamlines operations and improves data management but also heightens the organisation's vulnerability to system failures and cybersecurity threats (Liu et al., 2020).

like the above, systems integration within the supply chain network enhances the interdependence with other plants by enabling real-time data sharing and process alignment (Cheng et al., 2016). Organisations manage external and internal dependencies through strategic resource allocation, which is a key component of systems integration impacting interdependence (Jacobs, 1974). In this sense, improved integration and collaboration across business units enhances overall organisational agility and interdependence (Ma and Chang, 2024). Such data integration of organisational structures and operations reduce uncertainties between interdependent units by providing a unified information base (Badasjane et al., 2024). Conversely, systems integration can create a tightly coupled network where disruptions in one plant impact the entire supply chain. For instance, integration of enterprise resource planning (ERP) systems significantly affects plant-level outcomes by enhancing interdependencies (Gattiker and Goodhue, 2005). However, ERP-enabled coordination improvements at the plant level are not as significant due to alternative coordination mechanisms such as Just-in-Time practices already implemented by those plants. Also, plants with unique operational requirements may be forced to adopt suboptimal business processes dictated by the integrated system, which can lead to increased reliance on manual workarounds and localised systems (e.g., Excel spreadsheets, handwritten logs). On the other hand, centralised data architectures could introduce bureaucratic delays and information overload as managers must sift through vast amounts of data to extract relevant insights (Chapman and Kihn, 2009). Given the aforementioned studies highlighting the relation of systems integration with dependence on external resources such as dependence on IT and interdependence with other plants, it is hypothesised that:

H1a: Systems integration is positively linked to dependence on IT

H1b: Systems integration is positively linked to interdependence with other plants

3.2 Linking dependence on IT and interdependence with other plants to greater IT adoption

The dependence on information technology (IT) plays a crucial role in shaping IT adoption within organisations. Nevertheless, it is vaguely understood if dependence on external resources is constructive or hindering greater adoption of IT. Studies elaborate on how different IT governance mechanisms, influenced by the level of IT dependence, alter organisational strategies and IT adoption (Héroux and Fortin, 2014). The level of IT reliance determines the extent to which businesses align their strategies to optimise IT resources. The strategic importance of controlling IT resources to mitigate risks associated with high IT dependence is also discussed by Tarifa Fernández (2022), who highlight the need for strategic control to optimise IT resources and reduce vulnerabilities. Research highlights that IT governance mechanisms significantly influence IT adoption, with strategic IT control being critical to mitigating risks associated with high IT dependence (Gregory et al., 2018; Kearns and Lederer, 2004).

The literature indicates firms that heavily depend on IT for customer relationship management and operational efficiency tend to exhibit a stronger inclination toward more diverse IT adoption to sustain competitive advantage (Liang et al., 2007). Such dependency on IT for maintaining strong customer relationships can affect the overall business performance, particularly when IT is used to manage and analyse these relationships (Arthur et al., 2024).

Furthermore, the adoption of enterprise resource planning (ERP) systems illustrates how IT dependence influences IT adoption. plants with high IT reliance are more likely to integrate ERP systems to enhance data consistency and streamline decision-making processes (Gattiker and Goodhue, 2005). The multilevel analysis of IT adoption suggests that organisational culture, managerial attitudes, and external institutional pressures collectively shape IT adoption practices (Rizzuto et al., 2014). Thus, IT dependence serves as a driver for IT adoption, reinforcing the need for structured governance and risk management strategies.

The interdependence with other plants in a manufacturing network necessitates seamless information exchange and operational coordination, making IT adoption a strategic necessity. Research indicates that highly interdependent plants benefit more from integrated IT systems, as they facilitate real-time data sharing, supply chain synchronisation, and process alignment (Gattiker and Goodhue, 2005). For instance, ERP implementations improve coordination between plants, particularly when production schedules and inventory management require integration across multiple locations. The adoption of IT in interconnected plant environments enables better decision-making, reduces operational uncertainties, and fosters a collaborative ecosystem for implementing more advanced IT. However, the effectiveness of IT adoption in interdependent plants depends on factors such as workforce skill levels, IT governance policies, and the degree of technological integration (Lal, 1999). On the other hand, IT adoption in interdependent manufacturing environments can lead to unintended consequences, such as excessive standardisation that limits flexibility or increased complexity in system maintenance (Straub et al., 2008). Given the above evidence for the link between external resource dependence such as dependence on IT and interdependence with other plants on adopting more capable and greater diversity of IT, it is hypothesised that:

H2a: Dependence on IT is positively linked to greater IT adoption

H2b: Interdependence with other plants is positively linked to greater IT adoption

3.3 Linking systems integration to greater IT adoption

Systems integration is increasingly recognised as a pivotal factor influencing IT adoption across various industries, particularly within the manufacturing sector where it crucially dictates operational efficiency and innovation capabilities. Despite widespread discussion, significant gaps persist in understanding how systems integration specifically impacts IT adoption within the nuanced context of plant operations, where the scale and scope of technology deployment can significantly vary (Saeed and Abdinnour-Helm, 2008). Integrated systems enhance management practices and support innovation, crucial for adaptive IT strategies in dynamic environments (Henri and Wouters, 2020). Similarly, Barua et al. (2004) suggest that net-enabled transformations, which rely heavily on sophisticated systems integration, significantly improve organisational performance through enhanced IT across the value chain. Moreover, Giacomazzi et al. (1997) present a model where systems integration serves as a strategic enabler in mergers and acquisitions, illustrating its role in streamlining operations and fostering IT adoption in complex corporate manoeuvres. In this sense, both internal and external IS integration improve operational outcomes, which in turn facilitates broader IT adoption strategies within organisations (Maiga et al., 2015). Given the above, systems integration is a strategic tool organisations use to manage resource dependencies, reduce uncertainty, and gain control over vital operational processes, thus increasing the likelihood of broader IT adoption. Based on these insights, the proposed hypothesis is:

H3: Systems integration is positively linked to greater IT adoption

3.4 The mediating role of dependence on IT and interdependence with other plants

The mediating role of IT dependence and interdependence among plants is pivotal in understanding the broader impact of systems integration on IT adoption. Research has demonstrated that systems integration not only facilitates seamless operations but also significantly enhances the dependence on IT infrastructure across manufacturing settings (Giacomazzi et al., 1997; Kearns and Lederer, 2004). This dependence on IT arises as systems integration often leads to more sophisticated IT architectures and more advanced bundles of IT resource adoption. This however requires continuous engagement and familiarity with IT processes, thus influencing the overall adoption and effectiveness of new IT systems (Liang et al., 2007). Additionally, the degree of interdependence among plants, exacerbated by integrated systems, suggests a complex layer where operations are no longer siloed but interlinked, requiring a coordinated IT approach that can handle multi-faceted, interconnected processes (Maiga et al., 2015).

The intricacies of how IT dependence mediate between integration and IT adoption are nuanced and vary significantly across different organisational contexts. For example, Reich and Benbasat (2000) explore how the alignment between business and IT strategies can critically affect the efficacy of IT dependence in fostering successful IT adoption. This alignment is further complicated by inter-plant interdependence, where the need for a unified IT infrastructure across different units can either facilitate streamlined operations or lead to complexities in IT implementation if there is a lack of standardisation and interoperability (Barua et al., 2004). Saeed and Abdinnour-Helm (2008) support the notion that systems integration can complicate IT adoption in environments where technological and operational changes are frequent, and dependencies constantly shift. The interplay between IT dependence and inter-plant interdependence illustrates a dynamic scenario where systems integration acts as both an enabler of enhanced coordination and efficiency and as a source of challenges that can impede smooth IT adoption if resource dependency not managed properly (Gregory et al., 2018). These complexities underscore the necessity for a deeper exploration of how IT dependence and inter-plant interdependence mediate the relationship between systems integration and IT adoption. Given the above we hypothesise that:

H4a: Dependence on IT positively mediates between systems integration and IT adoption

H4b: Interdependence with other plants positively mediates between systems integration and IT adoption

4. Methodology

This study employed constructs related to IT adoption, dependence on IT, system integration, and interdependence with other plants to develop hypotheses, which were subsequently tested to validate the proposed conceptual model. An empirical research approach was adopted, following the guidelines of Flynn et al. (1990) and Hulland et al. (2018). Empirical research involves systematically collecting and analysing data through surveys, experiments, and real-world observations. Instead of relying on pre-existing assumptions, this study empirically tested the relationships between the constructs by analysing real-world data. Such an approach provides a more precise and objective understanding of IT adoption in various industries, offering valuable insights for business managers, policymakers, and industry stakeholders.

4.1 Sample, data collection, and common method bias

Data collection was conducted from October 2022 to March 2023, with 286 responses gathered from UK-based plant managers. Table 2 shows the diversity of plant sizes and plant ages involved in the survey. The plants operate in a variety of industrial sectors such as heavy machinery, automotive, aerospace, food and beverage, consumer electronics and electrical equipment, and pharmaceutical and medical equipment. Controlling and minimizing common method bias (CMB) is essential to prevent biased results. Survey-based research, by its nature, is particularly prone to CMB (Podsakoff et al., 2003). Harman's single-factor test was conducted to test for CBM. The results revealed that a single factor explained 24.67% of the variance, which is below the threshold of 50%, suggesting that common method bias is not a significant concern in this study (see Appendix 1). We evaluated the measurement model once it was confirmed that CMB did not contaminate the data.

Table 2 Sample description

plant size (employees)	Frequency	Percentage (%)
1-100	109	38.11
101-200	49	17.13
201-300	36	12.59
301-400	14	4.90
401-500	20	7
More than 500	58	20.28

plant age (years)	Frequency	Percentage (%)
Up to 5	13	4.54
6-10	30	10.49
11-15	39	13.63
16-20	43	15.03
21 or more	161	56.30
Total	**286**	

4.2 Instrument development

Existing measures were used for this survey, shown in Table 3. The dependent variable (IT Adoption) was adopted from studies measuring Industry 4.0 information and communication technologies such as Büchi et al. (2020), Cugno et al. (2021); Cugno et al. (2022). Our study included I4.0 and I5.0 information technologies such as: augmented reality, IoT, big data analytics, cloud computing, cyber security, simulation, and horizontal and vertical integration (such as ERP, SCADA). Dependence on IT was adapted from a firm-level study to plant level (Kearns and Lederer, 2004) and interdependence with other plants was adopted from Gattiker

(2007); Gattiker and Goodhue (2005). Lastly systems integration was adopted from Barua et al. (2004).

Table 3 Results of the measurement model

	Measurement items	Code	Factor Loading	α; CR; AVE
Dependence on IT	A one-hour shutdown of computers would have serious consequences	(DOIT _1)	0.797	α =0.879; CR =0.912; AVE =0.674
	Programming errors could have serious consequences on customer satisfaction	(DOIT _2)	0.821	
	It is not feasible, in the short run, to operate the business manually in the absence of our computers	(DOIT _3)	0.799	
	The daily operations of the business are critically dependent on IS	(DOIT _4)	0.874	
	We have many critical on-line or batch information systems	(DOIT_5)	0.813	
IT Adoption	Augmented reality enhances sensory perception by adding virtual elements like sound, smell, or touch via devices like AR glasses, earphones, or gloves	(AR)	0.550	α =0.707; CR =0.803; AVE =0.408
	Big data analytics captures, analyzes, and shares large data from products, processes, machines, people, and the surrounding environment	(IBDA)	0.752	
	Cloud computing enables fast, flexible, and efficient data processing and storage while supporting data-driven services for monitoring, control, and production improvement	(CC)	0.599	
	Horizontal and vertical integration in Industry 4.0 connect internal company areas (horizontal) and external relationships with suppliers and customers (vertical)	(H&V)	0.628	
	The Internet of Things enables communication between people, products, and machines through smart devices and sensors	(IOT)	0.728	
	Simulation creates virtual models of the physical world, enabling operators to test and optimize materials, processes, and products	(IS)	0.544	
Interdependence with other plants	To be successful, this plant must be in constant contact with other external plants	(IWOP _1)	0.830	α =0.931; CR =0.946; AVE =0.746
	If this plant's communication links to other external plants were disrupted things would quickly get very difficult	(IWOP _2)	0.814	
	Frequent information exchanges with other external plants are essential for this plant to do its job	(IWOP _3)	0.919	
	Close coordination with other external plants is essential for this plant to successfully do its job	(IWOP _4)	0.933	
	Information provided by other external plants is critical to the performance of this plant	(IWOP _5)	0.878	
	The actions or decisions of other external plants have important implications for the operations of this plant	(IWoP_7)	0.798	
Systems Integrati	Data can be shared easily among various internal systems	(SI_1)	0.742	α =0.870; CR =0.904; AVE =0.655
	Order changes are automatically reflected in downstream processes or systems	(SI_2)	0.825	

	Our system can easily transmit, integrate and process data from suppliers/vendors and customers	(SI_3)	0.880
	Our system shows continuous monitoring of order status at various stages in the process	(SI_4)	0.846
	Employees can easily retrieve information from various databases for decision support	(SI_5)	0.744

Note: α (Alpha de Cronbach); AVE (Average Variance Extracted); CR (Composite Reliability)
a Factor Loadings > 0.5 indicates the indicator reliability (Hulland, 1999));
b Cronbach Alpha > 0.7 indicates the indicator reliability (Bernstein and Nunnally, 1994));
c Composite Reliability (CR) > 0.7 indicates the internal consistency of a set of indicators (Gefen et al., 2000));
d Average Variance Extracted (AVE) > 0.5 indicates the convergent reliability (Bagozzi and Yi, 1988; Fornell and Larcker, 1981)

5. Result

This study employed SmartPLS 3, a statistical software, to analyse the data using partial least squares structural equation modelling (PLS-SEM). A two-step procedure was adopted to analyse the results (Joe F Hair et al., 2011). Initially, the proposed model's inter-item reliability, internal consistency reliability, and convergent validity were assessed. Subsequently, the hypotheses were tested (Henseler et al., 2009). The subsequent sections present the outcomes of the reliability and validity assessment of the measurement scales.

5.1 Reliability and discriminant validity

The reliability and validity of the constructs were assessed using Anderson and Gerbing (1988) two-step procedure, including confirmatory factor analysis (CFA), composite reliability (CR), and average variance extracted (AVE). According to Joseph F Hair et al. (2019), factor loadings should ideally exceed 0.7; however, loadings above 0.5 are considered acceptable. Factor loadings ranged from 0.544 to 0.933, meeting the reliability criteria. It is noteworthy that measurement item I4.0_CS (cyber security) from the IT Adoption construct and IWOP_6 from the Interdependence with Other Plants construct were removed due to factor loadings below 0.5. CR values ranged from 0.803 to 0.946, satisfying internal consistency requirements (Joe F Hair et al., 2011). AVE values ranged from 0.408 to 0.746. While an AVE of 0.50 or higher is generally preferred, Fornell and Larcker (1981) stated that if AVE is below 0.50 but the composite reliability (CR) is above 0.60, the convergent validity of the construct is still acceptable. Therefore, the AVE values in this study confirm convergent validity. Detailed results are in Table 2 and the measurement model is shown in Figure 1.

Two primary methods are used to evaluate discriminant validity, as noted by Khan et al. (2021): (1) the Fornell and Larcker (1981) criterion and (2) the Heterotrait-Monotrait (HTMT) ratio of correlations, proposed by Henseler et al. (2015). According to the Fornell and Larcker (1981) criterion, the square root of each construct's AVE must exceed its correlations with other constructs in the model and should not fall below 0.50. In contrast, the HTMT, as described by Henseler et al. (2015), represents the average of item correlations across different constructs divided by the average of within-construct item correlations. Hair et al. (2019) suggest that HTMT values should be below 0.90 for conceptually similar constructs. Wang et al. (2024) showed that most researchers use the Fornell-Larcker criterion (48.25%), while some apply cross-loadings (0.50%) or a combination (17.75%), and others use the HTMT criterion

(31.50%). The results of Tables 4 and 5 indicate that discriminant validity has been confirmed for all constructs in the conceptual model.

Table 4 Discriminant validity- Fornell-Larcker criterion.

	Dependence on IT	IT Adoption	Interdependence with other plants	Systems Integration
Dependence on IT	**0.821**			
IT Adoption	0.304	**0.637**		
Interdependence with other plants	0.163	0.324	**0.863**	
Systems Integration	0.245	0.255	0.138	**0.809**

The bolded diagonal values represent the Average Variance Extracted (AVE) square root for each latent variable and indicate the highest value in each corresponding column or row.

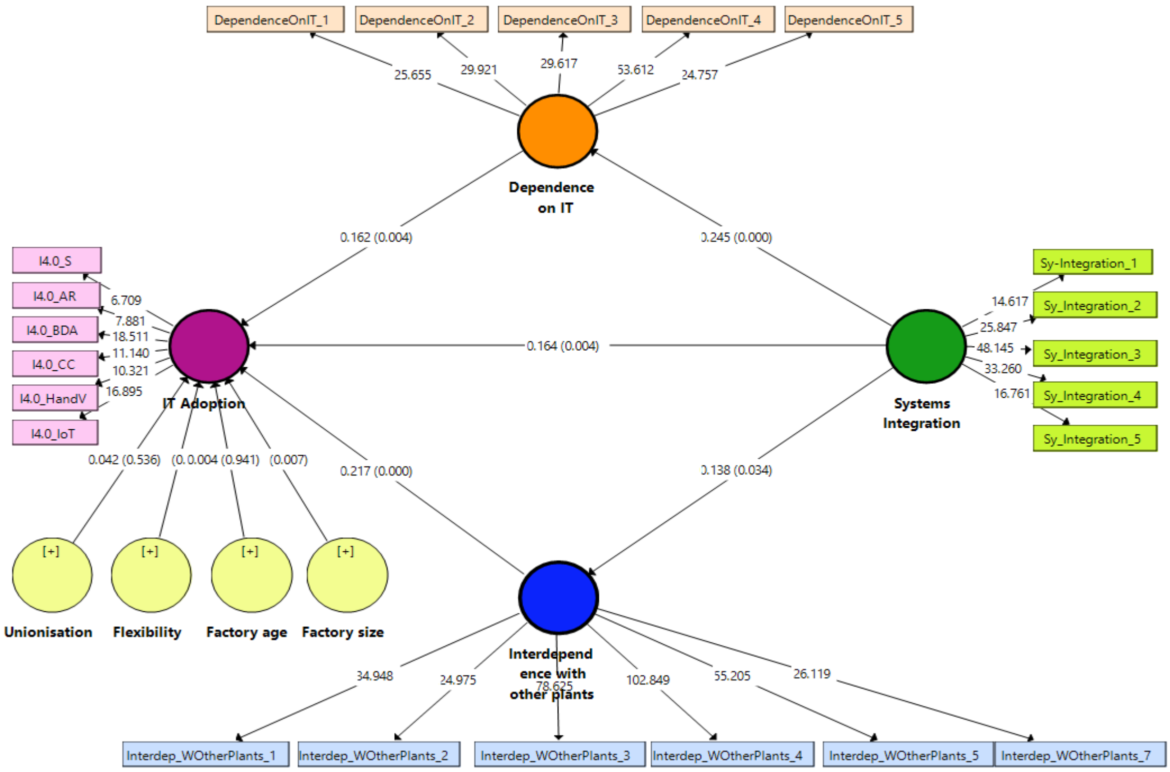
Table 5 Discriminant validity- HTMT criterion.

	Dependence on IT	IT Adoption	Interdependence with other plants	Systems Integration
Dependence on IT	-			
IT Adoption	0.390	-		
Interdependence with other plants	0.177	0.383	-	
Systems Integration	0.269	0.287	0.142	-

5.2 Structural model

The hypotheses in this study were tested using the PLS-SEM method. The structural model is shown in figure 2. To determine the significance of the path coefficients, bootstrapping with 10,000 resamples was employed (Hair et al., 2019). Firstly, we checked the R^2 value, which indicates in-sample predictive power, for the endogenous construct. In this study, the R^2 values for the constructs were as follows: 0.060 for the construct "Dependence on IT," 0.232 for "IT Adoption," and 0.019 for "Interdependence with other plants". According to Cohen (1992), the R^2 values of 0.02, 0.13, and 0.26 are generally interpreted as small, medium, and large, respectively. However, in certain disciplines or exploratory studies, an R^2 value as low as 0.10 may still be considered acceptable (Hair et al., 2019). Based on the R^2 values obtained in this study and Cohen (1992) guidelines, the construct "Dependence on IT" ($R^2 = 0.060$) falls within the small-to-medium range, indicating a modest explanatory power. The construct "IT Adoption" ($R^2 = 0.232$) falls within the medium-to-large range, suggesting a relatively strong explanatory power. Finally, the construct "Interdependence with other plants" ($R^2 = 0.019$) falls within the small range, indicating a weak explanatory power. Next, we assessed the predictive relevance by calculating Stone-Geisser's Q^2 value using the blindfolding method (Ringle et al., 2015). According to Hair et al. (2019), Q^2 values greater than 0, 0.25, and 0.50 indicate small, medium, and large predictive relevance, respectively. In the present study, the Q^2 values for "Dependence on IT," "IT Adoption," and "Interdependence with Other Plants" were 0.036, 0.083, and 0.012, respectively, confirming the structural model's predictive relevance, though at a relatively low level.

Figure 2 Summary of SEM results (Structural model).



Finally, We tested the proposed hypotheses using the bootstrapping method (Ringle et al., 2015), calculating path coefficients (standardised beta), significance levels, and t-values to assess the relationships between the constructs. We found that the direct effect of System Integration on Dependence on IT is significant, with a value of 0.252 ($p < 0.01$), providing empirical support for Hypothesis 1a. Similarly, the direct effect of Dependence on IT on IT Adoption is significant at 0.166 ($p < 0.01$), confirming Hypothesis 2a. The direct effect of System Integration on Interdependence with Other Plants is significant at 0.144 ($p < 0.05$), supporting Hypothesis 1b. The direct effects of Interdependence with Other Plants on IT Adoption is significant at 0.221 ($p < 0.01$), confirming Hypotheses 2b. Control variable analysis revealed no significant effects of plant age ($\beta = 0.005$, $p > 0.05$), flexibility ($\beta = 0.004$, $p > 0.05$), unionisation ($\beta = 0.042$, $p > 0.05$), and plant size ($\beta = 0.193$, $p < 0.05$) on IT Adoption (Detailed results are in Table 6).

Table 6 Structural path analysis.

Hypothesis	Path	Path coefficient	Standard deviation	t- statistics	p-value	Decision

H1a	System Integration → Dependence on IT	0.252	0.064	3.842***	0.000	Supported
H1b	System Integration → Interdependence with other plants	0.144	0.065	2.116**	0.034	Supported
H2a	Dependence on IT→ IT Adoption	0.166	0.056	2.887***	0.0004	Supported
H2b	Interdependence with other plants → IT Adoption	0.221	0.051	4.251***	0.000	Supported
H3	System Integration → IT Adoption	0.166	0.055	2.957***	0.003	Supported
Control Variables						
Plant size → IT Adoption		0.193	0.071	2.730	0.006	supported
Plant age → IT Adoption		0.005	0.060	0.075	0.940	Not supported
Flexibility → IT Adoption		0.004	0.057	0.019	0.984	Not supported
Unionisation → IT Adoption		0.042	0.069	0.613	0.540	Not supported

**p < 0.05 and ***p < 0.01.

The t Values around 1.65, 1.96, and 2.58 are considered with the significance level of 10%, 5% and 1%, respectively (Two-Tailed Test).

5.3 Mediation analysis

An examination of the three forms of indirect impact caused by the factors, a mediation analysis, is conducted. When the mediation variable has a complete mediation role and is powerful enough to cancel the direct impact, as in the case of full mediation when the direct effect among the factor says A » B is not significant, but the indirect effect among A » C » B is considerable. The second type of partial mediation emphasises the importance of both direct and indirect links. When the indirect impact is negligible, as in the third case, there is no mediation effect (Hair et al., 2022).

Based on the mediation analysis presented in Table 7, the findings indicate that the mediating role of Dependence on IT in the relationship between System Integration and IT Adoption (H4a) is statistically significant, with a path coefficient of 0.041, a t-statistic of 2.435, and a p-value of 0.015 (< 0.05). This suggests that Dependence on IT partially mediates the relationship between System Integration and IT Adoption, supporting H4a. However, the mediation effect of Interdependence with other plants in the relationship between System Integration and IT Adoption (H4b) was not statistically significant, as indicated by a path coefficient of 0.032, a t-statistic of 1.792, and a p-value of 0.073 (> 0.05). Since the p-value exceeds the 0.05 threshold, this result does not provide sufficient evidence to support H4b, meaning Interdependence with other plants does not significantly mediate the relationship between System Integration and IT Adoption.

Table 7 Mediation analysis.

Hypothesis	Indirect Path	Path coefficient	Standard deviation	t- statistics	p-value	Decision
H4a	System Integration → Dependence on IT → IT Adoption	0.041	0.016	2.435**	0.015	Supported
H4b	System Integration → Interdependence with other plants → IT Adoption	0.032	0.017	1.792	0.073	Not supported

**p < 0.05 and ***p < 0.01.

5.4 ANOVA Results

This section compares the average IT adoption levels across different factory sizes using ANOVA. First, the normality of the IT adoption variable was assessed using skewness and kurtosis indices to ensure that the assumptions of parametric testing were met. Skewness measures the asymmetry of the distribution, where a coefficient of zero indicates perfect symmetry. A positive skewness value suggests a right-skewed distribution, whereas a negative value indicates a left-skewed distribution. Kurtosis, on the other hand, measures the "tailedness" of the distribution, where extreme values indicate whether the data have heavier or lighter tails than a normal distribution. In general, if the skewness is not in the range (-2,2) and the kurtosis is not in the range (- 10,10), the data is very far from a normal distribution (Kline, 2023; Cain et al., 2017). For our data, the observed skewness and kurtosis values for IT adoption were within these acceptable ranges, indicating that the distribution does not deviate significantly from normality. Therefore, the assumption of normality is satisfied, justifying the use of ANOVA to analyse differences in IT adoption across factory size groups.

5.4.1 Comparing IT Adoption across plant size levels

Given the normal distribution of the IT Adoption variable, a one-way ANOVA was used to compare the mean of this variable across different plant size levels. Before conducting the ANOVA, Levene's test was performed to assess the assumption of homogeneity of variances. The results indicated that the assumption of homogeneity of variances was met ($p = 0.090 > 0.05$). The ANOVA results are presented in Table 8. The results indicate that there is a significant difference across company size levels. To perform pairwise comparisons, Tukey's post hoc test was used, and the results are presented in Table 9.

Table 8 Results of One-Way ANOVA Across Plant Size Levels.

plant Size	N	Mean	Standard Deviation	F	df	Sig.
1-100 employees	109	1.41	0.41	8.278	(5,280)	0.001
101 - 200 employees	49	1.43	0.36			
201 - 300 employees	36	1.70	0.49			

301- 400 employees	14	1.61	0.32			
401-500 employees	20	1.79	0.42			
More than 500 employees	58	1.74	0.37			
Total	286	1.55	0.43			

Table 9 Results of Tukey's Post Hoc Test for Pairwise Comparisons of Practices Across Plant Size Levels.

plant size	The size of the plant being compared	Mean difference	Std.Error	Sig.
1-100 employees	101 - 200 employees	-.01454	.07024	1.000
	201 - 300 employees	-.29090*	.07850	.003
	301- 400 employees	-.20162	.11593	.507
	401-500 employees	-.37424*	.09934	.003
	More than 500 employees	-.32682*	.06637	.000
101 - 200 employees	1-100 employees	.01454	.07024	1.000
	201 - 300 employees	-.27636*	.08964	.027
	301- 400 employees	-.18707	.12375	.657
	401-500 employees	-.35969*	.10835	.013
	More than 500 employees	-.31228*	.07923	.001
201 - 300 employees	1-100 employees	.29090*	.07850	.003
	101 - 200 employees	.27636*	.08964	.027
	301- 400 employees	.08929	.12862	.982
	401-500 employees	-.08333	.11388	.978
	More than 500 employees	-.03592	.08664	.998
301- 400 employees	1-100 employees	.20162	.11593	.507
	101 - 200 employees	.18707	.12375	.657
	201 - 300 employees	-.08929	.12862	.982
	401-500 employees	-.17262	.14230	.830
	More than 500 employees	-.12521	.12160	.908
401-500 employees	1-100 employees	.37424*	.09934	.003
	101 - 200 employees	.35969*	.10835	.013
	201 - 300 employees	.08333	.11388	.978
	301- 400 employees	.17262	.14230	.830
	More than 500 employees	.04741	.10589	.998
More than 500 employees	1-100 employees	.32682*	.06637	.000
	101 - 200 employees	.31228*	.07923	.001

	201 - 300 employees	.03592	.08664	.998
	301- 400 employees	.12521	.12160	.908
	401-500 employees	-.04741	.10589	.998

The results indicate significant differences in IT adoption across different plant sizes. The implications are discussed in section 6. Smaller plants (1-100 employees) exhibit significantly lower IT adoption compared to larger plants, particularly those with 201-300 employees ($p = 0.003$), 401-500 employees ($p = 0.003$), and more than 500 employees ($p = 0.000$). Similarly, plants with 101-200 employees show significantly lower IT adoption than those with 201-300 employees ($p = 0.027$), 401-500 employees ($p = 0.013$), and more than 500 employees ($p = 0.001$). However, there are no significant differences in IT adoption among plants with 301-400, 401-500, and more than 500 employees, suggesting that once a plant reaches a certain size threshold, IT adoption levels tend to stabilize.

These findings suggest that smaller plants (fewer than 200 employees) face significant challenges in IT adoption, potentially due to limited financial resources, technical expertise, or strategic priorities. In contrast, larger plants (more than 200 employees) are better positioned for IT adoption, benefiting from greater investment capacity, workforce capabilities, and organisational infrastructure. Overall, the results highlight the strong relationship between plant size and IT adoption, emphasising the need for tailored policies and support mechanisms to facilitate IT adoption in smaller plants. Given the increasing role of digital transformation in manufacturing, addressing these disparities could enhance competitiveness and operational efficiency across the industry.

6. Discussion

Despite extensive research on IT adoption and systems integration, significant gaps remain in understanding their nuanced impact specifically at the manufacturing plant level. Prior studies have largely focused on broad organisational benefits of IT adoption without addressing how the resulting dependence on IT and interdependence with other plants collectively shape the adoption process in manufacturing environments (Chen and Fu, 2001; Chuang et al., 2009; Simon and Yaya, 2012). Moreover, the existing literature predominantly examines systems integration from an efficiency standpoint, often neglecting its potential drawbacks, such as overdependence, increased operational rigidity, cybersecurity vulnerabilities, and higher coordination costs (Gattiker and Goodhue, 2005; Chapman and Kihn, 2009). Motivated by these limitations in the current literature and the growing importance of data and advanced IT for manufacturing competitiveness (Krakowski et al., 2023), our study empirically explores and quantifies the influence of systems integration, dependence on IT, and interdependence with other plants on the adoption of more advanced IT systems at the plant level, including technologies such as IoT, augmented reality, big data analytics, simulation, cloud computing, and horizontal and vertical integration technologies.

Our research also contributes to clarifying the contextual contingencies of IT adoption (Kearns and Lederer, 2004). The results from the ANOVA and structural model analysis indicated that larger plants (with more than 200 employees) exhibit significantly higher IT adoption rates compared to smaller plants (fewer than 200 employees). This finding aligns with expectations that larger organisations typically possess greater financial resources, technical expertise, and dedicated IT departments necessary to manage the complexities of IT infrastructure and integration challenges (Liang et al., 2007). This suggests that for larger plants, while IT dependence exists, they are better equipped to manage it, making it less likely to create significant bottlenecks in further IT adoption. Conversely, the effects of interdependence with other plants on IT adoption appear stronger in larger plants, likely because their scale of operations often involves more complex supply chain networks and reliance on advanced IT systems for coordination across multiple locations (Gattiker and Goodhue, 2005; Cheng et al., 2016). On the other hand, high IT dependence in smaller plants may indeed create risks rather than solely benefits, as they may struggle with the necessary IT maintenance, cybersecurity measures, and mitigating operational disruptions if systems fail. Similarly, interdependence with other plants may introduce greater coordination challenges for smaller plants, which may not possess the same level of operational flexibility or dedicated resources as larger firms to manage these external linkages effectively (Chapman and Kihn, 2009).

6.1 Theoretical Implications

This study makes a significant contribution to the literature by integrating Resource Dependence Theory (RDT) to explain the complex interplay between systems integration, IT dependence, interdependence with other plants, and IT adoption. Unlike much prior research that has treated IT adoption as a direct outcome of systems integration or examined these constructs in isolation (e.g., Henri and Wouters, 2020 on control practices and innovation; Chen and Fu, 2001 on IT adoption drivers), this study highlights the crucial mediating role of Dependence on IT. Our findings empirically demonstrate that the impact of systems integration on IT adoption is partially channelled through the increased dependence on IT that integration creates (supporting H4a). This advances RDT by showing how a strategic action to manage internal fragmentation (systems integration) can lead to a new form of external dependence (on the integrated IT resource itself), which in turn influences subsequent resource acquisition (IT adoption).

The study also applies RDT to understand the role of interdependence with other plants. While our results confirmed that interdependence with other plants is directly associated with greater IT adoption (supporting H2b), it did not act as a significant mediator between systems integration and IT adoption (not supporting H4b). This finding offers a nuanced insight for RDT, suggesting that while interconnectedness with other entities (interdependence) motivates IT adoption, the process of systems integration may not necessarily increase this specific form of external dependence in a way that drives further adoption, or perhaps its influence is more direct or mediated through other factors not captured in this model.

The findings corroborate prior work by Gattiker and Goodhue (2005), who applied RDT to understand the impact of ERP implementation on plant-level outcomes based on interdependence and differentiation. Our study extends these insights by contextualising them within the broader adoption of a *variety* of advanced IT technologies (IoT, AR, Big Data, etc.) beyond just ERP (Büchi et al., 2020; Cugno et al., 2021; Cugno et al., 2022). Furthermore, the study aligns with the work of Gregory et al. (2018) on IT governance transformation by demonstrating that increased dependence on IT necessitates strategic IT management to mitigate risks and ensure sustainable adoption, thereby providing empirical support for RDT's focus on managing critical dependencies. By confirming that systems integration can have both enabling (direct link to adoption, H3 supported) and potentially constraining (via increased dependence, H4a supported) effects on IT adoption, the study advances theories on digital transformation by highlighting that over-integration, if not accompanied by strategic dependence management, may lead to vulnerabilities that impede the adoption process.

6.2 Practical Implications

From a managerial perspective, the findings underscore the critical need for manufacturing plants to adopt balanced IT integration strategies. While increased integration enhances data sharing, operational efficiency, and decision-making capabilities (Arthur et al., 2024), managers must actively prevent over-reliance on centralised IT infrastructures. Excessive dependence can expose plants and potentially the entire firm to cascading failures, cybersecurity risks, and operational rigidity if not properly managed (Chapman and Kihn, 2009; Liu et al., 2020). Therefore, IT managers must implement robust risk mitigation strategies as a core component of their integration efforts, including investing in redundancy planning, strengthening cybersecurity defences, and establishing clear disaster recovery protocols to prevent systemic vulnerabilities.

Our study highlights that interdependence with other plants, while driving IT adoption, requires adaptive IT governance frameworks that balance standardisation with flexibility. While tighter integration facilitates supply chain efficiency and operational coordination (Straub et al., 2008; Klein et al., 2007), rigid standardisation can stifle local innovation and responsiveness to unique plant-level needs or market changes (Sahin and Robinson Jr, 2005; Chapman and Kihn, 2009; Tarifa Fernández, 2022). Managers should advocate for and adopt modular IT architectures that allow for interoperability and data exchange between plants while accommodating site-specific customisations and maintaining a degree of local autonomy where necessary.

For policymakers and industry leaders, our study emphasises the need for sector-specific IT adoption policies that recognise the inherent heterogeneity of manufacturing environments, particularly concerning plant size. Smaller plants, which often face resource constraints and may experience higher risks associated with IT dependence, may struggle with integrating and adopting advanced IT at the same scale as larger enterprises. Government incentives for IT adoption should therefore be tailored to plant size and industry needs, ensuring that SME plants receive adequate financial support, technical assistance, and guidance on IT governance to facilitate upgrading their technological capabilities and manage resulting dependencies effectively (Chuang et al., 2009; Nguyen, 2009). Industry associations can play a vital role in developing tailored resources, facilitating knowledge sharing among SMEs, and advocating for policies that address the specific challenges faced by smaller manufacturing operations in the digital era.

At a broader level, this research contributes to digital transformation strategies by demonstrating that IT adoption is not merely a matter of technology availability but is deeply intertwined with organisational structure, interdependencies, and governance mechanisms. The findings support the notion that Industry 4.0 initiatives should prioritise adaptive integration strategies and strategic dependence management, rather than enforcing a one-size-fits-all approach to IT implementation. This is particularly relevant in the post-pandemic era, where manufacturing resilience is increasingly contingent on flexible, secure, and interoperable IT systems that effectively manage inherent dependencies and interdependencies.

7. Conclusion

This study provides empirical evidence on how systems integration, IT dependence, and interdependence with other plants influence IT adoption in manufacturing plants. Key findings confirm that systems integration enhances IT adoption but creates dependencies requiring strategic management to prevent risks like over-reliance and cybersecurity vulnerabilities. Interdependence with other plants also facilitates IT adoption, though not as a mediator of systems integration, with benefits depending on managing coordination and standardisation challenges. Plant size significantly impacts IT adoption, with larger plants showing higher rates due to greater resources and expertise, while smaller plants face struggles necessitating targeted support.

This study makes several key contributions. It addresses a significant gap by empirically examining the interplay of systems integration, IT dependence, and interdependence at the manufacturing plant level. The finding that IT dependence mediates the systems integration-IT adoption relationship offers a nuanced understanding, highlighting the 'dark side' of increased reliance. We illustrate how these factors shape IT adoption practices in manufacturing, providing a more granular perspective than broader studies. Applying Resource Dependence Theory offers a robust theoretical explanation, showing how managing dependencies and interdependencies is central to strategic IT adoption decisions in manufacturing plants.

Despite contributions, limitations exist. The study does not fully account for external factors (regulatory changes, disruptions, macroeconomic conditions) impacting IT adoption. Its focus on UK manufacturing plants may limit generalisability. The static, cross-sectional design doesn't capture the dynamic evolution of IT adoption over time. While mediating roles are identified, potential moderating variables (organisational culture, leadership, IT capability maturity, acceptance, ease of use) are not explored. Future research should address these limitations through longitudinal studies, diverse international contexts, investigation of moderators, and exploring the interplay with specific automation technologies like robotics.

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Appendix 1: Single Factor Harman's Test

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.799	26.359	26.359	5.429	24.678	24.678
2	3.526	16.026	42.385	3.185	14.477	39.155
3	2.635	11.977	54.363	2.224	10.109	49.264
4	1.790	8.135	62.498	1.243	5.649	54.913
5	1.006	4.571	67.068	.417	1.896	56.810
6	.824	3.747	70.816			

7	.717	3.259	74.075
8	.650	2.952	77.027
9	.619	2.814	79.841
10	.571	2.594	82.435
11	.530	2.410	84.844
12	.474	2.156	87.000
13	.457	2.076	89.076
14	.397	1.802	90.879
15	.372	1.693	92.571
16	.313	1.421	93.993
17	.312	1.418	95.411
18	.283	1.284	96.695
19	.248	1.127	97.822
20	.226	1.025	98.847
21	.144	.654	99.501
22	.110	.499	100.000

Extraction Method: Principal Axis Factoring.