A longitudinal study of ERP system capabilities and value

Abstract

Purpose

With a focus on three essential ERP capabilities—routinization, collaboration, and analytics—this study explores the long-term significance of enterprise resource planning (ERP) systems and their contribution to firm value. Grounded in the resource-based view (RBV), it aims to understand their evolving contribution to firm value and provide strategic guidance for long-term ERP value generation as well as insights into preserving and optimizing ERP business value.

Design/methodology/approach

The model links three ERP capabilities based on the resource-based view (RBV) to explain ERP value. It was tested using generalized estimating equations (GEE) on longitudinal survey data collected from 552 ERP-using firms in 2015 and 2020. This method accounts for within-firm correlation across time and assesses how the influence of routinization, collaboration, and analytics evolves over a five-year period.

Findings

Empirical evidence demonstrates that ERP routinization, collaboration, and analytics capabilities positively influence ERP value. However, their relative contributions significantly differ over time. Analytics and routinization capabilities exhibit a gradual decrease in importance over the studied five-year period. Collaboration, however, undergoes a more pronounced decline in contribution to ERP value unless proactively maintained. These findings underline the critical necessity of ongoing managerial commitment to fostering cross-functional collaboration, ensuring the continuous evolution of analytics capabilities, and maintaining routine ERP system usage to preserve and maximize business value derived from ERP investments.

Originality/value

This study addresses a notable gap in ERP literature by focusing explicitly on the post-adoption stage and longitudinally analysing capability evolution over multiple years. This study is among the first to longitudinally assess ERP capabilities in the post-adoption phase using data from two time points. Unlike prior research focused on adoption or short-term effects, it reveals how the influence of routinization, collaboration, and analytics on ERP value changes over time, offering novel insights for both researchers and practitioners on ERP-driven value creation.

Keywords: ERP, Analytics, Collaboration, Routinization, IT Value, Resource-based view, Longitudinal study

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1. Introduction

Over the last two decades, enterprise resource planning (ERP) systems have drastically changed the way firms operate around the world. Initially created to automate back-office tasks, ERP solutions have evolved into essential platforms that combine a firm's financial, material, and information, resources into a single environment (Nwankpa, 2015; Romero & Vernadat, 2016). Over the past ten years, the ERP market's expansion has been notable, valued at approximately $21.2 billion in 2010, it doubled to $51 billion by 2023 (Gartner 2024), and projections indicate it could reach $139.4 billion by 2033 (Future Market Research, 2023). This quick ascent highlights ERP's changing function as a potent catalyst for creating business value rather than just a transactional system. They facilitate cooperation, strong analytics, and better-informed strategic decision-making by bringing stakeholders and functional areas together (Eslami et al., 2023).

Despite these developments and the rapid shift to more sophisticated ERP 4.0 features, such as inter-organizational collaboration, expanded automation, and artificial intelligence (AI)-driven analytics, an estimated 90% of firms still use ERP 2.0 frameworks (Mandava, 2024). Optimizing current ERP features becomes increasingly crucial as competition intensifies and digital ecosystems proliferate. Understanding how these systems can be adapted and improved over time provides important insights into preserving operational effectiveness while preparing for future technological changes. Therefore, studying ERP solutions not only identifies the foundations of their current success thus far but also highlights strategic pathways that firms can leverage to gain a competitive advantage in ever-changing markets.

Since the 2000s, ERP systems have drawn a lot of attention from both industry and academia, making them a highly researched topic. Despite this potential, a large portion of the research that has already been done has been cross-sectional in nature and has concentrated on topics such as ERP implementation, critical success factors, and post-implementation challenges. These areas illuminate how firms can achieve immediate benefits, but they usually ignore the long-term evolution of ERP use and value creation (Ruivo et al., 2020). After being initially implemented, many systems continue to be underutilised (Maas et al., 2018), underscoring the necessity of investigating the ways in which ERP capabilities can be developed and sustained (Ruivo et al., 2015). Chae et al. (2014) emphasise the long-term effects of the capabilities of information systems, while Conboy et al. (2020a) support longitudinal research to document how capabilities such as analytics can influence competitiveness over time. In response to these claims, this study aims to answer the following **RQ:** How do ERP routinization, collaboration, and analytics evolve over time as ERP systems create value?

To address this question, we extend previous research (Ruivo et al. (2015, 2020b; Schreieck et al., 2021) initial insights by adopting a five-year longitudinal approach to examine how ERP capabilities—routinization, collaboration, and analytics—evolve in practice. Motivated by these studies grounded in the resource-based view (RBV) theory, we empirically investigate how these ERP capabilities collectively drive organisational outcomes across different stages of ERP use. Our goal is to present a deeper understanding of ERP's capacity for value creation as firms adapt to evolving market demands and technological advances speaking directly to practitioners and researchers aiming to strengthen real-world industrial applications of ERP. Through a multi-year analysis, we illustrate how firms can systematically refine these capabilities over time, thereby offering tangible guidance on sustaining IT value. Notably, our results challenge the traditional view of capabilities as intrinsically stable and highlight that analytics and collaboration are a dynamic process that need constant revision, rather than a one-time, static approach.

2. Theoretical background and conceptual model

2.1. Resource-based view and longitudinal studies

According to the RBV theory, ERP systems are considered a valuable resource that contributes to firm value. Longitudinal studies, which involve repeated observations of the same variables over extended periods, are particularly valuable in RBV research. This approach provides a valuable lens for ERP systems, as it helps to capture the long-term impact of ERP capabilities on firm value. In this context**, Appendix A** identifies 44 relevant studies that applied longitudinal methods from ABS-ranked 3 and 4, yet only two employed a quantitative approach grounded in RBV theory. The first of these, by Bendoly et al. (2009), explored how efficient ERP information use supports strategic performance over one month, stressing the importance of aligning system usage with broader organisational goals to achieve competitive advantage. The second, Schreieck et al. (2021) examined capabilities required for value co-creation and value capture in emergent platform ecosystems over three years and four months. Their findings pointed to both technology-related capabilities (e.g., cloud-based platformisation, open IT landscape management) and relationship-driven capabilities (ecosystem orchestration, platform evangelism, platform co-selling) as being essential for sustaining ERP success.

Despite of ERP research, there is a notable gap in studies that specifically analyse the capabilities of routinization, collaboration, and analytics over time. By integrating the RBV framework, this unique focus on the evolution of ERP capabilities over time distinguishes this study from previous research.

2.2. Conceptual model

ERP Value

The ERP value construct provides a holistic view of how ERP systems affect business value. Conceptualised as a second-order measure, it encompasses three key dimensions: impact on upstream coordination (IUC), impact on internal operations (IIO), and impact on downstream sales (IDS). The first dimension, IUC, assesses how ERP systems enhance supplier relationships, reduce procurement costs, and decrease inventory levels. By streamlining supply chain processes and optimising inventory management, ERP contributes to greater operational effectiveness and cost savings (Deb et al., 2023; Dehning et al., 2007). The second dimension, IIO, focuses on enhancements to internal workflows, such as higher productivity and lower operational costs. By automating routine tasks, reducing overheads, and improving the accuracy of management accounting measures, ERP helps firms use their resources more effectively (Chang et al., 2014; Lemonakis et al., 2020). The third dimension, IDS, encapsulates how ERP affects customer satisfaction and market expansion. Firms can improve customer satisfaction and build stronger client relationships by providing accurate, real-time information about inventory, product availability, and delivery times (de Vries & Boonstra, 2012; Sadeghi R et al., 2025). When combined, these dimensions highlight how ERP systems can support both strategic objectives and everyday operations, thereby underscoring how significant ERP value is to a firm's overall success (Ruivo et al., 2015).

Analytics in ERP

Analytics construct is the ERP system's ability to generate accurate, real-time information that supports firms' data-driven decisions (Lin et al., 2024). When applied to ERP, analytics is a core capability for converting raw data into actionable insights that enhance both efficiency and effectiveness (Müller, Fay, & Brocke, 2018; Wu et al., 2024). This capability is measured through features such as comprehensive reporting, business intelligence, data mining, neural networks, machine learning, and advanced data visualisation tools (Grover et al., 2020)**,** all of which support forecasting and strategic decision-making (Chatterjee et al., 2023). Moreover, analytics can be measured by how well an ERP provides real-time access to information, thereby increasing responsiveness and lowering uncertainty (Bandara et al., 2024; Chen et al., 2021).

An important component of this analytics construct is data visibility—the availability of accurate, up-to-date information about all activities and processes, such as purchasing, manufacturing, and distribution processes, which further enriches performance by fostering collaboration among stakeholders and cultivating advanced analytics capabilities (Awan et al., 2021; Xia et al., 2024). Through analytics, firms may discover new business opportunities, deepen customer understanding, mitigate risks, and improve both financial and operational outcomes (Maass et al., 2018; Oesterreich et al., 2022). This ultimately leads to a competitive advantage in dynamic market conditions (Pesce & Neirotti, 2023). From this, the following hypothesis is suggested:

H1a: Analytics positively influences ERP value.

Collaboration in ERP

Collaboration is the process by which two or more individuals work together to achieve a shared goal or create mutual value (Salvato et al., 2017). This collaborative capability includes resolving conflict, alignment of divergent objectives, and building trust with internal and external stakeholders (Jin et al., 2019; Yeow et al., 2018). The collaboration construct in ERP contexts is measured by how seamlessly coworkers use the system to create new products, services, or processes, as well as how well they communicate with partners and clients (Al-Omoush et al., 2023). Such dynamic collaboration supports agility and adaptability, particularly under uncertain conditions (Li et al., 2017; Schoch et al., 2023; Zhou et al., 2024). Through training and development programs, along with transparent and trust-based organisational cultures, firms can maximise collaborative efforts that, in turn, enhance the value they derive from ERP systems (Jin et al., 2019; Weritz et al., 2024). From this reasoning, we propose the following hypothesis:

H1b: Collaboration positively influences ERP value.

ERP Routinization

Routinization is the long-term adjustment of a firm's structure and processes so that new technology becomes fully integrated into everyday work (Gunasekaran et al., 2017). Achieving this requires both a solid technical foundation and continuous user engagement (Wohlgemuth & Wenzel, 2016). As Baskerville & Myers (2023) note, users are not merely passive operators; they occupy multiple roles, actively shaping—and being shaped by—the ERP system. A practical way to gauge ERP routinization is to assess how critical processes (e.g., sales, services, procurement) are executed through the ERP, ensuring that routine activities align with the organisation's objectives while promoting scalability and consistency (Hornyak et al., 2020; Li et al., 2019). Over time, users adapt and refine these procedures, causing ERP and firm routines to co-evolve (Rossi et al., 2020). Embedding the system into day-to-day operations ultimately drives greater efficiency, fewer errors, better decision-making, and improved overall performance (Maier et al., 2021a; Venkatesh et al., 2016). In this sense, we posit:

H1c: ERP routinization positively influences ERP value.

Time

ERP systems are widely recognised for positively contributing to firm's business value, yet their impact may evolve over time as firms refine analytics, collaboration, and routinization practices (Ruivo et al., 2020). Rather than providing immediate value, ERP systems often provide increasing value as organisations gradually learn to exploit these capabilities more effectively.

Firms increasingly appreciate the importance of analysing large data sets to support efficient business operations (Fosso Wamba et al., 2024). Batistič & van der Laken (2019) note that firms using data-driven strategies tend to be more profitable and productive, suggesting that analytics can become more influential as organisations gain expertise. Similarly, Lin et al. (2024) and Aral et al. (2024) show that analytics strengthens performance by improving organisational resilience, with phased ERP implementations yielding progressive value gains as analytics is embedded in decision-making. Chen et al. (2015) also confirms that analytics has an increasing impact on ERP value as organisations improve their data capabilities. Based on this, the following hypothesis is suggested:

H2a: Time moderates the relationship between analytics and ERP value, such that the effect becomes stronger over time.

Collaboration likewise plays a crucial role in building a culture of trust and learning, thereby maximising value from Information Systems investments and driving long-term success (Chatterjee et al., 2023; Tafti et al., 2022; Zhou et al., 2024).This collaborative capability is especially beneficial for value creation in human resources, customer service, and strategic or financial operations(Son et al., 2016). In times of disruption, ERP-enabled collaboration helps maintain competitiveness by facilitating real-time information-sharing and quick decision-making (Duong & Chong, 2020). Empirical work by Smolander et al. (2021) suggests that collaboration in ERP projects matures across phases, raising productivity through more efficient cross-functional workflows. Ruivo et al. (2015) additionally find that collaboration positively affects ERP value over time, indicating that stronger collaborative processes can magnify ERP outcomes. Thus, we posit:

H2b: Time moderates the relationship between collaboration and ERP value, such that the effect becomes stronger over time.

Finally, ERP routinization helps organisations overcome inertia by embedding new processes in day-to-day practices (Gunasekaran et al., 2017). As users interact with the system, they discover innovative ways to exploit its features, continually adapting existing routines to match local needs. Over time, these revised routines become deeply ingrained, creating a co-evolution of ERP modules and work patterns (Maier et al., 2021; Rossi et al., 2020; Venkatesh et al., 2022). Haberli Junior et al. (2019) further illustrate that routinization can moderate the impact of ERP on performance, suggesting that the system's value intensifies as it is woven into everyday operations. Accordingly, we propose:

H2c: Time moderates the relationship between ERP routinization and ERP value, such that the effect becomes stronger over time.

Emerging model Figure 1 depicts how analytics, collaboration, and ERP routinization collectively drive ERP value, which in turn leads to improved upstream coordination, downstream sales, and internal operations. Furthermore, time and several control variables (e.g., years of ERP use, firm size, country, industry) are incorporated to account for contextual influences on ERP outcomes.

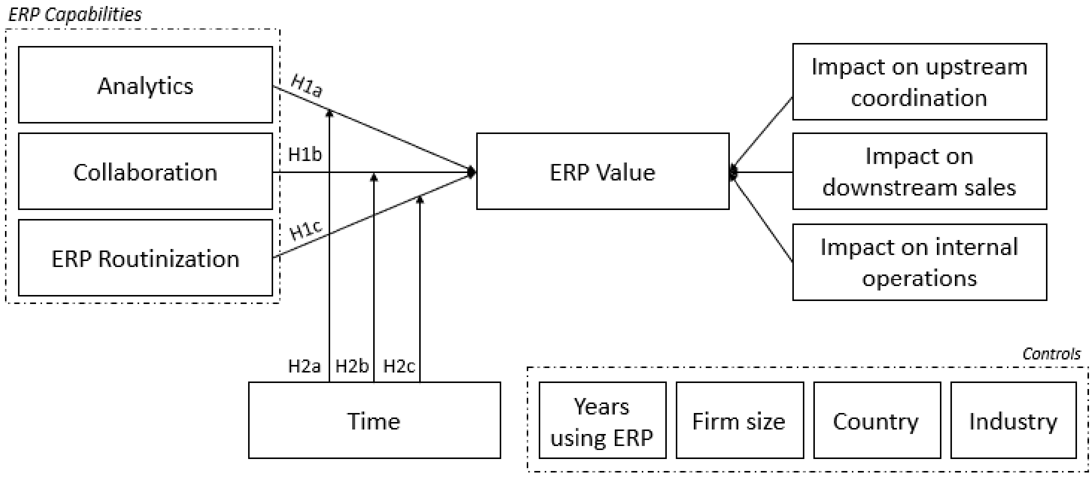

Figure 1. Conceptual Model for ERP Value Creation through integrated Analytics, Collaboration, and Routinization

3. Data Collection

A meticulously constructed web-based survey, developed using items from the existing literature, served as the foundation for our confirmatory phase. In partnership with the International Data Corporation, the survey was distributed to 2,000 firms actively using ERP systems, collecting responses during 5 years, the first time frame in 2015 and the second time frame in 2020. We stratified the sample by different cultural countries (Hofstede, 2001) (Germany and Portugal), industry (manufacturing, consumer goods, energy and telco, and professional services), and firm size, ensuring a diverse range of perspectives.

Table 1 presents the final sample of 552 firms, with 80.8% (446 firms) based in Germany and 19.2% (106 firms) in Portugal. Industries are well represented across manufacturing (29.7%), consumer goods (26.8%), energy and telco (22.3%), and professional services (21.2%). Respondents also held varied positions: 62.5% were business managers, 19.0% were IT/IS managers, and 2.2% were CEOs/owners, offering strategic, technical, and executive viewpoints.

In terms of annual business volume, most firms were originally small and medium-sized enterprises. However, between 2015 and 2020, the proportion of firms reporting turnover between €10 million and €25 million rose from 24% to 39%, indicating potential growth. The number of employees showed a similar trend: while the largest group still had fewer than 150 employees, the percentage of firms exceeding 150 employees climbed from 20% to 39%, suggesting an increasing representation of larger businesses.

Lastly, we looked at years of ERP use. In 2015, 55.4% of firms reported having used ERP for 10–15 years. Although this percentage remained steady in 2020, there was a marked jump in firms with over 20 years of ERP experience, moving from 2.0% to 14.5%, underscoring ERP's deepening role in daily operations.

Sample Characteristics (N=552)		N	(%)			2015 (N=552)	(%)	2020 (N=552)	(%)
Country	Germany	446	80.8%		**< 1M**	75	13.6%	75	13.6%
	Portugal	106	19.2%	**Annual Business Volume (€)**	**1M to 10M**	330	59.8%	243	44.0%
					10M to 25M	131	23.7%	213	38.6%
Industry Type	Manufacturing	164	29.7%		**25M to 50M**	16	2.9%	2	0.4%
	Consumer Goods	148	26.8%		**> 50M**	0	0.0%	19	3.4%
	Energy and Telco	123	22.3%						
	Professional Services	117	21.2%	**Number of employees**	**10-50**	177	32.1%	47	8.5%
					50-150	263	47.6%	271	49.1%
Respondent Position	Business Manager	345	62.5%		**150 to 250**	112	20.3%	215	38.9%
	IT/IS Manager	105	19.0%		**>250**	0	0.0%	19	3.4%
	CEO/Owner	12	2.2%						

Table 1. Characteristics of the sample

Finally, the common-method bias was assessed using two methods: (1) Harman one-factor test, in which no individual variable explained more than 50% of the variance (Podsakoff et al., 2003), and (2) analysing the variance inflation factor (VIF), which was lower than 3.3, suggesting no common method bias issues (Kock, 2017).

Appendix B illustrates the constructs and measurement items that were created using the theoretical framework covered in the preceding section. Statement items were used to measure the constructs, and for each item question, respondents were asked to rate their perception using a five-point Likert scale, where 1 denotes "low" and 5 denotes "high."

4. Results

The model was tested using generalized estimating equations due to the repeated measures of the constructs involved. This approach adjusts for the correlation of constructs within the same individuals over time, thereby minimizing potential bias in the estimates (Morris & Venkatesh, 2010). An unstructured correlation model was specified for the correlation structure, as we do not anticipate within-subject correlations to diminish over time (Ballinger, 2004); the individuals engaged in the same behaviour across both data collection points. Before calculating the estimates, the reliability and validity of scales were evaluated for the pooled variables. All constructs demonstrated a composite reliability (CR) exceeding 0.7, ensuring the reliability of the scales (Table 1). To achieve this, three items were deleted, one from ERP routinization, impact on internal operations and impact on upstream coordination constructs. Furthermore, the average variance extracted (AVE), represented as the square of the diagonal value, exceeded 0.5 for all constructs, confirming convergent validity (Hair et al., 2016). Discriminant validity was evaluated using three criteria. First, based on the Fornell-Larcker criterion, we confirmed that all diagonal values were greater than the correlations between constructs, which was verified (Fornell & Larcker, 1981). Loadings were also compared with the cross-loadings (Appendix C), always being higher than the latest. Additionally, we assessed the heterotrait-monotrait ratio, with all values found to be below 0.9 (Appendix C). Thus, no discriminant validity issues were found.

Since the ERP value is conceptualized as a reflective-formative second-order construct, the weights, their statistical significance, and the variance inflation factor (VIF) were analysed (see Table 2). As presented, all weights are statistically significant, and there are no multicollinearity issues, since VIF values are lower than 3.3 (Hair et al., 2017).

After assessing the measurement model, the model can be estimated. To do so, we had two records per individual, one per each moment of time. Time was therefore used as a dummy variable and tested as a moderator.

Three models were evaluated: Model 1 – without time and time interactions; Model 2 – excluding time interactions; and Model 3 – the final model. Table 3 summarizes the results of the comparison, including their adjusted R-squared values. The analysis indicates that the proposed model performs slightly better when time interactions are included. Although the increase in explained variance is modest, it is noteworthy due to the statistical significance of the time interactions, which reveal important findings. Regarding direct effects, all variables had a statistically significant and positive impact, confirming support for H1a, H1b, and H1c. Among the moderation hypotheses, one out of three (H2b) was found to be statistically significant. Overall, four of the six hypotheses are supported.

Variable	Control variables	Main effects	Moderated model	Conclusion
Adjusted R2 (R2)	18.3% (19.1%)	27.6% (28.7%)	28.2% (29.8%)	
Years	0.283***	0.199***	0.024	-
Firm size	-0.021	-0.007	0.001	-
Portugal	-0.380***	-0.332***	-0.373***	-
Consumer goods	-0.046	-0.026	-0.017	-
Energy telco	-0.102**	-0.087*	-0.066	-
Manufacturing	-0.0668	-0.0665	-0.042	-
AN		0.090***	0.069***	H1a supported
COL		0.134***	0.123***	H1b supported
ERPR		0.090**	0.087**	H1c supported
Time			0.121***	-
AN*time			0.008	H2a not supported
COL*time			-0.029***	H2b not supported
ERPR*time			0.008	H2c not supported

*Table 2. Estimates (p-value<0.10 *; <0.05 **; <0.01 ***)*

5. Discussion

Many have cited the need for a longitudinal examination of ERP capabilities and value (Conboy et al., 2020b; Ruivo et al., 2020a). For this reason, we developed and tested a model to investigate how analytics, collaboration, and ERP routinization jointly shape the ERP value over time. The results underscore the importance of these capabilities for maximising the benefits of ERP systems, yet they also reveal notable nuances in how time moderates these relationships.

Firstly, our results support H1a, H1b, and H1c by confirming that all three capabilities—analytics, collaboration, and ERP routinization—contribute to ERP's incremental value. This is consistent with earlier studies showing that data-driven (Müller, Fay, & vom Brocke, 2018) , seamless coordination among stakeholders (Jin et al., 2019), as well as incorporating ERP into routine tasks (Maier et al., 2021b), enhance business value. Additionally, it aligns with the Resource-Based View (RBV), which emphasizes how important firm-specific capabilities are to obtaining a competitive advantage.

In the context of ERP 2.0, collaboration has traditionally been viewed as an internal mechanism that facilitates interactions among colleagues, suppliers, and customers (Grabot et al., 2014). Indeed, our item questions—specifically focused on ERP 2.0—asked respondents to rate the ease of collaborating with colleagues, with the system itself, and with partners and customers. These findings initially underscored the critical importance of collaboration in driving organizational value. Over the past five to ten years, however, more advanced collaborative networks—often referred to as Business Networks (e.g., SAP Business Network, Oracle Business Network)—have emerged to interlink multiple ERP systems. Consequently, a single ERP platform holds less significance compared to these broader ecosystems, where collaboration increasingly relies on specialized platforms offered by major vendors such as Oracle and SAP (Gebhardt et al., 2022). Although ERP 2.0 featured highly intrinsic collaborative capabilities, the advent of more sophisticated systems—including ERP 4.0—has further diminished the centrality of traditional ERP-based collaboration (Eslami et al., 2023; Weritz et al., 2024).

At the same time, our findings indicate a distinctive temporal decline in collaboration's overall impact, even when it is rated favourably in terms of ease of use. While collaboration initially contributes strongly to ERP value, such benefits can erode unless firms continually invest in and refine their collaborative practices (Melendez et al., 2022; Smolander et al., 2021). As Farshchian (2020) notes once rival companies use comparable groupware and cross-functional workflows, collaboration runs the risk of becoming a "commodity," reducing its incremental advantage. Similar to this, Barnett (2018) notes that commoditization occurs when methods that were previously deemed unique become widespread, limiting their ability to produce long-term performance improvements. Whether through cross-unit incentives, specialized teams, or continuous training, firms must proactively strengthen their collaborative processes to prevent stagnation. They also need to stay aware of the changing needs of larger, externally focused business networks. (Eslami et al., 2023).

Thirdly, there is a degree of stability in the way that analytics (H2a) and ERP routinization (H2c) contribute to overall ERP value and no statistically significant changes in their impact over time. Nevertheless, analytics is still susceptible to becoming a commodity. As Delen & Demirkan (2013) warn that if they are extensively replicated without significant innovation, even sophisticated analytics modules may turn into standardized solutions. Our study's analytics item questions cover comprehensive reporting (KPIs, dashboards, etc.), real-time access to information, and data visibility across departments— all of which primarily reflect an ERP 2.0 paradigm that was novel 15 years ago. However, digital proficiency has increased substantially since then, making these 2.0-level analytics more routine for today's workforce. According to recent meta-analyses, improved firm performance is closely linked to ongoing improvements in analytics capabilities (Côrte-Real et al., 2017, 2019). Newer ERP 4.0 solutions, on the other hand, incorporate sophisticated machine learning, AI, and predictive analytics, underscoring the necessity of integrating new data sources, implementing cutting-edge algorithms into practice, and more thoroughly integrating analytical insights into strategic decision-making (Davenport, 2018; Wu et al., 2024b).

Meanwhile, once employees integrate core ERP transactions into their everyday routines, ERP routinization keeps yielding reliable results. To prevent performance stagnation, small adjustments are still essential, such as improving user interfaces or automating tedious tasks (Parhizkar & Comuzzi, 2017). If companies want to maintain long-term competitive advantages, they must continue to be proactive in updating and changing their systems, even in fields where stability is evident.

5.1. Managerial Implications

In practical terms, the results provide a valuable roadmap for managers looking to extend and optimize ERP value. First, the seeming stability of analytics and routinization indicates that fundamental capabilities can produce long-term performance improvements, but only if they are updated on a regular basis to meet evolving operational needs. As a result, firms need to consistently allocate in analytics-driven innovations, system improvements, and user training.

Second, the more pronounced decline in collaboration emphasizes how crucial it is to avoid complacency after establishing an initial collaborative environment. Certain management actions, like creating cross-functional councils, creating strong incentive programs, or switching employees between departments, can prevent collaboration from becoming monotonous and losing its unique selling point.

Thirdly, managers should actively invest in new data pipelines, sophisticated modelling techniques, and innovative data-driven business processes to stay vigilant against the risk of analytics commoditization. The strategic relevance of the capability will be maintained by coordinating these continuing analytics initiatives with business strategy.

Ultimately, routinization is still very important, but in order to prevent performance gains from plateauing, the routine needs to be continuously improved. In order to ensure long-term competitiveness and resilience, senior leaders can build a more resilient and flexible ERP-based platform by managing collaboration, analytics, and routinization as a cohesive portfolio of capabilities, each with unique temporal dynamics.

5.2. Limitations and Suggestions for Future Research

Although this study illuminates how analytics, collaboration, and ERP routinization evolve over time to generate ERP value, it has some limitations. First, the finer transitions through which firms develop these capabilities might not be fully captured by our five-year data collection (2015–2020). Future research could adopt a multi-wave longitudinal design, incorporating additional measurement points or using panel data, to capture more continuous changes and feedback loops as ERP development and use advance.

Second, our questionnaire items (Appendix B) closely matched the features of ERP 2.0, reflecting technologies and practices that are still used in about 90% of firms (Mandava, 2024). However, as digital proficiency has grown among employees and ERP solutions move toward 4.0—including big data, advanced automation, IoT integration, machine learning, and higher-level analytics—the once-novel features of ERP 2.0 may become increasingly commoditized. Researchers could thus extend this study by integrating questions that address newer digital capabilities, exploring how emerging technologies reshape collaboration, analytics, and routinization, and the degree to which broader digital fluency either fosters or diminishes their distinctiveness.

Last but not least, other moderators—such as generational perspectives on technology, organizational learning, or external disruptions—might further enrich our understanding of how and when ERP capabilities have the biggest impact (AlMuhayfith & Shaiti, 2020). Addressing these limitations would help our understanding of how ERP systems are dynamic, and technologically evolving, as well as guide more flexible approaches to implementing ERP 4.0 innovations.

5.3. Practical Implications

The findings of this study offer several important insights for practitioners seeking to optimise ERP investments. First, managers should recognise that analytics, collaboration, and routinization each contribute distinctly to ERP value. By developing all three capabilities in tandem, fostering strong data analysis tools, incorporating cross-functional teamwork, and integrating ERP usage into daily routines—firms can create a stable yet flexible environment for value creation.

Second, our findings suggest that if collaboration is not actively fostered, it may diminish over time, leading firms to adopt strategies such as incentive programs, cross-departmental task forces, or focused training to maintain participation. Beyond these internal measures, using more comprehensive collaboration solutions—such as Business Networks (e.g., SAP Business Network, Oracle Business Network)—can further extend ERP value by connecting multiple partners and stakeholders. Through continuous cross-organizational collaboration, firms can prevent silos and ensure that collaboration remains a dynamic and evolving aspect of their operational ecosystem.

Third, although analytics and routinization continue to exert relatively stable effects, both require ongoing commitments to user education, technological enhancements, and process re-engineering to remain effective. In particular, advanced analytics solutions involving AI and machine learning can significantly extend ERP value—provided that employees possess the necessary proficiency to interpret complex data and translate insights into tangible actions. At the same time, routinization efforts must evolve periodically to accommodate shifting market demands or changes in firm structure, ensuring that day-to-day processes do not become outdated.

Finally, the evolution toward ERP 4.0—featuring advanced data-driven decision support—underscores the value of continual enhancement in analytics, collaboration, and routinization. As these emerging technologies introduce novel data streams and complex processes, managers should proactively develop employee skills through focused training and robust knowledge-sharing initiatives. Firms can continue to reap the returns from their ERP investments by upgrading infrastructure and refining workflows to ensure that new capabilities align with strategic goals. By keeping this future-oriented posture, practitioners will be more capable of handling technological changes and retaining a long-term competitive advantage.

6. Conclusions

This longitudinal study confirms that analytics, collaboration, and routinization each contribute to ERP value, yet they follow different trajectories over time. While analytics and routinization usually provide consistent benefits once incorporated into daily operations, collaboration necessitates continuous renewal to prevent diminishing returns. Notably, as firms move from ERP 2.0 to ERP 4.0, collaboration becomes more than just connecting internal departments and integrates wider business networks, providing new opportunities to strengthen interorganizational partnerships. These results support the notion that ERP capabilities work best when combined with organizational procedures and technology solutions, rather than operating as standalone IT resources. Managers must maintain strong collaborative mechanisms (particularly in networked environments), update routine tasks to reflect changing market and operations demands, and periodically refresh analytics to stay ahead of commoditization in order to maintain the strategic relevance of ERP. Future research could investigate how emerging ERP 4.0 technologies, along with cultural and generational factors, further shape the dynamic evolution of these capabilities across various business contexts.

References

Alhirz, H., & Sajeev, A. S. M. (2015). Do cultural dimensions differentiate ERP acceptance? A study in the context of Saudi Arabia. Information Technology and People, 28(1), 163–194. https://doi.org/10.1108/ITP-07-2013-0127

AlMuhayfith, S., & Shaiti, H. (2020). The impact of enterprise resource planning on business performance: With the discussion on its relationship with open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 6(3). https://doi.org/10.3390/JOITMC6030087

Al-Omoush, K. S., de Lucas, A., & del Val, M. T. (2023). The role of e-supply chain collaboration in collaborative innovation and value-co creation. Journal of Business Research, 158. https://doi.org/10.1016/j.jbusres.2023.113647

Aral, S., Brynjolfsson, E., Gu, C., Wang, H., & Wu, D. J. (2024). UNDERSTANDING THE RETURNS FROM INTEGRATED ENTERPRISE SYSTEMS: THE IMPACTS OF AGILE AND PHASED IMPLEMENTATION STRATEGIES1. MIS Quarterly: Management Information Systems, 48(2), 749–774. https://doi.org/10.25300/MISQ/2023/17420

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. Technological Forecasting and Social Change, 168. https://doi.org/10.1016/j.techfore.2021.120766

Ballinger, G. A. (2004). Using Generalized Estimating Equations for Longitudinal Data Analysis. In Organizational Research Methods (Vol. 7, Issue 2, pp. 127–150). SAGE Publications Inc. https://doi.org/10.1177/1094428104263672

Bandara, F., Jayawickrama, U., Subasinghage, M., Olan, F., Alamoudi, H., & Alharthi, M. (2024). Enhancing ERP Responsiveness Through Big Data Technologies: An Empirical Investigation. Information Systems Frontiers, 26(1), 251–275. https://doi.org/10.1007/s10796-023-10374-w

Baskerville, R. L., & Myers, M. D. (2023). Reconceptualizing users: The roles and activities of people as they engage with digital technologies. Journal of Information Technology, 38(4), 487–501. https://doi.org/10.1177/02683962231183455

Batistič, S., & van der Laken, P. (2019). History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations. British Journal of Management, 30(2), 229–251. https://doi.org/10.1111/1467-8551.12340

Bendoly, E., Rosenzweig, E. D., & Stratman, J. K. (2009). The efficient use of enterprise information for strategic advantage: A data envelopment analysis. Journal of Operations Management, 27(4), 310–323. https://doi.org/10.1016/j.jom.2008.11.001

Chae, H.-C., Koh, C. E., & Prybutok, V. R. (2014). Information Technology Capability and Firm Performance. Source: MIS Quarterly, 38(1), 305–326. https://doi.org/10.2307/26554879

Chang, S. I., Yen, D. C., Chang, I. C., & Jan, D. (2014). Internal control framework for a compliant ERP system. Information and Management, 51(2), 187–205. https://doi.org/10.1016/j.im.2013.11.002

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023a). Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. Technological Forecasting and Social Change, 196. https://doi.org/10.1016/j.techfore.2023.122824

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023b). Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. Technological Forecasting and Social Change, 196. https://doi.org/10.1016/j.techfore.2023.122824

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. Journal of Management Information Systems, 32(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364

Chen, D. Q., Preston, D. S., & Swink, M. (2021). How big data analytics affects supply chain decision-making: An empirical analysis. Journal of the Association for Information Systems, 22(5), 1224–1244. https://doi.org/10.17705/1jais.00713

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020a). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. European Journal of Operational Research, 281(3), 656–672. https://doi.org/10.1016/j.ejor.2019.06.051

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020b). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. European Journal of Operational Research, 281(3), 656–672. https://doi.org/10.1016/j.ejor.2019.06.051

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. Journal of Business Research, 70, 379–390. https://doi.org/10.1016/j.jbusres.2016.08.011

Côrte-Real, N., Ruivo, P., Oliveira, T., & Popovič, A. (2019). Unlocking the drivers of big data analytics value in firms. Journal of Business Research, 97, 160–173. https://doi.org/10.1016/j.jbusres.2018.12.072

Davenport, T. H. (2018). From analytics to artificial intelligence. Journal of Business Analytics, 1(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

de Vries, J., & Boonstra, A. (2012). The influence of ERP implementation on the division of power at the production-sales interface. International Journal of Operations and Production Management, 32(10), 1178–1198. https://doi.org/10.1108/01443571211274512

Deb, P., Naskar, S., Devaraj, S., & Basu, P. (2023). Impact of working capital on firm performance: Does IT matter? Journal of Operations Management, 69(6), 983–1007. https://doi.org/10.1002/joom.1244

Dehning, B., Richardson, V. J., & Zmud, R. W. (2007). The financial performance effects of IT-based supply chain management systems in manufacturing firms. Journal of Operations Management, 25(4), 806–824. https://doi.org/10.1016/j.jom.2006.09.001

Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. In Decision Support Systems (Vol. 55, Issue 1, pp. 359–363). Elsevier B.V. https://doi.org/10.1016/j.dss.2012.05.044

Duong, L. N. K., & Chong, J. (2020). Supply chain collaboration in the presence of disruptions: a literature review. In International Journal of Production Research (Vol. 58, Issue 11, pp. 3488–3507). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2020.1712491

Eslami, M. H., Achtenhagen, L., Bertsch, C. T., & Lehmann, A. (2023). Knowledge-sharing across supply chain actors in adopting Industry 4.0 technologies: An exploratory case study within the automotive industry. Technological Forecasting and Social Change, 186. https://doi.org/10.1016/j.techfore.2022.122118

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. In Source: Journal of Marketing Research (Vol. 18, Issue 1).

Fosso Wamba, S., Queiroz, M. M., Wu, L., & Sivarajah, U. (2024). Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture. Annals of Operations Research, 333(2–3), 559–578. https://doi.org/10.1007/s10479-020-03812-4

Gebhardt, M., Kopyto, M., Birkel, H., & Hartmann, E. (2022). Industry 4.0 technologies as enablers of collaboration in circular supply chains: a systematic literature review. In International Journal of Production Research (Vol. 60, Issue 23, pp. 6967–6995). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2021.1999521

Grabot, B., Mayere, A., Lauroua, F., & Houe, R. (2014). ERP 2.0, what for and how? Computers in Industry, 65(6), 976–1000. https://doi.org/10.1016/j.compind.2014.02.017

Grover, V., Lindberg, A., Benbasat, I., & Lyytinen, K. (2020). The perils and promises of big data research in information systems. In Journal of the Association for Information Systems (Vol. 21, Issue 2, pp. 268–291). Association for Information Systems. https://doi.org/10.17705/1jais.00601

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017a). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research, 70, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017b). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research, 70, 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Haberli Junior, C., Oliveira, T., Yanaze, M., & Spers, E. E. (2019). Performance, farmer perception, and the routinisation (RO) moderation on ERP post-implementation. Heliyon, 5(6). https://doi.org/10.1016/j.heliyon.2019.e01784

Hair, J. F. ., Hult, G. T. M. ., Ringle, C. M. ., & Sarstedt, Marko. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). Sage.

Hair, J., Hult, G. T., Ringle, C., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). In Sage.

Hofstede, G. (2001). Culture's consequences: Comparing values, behaviors, institutions and organizations across nations.

Hornyak, R., Rai, A., & Dong, J. Q. (2020). Incumbent system context and job outcomes of effective enterprise system use. Journal of the Association for Information Systems, 21(2), 364–387. https://doi.org/10.17705/1jais.00605

Jin, Y. "Henry," Fawcett, S. E., Fawcett, A. D., & Swanson, D. (2019). Collaborative capability and organizational performance: Assessing strategic choice and purity. International Journal of Production Economics, 214, 139–150. https://doi.org/10.1016/j.ijpe.2019.04.006

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. In Partial Least Squares Path Modeling (pp. 245–257). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_11

Lemonakis, C., Sariannidis, N., Garefalakis, A., & Adamou, A. (2020). Visualizing operational effects of ERP systems through graphical representations: current trends and perspectives. Annals of Operations Research, 294(1–2), 401–418. https://doi.org/10.1007/s10479-018-2851-x

Li, Y., Huang, J., & Song, T. (2019). Examining business value of customer relationship management systems: IT usage and two-stage model perspectives. Information and Management, 56(3), 392–402. https://doi.org/10.1016/j.im.2018.07.012

Li, Y., Wu, F., Zong, W., & Li, B. (2017). Supply chain collaboration for ERP implementation: An inter-organizational knowledge-sharing perspective. International Journal of Operations and Production Management, 37(10), 1327–1347. https://doi.org/10.1108/IJOPM-12-2015-0732

Lin, J., Wu, S., & Luo, X. (2024). How does big data analytics capability affect firm performance? Unveiling the role of organisational resilience and environmental dynamism. European Journal of Information Systems. https://doi.org/10.1080/0960085X.2024.2375262

Maas, J. B., Van Fenema, P. C., & Soeters, J. (2018). Post-Implementation ERP Usage: A Longitudinal Study of the Impact of Control and Empowerment. Information Systems Management, 35(4), 330–347. https://doi.org/10.1080/10580530.2018.1503804

Maass, W., Parsons, J., Purao, S., Storey, V. C., & Woo, C. (2018). Data-driven meets theory-driven research in the era of big data: Opportunities and challenges for information systems research. In Journal of the Association for Information Systems (Vol. 19, Issue 12, pp. 1253–1273). Association for Information Systems. https://doi.org/10.17705/1jais.00526

Maier, C., Laumer, S., Tarafdar, M., Mattke, J., Reis, L., & Weitzel, T. (2021a). Challenge and Hindrance IS Use Stressors and Appraisals: Explaining Contrarian Associations in Post-Acceptance IS Use Behavior. Journal of the Association for Information Systems, 22(6), 1590–1624. https://doi.org/10.17705/1jais.00709

Maier, C., Laumer, S., Tarafdar, M., Mattke, J., Reis, L., & Weitzel, T. (2021b). Challenge and Hindrance IS Use Stressors and Appraisals: Explaining Contrarian Associations in Post-Acceptance IS Use Behavior. Journal of the Association for Information Systems, 22(6), 1590–1624. https://doi.org/10.17705/1jais.00709

Mandava, H. (2024). The use of contemporary Enterprise Resource Planning (ERP) technologies for digital transformation. Journal of Artificial Intelligence and Big Data, 4(1), 31–35. https://doi.org/10.31586/jaibd.2024.881

Morris, M. G., & Venkatesh, V. (2010). Job Characteristics and Job Satisfaction: Understanding the Role of Enterprise Resource Planning System Implementation. In Source: MIS Quarterly (Vol. 34, Issue 1).

Müller, O., Fay, M., & Brocke, J. Vom. (2018). The Effect of Big Data and Analytics on Firm Performance. Source: Journal of Management Information Systems, 35(2), 488–509. https://doi.org/10.2307/26613939

Müller, O., Fay, M., & vom Brocke, J. (2018). The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics. Journal of Management Information Systems, 35(2), 488–509. https://doi.org/10.1080/07421222.2018.1451955

Nwankpa, J. K. (2015). ERP system usage and benefit: A model of antecedents and outcomes. Computers in Human Behavior, 45, 335–344. https://doi.org/10.1016/j.chb.2014.12.019

Oesterreich, T. D., Anton, E., & Teuteberg, F. (2022). What translates big data into business value? A meta-analysis of the impacts of business analytics on firm performance. Information and Management, 59(6). https://doi.org/10.1016/j.im.2022.103685

Parhizkar, M., & Comuzzi, M. (2017). Impact analysis of ERP post-implementation modifications: Design, tool support and evaluation. Computers in Industry, 84, 25–38. https://doi.org/10.1016/j.compind.2016.11.003

Pesce, D., & Neirotti, P. (2023). The impact of IT–business strategic alignment on firm performance: The evolving role of IT in industries. Information and Management, 60(5). https://doi.org/10.1016/j.im.2023.103800

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. In Journal of Applied Psychology (Vol. 88, Issue 5, pp. 879–903). https://doi.org/10.1037/0021-9010.88.5.879

Romero, D., & Vernadat, F. (2016). Enterprise information systems state of the art: Past, present and future trends. Computers in Industry, 79, 3–13. https://doi.org/10.1016/j.compind.2016.03.001

Rossi, M., Nandhakumar, J., & Mattila, M. (2020). Balancing fluid and cemented routines in a digital workplace. Journal of Strategic Information Systems, 29(2). https://doi.org/10.1016/j.jsis.2020.101616

Ruivo, P., Johansson, B., Sarker, S., & Oliveira, T. (2020a). The relationship between ERP capabilities, use, and value. Computers in Industry, 117. https://doi.org/10.1016/j.compind.2020.103209

Ruivo, P., Johansson, B., Sarker, S., & Oliveira, T. (2020b). The relationship between ERP capabilities, use, and value. Computers in Industry, 117. https://doi.org/10.1016/j.compind.2020.103209

Ruivo, P., Oliveira, T., Johansson, B., & Neto, M. (2013). Differential effects on ERP post-adoption stages across Scandinavian and Iberian SMEs. Journal of Global Information Management, 21(3), 1–20. https://doi.org/10.4018/jgim.2013070101

Ruivo, P., Oliveira, T., & Neto, M. (2012). ERP use and value: Portuguese and Spanish SMEs. Industrial Management & Data Systems, 112(7), 1008–1025. https://doi.org/10.1108/02635571211254998

Ruivo, P., Oliveira, T., & Neto, M. (2015). Using resource-based view theory to assess the value of ERP commercial-packages in SMEs. Computers in Industry, 73, 105–116. https://doi.org/10.1016/j.compind.2015.06.001

Sadeghi R, K., Ojha, D., & Azadegan, A. (2025). Data systems in supply chain resilience: moderated moderating effects of enterprise resource planning. Industrial Management and Data Systems. https://doi.org/10.1108/IMDS-08-2024-0752

Salvato, C., Reuer, J. J., & Battigalli, P. (2017). Cooperation across disciplines: A multilevel perspective on cooperative behavior in governing interfirm relations. Academy of Management Annals, 11(2), 960–1004. https://doi.org/10.5465/annals.2014.0001

Schoch, M., Gimpel, H., Maier, A., & Neumeier, K. (2023). From broken habits to new intentions: how COVID-19 expands our knowledge on post-adoptive use behaviour of digital communication and collaboration. European Journal of Information Systems, 32(6), 989–1010. https://doi.org/10.1080/0960085X.2022.2096489

Schreieck, M., Wiesche, M., & Krcmar, H. (2021). Capabilities for value co-creation and value capture in emergent platform ecosystems: A longitudinal case study of SAP's cloud platform. Journal of Information Technology, 36(4), 365–390. https://doi.org/10.1177/02683962211023780

Smolander, K., Rossi, M., & Pekkola, S. (2021). Heroes, contracts, cooperation, and processes: Changes in collaboration in a large enterprise systems project. Information and Management, 58(2). https://doi.org/10.1016/j.im.2020.103407

Son, B. G., Kocabasoglu-Hillmer, C., & Roden, S. (2016). A dyadic perspective on retailer-supplier relationships through the lens of social capital. International Journal of Production Economics, 178, 120–131. https://doi.org/10.1016/j.ijpe.2016.05.005

Tafti, A., Rahmati, P., Mithas, S., & Krishnan, M. S. (2022). How Human Resource and Information Systems Practices Amplify the Returns on Information Technology Investments. Journal of the Association for Information Systems, 23(5), 1150–1183. https://doi.org/10.17705/1jais.00758

Venkatesh, V., Speier-Pero, C., Aljafari, R., & Bala, H. (2022). IT Use and Job Outcomes: A Longitudinal Field Study of Technology Contingencies. Journal of the Association for Information Systems, 23(5), 1184–1210. https://doi.org/10.17705/1jais.00760

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). A I S ssociation for nformation ystems Unified Theory of Acceptance and Use of Technology: A Synthesis and the Road Ahead. J Ournal, 17, 328–376.

Weritz, P., Braojos, J., Matute, J., & Benitez, J. (2024). Impact of strategic capabilities on digital transformation success and firm performance: theory and empirical evidence. European Journal of Information Systems. https://doi.org/10.1080/0960085X.2024.2311137

Wohlgemuth, V., & Wenzel, M. (2016). Dynamic capabilities and routinization. Journal of Business Research, 69(5), 1944–1948. https://doi.org/10.1016/j.jbusres.2015.10.085

Wu, D., Lin, X., Gupta, S., & Kar, A. K. (2024a). Big Data Analytics Capability, Dynamic Capability, and Firm Performance: The Moderating Effect of IT-Business Strategic Alignment. IEEE Transactions on Engineering Management, 71, 11638–11651. https://doi.org/10.1109/TEM.2024.3429648

Wu, D., Lin, X., Gupta, S., & Kar, A. K. (2024b). Big Data Analytics Capability, Dynamic Capability, and Firm Performance: The Moderating Effect of IT-Business Strategic Alignment. IEEE Transactions on Engineering Management, 71, 11638–11651. https://doi.org/10.1109/TEM.2024.3429648

Xia, S., Song, J., Ameen, N., Vrontis, D., Yan, J., & Chen, F. (2024). What Changes and Opportunities Does Big Data Analytics Capability Bring to Strategic Alliance Research? A Systematic Literature Review. International Journal of Management Reviews, 26(1), 34–53. https://doi.org/10.1111/ijmr.12350

Yeow, A., Kien Sia, S., Soh, C., & Chua, C. (2018). Boundary Organization Practices for Collaboration in Enterprise Integration. Research, 29(1), 149–168. https://doi.org/10.2307/48747885

Zhou, J., Xu, T., Chiao, Y., & Fang, Y. (2024a). Interorganizational Systems and Supply Chain Agility in Uncertain Environments: The Mediation Role of Supply Chain Collaboration. Information Systems Research, 35(1), 184–202. https://doi.org/10.1287/isre.2023.1210

Zhou, J., Xu, T., Chiao, Y., & Fang, Y. (2024b). Interorganizational Systems and Supply Chain Agility in Uncertain Environments: The Mediation Role of Supply Chain Collaboration. Information Systems Research, 35(1), 184–202. https://doi.org/10.1287/isre.2023.1210

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. In Information Systems Research (Vol. 16, Issue 1, pp. 61–84). INFORMS Inst.for Operations Res.and the Management Sciences. https://doi.org/10.1287/isre.1050.0045

Zhu, K., Kraemer, K. L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: A technology diffusion perspective on e-business. Management Science, 52(10), 1557–1576. https://doi.org/10.1287/mnsc.1050.0487

Appendix A – Longitudinal Studies Research

Author and Year	**Journal**	**Theoretical Framework**	**Type of longitudinal study**	**Total Duration of data collection**	**Temporal Frames/ Points of measurement**
Alvarez (2008)	Information Systems Journal	Critical Discourse Analysis (CDA)	Qualitative	5 years	**T1:** Fall of 1998 **T2:** Fall of 2002 to Spring of 2003
Hospitals et al. (2017)	MIS quarterly	Institutional theory	Quantitative	9 years old	From 2005 to 2013
Arvidsson et al. (2014)	*The Journal of Strategic Information Systems*	Strategy-as-Practice	Qualitative	18 months	**T1:** Prior to implementation **T2:** During implementation
Bala & Bhagwatwar (2018)	Information Systems Journal	Expectation Disconfirmation Theory (EDT)	Quantitative	6 months	**T1:** Immediately before training **T2:** 3 months after T1 **T3:** 3 months after T2
Bala & Venkatesh (2013)	MIS quarterly	Job Strain Model (JSM)	Quantitative	6 months	**T0:** Immediately before training and ES use. **T1:** 1 month after training and ES use. **T2: 2** months after T1. **T3:** 3 months after T2.
Beard & Sumner (2004)	The Journal of Strategic Information Systems	Resource-Based View (RBV) VRIO framework	Qualitative	4 years and 3 months	Articles published between January 1998 and March 2002
Bendoly & Cotteleer (2008)	Journal of Operations Management	Valence-Instrumentality-Expectancy (VIE) Theory	Quantitative	24 months	24 months
Benlian (2015)	Journal of the Association for Information Systems	Technology Capability Broadening and Deepening	Quantitative	4 months	**First study:** October 2011 and February 2012 **Second study:** April and July 2013
Clegg & Wan (2013)	*International Journal of Operations & Production Management*	Contingency Theory	Qualitative	2 years	From 2009 to 2011
Cotteleer & Bendoly (2006)	*MIS quarterly*	Theory of Swift, Even Flow	Quantitative	36 months	**T1:** 12 months prior to the ERP deployment **T2:** 24 months following the ERP deployment
Deng & Chi (2012)	*Journal of Management Information Systems*	Revealed Causal Mapping (RCM) Social Network Analysis (SNA)	Mixed-methods approach	9 months	**T1:** April to August 2007, initial Usage Phase. **T2:** September to December 2007, continued Usage Phase.
Gallivan et al. (2005)	*Journal of Management Information Systems*	Social Information Processing (SIP) Theory	Quantitative	8 to 12 months after implementation	8 to 12 months after implementation

Heim & Peng (2010)	*Journal of operations management*	Jaikumar's theoretical framework on the evolution of process control	Quantitative	2 years	From 2005 to 2007
Po-An Hsieh et al. (2011)	Management science	Sensemaking theory	Quantitative	5 months	**T1**: The first wave of the survey was conducted in April 2007. **T2:** 4 months after T1. **T3:** 1 month after T2.
Kim & Malhotra (2005)	Management science	Technology Acceptance Model (TAM) Theory of Belief Updating Self-Perception Theory	Quantitative	3 months	**T1:** 1 month after the start of the new semester. **T2:** 2 months after the initial data collection, i.e., three months after the start of the same semester.
Liang et al. (2015)	Journal of Management Information Systems	Theory of Effective Use (TEU) Adaptive Structuration Theory (AST)	Quantitative	6 firms that implemented ERP for an average of 3.67 years	----
Malaurent & Karanasios (2020)	Information Systems Journal	Activity Theory	Quantitative	4 years	**Year 1:** Jan – Feb; Mar–Jun; Jul–Aug; Sep–Dec. **Year 2:** Apr–Jul; Aug–Oct; Nov–Feb. **Year 3:** Apr–Aug **Year 4:** Aug–Sep; Oct–Nov; Dec–Jan
Morris & Venkatesh (2010)	MIS quarterly	Job Characteristics Model (JCM)	Quantitative	12 months	**T1:** 4 months before implementation **T2:** 8 months after implementation
Müller, Fay, & vom Brocke (2018)	*Journal of management information systems*	Econometric Analysis	Quantitative	7 years	From 2008 to 2014
(Murphy et al., 2012)	New Technology, Work and Employment	Job Characteristics Model (JCM)	Mixed-methods approach	8 months	**T1:** Data collected 2 months before the ERP system went live. **T2:** Data collected 4 months after the ERP system went live. **T3:** Semi-structured interviews conducted 6 months after the ERP system implementation.
Ranganathan & Brown (2006)	Information systems research	Organizational Integration (OI) Options Thinking Logic	Quantitative	5 years	From 1997 to 2001
Saeed et al. (2010)	Decision Sciences	Technology Acceptance Model (TAM) Technology sensemaking	Quantitative	6 months	**T1:** 1 month before the enterprise system went live **T2:** 5 months after the enterprise system had been activated
Saraf et al. (2013)	*Information systems journal*	Absorptive Capacity (ACAP)	Quantitative	4 months	From February to May 2004
Sasidharan et al. (2012)	*Information Systems Research*	Social Network Analysis (SNA)	Quantitative	12 months	**T1:** Immediately following implementation **T2:** 6 months after implementation **T3:** 12 months after implementation
Schlichter et al. (2021)	*Journal of Small Business Management*	Liability of Newness Liability of Smallness	Quantitative	1 month	January 2015
Snider et al. (2009)	*International Journal of Operations & Production Management*	Critical Success Factors (CSFs) Theory	Qualitative	2 months	2 months
Staehr et al. (2012)	Journal of the Association for Information Systems	Emergent Process Theory	Qualitative	2 years	From 2001 to 2003
Sykes (2015)	MIS quarterly	Social Network Theory	Quantitative	12 months	**T0: 5** months before the implementation of the new ERP module. **T1:** 3 months after the implementation of the ERP module. **T2:** 6 months after the implementation of the ERP module.

Sykes & Venkatesh (2017)	MIS quarterly	Social Network Theory	Quantitative	12 months	**T1:** 6 months before the implementation of the new ERP system module **T2:** 6 months after the implementation of the new ERP system module
Sykes et al. (2014)	MIS quarterly	Social network theory	Quantitative	12 months	**T0:** 5 months prior to the ES implementation, concurrent with the annual employee performance review. **T1:** Immediately before the formal training program, which was three days long. **T2:** months post-implementation, over a 1-month period, concurrent with the next organizational performance evaluation process (approximately 1 year after T0).
Tian & Xu (2015)	Mis Quarterly	Theory of Organizational Information Processing (TOIP)	Quantitative	3 years	From 2001 to 2003
Veiga et al. (2014)	European Journal of Information Systems	Expectancy Theory Enactivist Approach	Quantitative	3 months	**T1:** Prior to adoption **T2: 3** months after adoption
Venkatesh et al. (2010)	Production and Operations Management	Socio-Technical Systems (STS) Theory Job Characteristics Model (JCM)	Mixed-methods approach	32 months	**T1:** 8 months before the ICT implementation. **T2:** 12 months after the initial rollout. **T3:** 24 months after the initial rollout.
Venkatesh et al. (2008)	MIS quarterly	Unified Theory of Acceptance and Use of Technology (UTAUT)	Quantitative	12 months	**T1:** Immediately post-training. **T2:** 3 months of system use. **T3:** 6 months of system use. **T4:** 9 months of system use. **T5:** 12 months of system use.
Venkatesh et al. (2003)	MIS quarterly	Unified Theory of Acceptance and Use of Technology (UTAUT)	Quantitative	6 months	**T1:** Post-training **T2:** One month after implementation **T3:** Three months after implementation Actual usage behaviour was measured over the six-month post-training period
Wang et al. (2019)	MIS quarterly	Multilevel Criminal Opportunity Theory	Quantitative	6 months	From February to July 2014
W. Wang & Po-An Hsieh (2006)	MIS quarterly	Symbolic Adoption Theory	Qualitative	2 years	
Wessel et al. (2021)	Journal of the Association for information systems	Organizational Identity Theory Value Proposition Theory	Qualitative	Alpha case: 18 months Beta Case: 13 months	Alpha case: 18 months Beta Case: 13 months
Yen et al. (2015)	Journal of Management Information Systems	Situational Strength Theory	Quantitative	4 weeks	**T1:** Initial 2-week period for respondents to complete the survey online. **T2:** Extended 2 week response window for respondents to complete the survey.
Yeow et al. (2018)	*The Journal of Strategic Information Systems*	Dynamic Capabilities Theory	Qualitative	4 years and 4 months	**T1:** January 2010 - December 2010 **T2:** December 2010 - March 2012 **T3:** April 2012 - December 2014

Appendix B – Questionnaire items

Construct	***Item Statement***	***Source***
ERP Routinization (ERPR)		Adapted from (Zhu et al.. (2006) and Alhirz & Sajeev (2015)
ERPR1	*Please rate the degree of your total sales are conducted through the ERP?*	
ERPR2	*Please rate the degree of your total services are conducted through the ERP?*	
ERPR3	*Please rate the degree of your total procurement is conducted through the ERP?*	
Collaboration (Col)		Adapted from Ruivo et al. (2012) and Ruivo et al. (2013)
COL1	*Please rate the degree of how ease for them collaborate with colleagues.*	
COL2	*Please rate the degree of how ease for them collaborate with the system.*	
COL3	*Please rate the degree of how ease for them collaborate with partners and customers.*	
Analytics (An)		Adapted from Ruivo et al. (2012) and Ruivo et al. (2013)
AN1	*Please rate the degree of comprehensive reporting (KPIs, Dashboards, etc.).*	
AN2	*Please rate the degree of real-time access to information.*	
AN3	*Please rate the degree of data visibility across departments.*	
ERP Value	***Impact on upstream coordination (IUC)***	Adapted from Zhu & Kraemer (2005) and Zhu et al. (2006)
	IUC1 Please rate the degree to which ERP improved coordination with suppliers.	
	IUC2 Please rate the degree to which ERP decreased procurement costs.	
	IUC3 Please rate the degree to which ERP decreased inventory costs.	
	Impact on internal operations (IIO)	
	IIO1 Please rate the degree to which ERP increased the efficiency of the internal processes.	
	IIO2 Please rate the degree to which ERP increased employee productivity.	
	IIO3 Please rate the degree to which ERP decreased operational costs.	
	Impact on downstream sales (IDS)	
	IDS1 Please rate the degree to which ERP widened sales area.	
	IDS2 Please rate the degree to which ERP improved customer service.	

Appendix C – Measurement model

	Analytics (AN)	Collaboration (COL)	ERP Routinization (ERPR)	Impact on downstream sales (IDS)	Impact on internal operations (IIO)	Impact on upstream coordination (IUC)
AN1	**0.796**	0.364	0.127	0.270	0.206	0.168
AN2	**0.841**	0.293	0.084	0.266	0.200	0.160
AN3	**0.725**	0.379	0.077	0.317	0.108	0.107
COL1	0.377	**0.886**	0.082	0.451	0.207	0.076
COL2	0.349	**0.783**	0.036	0.300	0.103	0.068
COL3	0.328	**0.745**	-0.014	0.284	0.159	0.018
ERPR2	0.069	0.049	**0.708**	0.047	0.165	0.164
ERPR3	0.119	0.037	**0.859**	0.028	0.250	0.236
IDS1	0.220	0.296	-0.007	**0.802**	0.107	0.078
IDS2	0.363	0.431	0.076	**0.858**	0.086	0.146
IIO1	0.266	0.185	0.205	0.104	**0.753**	0.153
IIO3	0.067	0.115	0.201	0.068	**0.751**	0.170
IUC2	0.183	0.049	0.272	0.117	0.235	**0.900**
IUC3	0.150	0.080	0.190	0.130	0.148	**0.892**

Table 1. Loadings and cross-loadings

	AN	COL	ERPR	IDS	IIO	IUC
Analytics (AN)						
Collaboration (COL)	0.610					
ERP Routinization (ERPR)	0.224	0.113				
Impact on downstream sales (IDS)	0.572	0.658	0.136			
Impact on internal operations (IIO)	0.541	0.467	0.871	0.325		
Impact on upstream coordination (IUC)	0.253	0.090	0.462	0.209	0.513	

Table 2. Heterotrait-Monotrait Ratio

	Mean	Std	CR	AN	COL	ERPR	IDS	IIO	IUC
Analytics (AN)	4.127	0.522	0.831	0.789					
Collaboration (COL)	3.920	0.556	0.848	0.434	0.807				
ERP Routinization (ERPR)	3.905	0.628	0.763	0.123	0.052	0.787			
Impact on downstream sales (IDS)	3.799	0.549	0.816	0.357	0.443	0.045	0.830		
Impact on internal operations (IIO)	3.969	0.584	0.722	0.227	0.202	0.270	0.116	0.752	
Impact on upstream coordination (IUC)	4.030	0.713	0.891	0.187	0.071	0.259	0.138	0.215	0.896

Table 3. CR, and Fornell-Larcker table. The diagonal elements are the square-root of AVE

		Weights	VIF
ERP value	**Impact on downstream sales**	0.387***	1.335
	Impact on internal operations	0.312***	1.290
	Impact on upstream coordination	0.740***	1.265

Table 4. Weights and VIF