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Dedication

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Table of contents

Introduction **1**
Chapter 1. Exploring BI adoption through the lens of DOI theory **15**
1.1 Introduction **16**
1.2 Theoretical background **17**
1.2.1 BI overview **17**
1.2.2 Business Process Management capabilities **19**
1.2.3 DOI theory **20**
1.2.4 Heading towards a double-track conceptual framework **21**
1.3 Methodology **22**
1.3.1 Sampling **23**
1.3.2 Descriptive statistics **24**
1.4 Findings **27**
1.4.1 Awareness **28**
1.4.2 Experimentation **30**
1.4.3 Transition **32**
1.4.4 Cross-cutting features between dimensions **34**
Awareness & Experimentation **34**
Awareness & Transition **34**
1.5 Analysis and results **35**
1.6 Conclusions and future research avenues **38**
Sustainability directions **39**
Digital transition directions **39**
Implications and concluding remarks **40**
Chapter 2. Orchestrating knowledge through BI **43**
2.1 Introduction **43**
2.2 Theoretical background **46**
2.2.1 BISs: an overview of relevant literature **46**

2.2.2 Knowledge-based view (KBV) **46**

2.2.3 Resource Orchestration Perspective (ROP) **47**

2.2.4 Conceptual framework **48**

2.3 Research methodology **50**

2.3.1 The case study **51**

2.3.2 Data gathering **52**

2.3.3 Data analysis **54**

2.4 Results **55**

2.4.1 The information flow within the firm **55**

2.4.2 Main challenges and 'bottlenecks of information' **57**

2.4.3 Adopting BI for overcoming information bottlenecks **59**

2.4.4 BI and CSR: a validated path for data-driven responsibility **60**

2.5 Conclusion **61**

Contributions and implications for research **62**

Implications for practice **62**

Limitations and future research avenues **63**

Chapter 3. Making sense of digital transformation in family firms: Why BI investments need managers to make sense of data **65**

3.1 Introduction **65**

3.2 Theoretical background **67**

3.2.1 BISs: an overview of relevant literature **67**

3.2.2 The sensemaking process **69**

3.2.3 The TAM **71**

3.2.4 HRM interventions and organisational factors **73**

3.2.5 The conceptual framework **74**

3.3 Material and methods **76**

3.3.1 The case study **77**

3.3.2 Data gathering **78**

3.3.3 Data analysis **79**

3.4 Case results **82**

3.4.1 Managerial sensegiving as interpretive mediation **82**

3.4.2 Perceived benefits as pragmatic justification **84**

3.4.3 Employee-level adoption barriers **85**

3.4.4 System design attributes and usability **87**

3.4.5 Organizational enablers and HRM interventions **88**

3.5 Conclusion **90**

Theoretical implications **91**

Practical contributions and managerial implications **92**

Limitations and future avenues for research **93**

Chapter 4. Closing the production-to-R&D loop **95**

4.1 Introduction **95**

4.2 Theoretical background **98**

4.2.1 Organizational Information Processing Theory **98**

4.2.2 BISs **98**

4.2.3 Manufacturing Execution Systems **100**

4.2.4 Polymer Informatics and the process gap **103**

4.2.5 An integrated PI-MES-BI framework **104**

4.3 Methodology **106**

4.3.1 Research design **106**

4.3.2 Data collection **108**

4.3.3 Data analysis **109**

4.4 Results **109**

4.4.1 Escalating information processing requirements **110**

4.4.2 Architectural fragmentation as a capacity constraint **112**

4.4.3 The integrated PI-MES-BI framework **113**

MES as slack resources **114**

BI as vertical IS and lateral relations 114

PI as self-contained task 115

4.4.4 Production-to-R&D feedback loop: closing the gap 116

4.4.5 Implementation barriers and enablers 116

4.5 Discussion 118

4.6 Conclusion 120

Limitations and future research avenues 122

Conclusions 125

Technological perspective 126

Innovation perspective 127

Managerial perspective 130

Implications for managers: from industrial research to organizational practice 134

List of Figures 143

List of Tables 144

References 145

Introduction

Modern organisations inhabit informational ecosystems with unprecedented scale, complexity, and dynamism. Across industries, the diffusion of digital infrastructures, the proliferation of interconnected systems and the acceleration of global competition have generated an overload of signals that exceed the interpretative capacity of traditional decision-making routines (Nolan, 2012). Contemporary firms face not only the challenge of collecting data but also the demanding task of discerning which information is relevant, how patterns evolve over time, and how signals should be transformed into strategic action. As a consequence, it is widely acknowledged that contemporary organisations encounter a critical paradox: despite the ubiquitous nature of data, actionable strategic insight remains a scarce and complex commodity. Information is ubiquitous, but knowledge is unevenly distributed, fragile, and often poorly integrated. On the opposite, the capacity to convert data into coherent, actionable and strategically aligned knowledge has emerged as a defining capability for organizational longevity and innovation (Negash, 2004; Davenport, 2006), thereby redefining the foundations of competitive advantage (Porter, 1985).

The intellectual origins of this shift can be traced back to early conceptualisations of *organizational intelligence*. Luhn (1958) observed that the productivity of organisations depends on systems capable of identifying, classifying, and disseminating relevant information to the appropriate actors at the right time. His proposition anticipated a core issue of the digital economy but also captured the essence of what modern analytics systems attempt to accomplish: his vision presupposed that information exists in a latent form and requires structured processes to become meaningful, interpretable and aligned with organizational objectives. The digital transformation has magnified this need by orders of magnitude (Chen et al., 2012; Phillips-Wren et al., 2015).

Today, organisations must continuously process data from sensors, machines, supply chain nodes, customer interfaces, laboratory instruments, financial systems and digital platforms (Yang et al., 2018). Data generation is immediate, often real-time, and increasingly automated, while data interpretation remains cognitively demanding, socially distributed, and organisationally complex (Zeshan et al., 2025a). Within the context of family firms, these dynamics are even further exacerbated. Although the digital age necessitates that organisations become data-driven, family firms encounter a distinctive "innovation paradox": the need to modernise to survive in saturated markets is at odds with the desire to preserve traditional governance, tacit knowledge, and socioemotional wealth (SEW), which is the affective endowment derived from the firm and includes family control, identification, and social ties (Gomez-Mejia et al., 2007; Berrone et al., 2012). This preservation motive typically results in risk aversion toward venturing activities that could potentially undermine traditional modes of operation or dilute control (Chrisman et al., 2015). However, especially in saturated manufacturing industries, dependency on tradition poses a significant performance risk that jeopardises the firm's sustainability and, therefore, the family's heritage (Gomez-Mejia et al., 2007).

To resolve the tension between the increasing abundance of information and the capacity of organisations to process it, especially family firms, this dissertation primarily examines the broad field of business intelligence (BI) for strategic decision-making.

BI systems (BISs) are designed to increase the interpretative and analytical capabilities of organisations by structuring data, integrating knowledge domains, and supporting decision frameworks across strategic, tactical, and operational levels (Watson & Wixom, 2007; Chaudhuri et al., 2011). Originally conceived as reporting and querying systems, BI has evolved into a rich ecosystem that supports predictive analytics, machine learning (ML) models, anomaly detection, trend identification, multidimensional visualisation and automated decision pipelines (Cebotarean, 2011; Sabherwal & Becerra-Fernandez, 2013). A broad array of literature demonstrates that BI enhances organizational learning, improves forecast accuracy, strengthens decision coherence and increases strategic agility (Elbashir et al., 2008; Popovič et al., 2019). Nonetheless, these outcomes are not guaranteed. They depend on a delicate combination of technological infrastructures, cognitive routines, cultural norms and strategic alignment (Yeoh & Koronios, 2010; Isik et al., 2013).

Generally speaking, BI can be conceptualised through multiple lenses. Technical perspectives emphasise the architecture of data warehousing, extract, transform, and load (ETL) processes and analytical platforms that enable data extraction, transformation, and reporting (Watson & Wixom, 2007a). Indeed, at the heart of any BI initiative lies the data warehouse, powered by ETL tools responsible for extracting data from diverse source systems, transforming raw information into structured formats and loading integrated datasets for analytical consumption. They rank among the most critical and complex components to select, as they establish the foundational data quality and accessibility that determine downstream analytical capabilities (Hwang & Xu, 2008).

On the other hand, organizational perspectives focus on BI capabilities that strengthen sensing, seizing and transforming mechanisms within firms (Watson & Wixom, 2007b). According to the resource-based view (RBV), BI represents a distinctive organizational capability that enhances information processing capacity and enables firms to respond effectively to environmental complexity (Ross et al., 1996; Negash, 2004).

In addition to these confined perspectives, Isik et al. (2013) identify key BI capabilities encompassing both technological and organisational dimensions: technological capabilities include data quality, connectivity, accessibility and flexibility of analytical infrastructures, whereas organizational capabilities encompass user management, risk governance, change management and analytical skill development. These capabilities interact to determine BI success, which varies substantially across contexts depending on decision environments, organizational readiness and cultural alignment (Gorry & Scott Morton, 1971; Popovič et al., 2012). Importantly, data quality alone does not guarantee superior outcomes. Organisations must ensure appropriate user access, integrate BI with existing systems, and incorporate necessary flexibility into their decision-making processes, regardless of the environment (Isik et al., 2013).

The selection of appropriate BI tools represents the foundational and most critical phase in achieving organizational strategic objectives (Yeoh & Koronios, 2010; Olszak & Ziemba, 2012). Empirical evidence reveals an alarmingly high failure rate for BI initiatives, with project abandonment and implementation failures occurring in approximately seventy to eighty percent of cases (Villamarín & Diaz Pinzon, 2017): a statistic that necessitates immediate consideration from both practitioners and researchers (Pham et al., 2016). These failures stem from a confluence of technological and managerial factors, with inappropriate tool selection emerging as a dominant contributor (Mudzana & Maharaj, 2015). The complexity of BI tool selection has intensified dramatically due to innovation cycles, the proliferation of vendor offerings, and rapid technological advancements (Chugh & Grandhi, 2013). Thus, organisations face the daunting challenge of evaluating heterogeneous products across multiple dimensions, including functionality, usability, reliability, maintainability, vendor reputation, technical support quality, cost structures and alignment with existing infrastructures (Jadhav & Sonar, 2011; Kara & Cheikhrouhou, 2014). The consequences of improper tool selection extend far beyond initial implementation difficulties. Organisations experience substantial economic losses, strategic misalignments, abandoned investments, and compromised competitive positioning (Hughes et al., 2017; Zeshan et al., 2025b). Even more concerning is that when firms conclude selection processes with inappropriate tools, organizational needs remain unmet, strategic objectives become unattainable and embedded problems persist unresolved. The challenge intensifies because no single software solution comprehensively addresses the diverse requirements of different organisations (Efe, 2016). Firms often rush selection decisions without fully understanding the evaluation criteria, leading to hasty commitments that culminate in project failure and weakened organizational performance. Moreover, the wrong technology choice can prove disastrous, resulting in significant losses of financial resources, time and organizational credibility (Malinin, 2016). In other words, the BI tool selection challenge encompasses multiple interrelated complexities. First, decision-makers frequently lack essential technical expertise and domain knowledge required for informed evaluation (Jadhav & Sonar, 2011). Second, incongruities between software and hardware systems determine obstacles to a successful integration. Third, rapid technological advancement renders evaluation frameworks obsolete (Farshidi et al., 2018). Fourth, the heterogeneity of available solutions complicates comparative assessment: the process typically receives insufficient time and operates under enormous organizational pressure, further compromising decision quality (Oztaysi, 2015). Selection processes often fall to information technology or BI department heads, who must collect information, engage vendors, conduct analyses, and reach final decisions within compressed timelines that preclude thorough due diligence (Damsgaard & Karlsbjerg, 2010).

Research identifies several categories of BI tools, including *data analysis and reporting* tools that read, process and format data into structured reports; *data mining* tools that apply statistical techniques to discover patterns and generate predictions; and *knowledge management* (KM) tools that store and retrieve organizational knowledge on demand (Sharda et al., 2014). Each category requires distinct evaluation criteria and presents unique selection challenges. However, empirical studies demonstrate that selection difficulties concentrate particularly on transformation, reporting and analysis tools, as these constitute the operational heart of BI capabilities (Hanine et al., 2016).

The academic literature on BI tool selection reveals four primary research streams: the evaluation and selection of software products, criteria for tool selection, selection methodologies, and automated decision-making systems (Jadhav & Sonar, 2011; Oztaysi, 2015). Researchers have proposed various frameworks to guide selection processes, including analytical hierarchy processes (AHP), fuzzy logic approaches and hybrid methodologies combining multiple techniques (Lin et al., 2009). Nevertheless, operational managers continue to encounter challenges in selecting a software that is truly in accordance with business needs, indicating that methodological sophistication alone is insufficient (Grandhi & Wibowo, 2018): organisations need clarity regarding their specific needs and explicit understanding of how software packages address these needs. This recognition underscores the fundamental importance of identifying and comprehending the critical factors that influence software tool selection across technical and non-technical dimensions (Mali & Bojewar, 2015; Villamarín & Diaz Pinzon, 2017). Empirical evidence from healthcare demonstrates that BISs improve diagnostic accuracy, optimise resource allocation and support clinical workflows only when aligned with collaborative culture, strong data governance and organizational learning mechanisms (Miah et al., 2017). In government institutions, the effectiveness of BI is mediated by bureaucratic constraints, political dynamics, infrastructural fragmentation and limited analytical skills. These studies reveal an insightful perspective: BI is not a purely technological intervention. It is an organizational and institutional transformation that requires coherence across technological, social and cognitive dimensions (Shollo & Galliers, 2016). Organisations must match users with appropriate skills and tasks to achieve acceptable levels of data access and analytical freedom. Without technical interest and cognitive readiness, BI initiatives fail to empower business users or enable self-reliant analytical practices (Alpar & Schulz, 2016).

Industrial research extends this observation. Large-scale manufacturing environments generate complex datasets that demand extensive preprocessing, including data cleansing, numerosity reduction, and high-dimensional visualisation. Baby Dayana et al. (2019) show that effective visualisation pipelines are essential for interpreting industrial data, enabling decision-makers to identify anomalies, understand process variability, and detect latent patterns. Without these preprocessing steps, BISs can distort interpretations, propagate noise and amplify uncertainty rather than reduce it. This understanding is broadly in accordance with the Information Processing View, which posits that organisations must enhance their processing mechanisms to keep up with the complexity of the environment (Galbraith, 1973, 1974). BISs precisely fulfil this function, enhancing the informational capability of organisations and facilitating cross-functional integration.

The dynamic capabilities perspective provides an even richer theoretical foundation for understanding BI's contribution to performance. According to Torres et al. (2018), BI enhances firm performance by strengthening sensing, seizing and transforming capabilities. BI enables organisations to detect weak signals, interpret emerging trends, coordinate responses across functions and reconfigure resources to exploit opportunities. This framework synthesises technological and organizational dimensions, suggesting that BI effectiveness depends on both analytical infrastructure and organizational readiness (Watson & Wixom, 2007b). Nonetheless, empirical research indicates that there is substantial variation among various industries. For instance, in Halal Food Manufacturing, BI adoption improves decision-making only when firms invest in knowledge sharing, training and structured governance (Jayakrishnan et al., 2019). Cultural resistance, data silos, incompatible systems, and insufficient competencies frequently impede BI adoption in public sector organisations (Sequeira et al., 2025). Financial services providers experience distinctive challenges related to regulatory compliance, data security, real-time processing requirements and stakeholder expectations (Dawson & Van Belle, 2013). Even in technologically advanced industries, BI's maturity is often limited by the absence of robust data governance, fragmented data architectures, and reliance on intuition rather than analytics (Popovič et al., 2012).

Critical success factors for BI implementation extend beyond technological considerations, encompassing organisational, environmental, and strategic dimensions (Hawking & Sellitto, 2010; Yeoh & Koronios, 2010). Literature identifies software tool characteristics, vendor capabilities and stakeholder opinions as three fundamental constructs that interact to determine selection outcomes (Jadhav & Sonar, 2009, 2011). Software tool factors include technical attributes such as functionality, ease of use, compatibility with existing systems, availability of integrated hardware and software packages, accessibility of the source code, reliability, efficiency, and maintainability (Farrokhi & Pokoradi, 2013). These technical factors assess the practical ability of software to deliver desired results without experiencing operational disruptions. Non-technical software attributes encompass cost structures, including licensing, installation, maintenance, training, and upgrade expenses, as well as considerations of the popularity, expected lifespan, and currency of available versions (Chau, 1995; Büyüközkan et al., 2018). Vendor factors represent a second critical construct (Ferland & Flachbarth, 2018). They encompass the availability and quality of technical support, the depth of technical skills, the provision of comprehensive user documentation, including manuals and diagnostics guides, and prior experience with products developed by the same vendor (Yeoh & Koronios, 2010). Non-technical vendor characteristics assess reputation, references from existing clients, past business relationships, adherence to ethical standards and demonstrated professionalism (Jadhav & Sonar, 2009). Organisations typically lack sufficient in-house expertise and depend substantially on vendor capabilities for successful implementation and ongoing support. The vendor relationship extends beyond initial procurement to include training, customisations, integration support, and long-term partnerships.

Opinion factors represent a third construct encompassing perceptions and recommendations from multiple stakeholder groups (Chau, 1995). Technical opinions are derived from in-house experts, external consultants, vendor representatives, and trade publications. Non-technical opinions represent the viewpoints of subordinates, end users, external associates, and evaluations of prospective enhancements in customer service. What professionals and decision-makers learn from peers, read about in evaluations, or hear from trusted sources significantly influences final selection decisions (Jadhav & Sonar, 2011). These opinion factors acknowledge that technology choices occur within social and organizational contexts where interpersonal influence, reputational signals and collective sensemaking shape outcomes as profoundly as objective technical assessments.

These findings converge toward a central insight: BI is fundamentally socio-technical. Its success depends on organizational culture, user competencies, learning orientation and managerial cognition (Popovič et al., 2012). In other terms, BI not only facilitates decisions but also reshapes them. It redefines how managers perceive uncertainty, assign meaning to signals, evaluate risks, interpret trends and coordinate collective action. Its introduction can alter power dynamics; challenge deeply established routines and shift the locus of expertise. The shift toward self-service (SS) BI further amplifies these dynamics by democratising access to analytical tools, enabling operational users to generate insights independently and reducing dependency on centralised IT functions (Imhoff & White, 2011; Schlesinger & Rahman, 2015). However, successful SSBI implementation requires carefully designed semantic layers, user training programmes and governance frameworks that balance empowerment with data integrity (Eckerson, 2012; Alpar & Schulz, 2016).

While previous research has often focused on the adoption of BI through a lens of system characteristics and technological readiness (e.g., Davis, 1989; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003), this work contends that BI is only consequential for organisations insofar as actors collectively construct its meaning, value, and legitimacy. By utilising sensemaking theory (Weick, 1995; Weick et al., 2005), the knowledge-based view of the firm (Grant, 1996), and resource orchestration theory (Sirmon et al., 2011), this dissertation portrays BI as a sensemaking-orientated organisational capability that facilitates the transformation of data into coordinated action and shared interpretations (Weick, 1995; Weick et al., 2005). Adoption is neither a binary outcome nor a linear progression of stages; rather, it is a dynamic process in which managers actively influence the implementation, comprehension, and integration of BI into organisational routines.

This socio-technical nature becomes particularly salient in family firms, which combine unique strategic orientations with distinct governance forms. They frequently embody extensive tacit knowledge, robust stewardship principles, relational governance frameworks, and long-term orientation. However, these traits may also hinder BI adoption due to risk aversion, path dependence, and reliance on experiential intuition (De Massis et al., 2018). Family firms often develop interpretive systems grounded in shared histories and intergenerational communication, which can be difficult to align with analytical methodologies that emphasise abstraction, standardisation, and formalisation. Thus, decision-making processes in family firms may privilege experience and personal judgement over data-driven insights, creating tension between traditional management styles and contemporary analytical practices (Stewart & Hitt, 2012). At the same time, they face increasing pressure to integrate digital technologies, analytical decision-making and data-driven innovation. They must balance the preservation of tacit knowledge with the institutionalisation of analytical routines. Moreover, family firms often exhibit organizational inertia in adopting externally developed systems, preferring customised solutions that align with established workflows (De Massis et al., 2013).

Due to the diversity of this organisational structure across legal, institutional, and cultural contexts, defining a "family firm" is challenging. Modern literature asserts that the defining feature of a family firm is the interplay between the family system and the business system, rather than mere fractional equity ownership or management involvement, as suggested by earlier definitions. According to Chua et al. (1999), a company qualifies as a family business if a family member significantly influences its strategic direction and corporate governance. However, the mere presence of family ownership cannot sufficiently explain the strategic uniqueness of these firms. This dissertation's theoretical framework asserts that family firms are characterised by their pursuit of Socioemotional Wealth

(SEW), defined as the non-financial elements that fulfil the family's emotional needs, encompassing identity, the ability to exert family influence, and the continuation of the family legacy (Gomez-Mejia et al., 2007). Unlike non-family firms, which often assume their principals to be risk-neutral profit maximisers, family principals prioritise the preservation of their accumulated socioemotional endowment. The family is prepared to tolerate financial risks, or "*performance hazards*", to prevent loss of socioemotional control, thereby establishing a unique decision-making framework (Gomez-Mejia et al., 2007).

This study implements the FIBER model, which was developed by Berrone et al. (2012), to operationalise the multidimensionality of these affective endowments. This model defines five critical dimensions that encapsulate the essence of family influence. First, family members exercise control over strategic decisions to preserve independence (Family Control). This is frequently demonstrated by a desire to maintain decision-making discretion rather than relinquish authority to algorithms or external experts. Secondly, the firm is regarded as an extension of the family self, resulting in a strong identification in which the firm's reputation is inextricably linked to the family name. Therefore, the family perceives technological errors as threats to their social status, not just as operational failures (Deephouse & Jaskiewicz, 2013). Third, family firms are distinguished by Binding Social Ties, which are reciprocal connections with employees and the community that frequently lead to "caring contracts" and a reluctance to disrupt long-standing relationships for the sake of efficiency. Fourth, the decision-making process is influenced by Emotional attachment, which penetrates the process due to the blurring of boundaries between family and business. This influence affects the interpretation and action of data. Lastly, the Renewal of family connections through dynastic succession is a defining intention of family firms.

This dissertation investigates this tension through a three-year longitudinal action research study at Radici Yarn S.p.A., a multi-generational family firm in the synthetic fibres industry. Radici Yarn provides an ideal empirical context for examining these dynamics, being an industry characterised by scientific complexity, demanding quality standards, energy-intensive processes and growing sustainability pressures. The polymer industry presents distinctive informatics challenges, as product characteristics result from the interaction between chemical composition, process parameters, environmental conditions and downstream transformations. Unlike crystalline materials with well-defined structures, polymers exhibit extraordinary chemical and physical diversity across multiple scales (Chen et al., 2021). Chain architecture, molecular weight distribution, processing history, morphological features, and end-use conditions are all factors that influence polymer properties, in addition to monomer chemistry. Such complexity renders conventional trial-and-error methodologies inefficient and requires data-driven methodologies (Audus & de Pablo, 2017). Polymer informatics represents an emerging frontier that applies ML and artificial intelligence (AI) to polymer design, synthesis and characterisation (Ramprasad et al., 2017; Li & Zheng, 2023). The field attempts to accelerate polymer discovery by training surrogate models on available data, enabling rapid property predictions and inverse design strategies (Cencer et al., 2021). However, polymer informatics faces substantial challenges. Available data remains limited, scattered across literature and poorly organised (Kumar et al., 2023). Most existing databases focus on single-property predictions from molecular descriptors, neglecting the critical influence of processing conditions (Tran et al., 2024). Research shows that predictive accuracy deteriorates dramatically when process variables are excluded from analytical models (Wu et al., 2019). This process gap represents a fundamental limitation: molecular-level predictions cannot reliably forecast performance when processing conditions determine morphology, crystallinity and mechanical behaviour (Breneman et al., 2013; Peerless et al., 2018).

In operational contexts such as Radici Yarn, bridging this gap requires the integration of data from Manufacturing Execution Systems (MES), laboratory analysis, quality assurance, customer specifications and R&D insights. Consequently, BI is essential for linking production conditions to product performance, enabling reverse knowledge flows, supporting innovation and strengthening strategic alignment. By incorporating real-time production data into predictive models, such an integration of BI with MES presents an opportunity to bridge the process divide in Polymer Informatics. Nonetheless, such an integration of BI with MES and R&D systems remains understudied in BI scholarship. Existing research has primarily focused on BI applications in ERP systems, financial dashboards and high-level strategic decision support (Watson & Wixom, 2010; Sabherwal & Becerra-Fernandez, 2013). Far fewer studies examine how BI supports knowledge flows between production and R&D, how BI integrates molecular design with process data or how BI accelerates innovation in process-intensive contexts. Furthermore, the polymer sector provides a particularly compelling context because synthetic fibre production requires continuous optimisation of extrusion parameters, control of molecular orientation, and management of thermal histories; small variations in processing conditions can significantly alter mechanical properties, dimensional stability, dyeability, and end-use performance. BISs that integrate MES data with laboratory characterisation create closed-loop feedback mechanisms that enable rapid process optimisation and accelerated product development.

Finally, the synthetic fibre industry faces mounting sustainability pressures, which intensify the need for data-driven optimisation. Energy consumption, waste generation, raw material efficiency and product lifecycle considerations all require comprehensive monitoring and continuous improvement (Abbate et al., 2025; Cerchione et al., 2025c). BI platforms that integrate production data with sustainability metrics enable firms to identify efficiency opportunities, reduce their environmental footprints, and demonstrate compliance with regulatory standards. The ability to track material flows, energy intensities and carbon footprints across production stages becomes increasingly valuable as stakeholder expectations and regulatory requirements evolve. Financial services providers similarly face escalating demands for real-time analytics, regulatory reporting, risk management and customer intelligence, creating parallel pressures for sophisticated BI capabilities that balance operational efficiency with compliance requirements (Dawson & Van Belle, 2013).

This dissertation addresses the abovementioned gaps through four interconnected chapters that collectively develop a comprehensive theoretical and empirical understanding of BI in mature, process-intensive and family-owned manufacturing firms. Rather than questioning the utility or usability of BISs, this research examines how organisations socially build the concepts of usefulness, legitimacy, and strategic significance with regard to data. The Author examines the mechanisms by which BI enables transgenerational bridging, transforming the idiosyncratic intuition of the founding generation into a data-driven strategy that is accessible to the succeeding generations.

More in detail, the *first chapter* systematically reviews BI literature through the lens of Diffusion of Innovation (DOI) theory by examining 158 publications from 2018-2023. The analysis constructs a two-dimensional framework intersecting three BI dimensions (i.e., process, technology, software) with three diffusion stages (i.e., awareness, experimentation, transition). Such an integration reveals persistent fragmentation across BI research domains and identifies critical gaps concerning adoption dynamics in mature industries. Moreover, the review documents an emerging cross-fertilisation between BIS and digital technologies, including AI, big data analytics, and blockchain, while simultaneously revealing that sustainability dimensions and family firm contexts remain conspicuously underexplored in current research streams.

The *second chapter* investigates how BISs enhance KM capabilities within mature manufacturing environments, drawing upon Knowledge-Based View (KBV) and Resource Orchestration Perspective (ROP). Through a qualitative case study conducted at Radici Yarn, the research examines how BI integration supports knowledge acquisition, storage, transfer and utilisation across organizational boundaries. The empirical evidence demonstrates that tailored BI architectures significantly strengthen organizational learning mechanisms, increase cross-functional information visibility and accelerate evidence-based decision processes. The findings reveal how BI platforms address information fragmentation challenges that are endemic to mature process industries, where production knowledge, quality data, R&D insights, and commercial intelligence traditionally remain isolated within functional silos. The chapter contributes theoretical advancement by empirically validating BI's role as a resource orchestration mechanism that coordinates heterogeneous knowledge assets to generate competitive intelligence.

The *third chapter* examines the socio-organisational mechanisms through which BISs achieve organizational acceptance and effective utilisation. Drawing upon Weick's sensemaking theory in conjunction with technology acceptance (TAM) frameworks, the research conducts an action-research investigation, combining semi-structured interviews, participant observation, system demonstrations, and document triangulation over twelve months at Radici Yarn. The analysis reveals that managers function as fundamental sense-givers who filter, contextualise and reframe BI outputs, thereby increasing plausibility and perceived trustworthiness of system-generated information among organizational members. The findings demonstrate that hands-on involvement practices, including personal data entry, collaborative report construction and direct system manipulation strengthen individual BI identity formation and foster adoption. Empirically, the research illuminates how targeted HR practices, including structured training programmes, participative implementation processes and thoughtful role design interact with managerial sensegiving to shape employee BI acceptance.

Finally, the *fourth chapter* addresses innovation acceleration challenges in mature process industries by developing an integrated framework connecting production operations with R&D functions. Grounding analysis in Organizational Information Processing Theory (OIPT), the research examines why technically proficient organisations within saturated markets frequently encounter difficulties when translating knowledge into innovative outcomes despite possessing requisite technical capabilities. Through longitudinal investigation at Radici Yarn, the study identifies a structural misalignment between escalating information processing requirements and static organizational capacity as the primary constraint limiting innovation velocity. The chapter introduces a comprehensive Polymer Informatics-Manufacturing Execution Systems-Business Intelligence framework that bridges the production-to-R&D divide through concurrent deployment of multiple capacity-enhancement mechanisms. The framework fills a gap in the polymer informatics literature by adding real-time manufacturing parameters to predictive models. This makes property forecasting more accurate and speeds up experimentation cycles. For practitioners in established sectors where time-to-market increasingly determines competitive viability, the chapter provides both diagnostic frameworks for identifying information processing bottlenecks and practical architectures for systematically addressing them through integrated analytical infrastructure.

Together, these chapters advance literature on BI by offering theoretically grounded and empirically validated insights into BI as a transformative organizational capability. The dissertation demonstrates that BI effectiveness fundamentally depends on socio-technical alignment spanning technological sophistication, knowledge integration mechanisms, sensemaking processes and information processing capacity. Furthermore, it clarifies how organisations in mature process industries can utilise BISs to improve management control capabilities, accelerate product innovation, and fortify their competitive position in data-intensive business environments that are characterised by sustainability imperatives, family governance, experiential learning, and scientific and manufacturing complexity. By outlining the multiple factors influencing selection outcomes related to software attributes and organisational needs, it offers practical guidance for organisations embarking on BI projects. The findings suggest that successful implementations require hybrid approaches that combine analytical rigour with organizational pragmatism, respecting the distributed nature of expertise while building systematic capabilities for knowledge creation, storage and retrieval. This balance between formalisation and flexibility represents a critical design principle for organisations seeking to navigate digital transformation without undermining the relational and experiential foundations of their competitive advantages.

This dissertation draws its foundation from a three-year longitudinal study that took place within a family-owned company. Consequently, it is endowed with a plethora of empirical insights into the interpretation, negotiation, and integration of digital technologies, particularly BI, into the decision-making and governance practices of the family firm, as a result of sustained engagement with organisational actors and processes. The longitudinal design enabled repeated observations, temporal comparisons, and contextualised comprehension of the evolving phenomena. The subsequent chapters provide an in-depth discussion of the insights that have been derived from this extended field engagement, which have the potential to further enrich the theoretical understanding and practical implications of family business research. First, the FIBER model is employed to illustrate that BI and AI-enhanced systems do not erode Family Control (F) but rather reinforce it by formalising the "*digital stewardship*" of the proprietors and reducing information asymmetry. Secondly, it demonstrates how managers engage in the role of "*sensegivers*", utilising Explainable AI (XAI) to reduce algorithmic opacity and ensure that data-driven accountability is consistent with the family's high-trust culture and Binding Social Ties (B). Third, it offers an integrated framework (PI-MES-BI) that transforms the implicit knowledge of senior generations into explicit organisational assets, thereby ensuring the Renewal (R) of the family legacy across generations. This dissertation ultimately contends that the weaving of data into strategy is equivalent to the integration of data into the identity of family firms, thereby resolving the conflict between tradition and innovation.

For these reasons, this dissertation's core contribution is showing that perceptions of usefulness and ease of use of BI, which are central constructs in dominant adoption models, are not primarily individual cognitive assessments but rather socially produced interpretations that emerge from managerial sensegiving, human resource management (HRM) practices, and organisational storytelling. In doing so, this research redirects the focus of the analysis from the attitudes of consumers toward technology to the collective processes by which organisations render BI meaningful. By combining several theoretical perspectives, this study suggests a unified perspective on the adoption of BI as a multi-level phenomenon. Such reconceptualisation challenges the prevailing techno-centric approaches and provides a theoretically richer explanation for the profoundly different adoption trajectories and outcomes that organisations with similar technologies frequently experience.

Chapter 1. Exploring BI adoption through the lens of DOI theory

Enterprises in all sectors of business are increasingly inclined to employ BI in their decision-making processes due to the favourable results they have experienced through the implementation of digital support systems in response to an increasingly competitive market. Scholars and practitioners have conducted broad research into the impacts and fields of application associated with its use so far, determining that BI can have a positive impact on the operational capability of firms and strategic decisions in most of cases. Given the strategic importance of BI implementation among business practices and the lack of research within the field of business process management (BPM) assessing the gradual integration of BI analytical capabilities into organisational processes, this study endeavours to conduct a systematic review of the extant literature on BI from a Diffusion of Innovation (DOI) theory perspective.

A structured framework has been proposed to investigate the three primary dimensions of BI (i.e., process, technology, and software) and the stage of firms' innovation diffusion (i.e., awareness, experimentation, and transition) as identified in a recent update of DOI theory, with a focus on the timeframe 2018-2023. By analysing a final sample of 158 papers, this study endeavours to provide a comprehensive assessment of how organisations are approaching BI as a game-changer. Additionally, it investigates the evolution of BI from a technological tool to a process-enabled organisational capability.

The findings suggest that the function of BI undergoes a systematic evolution throughout the three stages of adoption. In the awareness phase, BI primarily improves the visibility of analytical data, allowing organisations to develop a more comprehensive understanding of their existing processes and performance baselines. During experimentation, BI facilitates the refinement of operational practices and iterative learning by supporting localised process exploration and targeted development initiatives. Finally, during the transition phase, BI is integrated into the organisation's business architecture, which contributes to enhanced process governance, performance management, and mechanisms for continuous improvement. Such an evolving process is indicative of the gradual improvement of BPM capabilities, which is consistent with the more extensive adoption of BI technologies within organisations. This evolution is inextricably linked to the integration of complementary digital technologies, including blockchain, AI, and big data analytics, which collectively define a more comprehensive digital transformation trajectory (Cerchione et al., 2026b). The interaction between these technologies implies that the strategic value of BI increases as companies transition from isolated analytical tools to integrated platforms that inform decision-making, governance, and organisational adaptation. This integrative perspective is consistent with recent research (e.g., Daskalopoulos & Machek, 2025) that portrays digital transformation in family firms as a multi-stage socio-technical process that has implications for both long-term strategic alignment and operational effectiveness.

1.1 Introduction

Within the realm of BPM, analytical capabilities are key facilitators of process transparency, control, and continuous enhancement. A powerful tool offering analytical insights to produce internal and competitive information, ideally delivered at the right time, place, and format to support managerial tasks and strategic decision-making, is represented by BI. By enabling a coordinated integration of data collection, data storage, and KM (Negash, 2004), it provides rapid performance feedback, enables evidence-based process reengineering, and institutionalises procedures for continuous efficiency enhancement (Suša Vugec et al., 2020), thus notably transforming corporate processes.

Nonetheless, existing studies have predominantly viewed BI as a technological artefact rather than a component of process-oriented management, providing a limited understanding of the temporal aspect through which BI transitions from an exploratory application to a fully institutionalised BPM capability. When observed from a technological perspective, the progressive adoption of BI mostly reflects the need to employ software and tools to identify, gather, organise, and access a wider array of information from multiple data sources, thus privileging a standalone analytical tool perspective. On the other hand, research suggests that BI provides insights for business processes by enabling the exchange of information between business departments and across cross-functional business processes (Olszak, 2016). Thus, the managerial viewpoint introduces some room for adopting BI to orchestrate and administer processes to deliver prompt, actionable, high-value, and precise business insights (Chalmeta & Ferrer Estevez, 2023), thereby emphasising a correlation between BPM and BI.

Drawing upon recent findings from the literature on DOI theory (Cerchione et al., 2025b), this study conducts a systematic literature review conceptualising BI adoption as a multi-stage process encompassing awareness, experimentation, and transition phases.

Notwithstanding the publication of several literature reviews aimed at organising the current findings on BI, to the best of our knowledge, none of them has examined the diffusion of BI into a business process capability while simultaneously addressing three principal dimensions recognised as the most representative ones: (i) BI as a business process, (ii) BI as a technology, and (iii) BI as software. To investigate the relationship between these three phases of BI adoption and its principal features, we propose a two-dimensional framework centred on two key issues:

RQ1. How can BI be systematised into a comprehensive framework taking into account both its main dimensions and the phases of its progressive diffusion within enterprises?
RQ2. How does the choice to adopt BI whether it be the process, the technology or the software, influence firms' operational capability and decision-making in practice?

The results suggest that the transition phase is the most prevalent among enterprises that are experiencing improved organisational performance (Mangwayana & Budree, 2022). Additionally, case reports have demonstrated an ever-evolving ecosystem that encompasses a broad range of interests, from start-ups (Caseiro & Coelho, 2018) to small, medium, and micro-organisations (SMMEs) and large multinational corporations (Gomwe et al., 2022).
This study offers three primary contributions to the BPM literature. First, it reframes the process of BI diffusion as a maturation of process capabilities, rather than a solely technological adoption path. Second, it establishes a dynamic framework that connects the phases of BI diffusion to BPM concepts, such as process governance, performance measurement, and continuous improvement. Third, it offers theoretical and managerial insights that aid organisations in the alignment of BI initiatives with BPM objectives, thereby enhancing process performance and organisational learning.
The subsequent sections of the chapter are organised as follows: in Section 2, the theoretical background is presented, and a conceptual framework is proposed to comprehensively understand the progressive diffusion of BI. Section 3 clarifies the methodology employed for the collection and selection of relevant articles for review, while Section 4 presents an overview of the findings. Section 5 identifies potential routes for future investigation, whereas Section 6 addresses implications and limitations of our conceptual effort.

1.2 Theoretical background

1.2.1 BI overview

BI is a multilateral concept with several definitions, all of which converge in confirming its role as a strategic milestone for corporate governance (Ratia et al., 2018). Starting from the introduction of such a term within the banking environment by Richard Miller Devens (Devens, 1868), several authors attempted to propose an increasingly comprehensive definition of BI over the years.
In greater detail, the so-called BI systems (BISs) are characterised by functions related to data management, including data warehouses (DWs), data marts, online analytical processing (OLAP) and analytical tools such as ad hoc analytics, in-memory analytics, reporting, planning, alerts, forecasts, scorecards, dashboards, data mining (Bach et al., 2018), but also decision-support systems (DSSs), executive information systems (EISs), and extract, transform, load (ETL) tools (Sousa & Dias, 2020).

Caseiro and Coelho (2019) suggest that BI can be conceived as both a process and a product: the process involves techniques employed by organisations to achieve valuable information, or intelligence, while the product consists of information allowing the prediction of the behaviour of competitors, suppliers, customers, technologies, acquisitions, markets, products and services, and the overall business environment with a certain degree of accuracy.

Despite these unique characteristics, BI is frequently perceived as a technical concept with limited significance to business operations (Marjanovic, 2007). IT departments generally implement BI projects without alignment to corporate strategy and performance management agendas (Vukšić et al., 2017). Moreover, many businesses regard BI adoption as predominantly or solely an IT installation project, neglecting the fact that BI constitutes a business initiative.

Despite these premises, Talaoui et al. (2020) claim that the construct with the highest number of descriptive and prescriptive studies is BI as a process. As a matter of fact, being organisations centred on the flow of activities, they can be viewed as a series of functional processes. Thus, businesses have increasingly called for a more structured corporate intelligence approach to systematically and consistently identify opportunities and threats within their business environment (Calof & Wright, 2008). Suša Vugec et al. (2020) referred to the term "*process-centric business intelligence*" to describe BI's capability to transform business-relevant data into analytical insights, with the aim of generating new knowledge for relevant process changes and supporting operational decision-making during process execution.

On the other hand, the introduction of BISs in complex business environments has fostered awareness of the benefits deriving from the use of BI as a technology (Ouriniche et al., 2022). This shows that BISs can support operational processes by providing analytical information as an input for process execution. The novelty introduced by BISs lies in their capacity to deliver information swiftly, easily, and effectively while enabling users to comprehend the reasoning and meaning behind the data (Chen et al., 2012). Therefore, BISs and user interfaces meet the need to bridge the gap between the business user and the access to information.

Lastly, business applications, data management and interpretation processes find integration into BI tools (Ishaya & Folarin, 2012). From Sabanovic and Søilen's (2012) perspective, the BI software is used as an effective reporting and analysing tool to better understand a company's organizational environment. Moreover, Gartner characterises a BI platform as a software platform offering functionalities such as BI infrastructure, metadata management, development tools, collaboration, reporting, dashboards, ad-hoc queries, integration with Microsoft Office, searching tools, Mobile BI, OLAP, interactive visualisation, predictive modelling, data mining and scorecards (Hagerty et al., 2012).

The multi-faceted ways of adopting BI within the scenario of such a progressive digital transformation affecting enterprises led some scholars to regard BI as a novel culture of working with information as well as a specific philosophy and methodology for managing information and knowledge (Liautaud & Hammond, 2002). Furthermore, from a BPM perspective, BISs enable data transformation into meta-knowledge which can generate analytical insights for identifying bottlenecks, simulating scenarios, measuring performance, and monitoring progress (Mathrani, 2021).

The rise of BI has completely disrupted corporate practices, making it necessary for corporate executives, business managers and other operational workers to rely on it for enhanced and informed decision-making, to boost coordination within the supply chain (Caputo et al., 2026), to boost inventory planning and management (Naeini et al., 2019), to increase revenue (Kiani Mavi & Standing, 2018), and even to enhance resilience and adaptability during recent crises.

1.2.2 Business Process Management capabilities

BPM is a management approach that is designed to enhance the efficiency of business processes (Hammer, 2014). It is frequently referred to as a lifecycle that encompasses process identification, discovery, analysis, redesign, implementation, and monitoring. Consequently, numerous studies in the field of BPM underscore the necessity of Process Performance Measurement (PPM) as a critical component of process monitoring to evaluate and enhance the current performance of the process (Bosilj Vukšić et al., 2015).

BPM capabilities encompass both technical and managerial dimensions, including process governance structures, performance measurement systems, and improvement protocols. Process governance describes the distribution of roles, responsibilities, and decision rights within the context of process ownership and control. Accountability, cross-functional coordination, and alignment between organisational objectives and processes are ensured by the implementation of effective governance mechanisms. Finally, performance management assesses efficiency, quality, and effectiveness by methodically defining, measuring, and analysing process-level indicators.

Within such a scenario, the improvement of BPM dimensions is contingent upon the presence of analytical capabilities. For this reason, several authors argue in favour of the integration of BI into BPM, clarifying how BI can facilitate the execution of the operational process (Kung et al., 2005). In fact, BI enables real-time monitoring of process performance, thereby facilitating informed decision-making and process transparency. Furthermore, it encourages organisations to create feedback loops that connect process execution with performance evaluation and improvement initiatives, thereby reinforcing continuous improvement practices. Notably, the term "*process-centric business* *intelligence*" has been introduced to describe the capacity of BI to convert business-relevant data into analytic information with the intention of generating new knowledge to facilitate pertinent process changes (Bucher et al., 2009).

Despite this promising potential, current research frequently considers BI and BPM as separate domains, resulting in inadequate explanations for institutionalising analytical capabilities within BPM practices. This discrepancy suggests the importance of a dynamic perspective that considers the evolution of BI from exploratory use to a fully incorporated BPM capability. As a result, BI should not be regarded as an external analytical layer but rather as a critical component of BPM architectures. This maturation process is a critical theoretical challenge in BPM research, and it is essential to comprehend the role of analytical capabilities in this process.

1.2.3 DOI theory

According to Raber et al. (2013), the maturity of an organisation's BI capabilities significantly influences the advantages derived from BI. Therefore, to effectively capture the temporal dynamics of BI integration into BPM, this study utilises DOI theory (Rogers, 1983).

Jeyaraj et al. (2006) conducted a literature review and found that the DOI theory is the most frequently cited work on innovation adoption. It suggests that the diffusion of technologies can be influenced by their intrinsic characteristics, including advantages, complexity, observability of the end results deriving from implementation, and compatibility. In addition, it asserts that the decision-making process for technology adoption within an organisation progresses through a multi-stage process: knowledge, persuasion, decision, implementation and confirmation (Rogers, 1983). Although Rogers emphasised a five-stage diffusion process, most of studies have frequently proposed a specific focalisation that is limited to only three of them: evaluation, adoption, and routinisation (Chong & Chan, 2012). As the decision to implement BI and BISs in an organisation may vary based on several features across time and depending on the context-specific field of economy within which the firm is active, the DOI theory acts as a useful template for understanding BI diffusion.

Our analysis posits that the evaluation stage occurs when organisations, guided by their intention to adopt BI, consider the factors that may contribute to a successful implementation, typically informed by exploratory analyses and limited process integration. We opted for referring to an “awareness stage”, during which the firm is recognising BI’s potential value. The next stage is the actual adoption of BI, which takes place when an organisation is heading towards a BI adoption phase by allocating the necessary resources. We suggest considering it an "experimentation" stage, involving localised applications of BI to specific processes, supporting pilot initiatives, and incremental improvements. The final step we identified is the "transition" phase, when the use of BI is thoroughly integrated throughout the organisation and presumably with its supply chain partners (Aunyawong et al., 2020); hence, it reflects the routinisation stage. This stage pertains to the integration of BI inside BPM frameworks, where analytical insights consistently guide process governance, performance management, and continuous improvement.

While DOI has been widely applied in information systems (IS) research, such a multi-staged approach is not sufficiently covered by almost the totality of BI studies published so far, most of them being exclusively focused on a single diffusion stage. Furthermore, its potential to explain the development of BPM capabilities remains underexplored. Notably, the DOI theory has encountered criticism for its heavy reliance on the technology aspect of the adoption process (Fichman, 2000); indeed, organisations' adoption of IT innovations is still influenced by other social, organisational, and individual factors, even when technological superiority is guaranteed (Segal, 1994).

Moss and Atre (2003) reported that 60% of BI projects failed owing to inadequate planning, poor project management, unmet business needs, undefined tasks, inadequate data, and failure to understand the significance of some parameters such as metadata. Broadly speaking, many BI application programmes didn't succeed due to infrastructural, cultural, organisational, and technical issues, including the lack of commitment from representatives, the insufficiently skilled and trained personnel, the misinterpretation, and the non-utilisation of information acquired by users and staff (Rezaie et al., 2018). Additionally, the diffusion process outlined in DOI theory may exhibit non-linear patterns that are contingent upon the ownership structure of the firm. For instance, the awareness and experimentation stages in family firms are frequently influenced by the family's risk propensity, the founder's perspective, and the quality of owner-manager-employee relationships. In contrast to non-family firms, which are more susceptible to external competitive pressures, family-owned firms prioritise internal stability, the preservation of socioemotional capital, and long-term resilience (Arzubiaga et al., 2021). Consequently, in these specific cases, the diffusion of BI within BPM is not exclusively determined by technological availability; rather, it is contingent upon the degree to which family leaders actively frame BI as consistent with the family's strategic vision and encourage employees to integrate BI into daily process practices.

1.2.4 Heading towards a double-track conceptual framework

Based on the aforementioned perspectives, this study suggests an integrative framework that conceptualises BI diffusion as a BPM capability maturation path. The framework emphasises the co-evolution of analytical capabilities and process management practices, rather than considering BI adoption as an isolated technological process. BI transitions from supporting isolated analytical tasks to facilitating coordinated, organisational-wide BPM activities as organisations progress through the diffusion stages. This perspective establishes the groundwork for the systematic analysis that will be presented in the subsequent sections and serves as a theoretical bridge between the BI and BPM literatures.

Figure 1 depicts BI diffusion as a progression of BPM capability maturation: the framework incorporates the temporal logic of DOI theory with three BI capability domains, i.e., process, technology infrastructure, and software. Analytical capabilities undergo a gradual transformation from supporting descriptive visibility to becoming institutionalised within process governance and performance management routines while experiencing awareness, experimentation, and transition stages.

		DIFFUSION OF INNOVATION STAGES		
		AWARENESS	EXPERIMENTATION	TRANSITION
BI DIMENSIONS	Process	Process visibility through descriptive analytics	Process-level analytics and localized improvement initiatives	Institutionalized process governance and continuous improvement
	Technology	Recognition of BI technological potential	Pilot BI infrastructure and system integration	Enterprise-wide integrated BI architecture
	Software	Understanding BI software functionalities and data availability	Dashboards and performance indicators	Embedded analytics and data-driven decision routines
		→ BPM capability maturation		

Figure 1: Two-dimensional framework

1.3 Methodology

The methodological design of this study has its roots in a systematic literature review of peer-reviewed journal articles published between 2018 and 2023. This timeframe is significant as national industrial strategies, gradually implemented from 2011 to 2017, enabled the digital transformation of firms and established the essential conditions for a shift from technology-focused adoption to more integrated and process-oriented applications of digital technologies (Himang et al., 2020; Castagnoli et al., 2022). Therefore, the chosen time frame encompasses the shift from the experimental stage of Industry 4.0 technologies to a stage where their effects on business models, organisational practices, and process management are more evident (Marcon et al., 2022).

1.3.1 Sampling

To ensure methodological rigour, a systematic literature review was conducted in accordance with the guidelines proposed by Tranfield et al. (2003). This methodology advocates for the establishment of explicit criteria in the review protocol to be met all at once when selecting the publications to be reviewed. It also outlines the phases that must be followed when planning the review to implement a replicable, scientific and transparent process.

First and foremost, an initial set of keywords and search terms was formulated in accordance with the scope of the literature review. The search method integrated keywords pertaining to BI and analytics (e.g., "business intelligence" and "decision-support system") with terminology linked to BPM (e.g., "process capability" and "process management"), thus encompassing works situated at the convergence of both academic domains. The search concluded on April 21, 2024, and was conducted using the reputable online Scopus database, which is one of the largest abstract and citation databases of its kind, according to Bolden (2011). We started from exploring the contribution published in the literature between 2000-2023 to gain insight into the specific features of BI, but we ultimately set our sample to the period 2018-23, when an increasing adoption of digital technologies in conjunction with BI has emerged.

The published journals were required to encompass at least one of the following principal fields: business, management and accounting, decision sciences, engineering, economics, econometrics, or finance. In such a way, the range of articles producing instrumental insights for managers has been extended to other fields. By way of example, some notable journals mainly focused on environment and sustainability (e.g., Journal of Cleaner Production) as well as health and sport (e.g., Sport Mont) were not excluded.

The review was limited to peer-reviewed journal articles, whereas book chapters and conference proceedings were disregarded, apart from studies deriving from a snowball sampling. An initial sample of 440 articles was obtained by following these selection criteria. Subsequently, to restrict the review to high-quality journals, we considered only those with an impact factor. This selection resulted in a list of 293 papers, the titles and abstracts of which were examined to remove those deemed irrelevant to our study. A final set of 196 articles was collected and fully read. Among them, a total of 139 articles were deemed specifically relevant for the period 2018-2023. The content analysis for sample selection was directed by specific inclusion and exclusion criteria, including cover period, language, document type, research area, and categories, to ensure that the analysis focused solely on papers pertinent to the topic under investigation, as is standard practice in systematic literature reviews. Moreover, the decision to include exclusively the English language is a result of its widespread use as an international language for research.

More in detail, first, when considering the focus of their abstracts, the articles to be selected had to underline the interconnection between BI and organizational performance. Second, by considering the focus of the article, they had to offer beneficial perspectives on the domain of management. Third, any article considering conventional information on digital systems and decision-making (e.g., conventional ERPs) and not providing a comprehensive perspective on the selected inclusion criteria according to the authors' opinion was excluded. For instance, articles focusing on text mining, semantic network analysis, and visual analytics, although they provide valuable insights, were not included in the sample, since they do not directly address the comprehensive scope of BI explored in our study. On the opposite, any article analysing technical aspects and/or new algorithms related to BI hands-on applications was deemed relevant for inclusion in the set. The articles' content was thoroughly analysed using full-text reading, and those that did not focus on the research topic were discarded. Special emphasis was placed on clarifying the impact of BI on corporate processes, governance mechanisms, and performance management methods. Finally, to identify potentially pertinent studies, an additional inclusion criterion, known as the "snowball" technique, was implemented by examining a paper's reference or citation list (Greenhalgh & Peacock, 2005). As a result, we added 19 more papers into the text corpus. The entire selection process was collaborative, and discussions were encouraged when articles were deemed not entirely aligned with all the criteria. Finally, the collected papers were sorted according to the extent to which their content aligned with the scope of our research. This subsequent selection resulted in a final sample of 158 articles.

The analytical approach was based on a dual theory-driven logic. The reviews of the studies were initially classified based on three stages of adoption: awareness, experimentation, and transition, as per the DOI theory. These stages were employed to reflect the progression from initial recognition of BI's potential value to its institutionalisation within organisational practices, thereby capturing the temporal dynamics of BI diffusion. Secondly, the analysis focused on the role of BI in the development of process-related capabilities.

1.3.2 Descriptive statistics

As shown in Figure 2, the most significant number of articles in the sample (26%) was published in 2023, thus highlighting the current relevance of the topic under investigation. This is followed by 2019, with 17% of the publications, providing a clear preview that the object of our study has been deeply investigated at the time when an increasing attention to digital technologies, deriving from the transition phase of enterprises towards Industry 4.0, has emerged (Ardito et al., 2022).

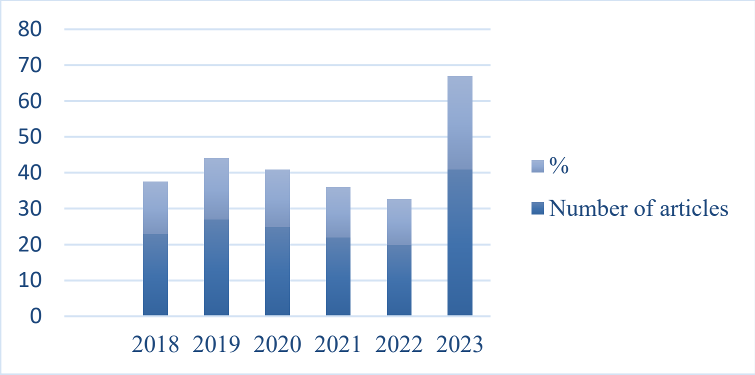

Figure 2: Number of collected articles

This is especially the case for papers focusing on AI and BI & Big Data analytics, which represent one-third (33%) of the sample, as per Figure 3.

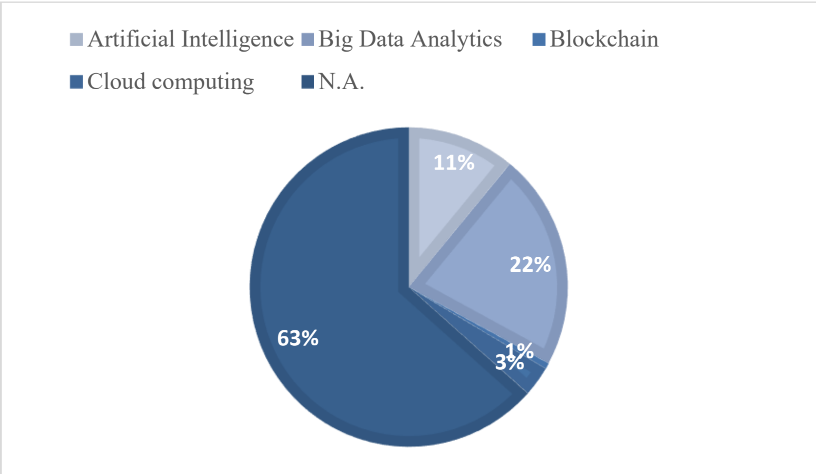

Figure 3: Percentage of articles taking into account both BI and digital technologies

The digital shift towards a fully integrated BI into the corporate routine, as it relates to the DOI theory stages, is analysed in Figure 4. More precisely, the data reveals a notable emphasis on the transition stage, with an equivalent number of studies focusing on the experimentation phase. This suggests a robust scholarly interest in understanding the complexities of transitioning from the initial adoption to the full-scale integration of BI solutions. Conversely, a smaller number of articles in the awareness stage suggests that, although the initial introduction of BI is crucial, the primary challenges arise during the practical stages of implementation and scaling.

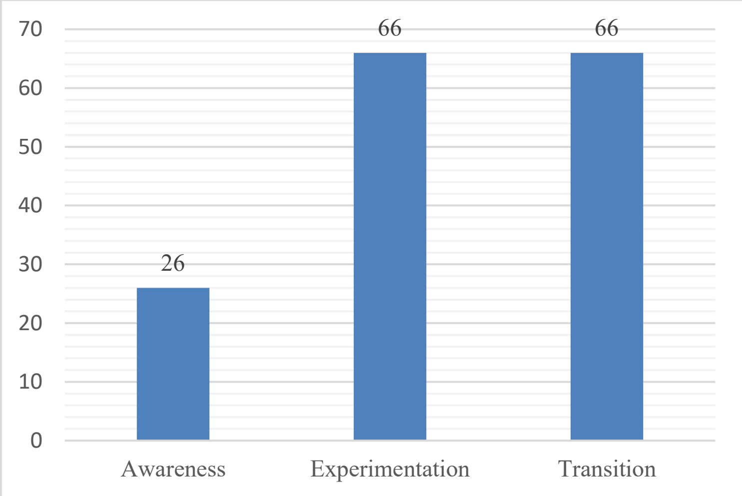

Figure 4: Number of articles per DOI dimension

Furthermore, with respect to the specific BI dimensions taken into account, the bars in Figure 5 exhibit a greater willingness to adopt BI as a technology, which means that organisations are mostly interested in transforming data into relevant information for decision-making.

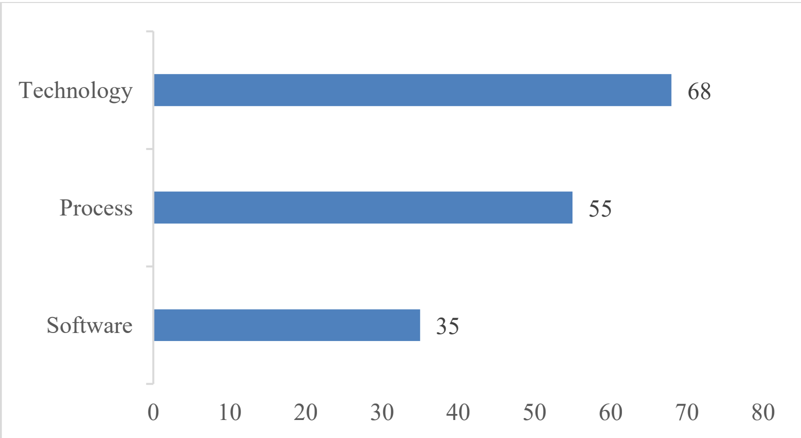

Figure 5: Number of articles per BI dimension

Lastly, Figure 6 consolidates the theoretical framework by concurrently illustrating the dimensions of BI and the stages of BI diffusion, thereby providing a cohesive perspective on the evolution of various BI capacities over the adoption-institutionalisation path. More in detail, the awareness stage is primarily linked to the technology dimension, whilst the software dimension receives comparably little focus. This pattern aligns with the exploratory characteristics of the awareness phase, which focuses on recognising the technological potential and strategic significance of BI, rather than assessing specific software functions. At this initial phase, organisations typically concentrate on determining the necessity of adopting BI rather than the methods of its implementation via specific tools. Conversely, the most frequently observed combination occurs between the transition stage and the process dimension. Once knowledge of BI is firmly established, it gradually becomes institutionalised as an organisational activity, integrated into routines, governance structures, and performance management processes. This indicates a transition from perceiving BI as an ancillary technology to recognising it as an essential element of BPM, facilitating ongoing enhancement and data-informed decision-making throughout the business.

In the experimental phase, while the technical dimension accounts for the greatest number of contributions in absolute terms, the significant focus on the software dimension suggests a more practical and operational approach. At this intersection, organisations progress beyond theoretical acknowledgement and begin evaluating dashboards, reporting tools, and performance indicators, experimenting with tangible BI solutions to determine their efficacy and user-friendliness.

Ultimately, during the transition phase, the focus is on the incorporation of BI into organisational processes, highlighting the essential need to link data-driven workflows with governance and control frameworks. Technology is a crucial facilitator at this stage, as strong and integrated infrastructures are essential to support embedded analytics and to guarantee the reliability, consistency, and timeliness of insights that uphold advanced BPM capabilities.

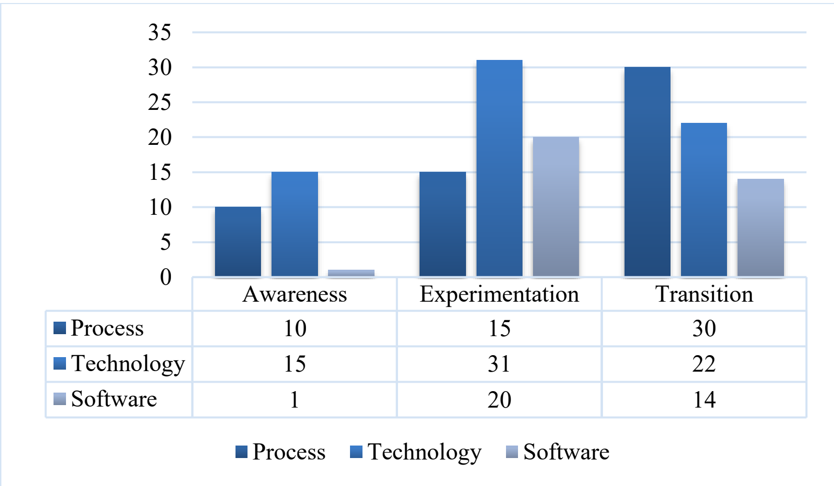

Figure 6: BI dimensions distribution per DOI theory stages during the period 2018-2023

1.4 Findings

The literature review suggests that the adoption of BI is not a static phenomenon; rather, it occurs in distinct stages that correspond to differing levels of capability development. In the subsequent subsections, we offer a thorough examination of the three main dimensions of BI (i.e., process, technology, and software) and the three phases of DOI theory (i.e., awareness, experimentation, and transition), as illustrated in figure 6.

1.4.1 Awareness

The project of adopting a DW technology like BI needs to be carefully evaluated and planned, thus implying that several studies have investigated the variables affecting the users' intention to adopt BI in the decision-making process (Rouhani et al., 2018; Grublješič et al., 2019), including self-service business intelligence (SSBI) applications (Passlick et al., 2020; Lennerholt et al., 2023). Similarly, the critical success factors (CSF) related to the implementation of a BIS (Eder & Koch, 2018; Jahantigh et al., 2019; Chaudhry & Dhingra, 2021) and, even more specifically, in an Enterprise Resource Planning (ERP) environment, have been deeply analysed (Adjie Eryadi & Nizar Hidayanto, 2020). Many authors paid attention to the factors influencing BI-enabled success across companies (Gonzales et al., 2019; Villamarín-García, 2020) as well as the barriers preventing organisations from adopting a BI open-source software (Poba-Nzaou et al., 2019).

Most of these studies emphasised the relevance of critical factors affecting the decision to adopt BI through the established technology-organisation-environment (TOE) framework, which posits that the adoption of an IT innovation is shaped by three primary dimensions: technology, organisation, and environment (Tornatzky & Fleischer, 1990). For example, Rouhani et al. (2018) identified four factors associated with technological attributes, i.e., perceived tangible benefits, perceived intangible benefits, perceived cost, and perceived complexity; three factors related to the organizational context, namely business size, organizational readiness, and strategy-related factors; and lastly, the impact of industry competition and absorptive capacity from the competitors' side as far as environmental attributes are concerned. In this manner, the extant contributions to the subject can be of support to managers and BIS specialists in identifying and effectively managing the most prevalent factors among a variety of endogenous and exogenous factors during the BI adoption process.

Awareness - Process

BI allows enterprises to access vast amounts of data to examine circumstances, trends and risks, thus explaining why, according to Nuseir (2021), it can be considered as the integrating axis of the information in the organisation, allowing sound business decisions as well as improved business processes and new opportunities.

A body of relevant research examined the relationship between BI considered in its dimension of business process and the phase of its awareness (as a stage preceding its adoption) in modern business environments. Numerous studies have found that the relative advantage perceived is a considerable predictor of the adoption of a variety of innovations across different industries (Rouhani et al., 2018), and considerable progress has been made worldwide in terms of awareness of the benefits deriving from BI as a corporate process. On the contrary, few studies have provided an in-depth analysis of the factors related to BI adoption in developing countries where the use of BI and other related technologies may be resisted. More precisely, Jaradat et al. (2022) specifically highlighted the correlation of certain factors potentially influencing the intention of insurance companies in Jordan to adopt BI into their decision-making processes. The authors specifically pointed out that compatibility, relative advantage, information and system quality positively influence user intention to embrace BI, whereas complexity has a negative one.

Among all the CSFs, user acceptance and participation play a vital role (Kikawa et al., 2019; Al-edenat & Alhawamdeh, 2022), which means that without active users, an increase in business value deriving from BI is at risk (Mangwayana & Budree, 2022). Indeed, the propensity to rely on experience and intuition for decision-making, rather than on structured and analytical approaches like BI, remains a common practice among enterprises, especially when operating in developing countries where users are resistant to technology adoption.

Awareness - Technology

The literature on the awareness stage related to BI in its dimension of technology has focused on assessing the potential benefits of BISs that organisations consider when aiming to improve the performance of value chain activities, for example, by means of cost reduction and market expansion (Puklavec et al., 2018). Indeed, as reported by Adjie Eryadi & Nizar Hidayanto (2020), the success of the BIS could be ensured by understanding and focusing on the factors that are most likely to facilitate the successful implementation of the system (Venter & Goede, 2018).

BISs differ from previous information system (IS) innovations by their ability to integrate data and perform analytical functions, which can subsequently provide valuable information for stakeholders' decision-making processes at various organizational levels. This is particularly true if the BIS is not maintained as a standalone IS solution but rather integrated into an ERP architecture (Alkraiji, 2020), allowing enterprises to automate processes over a centralised database, spreadsheet, or any type of tool that is routinely used by the organisation. Actually, BI technology empowers enterprises to develop BI applications through three primary capabilities: analytical tools, including OLAP; information dissemination, encompassing reports and dashboards; and platform integration, which involves BI metadata management and a development environment (Gartner IT Glossary, 2023).

Awareness - Software

The most consistent body of literature offered enhanced insight into the determinants of BIS adoption, with a specific focus on CSFs influencing such a choice. Despite this, according to our conceptual framework, in none of the articles collected into our study a specific attention to the phase of awareness of BI as a software was given so far, but Poba-Nzaou et al. (2019) explored the barriers preventing organisations from adopting a specific BI tool, i.e., Open Source Business Intelligence (OSBI). Indeed, the empirical evidence of the growing popularity of OSBI tools in firms worldwide is not matched by the limited adoption of these tools by organisations, and the study of their adoption is still in its early stages (Trieu, 2017). Broadly speaking, a company aiming to implement BI tools, either on-premises or via a cloud-based service, has three primary options: proprietary, custom, or open source. Consistent with the TOE framework, the study proposed by Poba-Nzaou et al. (2019) takes into consideration 23 barriers to the adoption of OSBI tools, including fear, uncertainty and doubt (FUD) concerning the product characteristics, lack of training programmes and reliable information or documentation, cultural and structural obstacles, and inadequate visibility and legitimacy within the market.

1.4.2 Experimentation

By applying the DOI theory to the BI context, we define the experimentation phase as making the decision to adopt BI. Given that the resource allocation necessary for the general deployment of innovation is determined by such a willingness, this phase is considered a critical step toward the generalised use of the technology (Puklavec et al., 2018).

In many cases, the implementation of BI solutions has been a critical measure in mitigating the revenue decline that has been caused by the absence of automated tools that could effectively and comprehensively support the BPM. For instance, Nuseir (2021) detailed a step-by-step guide for developing BI to enhance management decision-making at a UAE-based organisation. In more detail, the Pentaho products that were recommended to meet the business requirements and selected key performance indicators (KPIs) were as follows: Kettle for the ETL process, Mondrian for OLAP analysis, Jpivot to generate reports, and the community dashboard framework (CDF) to generate dashboards. In the field of institutions, Niño et al. (2020) proposed a BI governance framework that is easily replicable and designed to fulfil the needs of universities. Specifically, it was designed for the Universidad de la Costa to establish effective controls for the success of BI projects by aligning the objectives of the development plan with the institution's analytical vision.

Experimentation - Process

Some scholars have investigated the innovative impact of BI as a process combined with many other corporate processes, including Design Thinking (Chongwatpol, 2020), blockchain transactions (O'Leary, 2018), Customer Relationship Management (CRM) (Hadhoud & Salameh, 2020) and Project Procurement Management (PPM) (Rane et al., 2020). Being suitable for claim analysis and fraud prevention, for management of fleets, for reducing the information asymmetry when taking make-buy-rent decisions and estimating timelines and costs, and also for customer value management, enterprises from different sectors of the economy have deployed BI as a booster for the proactive development of strategies.

By focusing on another point of view, i.e., some limitations that organisations should be aware of, according to O'Leary's perspective, the use of open information deriving from blockchain transactions, which may be deemed a considerable opportunity to gather data for BI, can become a harbinger of the creation of illusory transactions, since spoofing and wash transactions may produce and disseminate manipulated information (O'Leary, 2018).

Experimentation - Technology

The stage of experimentation concerning BI as a technology has been deeply investigated across the most varied sectors, including Sports BI (Nova, 2018), the food processing industry (Jayakrishnan et al., 2018a; Jayakrishnan et al., 2018b; Bouaoula et al., 2019), the retail business industry (Sivamathi & Vijayarani, 2020), the telecommunications sector (Al-Eisawi et al., 2020), the cryptocurrency market (Yasir et al., 2023), digital workplaces (Schwade, 2021), the petrochemical industry (Farzaneh et al., 2018) and so on. Nonetheless, the process of using BI is not without issues, with individual user acceptance and effective utilisation being among the greatest challenges for BISs (Aws et al., 2021), as ineffective use can lead to problems such as data gathering, workflow, reporting, role authorisation, lack of user knowledge, and system errors (Mangwayana & Budree, 2022).

Indeed, a specific attention to human factors and users' business requirements has emerged when considering the correspondence between the adoption of BISs and the achievement of the company's goals (Venter, 2019).

Experimentation - Software

The examination of academic contributions revealed that the research on BI has evolved gradually, and a growing attention among scholars and practitioners has emerged over the last decade, evidently in line with the progressive adoption of BISs by enterprises.

Among all the features of a BIS, one of the most appreciated is the opportunity to obtain an immediate visualisation of business metrics, which allows for quick and informed decisions by exploring the gathered data (Mehanović & Durmić, 2022). Indeed, a combination of using open government data (OGD) to generate BI and topic modelling and visualisation tools has been proposed for the identification of market opportunities (Gottfried et al., 2021).

Several case studies in many sectors have been investigated so far, and a number of BI tools have been proposed, including Microsoft Platforms in the field of healthcare, OLAP cube and ETL for the Bank intelligence (Mathur et al., 2021; Al-Okaily et al., 2022), dashboards in the journalism field (Girsang et al., 2020), and Tableau software in the oil and gas and construction industries (Andiani et al., 2020). In journalism, for example, a BI dashboard has been introduced to display data collected from Social Media platforms in the form of a report. In such a way, by providing journalists with the content type that is attracting engagement of the public in certain specific hours of the day, viral news management can be facilitated.

1.4.3 Transition

Although in many cases the meaning of *adoption* and *use* may be mistaken, they consist of two distinct phases of BI diffusion within an enterprise. For such a reason, we opted for using the term “transition” when referring to the use stage of BI, so that the dividing line between the decision to adopt BI and its actual integration into corporate processes will not be blurred.
Over the years, many firms invested huge amounts of resources in BI among several sectors, including retail, banking, finance, manufacturing, telecommunications, luxury hotels and services (Masa’Deh et al., 2021). Such an extensive interest stemming from more and more enterprises further confirms an acquired and widespread awareness of BI benefits on corporate and supply chain performance (Jafari et al., 2023), already evident in academic literature (Havel et al., 2022).

Transition - Process

The improved performance deriving from the use of BI has been the most analysed subject as far as studies on the phase of transition to BI are concerned. Numerous authors have contributed to illustrating the influence of BI capabilities on the performance of new service products (Alsaad et al., 2022) and organisations (Zarine & Saqib, 2022), investigating the causal relationship between BI and both decision-making speed (Khaddam et al., 2023) and speed of internationalisation (Cheng et al., 2020), as well as assessing the level of BI within enterprise systems (Dahooei et al., 2018). Consequently, it is worth noting that the overall success of BI is positively influenced by its maturity level (Suša Vugec et al., 2020; Mathrani, 2021), particularly for larger organisations that achieve a higher degree of BI maturity and proficiency. By integrating data collection, storage and KM with analytical tools to deliver complex data (Shaqrah, 2018), BI attempts to enhance organizational performance (Elbashir et al., 2021; Paulino, 2022) as far as to acquire customer insights (Qhal & Mohammed, 2022) and to expedite information delivery (Pool et al., 2018).

Transition - Technology

By exploring the impact of BISs on management accounting practices (Youssef & Mahama, 2021), individual performance (Kapo et al., 2021), firms' operational capability (Yiu et al., 2020) and risk management (Bhosale & Patil, 2019; Yiu et al., 2021), a vast body of literature on the post-adoption phase of BISs aims to provide instrumental insights for managers and decision-makers (Abusweilem & Abualoush, 2019; Popovič et al., 2019). For instance, an accurate analysis regarding the correlation between the availability of information and its influence on the minds of managers for decision-making has been proposed by Ganesan and Gopalsamy (2019) with the aim to better design BI and advanced analytics (BI&AA) systems. Similarly, a critical attention to the influence of cognitive bias on decision-making had been highlighted by Ni et al. (2019), whereas Constantiou et al. (2019) investigated the role of intuitive judgements compared to BISs' output when making decisions.

Although many organisations have adopted BISs, the high failure rate is a real concern, and a number of studies investigated both the causes of their implementation failure (Gastaldi et al., 2018; Divatia et al., 2021) and the factors affecting users' intention to continue using them after their adoption (Hou, 2018).

Transition - Software

The overall scientific production regarding several sectors of the economy reveals that the effective use of BI tools has been investigated so far, including its impact on the decision-making process regarding human capital management by using, e.g., Talentia Software (Sousa & Dias, 2020), and the relevance of SSBI tools, e.g., Power BI, QlikView and Tableau, for university management (Arnaboldi et al., 2021). During the transition phase, software plays a crucial role in enhancing organizational efficiency and fostering innovation; indeed, these tools enable users to autonomously investigate and depict data, greatly improving decision-making processes.

A recent study conducted by Dai (2023) on modular architecture in digital platforms, particularly Microsoft Power BI, underscores the potential of BI software to leverage network effects. The modular architecture of Power BI enables the smooth integration of third-party graphics, thereby improving the functionality and user value of the solution. This approach not only supports the growth of Power BI's capabilities but also demonstrates how platform design can efficiently adjust and expand BI solutions to meet changing business requirements. Moreover, the continuous development of BI software has led to a greater and greater trend of integration between BI and Big Data Analytics over recent years (Božič & Dimovski, 2019; Pollono & Pupkevičs, 2023). In particular, a better understanding of the correlation between BI&A and the increase of organizational efficiency deriving from the redirection of decision-making towards appropriate areas has been provided (Al-Malahmeh, 2022), as well as some insights into the future-orientated Big Data potential (Ratia et al., 2018).

1.4.4 Cross-cutting features between dimensions

In light of the aspects that emerged when analysing the papers, over the years an increasing amount of research on BI has enlarged the object of investigation from understanding the activities that can be made more efficient or effective to identifying the reasons behind make-or-buy choices (reflecting the phase of awareness) to the necessary efforts required to ensure that the BI solution may be accepted and perceived as a normal part of organizational work (phase of experimentation) to the benefits at the strategic level deriving from BI implementation (phase of transition) (Vallurupalli & Bose, 2018). Nonetheless, a clear-cut distinction when categorising a few papers based on DOI theory was not easily achieved. Indeed, as further detailed below, some authors did not adopt an exclusive focus, but they took into account several features related to both the stages of awareness and experimentation, or awareness and transition, thus showing the existence of a cross-cutting nature connecting these different dimensions. Furthermore, for the sake of clarity, to identify the most appropriate dimension for each paper, priority was given to their prevailing dimension when categorising them, as per the abovementioned figure 4.

Awareness & Experimentation

To offer just a few examples, concerning a joint approach regarding the phases of awareness and experimentation, Rezaie et al. (2018) explored the factors affecting both the development and the effective implementation of BISs. The intersection of these two perspectives reveals a clear dyadic relationship that significantly impacts the implementation and efficacy of BI. More precisely, the authors investigated the interactions between a broad variety of factors, ranging from managerial to organisational to environmental to social ones and so on. Among them, the culture of continuous process improvement, the level of competition setting in business, the use of outside consultants, the level of security in the BIS and its compatibility with existing technologies were considered. An organisation's ability to provide sufficient resources, for example, has a significant impact on both the decision to adopt BI and its effective implementation.

Awareness & Transition

The content analysis of papers stressing the importance of BI functions and organizational performance leads to the stage of transition, thus showing a specific interest in the effects of BI on enterprises rather than in factors influencing such a strategic decision. Even so, Skyrius and

Valentukevičė (2020) correlated the relationship among organizational culture, BI culture, BI agility and organizational agility by pointing out the role of agile BI as a precondition for organizational agility. The study conducted by the authors provides a complete overview of managerial, cultural and technological factors building up agility competencies.
On the other hand, Arefin et al. (2021) triangulated the role of organizational learning culture, BISs and organizational performance. The study identified a mediating role of BISs concerning seven critical factors of an effective organizational learning culture, including continuous learning opportunities, inspiring collaboration, creating a system for acquiring and sharing learning, connecting the organisation to the external environment and delivering strategic leadership across all organizational levels. By integrating organizational learning culture and BIS, the study's findings suggest that collaboration, cooperation, and knowledge sharing are essential for achieving optimal organizational performance.

1.5 Analysis and results

By adopting a diffusion-based perspective, this study transcends static and technology-centric considerations regarding the adoption of BI. Rather, it offers a process-oriented explanation of the development of analytical capabilities. Indeed, the body of literature on the topic of BI clearly displays a growing interest towards its positioning and its moderating role within corporate practices (Torres et al., 2018).
The research findings allow for effectively answering the research questions of the study: a comprehensive framework simultaneously considering the phases of BI diffusion and its dimension of use has been identified and developed. Furthermore, the results provide a variety of theoretical insights that contribute to the BPM literature and expand the current understanding of BI-enabled process management.
Drawing upon a conceptual framework that encompasses these six constructs, namely process, technology, and software with respect to BI dimensions, and awareness, experimentation and process associated with the three stages of DOI theory, a comprehensive literature map that integrates drivers, barriers, success factors, and impacts has been proposed. As reported in Figure 7, several barriers have been identified for each phase of BI adoption within enterprises, ranging from the uncertainty about product characteristics and capabilities before adopting BI, to cultural and structural obstacles emerging after its implementation, such as the monopolisation of BI initiatives by IS departments, insufficiency of internal resources and lack of dissemination of knowledge concerning BI at the educational level. Many other factors, such as project leaders, technological skills and data sources, being them either-or factors, can play a crucial role in BI success or failure.

In terms of success factors, the engagement and training of specific and mixed-skills teams can be achieved by utilising BI solutions with a flexible architectural design, in conjunction with a strategic BI vision supported by top management. This suggests that senior managers, in particular, play an instrumental role in increasing awareness of the significance of implementing a context-specific BI solution within enterprises. The influence of managerial leadership in persuading and motivating individuals to adopt and integrate BI tools into everyday practices is exacerbated by the closer and more personal relationships between owners-managers and employees in family firms, which makes this aspect particularly salient (Bouncken et al., 2025).
With reference to the main impacts associated with the use of BI, a competitive advantage in the areas of operational efficiency, sustainability practices, supply chain management and information is among the most highly valued. Additionally, our results stress that, even though BI adoption is becoming common practice, the failure risk shouldn't be underestimated. Budgeting and financial commitment of firms should be considered a matter of high priority, since the benefits of using BI, which it can return be two or three times greater, require a long-term vision (Rouhani et al., 2018).

DRIVERS

BI awareness	BI experimentation	BI transition
BI requirements in terms of technological platform and knowledge; firm size based on number of employees, IT staff, and annual revenue; availability and planning of a high amount of budget; external political pressure; integrability and interoperability with existing ISs; organisational readiness	Information and system quality; perceived usefulness; clear vision and well-established business processes and needs; organizational culture; data accuracy and integrity; system reliability, flexibility, and scalability; compatibility with IT landscape; competitive pressure; effective project management.	BI efficiency and maturity evaluation models; user satisfaction and individual performance; positive impacts on internal operations, marketing, sales, and firm performance; innovative use of BISs; successful implementation; business goals alignment; net benefits obtained.

BARRIERS

Perceived complexity of BI adoption and governance; lack of reliable information and technical support; data collection quality; hidden costs; internal inertia.	Insufficiency of resources increasing the project time; failure in defining KPIs; data quality during the implementation; IT capability and compatibility; performance of BIS; insufficiency of management competency and user training; organisational culture and uncertainty of the decision-making process; resistance to change; insufficiency of human and financial resources; perceived barriers; unfulfilled expected contribution to individual information needs; wireless vulnerabilities.	

SUCCESS FACTORS

Assessment of BI capabilities for business needs; continuous monitoring systems; clear definition of right areas of interest; support of top management and external consultants; lightweight process.	Adherence to chosen terms/standards/KPIs; Project Leader or 'champion'; BIS upgradability and usability; change management; a project pilot; a dedicated taskforce; financial commitment; ability to solve non-technical issues; storage capacity; independence from other systems; data and information security policy; disaster planning.	Data quality; senior management support; already ISO standards certified processes; tailored solutions; collaboration quality; growth of skills; data sovereignty in the organisation (i.e., defined data access levels for each employee); user privacy; user acceptance and satisfaction; mobile platform.

IMPACTS

New and high-value knowledge; competitive advantage of information; improved data management and information flows; performance indicators concerning human resources; better understanding of different tasks and individual performance; higher staff productivity; real-time monitoring of customers and competitors; customer value anticipation; development of successful innovative products; speed to market; faster identification of deficiencies and bottlenecks in operations; lower operational costs; improvement of competitive position in the specific industry; identification of new business revenues; predictive and long-term analysis; flexibility; increase of the options and speeding up of decision-making; reduced resource wastage and firm risks; environmentally friendly and socially responsible processes; strategic and operational effectiveness; sustainable competitive advantage; improved profitability, financial performance and internationalisation speed; identification of new customers to target; collaborative decision-making and information sharing within the supply chain; improved supply chain agility and value chain alliances.

Figure 7: Literature map on BI per DOI theory stages by crossing drivers, barriers, success factors and impacts

1.6 Conclusions and future research avenues

In providing an in-depth overview of BI dimensions and relevant phases of diffusion among enterprises, this literature review has pointed out that such a strategic topic has been heavily explored by authors worldwide. In this study, BI is interpreted as a managerial tool, which encompasses the collection of technologies, software and processes that are deployed across companies to assist business users in addressing challenges and opportunities, monitoring organisational performance, and making more informed decisions. Additionally, the processes by which analytical capabilities are integrated into process management practices are identified as significant at three different diffusion stages: awareness, experimentation, and transition. The findings across these phases indicate a progressive maturation of BPM capabilities facilitated by BI.

More in detail, during the awareness stage, BI is predominantly introduced as an analytical tool, with the objective of facilitating descriptive reporting and improving data visibility. In this phase, the literature underscores the exploratory nature of BI use, which is frequently restricted to managerial or functional domains rather than incorporated into end-to-end business processes. Historical performance indicators are typically monitored using analytical outputs, which have little impact on formal process governance structures. As a result, process transparency increases, even if it does not result in systematic process control mechanisms or coordinated development initiatives. During the awareness stage, BI improves informational availability but is only weakly coupled with BPM practices, primarily serving as an auxiliary support to decision-making rather than a process-enabling capability. Conversely, the operational relevance and function of BI in BPM become more pronounced as organisations transition into the experimentation stage. The studies that were reviewed suggest that BI applications are becoming more closely associated with specific business processes, which opens up the possibility of localised performance analysis and targeted improvement initiatives. During this phase, organisations commence the experimentation of process-level indicators, dashboards, and analytical tools to evaluate responsiveness, quality, and efficiency. The increasing recognition of BI's potential to facilitate process optimisation is often reflected in the form of pilot projects or departmental implementations. Despite this, governance structures continue to be fragmented, with analytical responsibilities being dispersed across units and limited coordination at the organisational level.

A qualitative transformation in the integration of BI into BPM architectures is represented by the transition stage. During this phase, the consideration of BI as an isolated analytical resource is no

longer the case; rather, it is institutionalised within process governance and performance management systems. The proliferation of standardised process indicators, shared data repositories, and integrated interfaces facilitates cross-functional process oversight, as demonstrated by the literature. BI-enabled insights are systematically integrated into process monitoring procedures, facilitating the evaluation of performance in real-time and the promotion of evidence-based decision-making. BI becomes strategic by formalising process ownership and accountability, thereby reinforcing governance mechanisms that align process objectives with organisational strategy.
Nevertheless, and despite the timeliness of the topic, in the research conducted so far appears to be a trend still in the early stages in the matters of sustainability and digital technologies. This suggests that, regardless of the progressive expansion of BI characterisation, a void in the literature may offer novel and challenging pathways.

Sustainability directions
The necessary and extremely urgent cultural change in production processes which emerges from sustainable information societies will inevitably lead to more sustainable information systems. Within this field, BI can be of great support for sustainable development management by allowing better control of strategic corporate social responsibility (CSR) due to its ability to process a large volume of data with improved quality (Ouriniche et al., 2022) and analytical capabilities (Chalmeta & Ferrer Estevez, 2023; Cheng et al., 2023). However, the analysis we conducted so far did not reveal any specific attention to the sustainability of BIS itself. The sole study that proposed a method for designing and developing a BIS to ensure its sustainability, regardless of whether it is sensitive to resource consumption or designed for the future requirements of the organisation, was more future-oriented (Goede, 2021). A better understanding of the development of sustainable BISs when evaluating each phase of the software lifecycle, namely planning, analysis, design, implementation, maintenance and disposal, would certainly be of interest.

Digital transition directions
The body of literature on the topic of BI clearly displays a growing interest towards its positioning and its moderating role within corporate practices (Torres et al., 2018; Arefin et al., 2021; Sadeghzadeh & Rostamzadeh, 2021). Several studies have pointed out some almost inevitable close connections with digital technologies (Bordeleau et al., 2020), namely AI (Alzeaideen, 2019; Seidlova et al., 2019; Symeonidis et al., 2022; Yasir et al., 2023) and Big Data Analytics (Vallurupalli & Bose, 2018; Ilmudeen, 2021). Nonetheless, apart from the combination of BI and the aforementioned specific technologies, a knowledge gap emerges in literature as far as blockchain, AI

chatbots, additive manufacturing and robotics adopted in conjunction with BI are concerned. Future studies could be conducted in the proposed direction, especially owing to the increasing and appealing presence of enterprises into the new virtual reality of Metaverse. Furthermore, a specific focus on Mobile BI has emerged only in a study conducted by Adeyelure et al. (2018). Finally, according to our findings, this gap allows us to yet identify another resulting gap: a topic of such a huge interest and deeply contemporary, which is the integration of BI and digital technologies to enhance sustainability within enterprises, is still unexplored in literature.

Implications and concluding remarks

Our two-dimensional framework is intended to provide a structured analysis of the theoretical characterisations of BI and to examine the specific phases of BI diffusion among enterprises. This leads to two primary concluding remarks. First, our contribution delineates the unique characterisation of BI as a business process, a technological support, and a management tool, aligned with three diffusion phases: awareness of the benefits of its adoption, experimentation with its implementation, and transition through its integration into enterprise processes. Second, our systematisation of the primary findings into a literature map that encompasses drivers, barriers, success factors, and impacts offers valuable insights that are consistent with prior research emphasising the importance of user-centred ISs (Barua & Rahman, 2023). At the same time, it broadens the examination of BI as a strategic process that is integrated into the digital transformation of organisations (Al-Okaily et al., 2022).

This study expands the DOI theory's applicability to family firms by uncovering a distinctive adoption pattern that contradicts traditional linear models. Specifically, our data suggests that family firms experience a protracted or delayed awareness phase due to unique socioemotional and governance considerations that influence risk perception and decision-making within family-controlled firms. This first initial hesitance stems not from a deficiency of resources but from a safeguarding stance about SEW (De Massis et al., 2015). Indeed, depersonalised data systems are first regarded as risks to privacy and strategic decision-making (Gomez-Mejia et al., 2007). However, adoption progresses swiftly when the technology is successfully redefined as a stewardship instrument, as evidenced in the transition phase. This indicates that the dissemination of innovation in family firms is more significantly affected by the technology's ability to alleviate the "performance hazard" threatening the family's transgenerational heritage than by operational efficiency (Becerra et al., 2020). The shift from awareness to experimentation is a socio-cognitive process that necessitates the integration of digital competencies with the maintenance of family identity in family enterprises.

From the perspective of BPM, this research contributes to a dynamic and capability-orientated comprehension of the integration of BI into process management practices, thereby generating a multitude of theoretical implications. The results are consistent with Suša Vugec et al. (2020), which suggests that the term "BI-BPM alignment" is not frequently encountered in the literature and that research normally focuses on a limited number of the elements that define such an alignment.

First, the research contributes to the field of BPM by redefining BI as an intrinsic component of BPM architectures, rather than an external analytical support. Second, it clarifies the temporal nature of the development of BI capabilities: during the initial phases of diffusion, BI improves process visibility without significantly altering accountability structures or decision rights. Process ownership, performance-based governance, and cross-functional coordination are actively supported by BI only when they are institutionalised within BPM architectures in more advanced stages. Third, the incorporation of DOI theory into BPM research provides a novel theoretical contribution by providing a structured explanation of the emergence and stabilisation of BPM capabilities over time. This study establishes a connection between innovation adoption research and BPM theory by interpreting diffusion stages as aspects of BPM capability maturation. This integration enriches the BPM literature by introducing a temporal and evolutionary logic that elucidates the heterogeneity in BI-enabled BPM outcomes across organisations and contexts.

The findings of this review indicate that BI develops endogenously within BPM architectures, thereby progressively influencing the governance, monitoring, and enhancement of processes. Such an approach is consistent with the dynamic capability perspective in BPM research and emphasises the co-evolution of process management practices and analytical capabilities over time. The results, which are consistent across a variety of industries, serve as confirmation of the significant impact of BI adoption on corporate decision-making. The observed trends, in line with previous research (e.g., Ain et al., 2019), further reinforce the validity of our conclusions. The framework elucidates the reasons why analogous BI investments may result in divergent process management outcomes by explicitly linking BI diffusion stages to BPM mechanisms. This insight is especially relevant to BPM research, which is intended to comprehend the circumstances under which digital technologies effectively foster process excellence.

From a managerial perspective, our research provides strategic insights for firms that are interested in implementing BI to enhance performance. We examine the variables that influence the decision to adopt and fully integrate this business practice, the specific factors that contribute to its success, the advantages derived from its employment as well as the potential weaknesses and challenges. Managers are the principal users of BISs and are pivotal in the initial choice to adopt an IS. However, the engagement of other users is essential for utilising BI and for providing them with the necessary deliverables that enhance decision-making. The findings underscore the importance of developing BISs that are in alignment with user expectations and requirements to ensure their effectiveness. This is because the adoption along with the efficacy of ISs is significantly influenced by user satisfaction and perceived benefits.

Ultimately, our research demonstrates that the competitiveness and future-orientedness of organisations are improved by the adoption of BI and Big Data Analytics, which are also crucial for the promotion of product innovation. Managers should not evaluate BI investments solely on the basis of technological sophistication or analytical output, but rather on their capacity to support process-oriented governance and performance management. The findings underscore the importance of connecting BI initiatives to specific business processes and development objectives as organisations transition into the experimentation stage. It is recommended that managers promote pilot initiatives that integrate analytical insights into process-level decision-making and encourage learning across organisational units. The study cautions that fragmented experimentation in the absence of coordinated governance may restrict the scalability and sustainability of BI-enabled process enhancements. Indeed, at the advanced stages of diffusion, the managerial emphasis should transition to institutionalisation. The process entails the standardisation of process performance indicators, the integration of BI into BPM governance structures, and the clarification of duties and responsibilities in relation to analytical decision-making. Managers can utilise the framework developed in this study to evaluate their current level of BI diffusion and to develop BPM-aligned strategies that optimise the long-term value of analytical capabilities.

In conclusion, this study is not free from limitations that can be a starting point for future contributions. The proposed framework advocates for a shift in perspective that encourages researchers to adopt a more holistic understanding of BI, but an in-depth analysis has shown that a step-by-step guide starting from the diagnosis of an enterprise's digitalisation level to the design of a BIS and the monitoring of its alignment with the objectives and the vision of the firm didn’t find a match apart from a few cases. Future studies could help managers and decision-makers to find a replicable framework to approach BI into their organisations and integrate BI capabilities into BPM. Furthermore, further contributions could examine possible extensions to the current BISs to include the decisions that are not yet optimised by the decision-makers, such as the analysis of trade and the ongoing monitoring of their reference market.

Chapter 2. Orchestrating knowledge through BI

In a rich in data but poor in actionable insights business landscape, the ability to transform fragmented information into strategic knowledge represents a critical source of competitive advantage. By conducting an in-depth case study within Radici Yarn S.p.A., a global chemical manufacturing firm, this study aims to explore the role of BISs in improving the KM of firms. Specifically, drawing upon the knowledge-based view (KBV) and the resource orchestration perspective (ROP), this research investigates how BISs can enhance the acquisition, storage, transmission, and exploitation of knowledge. The findings demonstrate that a tailored BIS can significantly support organizational learning, increase information visibility and accelerate informed decision-making. Moreover, it reinforces strategic areas such as CSR through improved data monitoring and reporting.

This research contributes to KBV and ROP literature by offering empirical evidence of the strategic role of BISs in improving knowledge processes and addressing information management challenges in knowledge-intensive environments. Furthermore, this chapter provides valuable insights for managers seeking to adopt BI as strategic facilitators of KM and competitive intelligence. The findings underscore the importance of co-designing BI solutions that address internal operational challenges, reduce cultural resistance to change, and incorporate data-driven practices into decision-making processes, ultimately enhancing responsiveness, innovation capacity, and sustainability performance.

2.1 Introduction

> "Despite evolutions and changes, there are lessons learned during the early years that I still carry with me and that remain valuable to me today. Knowledge related to the world of synthetic fibres, which has been passed down here and will continue to be transmitted from person to person so that it is never lost. Knowledge is the very heritage of a company."[1]

In a world of rapid change and creative destruction (Schumpeter, 1961; Torres et al., 2018), the notion of intelligence is no longer associated with humans (Al-Malahmeh, 2022) but rather encompasses organisational and artificial domains.

[1] RadiciGroup. (2014). Voices: Storie di aziende e della loro umanità - 50 anni Radicifil, 40 anni Radici Yarn. Corporate magazine. RadiciGroup Information Magazine, Number 1, Year 19. https://www.radicigroup.com

The transition from a production-oriented to a data-driven economy has been catalysed by the escalating quantity of data generated on a daily basis (Mandel, 2012; Gupta et al., 2019). This transition is further reinforced by the synergistic relationship between information technology and entrepreneurship, wherein IT actively fosters business model innovation, improves responsiveness, and bolsters firms' competitive positioning (Del Giudice & Straub, 2011; Vujanović et al., 2022; Zhang et al., 2025).

Thus, the extensive proliferation of information and the necessity of using AI and big data analytics to extract value from it (Chau & Xu, 2012; Raisch & Krakowski, 2021; Caputo et al., 2023b) have compelled firms to enhance the quality of their decision-making (Chadwick et al., 2015). Furthermore, the transition into the so-called '*age of data*' has rendered the identification of new sources of competitive advantage as a competitive imperative (Varadarajan, 2020; Honig & Samuelsson, 2021).

Since the late 1980s, management theory and practice have been greatly influenced by the recognition of knowledge's importance in economic activities (Grant & Phene, 2022). Within a dynamic business environment, a firm's capacity to acquire, manage, and exploit knowledge assets has been recognised as a pivotal determinant of organisational competitiveness (Nonaka, 1994; Majuri, 2022; Zhi et al., 2025). In addition, due to changes in markets and customers' preferences, gaining competitive advantage has compelled firms to overcome the traditional boundaries of producing goods and services efficiently and effectively (Porter, 2008) to find new avenues for excelling.

Recent research reveals that today's conditions influencing the acquisition of a competitive advantage involve technological innovation (Ge & Liu, 2022; Gomwe et al., 2022; Gao & Rai, 2023). Thus, after investing significant time and resources in establishing a resilient technological infrastructure to enhance operational efficiency (Popovič et al., 2014; Puklavec et al., 2018) and leverage data analytics capabilities as valuable organizational assets (Yiu et al., 2020), a growing number of enterprises have reached a common stage within which the 'conventional' decision-making methods, based on experience and intuition (Pourshahid et al., 2014; Niu et al., 2021), are being increasingly replaced by the systematic reliance on DSSs, especially BI.

BISs are data-driven DSSs (Popovič et al., 2019) combining data gathering and data storage with advanced data mining and analytical capabilities (Negash & Gray, 2008; Davenport et al., 2010). Through BISs, new organizational intelligence and business insights can be provided, thereby optimising the ability to discover, create, manage and disseminate firms' information and knowledge (Shollo & Galliers, 2016; Campanella et al., 2017). From such a perspective, BI adoption represents a critical enabler of resource orchestration: by orchestrating strategic resources, such as assets for information gathering with data analysis capabilities, BISs enhance the organisation's ability to

leverage its intellectual capital and optimise resource allocation (Sirmon et al., 2011), enabling the organisation to stay ahead of competitors (Cerchione et al., 2025c).
Drawing upon the ROP, which posits that coordinating and synchronising strategic resources, capabilities, and management leads to notable competitive advantage (Koufteros et al., 2014), and consistent with the KBV, which considers a firm as a knowledge-creating entity (Rebolledo & Nollet, 2011; Yiu et al., 2020; Zámborský et al., 2023), this paper aims to analyse the transformative potential deriving from the introduction of a BIS to gain a competitive advantage of information. Specifically, by conducting a case study with several heads of departments and business functions of a global chemical firm, we seek to provide insights into the firm's current operational challenges, thus providing important context while defining the main requirements of a BI platform to meet specific strategic needs.
Building upon these premises, this study aims to address the following research questions:

RQ3. How does the integration of BISs enhance the collection of information for strategic decision-making processes?
RQ4. In what ways does BI support the development of a competitive advantage in information, as understood through the KBV and the ROP?

Through empirical evidence and theoretical insights, this study demonstrates that integrating BISs into firms' operational plans enables organisations to foster innovation, enhance competitiveness, and generate value. The findings reveal an intricate landscape of requirements for a BIS, encompassing technical, functional, and organizational dimensions, thus confirming the strategic importance of integrating customisable solutions within existing IT infrastructures to strengthen KM. Additionally, it illuminates that the integration of BISs in family firms is further complicated by the fact that strategic decisions are influenced by family involvement in ownership and governance, alongside efficiency considerations, consistent with prior research suggesting that the long-term orientation and distinctive governance structures of family firms affect their approach to innovation and knowledge deployment (Radu-Lefebvre et al., 2024; Skorodziyevskiy et al., 2024).
The subsequent sections of the chapter are structured as follows: Section 2 delineates the theoretical background with a particular focus on BISs and the specific requirements of firms operating within mature markets, particularly the chemical industry. Section 3 delineates the qualitative methodology and the systematic data collection process, which involved engaging both strategic decision-makers and shop-floor operators to capture a multi-level perspective on the firm’s knowledge dynamics. Then, Section 4 offers a summary of the key findings, followed by Section 5, which concludes the study while also suggesting implications, limitations and potential avenues for future research.

2.2 Theoretical background

2.2.1 BISs: an overview of relevant literature

The concept of BI embodies a broad variety of data management functions and tools, including data warehouses, data marts, alerts, data mining, OLAP, ad hoc analytics, scorecards, reporting, planning and forecasting (Sousa & Dias, 2020). Central to the transformative potential of BISs are their integrated dashboards and visualisation functionalities, which serve as the primary interfaces for managing knowledge. Rather than simple reporting tools, these platforms are designed to consolidate, interconnect, organise, and analyse diverse data streams, spanning from competitor intelligence to supply chain metrics and customers engagement (Yiu et al., 2021). By offering real-time insights into historical patterns and operational anomalies, these platforms enable both BI users and managers to detect process deviations and enhance productivity with meticulous accuracy (Fernández-López et al., 2018). In sectors characterised by high variability and stringent quality requirements, such as chemical manufacturing, this visual intelligence addresses organisational structural challenges by converting isolated raw data into actionable insights (Yiu et al., 2020). Ultimately, these digital interfaces enable a transition towards more informed decision-making, effectively closing the divide between information accessibility and strategic implementation (Brea, 2023).

To summarise all these functions, Berndtsson et al. (2015) asserted that BISs scrutinise data and information and distil them into concise and user-friendly managerial insights, which are instrumental for organisations in speeding up their R&D activities and enhancing their performance across all organisational levels. Not far from this perspective, Guarda et al. (2013) defined BI as a management strategy rather than a technology.

Numerous leading scholars (e.g., Herschel & Jones, 2005) have demonstrated that BI significantly impacts the practices of organizational actors, especially in how they perceive, generate, and share knowledge. Organisations establish and acquire competitive advantages by introducing BI, particularly due to its analytics capabilities (Kiron & Shockley, 2011; Owusu et al., 2017). As a result, BISs have become significant boosters of digital transformation due to their capacity to optimise the use of information (Popovič et al., 2014). It is becoming increasingly relevant to consider BI as a prospective source of competitive advantage, rather than merely a cost of doing business.

2.2.2 Knowledge-based view (KBV)

Situated at the intersection of significant research domains, including organisational learning, management of technology, managerial cognition, organisational capabilities, innovation theory, and epistemology of knowledge (Grant, 1996), the KBV conceptualises a firm as a knowledge-creating entity, where knowledge is a firm's preeminent strategic resource. It consists of a refinement, or 'an outgrowth', in Grant's (1996) words, of the RBV.

The main difference between RBV and KBV lies in the fact that, while the former posits that heterogeneous market positions result from effectively leveraging heterogeneous firm resources (i.e., all assets, capabilities, organizational processes, and firm attributes) that are valuable, rare, inimitable and non-substitutable (VRIN resources) (Barney, 1991), the latter refines this view by asserting that knowledge is the main resource that enables firms to achieve and sustain a competitive advantage.

Several scholars have supported this viewpoint. According to Nonaka (1994), the ability to create and process organisational knowledge can be crucial for establishing long-term competitiveness. Levin and Cross (2004) observe that organisations that successfully leverage collective expertise and knowledge are more likely to be competitive and innovative. In the same vein, Ray et al. (2023) assert that competitive advantage stems from the development of both tacit and explicit knowledge via organizational activities and experience, whereas Alavi and Leidner (2001) further expand this understanding by including pragmatic knowledge embedded in systems, processes, and organizational culture. To summarise, the capacity to create performance disparities and new income sources is predominantly contingent upon how organisations acquire, include and utilise knowledge (Rubera et al., 2016). Thus, companies exist and survive by generating and efficiently using knowledge (Rebolledo & Nollet, 2011).

In this context, BISs play a revolutionary role. Production research literature indicates that big data substantially enhances KM (Ekambaram et al., 2018; Ahmadpour et al., 2023), whereas BISs improve information management (Yiu et al., 2020) and operational capabilities by producing strategic insights that facilitate competitive differentiation. On this basis, Wade and Hulland (2004) reported that scholars who applied the RBV lens to IT capabilities concluded that the firm's capability to deploy and leverage IT effectively is what fuels value creation, rather than the technology itself. It is unsurprising that researchers have been utilising the RBV on more occasions to evaluate the impact of BISs on firm performance (Popovič et al., 2019).

2.2.3 Resource Orchestration Perspective (ROP)

As Sirmon et al. (2007) demonstrate, merely possessing VRIN resources is insufficient for organisations to gain a competitive advantage. Moreover, the RBV does not provide guidance on the exploitation of firm-specific resources to achieve a competitive advantage (Liu et al., 2013). It is widely acknowledged that sustainable competitive advantage is contingent upon the implementation of effective resource management (Nason & Wiklund, 2018), in relation to which the KBV may encourage entrepreneurs to recombine resources in innovative ways (Ray et al., 2023).

The ROP of RBV theory emphasises the importance of synchronising and coordinating strategic resources, including big data assets, across various organisational layers, functions, and units to establish a significant competitive advantage (Sirmon et al., 2011) and generate competitive outcomes (Liu et al., 2016). Furthermore, it emphasises how important it is for managers to synchronise and coordinate these resources (Simon et al., 2011). To accomplish competitive priorities, firms must be able to orchestrate, consolidate and leverage their resources (Chadwick et al., 2015).

In this specific context, once again, BISs have been found to be highly beneficial, as they enable firms to better align and coordinate resources, minimise transactional inefficiencies, and deliver strategic advantages. For these reasons, this study investigates the business value of BISs in achieving the competitive advantage of information by adopting the theoretical perspectives of both KBV and ROP.

2.2.4 Conceptual framework

Building upon the foundational contributions in the KM scholarly literature, including Nonaka et al. (1996), Zack (1999), and Bhatt (2001), and integrating insights from Varadarajan (2020), the framework in Figure 8 recognises knowledge as a dynamic and socially constructed asset, where creation and conversion processes occur through interactions between tacit and explicit forms. The complete trajectory of information flows is delineated through five interconnected dimensions that support the organisation's ability to create and utilise value from information. These dimensions reflect the core KM processes, from knowledge acquisition and creation to storage, transfer, and exploitation (Alavi & Leidner, 2001).

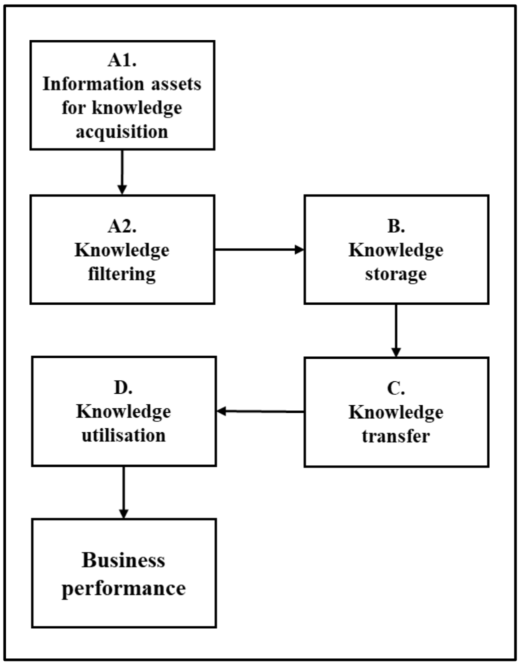

Figure 8: The conceptual framework

In greater detail, the initial phases of information asset acquisition (A1) and filtering (A2) are aligned with the knowledge creation and externalisation mechanisms that enable firms to structure raw data into meaningful insights. Category A1 is concerned with the firm's knowledge and data accumulation, including operational data, employee insights, customer feedback and internal databases. On the other hand, the firm's capacity to convert unprocessed data into actionable knowledge is the subject of category A2. Category A2 encompasses the technologies, tools, systems, and human expertise used to organise and process information. Information is defined as processed data that is meaningful and valuable, emphasising the critical role of interpretation in the knowledge creation process, as per Burton-Jones (1999).

According to the literature, it is essential to establish effective storage mechanisms, both technological and human, to prevent knowledge loss and maintain the continuity of learning processes (Alavi & Leidner, 2001). Thus, category B concentrates on the preservation and storage of organisational knowledge. This dimension draws on the notion of 'organisational memory', which allows firms to preserve and retrieve knowledge over time, ensuring continuity and reuse (Walsh & Ungson, 1991). It includes the systems and procedures that are employed to archive data, documents, and experiences in a manner that is both structured and retrievable. This encompasses both formal systems, such as databases and document management systems, and informal components, such as the personal knowledge base and experiential insights of individuals.

The subsequent stage of knowledge transfer (C) reflects the dissemination of knowledge across organisational units and individuals. Consistent with prominent authors in KM literature (i.e., Pitafi et al., 2023; Varshney & Jain, 2023), it underscores the importance of intra-organisational knowledge flows, which include interdepartmental collaborative platforms, regular knowledge-sharing meetings, and structured decision-making frameworks that facilitate the internal dissemination of insights. Knowledge transfer extends beyond mere communication (Jain & Gupta, 2019): it requires a medium, a willingness to share, and an intention to mutually benefit through increased understanding (Fabiano et al., 2021). It is imperative to disseminate knowledge, as information that is not shared remains hidden and fails to produce innovation and added value (Wang & Hu, 2020; Murtic et al., 2024).

Finally, knowledge utilisation (D) represents the point at which knowledge is operationalised in decision-making, becoming embedded in routines and actions that influence strategic outcomes. This encompasses applications such as the introduction of new product lines, the expansion into emerging markets, or the improvement of operational efficiency, all of which demonstrate how organisational strategies are informed and enhanced by data-driven and knowledge-based insights. Thus, the organisation's overall performance represents the last category, where these processes find expression in relation to the KM processes. This may be evidenced by accelerated innovation cycles, improved customer satisfaction, expanded market share, and enhanced profitability, thereby illustrating the tangible value of effective KM practices.

2.3 Research methodology

This research aims to conduct a comprehensive examination of the KM architecture employed by a chemical manufacturing family firm, conceptualised as a knowledge-creating entity. Drawing upon the KBV, the study investigates how the firm's digital infrastructure, specifically its BI configuration, acts as the technological backbone for orchestrating raw operational data into strategic intellectual assets. By adopting a qualitative methodology, this study seeks to identify the main bottlenecks in information flows and suggest potential functional requirements for the development of a customised BI platform designed as a KM system (KMS) (Jain & Gupta, 2019).

Case study research is particularly relevant in the realm of IS research, due to its focus on understanding 'how' and 'why' a phenomenon originates and how people's experiences and activities influence its implications and ramifications (Caputo et al., 2023a). Yin (1984) characterised such a methodological approach as an empirical investigation that examines a contemporary phenomenon within its authentic context, whereby the boundary between the phenomenon and its environment is not easily discernible.

This study unfolds in several phases, commencing with the identification and engagement of participants from diverse roles within the organisation associated with BI utilisation. To investigate participants' perceptions, expectations, and experiences, a protocol for conducting semi-structured interviews was developed and thoroughly reviewed and validated by a panel comprising three firm senior managers and three scholars with relevant expertise. Moreover, following the guidance of Darke et al. (1998), additional data sources (e.g., press publications and official websites) were collected to achieve theoretical triangulation and corroborate findings from many perspectives (Yin, 1994). To enhance the study's empirical depth, we adopted an action research approach: following Walsham (1995), one researcher was embedded within the organisation to gather nuanced contextual insights into the sociotechnical dynamics of BI implementation. This 'in-situ' engagement allowed for comprehensive 'walk-through sessions' of the firm's digital infrastructure, including ERP, Manufacturing Execution Systems (MES), and BI platforms, guided by the Strategic Sales Manager, who is an experienced BI practitioner. This methodology, aligned with Marjanovic (2022a), facilitated the triangulation of formal interview data with direct observations of technological workflows. As a result, we captured supplementary evidence on system interoperability and organizational routines that traditional interviews alone could not reveal (Annosi et al., 2021; Caputo

et al., 2023; Marinelli et al., 2024). This approach was further corroborated by analysing confidential documentation and public records to ensure rigorous theoretical triangulation.
The active involvement of the senior management was a critical factor in the development and effectiveness of the case study. As emphasised by Yeoh and Popovič (2016), the successful integration of BI into corporate processes is strongly contingent upon unwavering top management commitment. In this case, commitment extended well beyond formal endorsement, encompassing the personal presentation of the project to participants and the explicit recognition of their engagement's significance, thereby contributing to the establishment of a climate of trust and legitimacy around the initiative. Moreover, the project's resonance with the company's broader vision was consistently emphasised by a third-generation member of the founding family, who, although currently serving in an executive role at a different facility within the same division, expressed his sincere appreciation for the initiative prior to the interview phase:

> "I would like to thank you for accepting this invitation. The level of participation is truly encouraging. Many colleagues have agreed to contribute to such an initiative that we consider highly valuable for the research we are undertaking, and for that, I am sincerely grateful."

2.3.1 The case study

Headquartered in Villa d'Ogna (Bergamo), Italy, Radici Yarn S.p.A. represents a European benchmark in the synthetic fibres industry. The company specialises in manufacturing polyamide 6 polymers, which are transformed into a wide variety of textile and staple fibre products catering to various industrial applications. Owing to their cost-efficiency, chemical resistance, high tensile strength, and lightweight nature, synthetic fibres have been extensively utilised across a wide range of industrial sectors, including apparel, interior design, energy conversion devices, medical applications, and marine engineering (Hatakeyama-Sato, 2023; Di Giulio et al., 2024). Notably, Radici's polymers are employed in apparel, including technical garments, intimate wear, and sportswear, and in automotive components, such as structural parts, seat coverings, and engine elements, as well as in a broad spectrum of other industrial applications.
Radici Yarn's distinctive competitive advantage resides in its capacity to effectively integrate extensive industrial capabilities with artisanal craftsmanship. Furthermore, as an energy-intensive organisation, the company has intentionally established itself as a leader in the circular economy (CE). It contributes to the development of low-impact and high-performance fibres that are crucial

for addressing sustainability challenges across several industries, especially fashion (Baccoli et al., 2025; Cerchione et al., 2025b).

Based on these premises, the choice of a global chemical manufacturer such as Radici Yarn as the central focus of this investigation is based on both theoretical and empirical considerations. First, companies in the chemical industry operate within highly competitive and saturated markets, where the capacity to manage information flows efficiently is a determinant of success in converting market volatility into swift operational adjustments (Hutcheson et al., 1995). Second, the industry is experiencing an unprecedented digital transformation marked by the integration of ERP systems and MES (Xiong et al., 2010). Such a socio-technical development is progressively influenced by the advent of Polymer Informatics, wherein the combination of data science and computational capabilities is employed to expedite the design, processing, and management of complex macromolecular systems (Batra et al., 2021). In such a process-intensive context, BISs operate as a strategic resource for Manufacturing Integration and Intelligence (xMII), transforming basic chemical and operational data into significant strategic insights.

This study focuses on Radici Yarn to investigate how digital infrastructures can mitigate information bottlenecks in polymer manufacturing, illustrating how technology-enabled KMSs enhance differentiation by improving responsiveness and institutionalising sustainability-oriented practices.

2.3.2 Data gathering

Over a period of 10 months, from July 2024 to April 2025, a total of 22 managers were interviewed. Participants included top managers, IT specialists, and business function executives, averaging 17 years of expertise in the firm, with seniority levels spanning from 1 to 35 years. Among them, several participants held cross-functional or interim roles, enhancing the richness and diversity of insights and reflecting a broad cross-section of departments, including ICT (14%), production (14%), sales (9%), marketing (9%), purchasing and logistics (9%), legal/credit (9%), R&D (9%), HR (9%), and others, such as CSR, quality, technical assistance, and general management.

The heterogeneous composition of the interviewee sample facilitated the inclusion of various, sometimes opposing perspectives, which contributed to a more thorough understanding of the organisation. For instance, the ICT team provided detailed information concerning the design constraints and the existing functional deployment of BIS tools; conversely, stakeholders from various business units offered critical perspectives on user-centric needs, highlighting the importance of intuitive dashboard interfaces for facilitating real-time operational decision-making. Further details are presented in table 1.

The duration of each session was approximately 1.5 hours, and interviews were video-recorded and transcribed verbatim, with all participants providing informed consent for data recording and processing. While most of the interviews were conducted online to accommodate participants' availability, in-person interviews were also held with those present at the company site during the research team's on-site visits. Anonymity was preserved using role descriptors and business unit references.

To deepen the analysis and elaborate on insightful and constructive findings, the results of the formal interviews were cross-referenced with a series of informal interviews carried out directly on the shop floor. During these sessions, 15 employees from different production departments were consulted to validate the managerial insights and to gather additional reflections and observations regarding day-to-day operations deemed relevant to the research. These perspectives included those of department heads, shift supervisors, plant managers, and process technologists, among others, ensuring a well-rounded understanding of the production environment.

Table 1: Participants' details

ID	Gender	Function	Branch	Current role	Education	Seniority in the firm
I1	M	Legal / Credit Office	Holding	Head of Credit, Legal and Insurance areas	Master's Degree in Economics and Law	34 years
I2	M	Production	Same Division (Apparel & Technical)	Site Manager and Operations Manager (Polyester division)	Master's Degree in Economics and Business	25 years
I3	M	General Management	Business Area Advanced Textile Solutions (ATS)	General Director of the Apparel & Technical division (part of ATS); Interim roles in commercial and marketing	Master's Degree in Mechanical Engineering	3 years
I4	M	Sales	Business area ATS	Sales Manager Apparel & Technical	Bachelor's Degree in Management Engineering (Textile)	19 years
I5	M	ICT	Holding	IT Team	Master's Degree	6 years
I6	M	ICT	Radici Yarn	IT Team	Master's Degree	12 years
I7	F	ICT	Radici Yarn	IT Team	Bachelor's Degree	2 years
I8	M	Quality A&T and Site Manager	Same Division (Apparel & Technical)	Lab Manager; Interim Site Production Manager of Industrial Services in another facility	Master's Degree in Chemical Process Engineering	17 years
I9	M	Technical Assistance	Business area ATS	Technical Assistance Manager	PhD and Master's Degree	6 years
I10	M	Production	Radici Yarn	Production Manager	Master's Degree in Industrial Chemistry	1 year
I11	M	Purchasing	Holding	Purchasing Manager	Master's Degree	N.A.
I12	M	Marketing	Other Division (High Performance Polymers, HPP)	Marketing and Technical Assistance Manager	Master's in Mechanical Engineering	N.A.
I13	M	Purchasing & Logistics	Business area ATS (Apparel&Technical)	Purchasing / Supply Chain Manager	High School Diploma in Accounting	35 years
I14	F	CSR	Holding	CSR Manager	Master's Degree in Interpretation	17 years
I15	M	R&D	Business area ATS	R&D Manager for the textile area	Master's Degree	27 years
I16	F	Marketing	Holding	Strategic Marketing Manager	Master's Degree in Economics and Business	30+ years

I17	M	Sales	Business area ATS (Apparel&Technical)	Area Sales Manager	Master's Degree	15 years
I18	F	Strategic Sales	Radici Yarn	Strategic Sales Manager	Master's Degree in Engineering	5 years
I19	F	Credit	Radici Yarn	Credit Manager	Master's Degree	22 years
I20	M	R&D	Radici Yarn	Product Development Manager	Master's Degree in Engineering	5 years
I21	M	HR	Business area ATS	HR Manager	Master's Degree in Political Science	23 years
I22	F	HR	Business area ATS	HR Business Partner & Business area ATS Training Coordinator	Master's Degree in Law	8 years

2.3.3 Data analysis

Data analysis was guided by an interpretive, theory-informed approach aimed at capturing the complexity and richness of BI-enabled KM practices within a real-world industrial context. To ensure analytical rigour, thematic coding and triangulation methods were employed.

An inductive coding technique was employed by integrating "*in vivo*" codes, which mirror the respondents' language, with constructed codes, which represent fundamental theoretical constructs from the KBV and ROP. The initial "*open coding*" phase (Glaser & Strauss, 1967; Charmaz, 2014) facilitated the mapping of participants' perceptions concerning the strategic application of BI tools and their function in the organisational KM process. For instance, the Strategic Marketing Manager (I16) described the main scope of BI as:

> "to essentially capture the opportunities that arise in the market, leveraging the synergies that can be activated within a group like ours, which operates across different levels of the value chain, to optimise management, business development, and risk mitigation."

The next phase involved "*axial coding*", in which first-order codes were grouped and compared to identify relationships and higher-order concepts. This step allowed for the abstraction and reorganisation of preliminary codes into second-order themes, highlighting emergent patterns associated with information flow inefficiencies, cultural barriers, and challenges in BI adoption. The identified patterns were synthesised into aggregate dimensions, forming the conceptual framework of our empirical findings. Furthermore, the interviewees scrutinised and corroborated the case findings to rectify any inaccuracy or bias, thereby enhancing the precision of our interpretations.

Thematic analysis, as articulated by Fereday and Muir-Cochrane (2006), served as a method of pattern recognition to identify key themes that arose from the data. KBV and ROP were utilised as sensitising lenses (LeGreco & Tracy, 2009; Marjanovic, 2022a), providing interpretive guidance while allowing for the development of emergent and context-specific categories. QDA Miner, mixed-method software, was employed to assist in manual coding and enhance systematic data organization and comparison (Lewis & Maas, 2007). To enhance contextual understanding, interview data was triangulated with documentation sources, such as codes of conduct, annual reports, and sustainability reports, alongside informal observations collected during facilities visits. The coding tree is presented in greater detail in Table 2.

Table 2: Coding tree

First order categories	Second-order themes	Aggregate dimension
"*Field-based*" knowledge acquisition		
Customers for data acquisition	External knowledge sourcing	
Face-to-face data acquisition		Knowledge **acquisition**
Paid data subscriptions for Marketing intelligence	Structured external intelligence systems	
Participation in trade fair events	Market scouting	
Lack of infrastructure	Technological constraints	
Capability gaps in BISs	BISs usage	Knowledge **storage**
Limited access to information	External knowledge sourcing	
"*Overuse of emails*"	Communication tools	
Meeting for knowledge sharing	Knowledge transfer processes	Knowledge **transfer**
WhatsApp for internal communication	Informal communication channels	
Traditional decision-making	Inertia in decision-making processes	Knowledge **utilisation**
Sustainability dashboards, ESG indicators	Data usage for CSR and compliance	
Improved responsiveness	Strategic and performance outcomes	Business performance
Gap between intentions and actions	Strategic alignment issues	
Lack of interoperability		
Unstructured information Interoperability Lack of resources	*"Bottleneck of information"*	
Lack of trust in sustainability	Cultural resistance to change	Strategic and structural gaps
"*The challenge is change*"		
Excessive focus on daily operations	Operational myopia	
Handcrafted procedures	Lack of digitalisation	
Excessive input required	Data overload	
Misalignment with the firm's goals	Organizational misalignment	

2.4 Results

2.4.1 The information flow within the firm

The interviews conducted within Radici Yarn provide a multifaceted outlook of the firms' current approach toward KM, evidencing the challenges that both managers and operators face in daily operations as well as providing room for the strategic implications that could derive from the full integration of a BI platform. While there is a general recognition of BI's potential to enhance decision-making and improve competitiveness, the findings also reveal varying perceptions of its value across different business areas. The findings emphasise an organisational context within which the firm effectively utilises information assets and analysis capabilities to manage knowledge, which is a crucial resource for formulating business strategies. An in-depth analysis of the information flows has been reported in Figure 9.

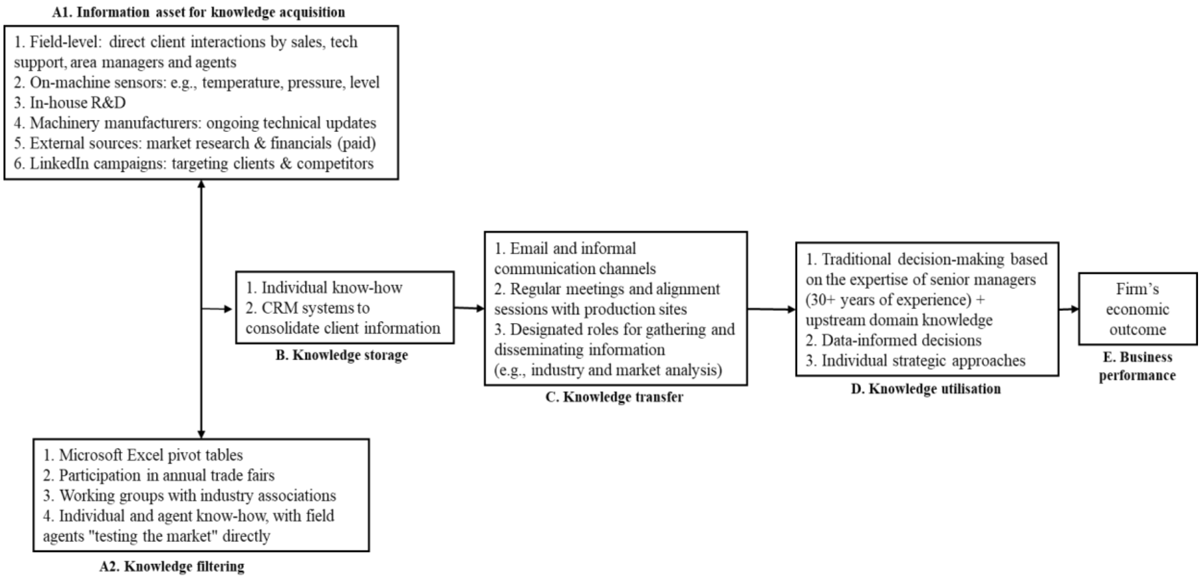

Figure 9: The information flow of the firm under investigation

As evidenced from several interviews, at the initial stage (A1) knowledge acquisition occurs through diverse and heterogeneous channels, including on-site data acquisition through machine-embedded sensors (e.g., temperature and pressure), field-level interactions, internal R&D activities and ongoing technical exchanges with machinery manufacturers. Additional external sources, such as paid market research and LinkedIn campaigns designed to collect insights about clients and competitors, enhance the firm's information ecosystem, facilitating knowledge exchange that actively participates in knowledge creation (Bereznoy et al., 2021). Such a diversification of information sources is essential for generating 'rich' knowledge (Davenport & Prusak, 1998). However, the transformation of raw data into usable organisational information requires filtering mechanisms. This stage (A2) is enabled by both individual expertise, often tacit in nature, and by digital infrastructures such as CRM systems. These tools facilitate the consolidation of data, enabling more structured and comparable insights.

Knowledge transfer (C) is an essential activity encompassing both structured and unstructured processes. The key difference lies in 'explicit knowledge', which is easily transferable, and 'tacit knowledge', which manifests through its practical application. Grant and Phene (2022) identified individuals as the primary repositories of tacit knowledge, which is frequently referred to as '*know-how*' and is exhibited through their practical skills and problem-solving actions (Marjanovic, 2022a).

The firm under investigation maintains designated knowledge dissemination roles and structured alignment meetings; however, most of the communication is conducted through unstructured and offline channels, including messaging platforms and email correspondence. This is indicative of a more general trend that has been observed in industrial environments, where informal networks and tacit knowledge frequently dominate cross-functional exchange (Borzillo & Kaminska-Labbé, 2011). The utilisation of knowledge (D) emerges as a structured process, where traditional decision-making by senior managers coexists with emerging data-informed approaches. In some areas, strategic decisions are still driven by the experiential intuition of long-tenured personnel, while others attempt to integrate upstream domain data into business planning. As declared by I13:

> "There are situations where you make a gut decision. Experience helps you, and in the end, you say: 'I don't need the data because I already know it's like this: I've been through it a hundred times before.' So, you go for it. Smoothly and confidently."[2]

During the last stage of information flow, firms' capacity to effectively mobilise knowledge finds expression in the firm's performance. As eloquently stated by Varadarajan (2020), in a digital, data-rich market environment, a firm's ability to accumulate more comprehensive, timely, granular, and proprietary information and to generate actionable insights from these information assets can have a transformative impact on its strategic decision-making.

2.4.2 Main challenges and 'bottlenecks of information'

Despite benefitting from a solid structure and a KM approach backed by half a century of experience, the findings of this research identify several structural and cultural obstacles that could hinder the effective transmission and exploitation of knowledge within the firm. Indeed, the mere presence of information sources and digital technologies does not inherently result in enhanced decision-making or improved economic results. Instead, it is the firm's systemic capability to create, acquire, contextualise, transfer, and exploit knowledge across functional and hierarchical boundaries that determines its strategic effectiveness.

The assessment of the main firms' challenges is illustrated by the red dotted arrows and boxes in Figure 10. These limitations, which have been described by the participants themselves as "*bottlenecks of information*", appear to be associated with unstructured communication and limited

[2] Supply Chain Manager, interview.

system integration. Left unaddressed, such barriers may compromise organisational learning and strategic responsiveness.

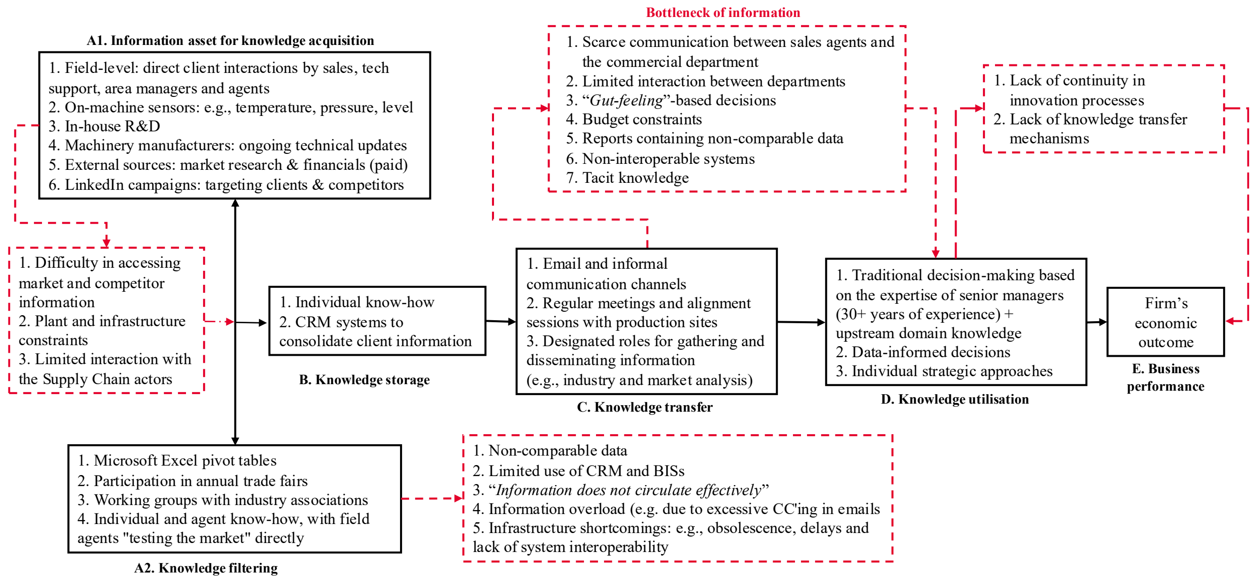

Figure 10: Firm's main bottlenecks of information

Among the main challenges, acquiring and consolidating market and competitor intelligence, sometimes scattered across departments or ingrained in people' tacit knowledge, represent a critical issue, widely recognised within the relevant industry sector. A further bottleneck refers to the limited interaction among functional divisions, e.g., between sales representatives and the R&D team. The prevalence of informal communication channels, such as emails and messaging applications, intensifies the issue of tacit knowledge dissemination and untraceable decision-making. These silos may result in inefficiencies in information transmission and hinder the company from utilising cross-functional insights. Furthermore, the challenge of information overload, evident in duplicate communications or excessive CC'ing, has been reported in many interviews.

From a technological perspective, non-comparable data formats and non-interoperable systems are identified as barriers to knowledge consolidation and reuse. On the other hand, the lack of clearly defined KPIs for BISs may lead to delays in decision-making and uneven performance evaluations. Finally, from an HRM perspective, the "*mental barrier*" encountered by those not employing BI may constitute a significant obstacle. Insights from various managers highlight the often inconsistent adoption of BISs, expressing scepticism regarding the effectiveness of generic BI tools within the unique context of Radici Yarn and claiming the need for "*tailor-made*" solutions.

2.4.3 Adopting BI for overcoming information bottlenecks

In the light of the ROP and the KBV, BISs can represent powerful resolution tools for these KM-related inefficiencies, being them able to aid the organisation in gathering, filtering, storing, transferring, and using knowledge in a coherent and scalable manner. More precisely, the case study conducted at Radici Yarn underscores how BI platforms, when tailored to departmental needs, can structure the collection of fragmented data, enabling a shift from intuition-driven to insight-driven decision-making (Popovič et al., 2019).

By integrating BISs into operational processes, firms like Radici can eliminate long-standing bottlenecks as well as develop dynamic capabilities that improve their adaptability, innovation potential and long-term competitiveness (Torres et al., 2018; Yiu et al., 2020). This function is especially critical in complex manufacturing ecosystems, where the integration of BI with MES platforms facilitates predictive maintenance, adaptive manufacturing and KPI monitoring, enhancing not only efficiency but also strategic foresight (Xiong et al., 2010; Salvadorinho et al., 2020). While MES platforms prioritise the real-time monitoring and management of manufacturing processes, BI adds a strategic layer by transforming core information into actionable insights. Therefore, their combined use signifies a paradigm shift in manufacturing intelligence, guaranteeing operational oversight and situational awareness, as well as long-term value creation through informed and data-driven decisions across the entire value chain. Moreover, BI enables the aggregation and centralised management of both internal and external data via interoperable platforms, consolidating this information into a metadata repository for multi-dimensional analysis (Trkman, 2010). This process enhances the firm's absorptive capacity (Cohen & Levinthal, 1990) and facilitates information prioritisation, ensuring that decision-makers receive filtered and actionable insights instead of unrefined data streams (Davenport et al., 2010). By developing shared dashboards, integrating data streams, and establishing "*standardised and comparable outcomes*" (I5), which enable real-time alignment and collaborative decision-making across business units (Berndtsson et al., 2015), BISs serve an indispensable role in addressing communication issues. Furthermore, the interviewees broadly acknowledge BI's ability to enhance customer satisfaction by delivering trustworthy and timely information, hence improving process efficiency and optimising supply chain management through integration with partners.

In relation to performance monitoring, BI platforms include performance management systems that provide real-time oversight and dynamic goal alignment, hence supporting the coordination of strategic resources in accordance with the ROP (Barney, 1991; Koufteros et al., 2014). Furthermore, ISO 9000-certified firms, such as Radici Yarn, are in a better position to integrate management ISs like BISs for knowledge codification and accumulation (Yoo et al., 2006), since the ISO 9000 series is based on quality management principles that advocate leadership, employee involvement, and a process management approach (Singh et al., 2011). The methodical application of BI at Radici Yarn reinforces the verification of these notions. The respondents declared that they correlate its use with expedited data certification, improved interdepartmental communication, and heightened responsiveness to market and consumer requirements.

In conclusion, the temporal variable has emerged as a common denominator across the research findings. This suggests that the respondents share a competitive necessity to assess data, integrate knowledge, and execute corrective actions promptly. From a time management perspective, BISs provide a wealth of data from historical, present and forecasted perspectives of an organisation's operations.

> "I believe that time is the only factor that can enable us to truly excel in today's market. Everything revolves around the speed at which we can become more sustainable through alternative products, innovative solutions, and recovery processes. In this sense, one of our main 'competitors', or rather one of our greatest challenges, is definitely time: our ability to react quickly."[3]

2.4.4 BI and CSR: a validated path for data-driven responsibility

The importance of a data-informed approach is further demonstrated in the realm of CSR, wherein BI facilitates the measurement and reporting of sustainability performance. A growing body of literature emphasises the potential of BISs to considerably improve an organisation's capacity to achieve sustainability objectives and report progress in a structured and transparent manner, especially when combined with green KM and big data analytics (Cheng et al., 2023). Indeed, the introduction of BI has commenced at Radici Yarn to tackle these concerns, particularly regarding energy use and Environmental, Social and Governance (ESG) performance (Radici Partecipazioni S.p.A., 2023). As evidenced by the CSR Manager, the monitoring of sustainability indicators as well as the granularity and accuracy of the data have been significantly enhanced by BISs. On the other hand, the Purchasing Manager recognised a connection between BI and data certification and traceability, emphasising their crucial role for following binding regulations and attaining rigorous objectives. Lastly, studies have shown that the implementation of BI enhances user productivity by reducing the time and effort required to complete individual activities. From a social sustainability

[3] General Director of the Apparel & Technical division, interview.

perspective, this results in increased users' satisfaction and a heightened sense of empowerment and efficacy in their professional responsibilities (Al-Okaily et al., 2023). When employees are assisted by efficient competitive intelligence tools, the strategic use of information results in greater competitive advantage for the organisation (Heinrichs & Lim, 2005).

2.5 Conclusion

Although business decision-making methods have been profoundly reshaped by globalisation, rapid economic fluctuations and technological progress (Niu et al., 2021), the process of making decisions remains a complex and challenging core activity, especially in high-volatility sectors (Pourshahid et al., 2014). Through a multi-level investigation involving both top management and shop-floor operators at a global chemical manufacturing firm, this research offers an in-depth understanding of how digital platforms transform KM practices. By adopting a conceptual framework grounded in the KBV and the ROP, the study identifies critical "*information bottlenecks*" that obstruct the strategic flow of corporate intelligence. These barriers reflect the challenges associated with knowledge integration, which remains a core capability for firms seeking to maintain a competitive edge in the digital era.

Consistent with prominent scientific literature (Spender, 1996; Yiu et al., 2020), the findings demonstrate that knowledge serves as a crucial asset for optimising organisational resources, fostering both operational efficiency and sustainable competitive advantage. In the specific context of the chemical industry, the integration of BISs represents a paradigm shift, enabling firms to address the escalating complexities of Polymer Informatics and sustainable production. By providing data integration and predictive capabilities, BISs act as strategic enabler for resource orchestration, allowing managers to align shop-floor operational technologies with enterprise-level goals.

Despite these promising results, scholarly literature also underscores that simply providing analytical tools to end-users is inadequate for achieving complete operationalisation. The findings indicate that the effectiveness of BISs is not exclusively a technical achievement but necessitates significant cultural and managerial changes to promote more integrated knowledge practices. In accordance with Jain and Gupta's (2019), this study illustrates that KM enhances performance only when aligned with specific organisational goals. Ultimately, to cultivate unique capabilities and attain sustainable competitive advantage, managers must move beyond data collection toward a holistic orchestration of strategic assets, placing human capital at the centre of the digital transformation journey.

Contributions and implications for research

This work enriches the body of literature on both Technology and Innovation Management (TIM) and KM by supporting and expanding on previous studies on the role of BISs in organisational knowledge processes. In accordance with Aloini et al. (2019), it acknowledges these DSSs as powerful tools for extracting and organising knowledge in complex decision-making environments. Building on Jain and Gupta's (2019) findings that the core of KMSs is stored and captured knowledge, particularly the tacit knowledge of experts that risks being lost, this study also positions BISs as a KM enabler. Specifically, BISs serve as KMSs by facilitating the gathering and transmission of both tacit knowledge, which is inherent in human judgement and routines, and explicit knowledge, which is generated from structured datasets and historical performance (Fernández-López et al., 2018). This dual function aligns with Nonaka and Toyama's (2015) knowledge creation model, emphasising the importance of knowledge transfer within companies and proving the strategic relevance of KM in allowing data-driven and context-sensitive decision-making (Gavrilova & Andreeva, 2012).

Implications for practice

As reported by Bossaller and Million (2023), firms have traditionally spent around 80% of their time on data collection and 20% on analysing it. The goal of BI is to invert these percentages (Ekionea et al., 2021) and improve both the efficiency and effectiveness of individual performance. Particularly within a context characterised by intense international competition, especially from the Far East, time constitutes a critical strategic factor for preserving market competitiveness. Therefore, the promptness of response to market challenges, the implementation of innovative and sustainable products, and the effectiveness of recovery processes facilitated by BI become critical factors. Managers are instrumental in the organisation of BI-related resources, thereby allowing their integration into organisational routines to facilitate strategic action.

Consistent with Olan et al. (2022), BISs allow the firm to capture tacit knowledge dynamics, also addressing the critical family business challenge of "*know-how loss*" during succession. Thus, this research offers practical advice to managers and decision-makers working in knowledge-intensive sectors, especially those managing complex and fragmented information environments within the manufacturing industry.

The findings demonstrate that BISs function as facilitators for knowledge orchestration and organisational learning. Therefore, it is recommended that managers adopt BISs as strategic assets for the creation, storage, dissemination, and use of knowledge across departments. The results suggest that there is a significant amount of variation in BI outcomes based on differences in orchestration practices, even among organisations that employ comparable technological platforms. This perspective transcends static perceptions of BI capabilities and underscores the dynamic processes through which data, technology, and human expertise are transformed into actionable knowledge. The results of the study also underscore the importance of tailored solutions that are aligned with the specific organisational practices, decision-making procedures, and cultural norms characteristic of specific industrial settings. Managers should promote the adoption of co-design methodologies in BI implementation, engaging end-users from different departments to ensure that the solution addresses diverse requirements while maintaining usability and intuitiveness. Furthermore, managers within sustainability departments should utilise BI capabilities to enhance the accuracy of ESG data in compliance with international standards and to strengthen stakeholder engagement (Cerchione et al., 2025a). From a performance management standpoint, BI solutions enable real-time monitoring and facilitate dynamic resource allocation. This fosters a focus on time-based competitiveness, which represents a strategic priority.

Limitations and future research avenues

Despite providing significant insights, this research encounters several limitations, representing avenues for further investigation. First, the study focuses on a singular case study within the chemical manufacturing sector. This methodological approach facilitates an in-depth contextual study, but it limits the generalisability of the results. Thus, future research may employ multiple case study design across various sectors and geographic contexts to validate and compare the findings presented.

Second, the study predominantly utilises qualitative data gathered through interviews and observations. This provides comprehensive insights, although it may be affected by interpretive bias. The adoption of quantitative performance metrics, including BI utilisation rates and alignment scores for KPIs, would enhance the empirical foundation and enable more objective assessments of the impacts of BISs.

Finally, the implementation phase of the BISs was underway during the research, thus restricting the ability to evaluate long-term organisational change. A longitudinal approach should be employed in future studies to track the development of BI-driven practices over time and their incorporation into the firm's strategy and culture.

Chapter 3. Making sense of digital transformation in family firms: Why BI investments need managers to make sense of data

Building upon the findings of the previous chapters, this study aims to investigate why BI investments, despite their strategic value for decision-making, do not automatically translate into effective organizational use. More specifically, this chapter explores whether and how managers function as sense-givers of BI outputs and how sensemaking practices interact with HR mechanisms to influence employees' acceptance and adoption of BI.
Drawing upon Weick's sensemaking perspective, we present an action-research single-case study of Radici Yarn, combining one-year semi-structured interviews with participant observation, system walk-throughs and document triangulation. Findings reveal that managers act as fundamental sense-givers: by filtering, contextualising and reframing system outputs, they increase the plausibility and perceived trustworthiness of BI information. Hands-on practices (e.g., personal data entry and co-creation of reports) strengthen individual BI identity and foster broader adoption. We offer an HR socio-technical model linking managerial sense-giving, targeted HR practices (e.g., training, involvement, role design), and technology acceptance as antecedents of employee BI use. The study extends sensemaking theory to BI contexts and provides actionable guidance for practitioners aiming to convert BI investments into trusted decision support.

3.1 Introduction

> "The challenges we face are far from simple, but we must look constructively to the future by bringing to bear, each one of us, the best of our capabilities and competencies."[4]

Similar to what happens in jazz orchestras, where members must listen closely to each other, take turns leading and following, and respond together in real-time to novel or unexpected performance (Hatch, 1999), much human activity in organisations is concerned with collective efforts to make sense. To make sense of business, individuals bring forward their capacity to act on and influence the organisation and leverage their vision when change runs over their immediate business environment (Namvar & Cybulski, 2014). Especially with reference to major organisational changes, like the

[4] From the letter by shareholders Angelo, Maurizio, and Paolo Radici to employees. Published in VOICES magazine, RadiciGroup, 2014.

introduction of new technologies and company-wide software packages, such as ERP, CRM and BISs, collective efforts to make sense must be managed carefully (Berente et al., 2021).

Empirical research has shown that treating software implementations merely as a technical initiative obscures the psychological and behavioural dynamics that shape their successful adoption. Much of the difficulty, as highlighted by Nickerson (1981) and Dillon and Morris (1996), stems from limited acceptance among organizational members, weakening their willingness to incorporate the technology into everyday practices.

Thus, the construction of identity, at both the individual and organizational levels, becomes a strategic lever for engaging with BI platforms and fostering data-driven transformation. Although end-user satisfaction and actual system use have long been acknowledged as central drivers of IS success, empirical evidence on how organisations can effectively support users in understanding and employing BISs remains relatively scarce.

Eckerson (2004) highlights a series of organisational conditions associated with successful BI initiatives, including a clearly articulated BI scope, a mature analytical structure, favourable executive perceptions, strong data stewardship, adequate financial resources, a robust technological infrastructure, and the adoption of sound change-management and administrative practices. Preparing the workforce for the change and mitigating the potential latent forms of resistance associated with it represents a strategic responsibility of HRM functions. Indeed, understanding the factors that hinder or facilitate BI adoption is essential for informing HRM strategies, which constitute a primary lever for shaping effective digitalisation.

Within the specific domain of family firms, strategic HRM manifests through distinctive HR practices, shaped by the intersection of family and business systems (Hoon et al., 2019; Flamini et al., 2020). A notable body of research has mostly focused on how the owner-family determines the design of the HR practices (e.g., Hauswald et al., 2016), highlighting the idiosyncratic nature of family business human capital (Sirmon & Hitt, 2003) and the prevalence of superior employee relations (De Massis et al., 2018). These dynamics are often rooted in deep-seated personal ties that foster a culture of stewardship and reciprocal loyalty between the owning family and the employees (Carmon et al., 2010; Åberg & Campopiano, 2026). Consequently, being family firms oriented toward the long term, they are perceived as providers of long-term stability and job security (Bassanini et al., 2013), fostering an environment of mutual gains. This unique organizational culture, rooted in familial values, generates a highly committed and productive workforce that constitutes a path-dependent and hard-to-imitate competitive advantage (Ferraro & Marrone, 2016).

Despite growing scholarly attention to these issues, previous research often examines digital tools, technology acceptance models (TAM) and sensemaking theory in isolation, with limited effort to integrate these perspectives into a unified framework. To improve the implementation process of BI and its relation to user acceptance, it seems reasonable to focus on understanding the human factors that are more likely to influence employees' willingness to adopt BISs. Individually, each theory offers only a partial explanation of how firms achieve digital change, but when integrated, they provide a holistic perspective.

Drawing upon general research on technology acceptance in software implementations, as well as the broader domain of one of the most influential perspectives for understanding organizational processes and decision-making, i.e., sensemaking theory (Weick, 1995), this study aims to provide a framework to structure and integrate important management aspects in the context of BI implementation processes within family firms. More precisely, this approach aims to analyse the distinctive features of successful BI implementation by investigating how managers' sense-giving efforts shape employee trust in BI-generated outputs. In addition, it highlights how BI adoption is intertwined with the everyday work practices of employees, shaping both their actions and their sense of meaning of the business environment and organizational life. The study aims to contribute to the literature by addressing the following research question:

RQ5. How do managers give sense to the information provided by BI and thus shape the construction of meaning for employees?

The subsequent sections are structured as follows: Section 2 delineates the theoretical background with a particular focus on the related literature on BISs, TAM, HRM practices and sensemaking theory to provide the necessary background information for the study. Section 3 details the methodological approach adopted to collect and analyse the data concerning the family firm under investigation. Section 4 offers a summary of the key findings, followed by Section 5, which concludes the study while also suggesting implications, limitations and potential avenues for future research.

3.2 Theoretical background

3.2.1 BISs: an overview of relevant literature

By delivering actionable information at the right time, at the right place and in the correct form to make the right decisions at all levels (Negash & Gray, 2008), BISs provide accessible knowledge that enhances business performance and enables superior organizational outcomes (Cerchione et al., 2025). Their capability to detect market opportunities and threats, as well as to respond to technological shifts and competitors' moves, makes BISs powerful tools for organisational adaptability (Park et al., 2017).

Nonetheless, despite allowing better knowledge processing, shorter decision time and smaller decision costs (Rouhani et al., 2016), and thus being an area of continuous interest, BI implementation processes do not necessarily translate into successful projects. As evidenced in prior IS research, common factors related to users' interpretations and attitudes, rather than technical features, can determine resistance to change, especially 'technophobia' (Townsend et al., 2000). These include lack of trust, belief that change is unnecessary and not feasible, fear of personal failure, threat to values, and loss of status and power. Furthermore, although most employees own basic technological competencies, many fail to recognise the necessity of BI adoption.

In line with the TAM, discrepancies between desired and actual performance of ISs persist when users do not perceive a system as useful, regardless of its objective benefits (Davis et al., 1989). Accordingly, the successful integration of BISs depends heavily on how employees interpret, trust, and enact BI outputs (Järvenpää et al., 2023). From this viewpoint, the introduction of a BIS represents an organizational change requiring targeted management strategies and clear communication plans to ensure higher levels of employees motivation, acceptance and satisfaction (Long & Spurlock, 2008). Consistent with Cox (2004), adequate supporting structures and communication plans should precede any major technological transformation. The socio-cognitive dimension of BI adoption is relevant across all organisational contexts, but it is especially significant in family firms. In such cases, the use of data-driven technology is motivated not only by efficiency but also by a fundamental commitment to preserving SEW. According to the FIBER model (Berrone et al., 2012; Swab et al., 2020), family enterprises are driven by non-economic objectives, including family control and influence (F), identification of family members with the firm (I), strong social bonds (B), emotional connections among family members (E), and the strengthening of family ties (R). Consequently, the deployment of BI transcends a merely instrumental purpose and serves to formalise and safeguard emotional commitment. This tension is further intensified by the widespread integration of predictive AI within traditional BI architectures.

Prior studies characterise this phenomenon as a '*techno-socio paradox'* (Smith & Lewis, 2011; Svahn et al., 2017): while AI-driven analytics promote innovative and intelligent capabilities (Di Meglio et al., 2025), their inherent algorithmic opacity undermines the trust, transparency, and proximity that are extremely important to family governance. As decision-making authority transitions from the discretionary judgement of family proprietors to sophisticated AI models, often referred to as 'black boxes', the perception of family control and cohesive social ties may diminish, and automated outputs may be perceived as detached from the family's identity and fundamental values. Recent studies underscore the essential function of a robust BI infrastructure in guaranteeing the reliability of BISs as a digital repository for tacit and experiential knowledge, thereby supporting the intergenerational transfer of the family's intellectual capital (Woodfield & Husted, 2017; Cirillo et al., 2022) and the effective deployment of Intelligent Agents (Olan et al., 2022; Wang et al., 2022). However, technological robustness alone is insufficient to address the techno-socio paradox. Conversely, the effective integration is strongly contingent upon the managerial responsibility of ‘giving sense’ to both the tool and the process. Defining the scope for BI to achieve a shared understanding of the necessary reports, in alignment with the organisation's goals, culture, and structure, constitutes a fundamental initial step in the formation of BI identity at the organisational level (Davenport, 2010). On the other hand, it necessitates a more efficient and meaningful use of analytical tools at the individual level (Namvar & Cybulski, 2014).

Within family businesses, the protection of SEW may explain resistance to digital investments, but it can also motivate digital innovation when such investments are perceived as mechanisms to sustain and transmit family legacy across generations (Appleton et al., 2025). This conceptualisation is consistent with the evidence that family firms' digital strategies are influenced by their objectives for long-term continuity and control, which demonstrates how SEW both facilitates and restricts digital transformation initiatives (Ko et al., 2025). The protection of SEW is the foundation of the resistance to 'black-box' algorithms in family firms (Asif et al., 2025). Thus, the managerial responsibility of giving sense should advance towards the adoption of XAI, enabling organisational leaders to make algorithmic results comprehensible, thereby guaranteeing that data-driven insights are transparent and aligned with the organisation's fundamental principles of legitimacy and trust (Asif et al., 2025). In this case, managerial sensegiving functions as a translation mechanism, aligning AI with the family's stewardship values and making it interpretable.

3.2.2 The sensemaking process

Defined as the process through which individuals work to understand novel, unexpected, or confusing events (Weick, 1995), sensemaking has generated various streams of research, especially burgeoning within the field of management studies (Maitlis & Christianson, 2014) since the publication of Weick’s (1995) classic text ‘Sensemaking in Organizations’.

At the basis of sensemaking there is a trigger, generally produced by discrepant events or surprises that are great and important enough to cause individuals to ask what is going on and what they should do next (Louis, 1980). Mostly portrayed as based on individual development of mental models, its aim is to “make sense” of what has occurred by extracting and interpreting cues from the environment (Weick, 1995; Maitlis, 2005). Crucially, sensemaking extends beyond simple interpretation, involving the active authoring of events and frameworks, as people play a role in constructing the situations they attempt to comprehend (Weick et al., 2005; Sutcliffe, 2013). In this perspective, several scholars emphasise the inherently social character of sensemaking, describing it as an interactive process through which individuals collectively construct, negotiate, and sustain shared interpretations of meaning (Gephart et al., 2010).

Sensemaking is closely connected to the complementary process of sensegiving, which refers to managerial efforts to steer how others interpret unfolding events and, ultimately, how they reframe their understanding of organizational realities (Gioia & Chittipeddi, 1991). Much of the literature examines sensegiving as a leadership practice, reflecting longstanding views of leadership as an activity aimed at shaping meaning within organisations and seeing sensemaking as a core component of effective leadership behaviour. At the same time, research has shown that middle managers can also be powerful sensegivers, given their position at the intersection of multiple managerial groups and their ability to mediate, integrate, and translate the interpretations emerging across the organisation (Beck & Plowman, 2009).

Leaders often initiate sensemaking by first engaging in sensebreaking, i.e., the "*destruction or breaking down of meaning*" (Pratt, 2000, p. 464), which can motivate people to reconsider the sense that they have already made, to question their underlying assumptions, and to re-examine their course of action (Lawrence & Maitlis, 2012). Following this, leaders or organisations fill this meaning void by shaping new positive understandings through sensegiving (Pratt, 2000). When leaders successfully influence members' sensemaking, individuals are motivated to change their roles and practices (Corley & Gioia, 2004). However, as they are not passive recipients, they engage in their own sensemaking and may adopt, alter, resist, or reject the meaning they have been given (Gioia et al., 1994; Sonenshein, 2010). When sensemaking or sensegiving fail, so too may a change initiative.

Weick (1995) identified seven properties of sensemaking, i.e., grounded in identity construction; retrospective; enactive of sensible environments; social; ongoing; focused on and by extracted cues; and critically, driven by plausibility rather than accuracy, among which identity covers the very first place. When individuals perceive that the basis of who they are is being questioned or undermined, they are prompted to interpret the source of the disruption and to rebuild meanings that help restore a coherent sense of self. Maitlis' (2009) study of professional musicians illustrates such a dynamic: an unexpected injury that prevented them from performing not only interrupted their work but also destabilised their very sense of identity, compelling them to re-examine and reconstruct who they understood themselves to be. Likewise, in turbulent environments characterised by hypercompetition, major technological advances and government regulatory changes, prior cognitive frameworks can suddenly lose their meaning, placing significant demands on managerial sensemaking (Bogner & Barr, 2000). In these cases, where market competition is defined by the ability of firms to change competitive posture quickly, an RBV emphasising the cumulative weight of past decisions on future strategy may cause counterproductive rigidity and may be deluding. On the opposite, theories like the dynamic capabilities theory, emphasising the importance of reconfiguring resources in response to environmental changes (Teece et al., 1997), may be helpful for developing cognitive diversity, implementing rapid decision-making, and taking experimental action (Eisenhardt, 1989b). In cases like this, organisations often rely on what is defined as '*adaptive sensemaking'* (Bietti et al., 2019): the literature on sensemaking in organisations identifies three specific activities that are frequently used to build frameworks at an intrafirm level in organisations facing turbulent environments: developing cognitive diversity (Lyles & Schwenk, 1992), implementing rapid decision-making (Eisenhardt, 1989b), and taking experimental action (Weick, 1995). Therefore, the successful integration of organizational initiatives is contingent upon managers actively convincing others of the value of change through sensegiving (Denis et al., 1996).

Consistent with scholars who emphasise the collective nature of sensemaking, this study focuses on the social dynamics of sensemaking in organisations, rather than on individuals' interpretive acts. Scientific literature recognises BI as supporting sensemaking in five areas of Weick's model, specifically, retrospection, social environment (Imhoff & White, 2011), cue extraction (Maitlis & Christianson, 2014), plausibility (Olinsky & Schumacher, 2010) and the ongoing nature of the sensemaking process (Foody, 2009). In particular, Järvenpää et al. (2023) elaborated on the role of BI in creating a retrospective view of the organisation by capturing data into enterprise systems and data warehouses. At the same time, prediction models are a major part of BI, used to provide decision-makers with advice on plausible outcomes of business activities. Environmental cues are continuously monitored via dashboards, scorecards and alerts to highlight changes in the business and its environment. Furthermore, some of the more recent BI tools are integrated with collaborative systems to facilitate communication and cooperation between managers and employees.

While innovation research in family enterprises has traditionally concentrated on product or process innovation (Röd, 2016), the burgeoning literature on digital transformation uncovers additional dimensions, foreshadowing the strategic role of managers in interpreting the strategic complexity of family-controlled organisations. Digital transformation necessitates simultaneous modifications to governance frameworks and technological competencies, representing a unique type of innovation (Bornhausen & Wulf, 2024).

3.2.3 The TAM

Notably, resistance towards technology, which can derive from the so-called '*technological anxiety'* (Kamal et al., 2020), i.e., the fear or apprehension that people experience when they begin to consider using or start using a technology they have not used before, decreases the intention of use. Thus,

understanding why people accept or reject new technologies has proven to be one of the most challenging issues in ISs research (Swanson, 1988).
In the last decades, different prominent theories, frameworks, and models have shaped the field of technology adoption, e.g., TAM (Davis, 1989; Davis et al., 1989), technology-organization-environment (TOE) framework (Tornatzky & Fleischer, 1990), the theory of planned behavior (Ajzen, 1991), DOI theory (Rogers, 1995), and unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2011). Following these research streams, several investigators have studied the impact of users' internal beliefs and attitudes on their usage behaviour (Swanson, 1987), and how these internal factors are, in turn, influenced by various external variables, such as the system's technical design characteristics (Malone, 1981), the user involvement in system development (Franz & Robey, 1986), the nature of the implementation process (Ginzberg, 1978), and the cognitive style (Huber, 1983). Fishbein and Ajzen's 1975 theory of reasoned action (TRA), "designed to explain virtually any human behaviour" (Ajzen & Fishbein, 1980, p. 4), is an especially well-researched intention model that has proven successful in predicting and explaining behaviours. According to TRA, a person's performance of a specified behaviour is determined by his or her behavioural intention to perform the behaviour, and behavioural intention is jointly determined by the person's attitude and subjective norm concerning the behaviour in question.
Davis (1989) introduced an adaptation of TRA, the TAM, which explains the intention to use through the constructs ‘attitude toward using’, ‘perceived usefulness’ and ‘perceived ease of use’. Perceived usefulness (PU) is defined as “*the degree to which an individual believes that using a particular system would enhance his or her job performance*", defined as ‘*performance expectancy*’ by Venkatesh et al. (2003). On the other hand, perceived ease of use (EOU), defined as “*the degree an individual believes that using a particular system would be free of effort*” (p. 320), has been described as ‘effort expectancy’ by Venkatesh et al. (2003). Finally, the TAM suggests that perceived usefulness is influenced by EOU.
Over the years, several approaches have been developed to explain users’ satisfaction and attitudes, especially to facilitate and enhance the level of technology acceptance for employees. The TAM framework has been enriched by incorporating additional constructs that account for social and organizational dimensions disregarded in the original formulation. Subjective norms, conceptualised as an individual's perception of whether significant others approve or disapprove of a particular behaviour (Fishbein & Ajzen, 1975), have emerged as particularly salient in organizational settings where hierarchical relationships and peer influences shape technology adoption decisions (Venkatesh & Morris, 2000). Empirical evidence demonstrates that social influences exerted by supervisors, colleagues and other organizational referents substantially affect perceived usefulness assessments,

thereby indirectly shaping behavioural intentions toward system adoption (Schepers & Wetzels, 2007). Beyond social factors, scholars have identified affective and experiential dimensions as meaningful determinants of technology acceptance. For instance, Yang et al. (2015) demonstrated that perceived enjoyment and perceived self-expression constitute distinct antecedents influencing adoption intentions. The hedonic dimension of technological use has also received growing attention, with research examining how pleasure, intrinsic satisfaction, and value creation for users complement utilitarian motivations in driving adoption (Wang & Sun, 2016). Conversely, perceived risk has been identified as a significant inhibitor of technology acceptance, particularly when employees anticipate negative consequences from system failures and data security violations (Magni et al., 2021). Even though HRM variables are particularly relevant for guiding a successful implementation, few attempts have been undertaken to integrate them into the TAM. Few authors, especially adopting a change management perspective, such as Amoako-Gyampah and Salam (2004), proposed training, communication and shared beliefs as primary antecedents of TAM variables in organizational IT implementation projects. As such, even less is known about the combined adoption of the TAM and the sensemaking theory during technology implementation processes, especially in the case of BISs within family firms.

3.2.4 HRM interventions and organisational factors

These theoretical foundations establish that effective IT integration necessitates coordinated technical and social change. Despite this recognition, such implementation projects frequently proceed without the systematic engagement of HRM professionals at the conceptual or operational levels. On the contrary, strategic HR interventions, i.e., "organisational *actions or processes and job characteristics that focus on attracting, developing and motivating employees*" (Boon et al., 2019, p. 2518), are essential to reconcile technological affordances, organizational objectives and individual user needs, thereby constituting a fundamental facilitating condition for BI adoption (Venkatesh et al., 2003; Bondarouk & Looise, 2005). Individuals' acceptance of new information can lead to changes in their existing beliefs or the creation of new ones regarding technology adoption. Consequently, communicating knowledge about possible benefits deriving from new software can cause changes in users' attitudes toward system use. Reference groups may convey the expectation or request for system use, which in turn shapes end users' perceptions through social influence mechanisms. Likewise, user training represents a crucial process variable for successful implementation (Nah & Delgado, 2006) and constitutes an important factor influencing user acceptance (Schillewaert et al., 2005). Multiple studies have demonstrated effects of training programmes on PU and PEOU (Rouibah et al., 2009).

Strategic HRM and the related practices are crucial in the innovation process, since scholars assume that a firm's ability to innovate resides in its employees and thus their capabilities and motivation (Jimenez-Jimenez & Sanz-Valle, 2008). For these reasons, many efforts to address failures and problems of technology introduction have been reconducted to the execution of specific HR practices (e.g., Jiang et al., 2012). Among them, Boon et al. (2019) identify six primary practices: training and development, participation/autonomy, incentive compensation, performance evaluation, selection, and job design. These necessary HR interventions span several critical dimensions, including job design, which involves the explicit definition and reassignment of tasks to be automated, and resource flow, which focuses on the structural management of personnel, including defining a recruiting policy oriented toward developing career plans in response to the new technological work situation (Bondarouk & Looise, 2005). Another critical dimension involves communication and participation, ensuring active user participation in decision-making and defining their training needs. Finally, performance and reward focus on adapting compensation plans, regularly evaluating IT use, and formally recognising progress to reduce the behavioural friction of change (Bondarouk & Looise, 2005). The implementation must incorporate mechanisms that provide an immediate benefit or a sufficient feedback loop to the employees who input data, as the lack of incentive diminishes the stimulus for consistent usage. From a broader perspective, considering the complex interaction between employers and employees and their often divergent interests (Guest, 2017), achieving congruence between organizational and employees' goals can be challenging (Argyris, 2017). In this context, successful BI assimilation requires organizational support that accounts for cultural and behavioural complexities, as technological potential alone remains insufficient without the human 'sensegiving' component. This process is further moderated by top management commitment (El-Kassar & Singh, 2019), which, when coupled with a proactive HR function, becomes instrumental for establishing a receptive organizational culture and mitigating employee resistance.

3.2.5 The conceptual framework

Although the TAM has been widely used to explain why individuals choose to adopt or reject a system, its focus remains largely on cognitive evaluations made by users, leaving in the background the social and interpretive processes through which these evaluations emerge. By contrast, sensemaking scholarship highlights how people within organisations jointly develop meanings when confronted with novel or uncertain circumstances, yet its application to IS contexts is still relatively limited. At the same time, strategic HRM research underscores the importance of HR practices in enabling organisational change but seldom examines how these practices intersect with technology adoption or with the interpretive work required in transitions toward data-driven ways of operating. This theoretical fragmentation creates significant explanatory gaps.

The framework proposed in Figure 11 addresses these gaps by positioning managerial sensegiving as the critical mediating mechanism linking BISs to employee acceptance. Drawing upon Weick's (1995) conceptualisation of sensemaking as an ongoing, social, and identity-driven process, we argue that managers, particularly middle managers occupying boundary-spanning positions, function as essential sense-givers who actively construct plausibility around BI outputs. This sensegiving involves three interconnected activities: filtering data streams to direct attention toward strategically relevant information, contextualising metrics by anchoring them within specific business realities, and reframing results through narrative construction that renders machine-generated conclusions credible to human decision-makers. Through these interpretive efforts, managers transmit information while also actively authoring the organizational meaning of data, thereby influencing the very perceptions that TAM identifies as determinative of acceptance.

The empirical investigation that follows examines how these theoretical relationships manifest within a manufacturing firm navigating the complex transition toward data-driven operations, revealing both the enabling mechanisms and persistent obstacles encountered when attempting to bridge technological potential with human acceptance in practice. The specific patterns, relationships, and contingencies identified through inductive case analysis will elaborate and refine the conceptual relationships presented here, demonstrating how sensegiving, HRM practices, and technology characteristics interact to shape adoption trajectories in real organizational contexts.

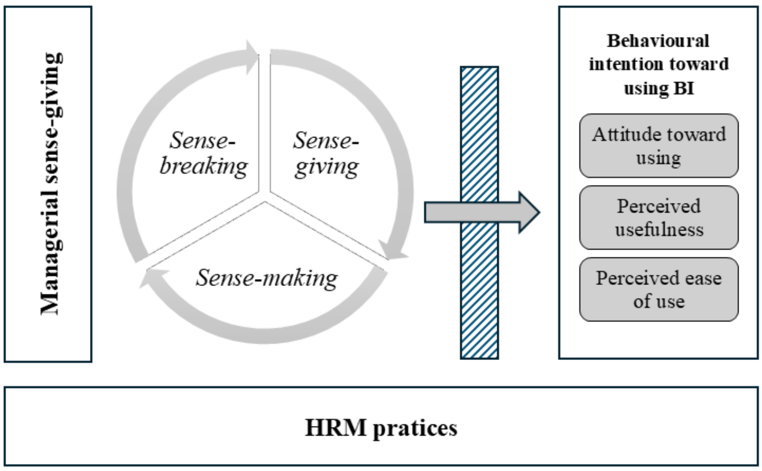

Figure 11: The sense-making theoretical framework

3.3 Material and methods

This study draws on an exploratory single-case design (Stake, 1995), enriched by an ethnographic orientation (Atkinson & Hammersley, 1994). This approach is based on the examination of a contemporary phenomenon within its real-life context, especially where the boundaries between the phenomenon and its environment are blurred (Yin, 1984). In addition, the ethnographic stance is strategic for observing sensegiving in action, offering a privileged point of view to insights that would otherwise remain inaccessible. Such a methodological configuration is well suited for investigating dynamic and socially embedded processes that depend heavily on actors' interpretations (Hinings, 1997), making it particularly apt for analysing BI sensemaking and sensegiving dynamics; while semi-structured interviews provide the articulation of explicit views and retrospective accounts, participant observation allows for the capture of tacit practices, specifically how managers filter, contextualise, and legitimise BI outputs in their daily workflows.

The fieldwork was conducted at Radici Yarn S.p.A., a family firm undergoing a strategic digital transformation centred on the integrated implementation of both a BI platform and MES. This empirical investigation spanned over one year, from July 2024 to September 2025, and was designed following a triangulated qualitative strategy combining semi-structured interviews, semi-participant observations, and document analysis (Yin, 1984). Following Miles and Huberman's (1984) principle that social behaviour must be interpreted within its context, this study acknowledges that organizational actions and meanings cannot be understood independently of the social, technological, and structural environment in which they occur. Thus, central to the research design was the role of one of the researchers as an 'action researcher' (Walsham, 1995; Marjanovic, 2022b), fully embedded within the organisation, attending the workplace five days per week. This immersive role allowed the researcher to participate in daily operations, strategic meetings, and informal exchanges, gaining access to both formal and tacit dimensions of organizational life. In exchange for this privileged access, the researcher contributed to support activities such as data analysis, BI user training and the facilitation of internal communication. This two-way interaction created an atmosphere of trust and legitimacy, which was necessary for getting authentic and detailed information. Finally, comprehensive 'walk-through sessions' of the company's technological platforms, conducted with the IT team and experienced BI practitioners, offered a detailed understanding of the socio-technical infrastructure underlying managerial decision-making and knowledge-sharing processes. This methodological approach is essential for the theoretical advancement of the family business field: this longitudinal action research captures the micro-foundations of SEW in real-time, in contrast to quantitative studies that infer SEW from proxy variables such as ownership percentages or board composition (e.g., Gomez-Mejia et al., 2007). By observing the "*sensegiving process*" from within,

this study reveals the concealed mechanisms, such as emotional reassurance and identity alignment, through which family owners and managers reconcile the conflicting logics of tradition and digitalisation. This approach enables an examination of the "black box" of familial decision-making amid substantial technological transformations, so providing comprehensive evidence of the preservation of Binding Social Ties (specifically, “B” of the FIBER model).
The study further benefited from the active involvement of senior management, whose visible commitment to the research facilitated participant engagement and reinforced the project’s legitimacy within the organisation. Additional data sources, including internal documents, press releases, and corporate websites, were examined to ensure theoretical triangulation and strengthen interpretive validity (Darke et al., 1998).

3.3.1 The case study

Established in Villa d’Ogna (Bergamo), Italy, Radici Yarn distinguishes itself as a company of excellence. The firm is specialised in producing polyamide 6 polymers, which are then transformed into a diverse portfolio of yarn and staple fibre solutions serving multiple industrial applications.
This study focuses on this specific firm for three main reasons. First, companies operating in this sector face saturated and highly competitive markets, where the ability to promptly manage information flows is a critical success factor (Hutcheson et al., 1995), along with the use of advanced ISs to swiftly adapt to market changes and customer needs (Guisinger & Ghorashi, 2004). Second, the escalating digitalisation of chemical manufacturing processes has determined a wider adoption of technological platforms aimed at enhancing responsiveness, visibility, and decision-making quality, including BI and shop-floor operational technologies, like MES (Xiong et al., 2010). Moreover, as a global firm prioritising innovation and HRM, Radici Yarn represents a relevant case study for examining how managerial sense-giving mediates between BI implementation and employee acceptance.
On the other hand, Radici Yarn is particularly relevant as a family firm not only due to its ownership structure, which is rooted in eight decades of manufacturing tradition, but also because of the way family influence manifests through HR practices that are deeply embedded in the local territory. Located in an Italian inner mountain area marked by demographic decline and limited career opportunities, it operates as a place-based industrial steward, offering stable employment, skill development, and career paths that allow individuals to remain rooted in the community while engaging with global markets. This territorial embeddedness, coupled with strong family involvement in governance, has fostered long organizational tenures, dense relational ties, and a culture centred on people as the firm’s primary strategic asset. In such a context, employees’ acceptance of digital

transformation is closely intertwined with issues of identity, trust, and perceived continuity of work practices. In light of these peculiarities, Radici Yarn represents a robust empirical setting to examine how family-driven values and strategic HRM practices shape managerial sensegiving and sustain employee engagement amidst data-driven change.

3.3.2 Data gathering

A total of 30 organizational members participated in the study. The sample was intentionally structured to capture heterogeneous perspectives across hierarchical layers and functional domains. Specifically, 16 participants were managers and executives (reported in Table 3 as #I), holding roles such as heads of finance, IT, and quality departments, whereas the remaining 14 participants were operational and technical staff from production units on the shop floor (reported as #O), including department heads, shift supervisors, plant managers, line supervisors, and process technologists. This sampling strategy ensured exposure to both strategic and operational decision-making processes, enabling the study to validate managerial interpretations while simultaneously incorporating the day-to-day experiences of those who interact with BISs in practice. Table 3 summarises the profile of the interviewees.

Table 3: Participants' details

ID	Gender	Function	Current role	Management tenure	Date of interview
I1	M	General Management	General Director of the Apparel & Technical division (part of ATS); Interim roles in commercial and marketing	3 years	29/07/2024
I2	M	Sales	Sales Manager Apparel & Technical	19 years	29/07/2024
I3	M	ICT	IT Team	12 years	29/07/2024
I4	M	Quality A&T and Site Manager	Lab Manager; Interim Site Production Manager of Industrial Services in another facility	17 years	30/07/2024
I5	M	Technical Assistance	Technical Assistance Manager	6 years	30/07/2024
I6	M	Production	Production Manager	1 year	01/08/2024
I7	M	Purchasing & Logistics	Purchasing / Supply Chain Manager	35 years	01/08/2024
I8	F	CSR	CSR Manager	17 years	02/04/2025
I9	M	R&D	R&D Manager for the textile area	27 years	02/08/2024
I10	F	Marketing	Strategic Marketing Manager	30+ years	22/08/2024
I11	M	Sales	Area Sales Manager	15 years	01/04/2025
I12	F	Strategic Sales	Strategic Sales Manager	5 years	03/04/2025
I13	F	Credit	Credit Manager	22 years	07/04/2025
I14	M	R&D	Product Development Manager	5 years	08/04/2025
I15	M	HR	HR Manager	23 years	09/04/2025
I16	F	HR	HR Business Partner & Business area ATS Training Coordinator	8 years	12/04/2025
O1	M	POY	Department Manager	37 years	19/03/2025

O2	F	POY	Assistance Department	2 years	19/03/2025
O3	M	Warehouse	Warehouse Manager	37 years	19/03/2025
O4	F	Maintenance & Utilities	Utilities Manager	6 years	11/04/2025
O5	M	Staple Fibre	Shift Supervisor	10 years	21/03/2025
O6	M	Filtration & Sorting Room	Department Manager	2 years	25/03/2025
O7	M	Filtration Room	Department Manager	5 years	25/03/2025
O8	M	Production	Process technologist	18 years	25/03/2025
O9	M	Quality	Quality Manager	1 year	26/03/2025
O10	M	Production	Site Manager	14 years	27/03/2025
O11	M	Polymerisation	Department Manager	40 years	07/04/2025
O12	M	Polymerisation	Deputy Supervisor	30 years	07/04/2025
O13	M	Safety	SPP (Prevention & Protection Service)	30 years	09/04/2025
O14	M	Quality	Lab Manager	40 years	16/04/2025

The heterogeneous composition of the interviewee sample facilitated the inclusion of various, sometimes opposing perspectives, which contributed to a more thorough understanding of how BI contributes to organizational sensemaking across different levels. For instance, the ICT team provided detailed input on the technical aspects and current usage of BI tools, whereas end-users from various functions emphasised practical needs and preferences, such as regarding easy-to-use dashboard interfaces. The sample offers substantial analytical value, as many interviewees have spent several decades within the organisation. Such lengthy tenures, peculiar to family firms, provide a deep knowledge of the firm's routines, cultural norms, and decision-making practices, allowing for a rich understanding of how BI can be interpreted, incorporated, and negotiated within a long-established managerial context.

The duration of each session was approximately 1.5 hours, and interviews were video-recorded and transcribed verbatim, with all participants providing informed consent for data recording and processing. While most of the interviews were conducted online to accommodate participants' availability, in-person interviews were also held with those present at the company site during the research team's on-site visits. Anonymity was preserved using role descriptors and business unit references.

3.3.3 Data analysis

The analytical approach followed an interpretive, theory-informed orientation aimed at tracing how sensemaking dynamics and HR practices emerged, evolved, and intertwined within the flow of everyday interactions and technology use. Analytical rigour was ensured through a systematic combination of thematic coding procedures and triangulation techniques.

Drawing on Fereday and Muir-Cochrane's (2006) conceptualisation, thematic analysis served as the primary method for pattern recognition, enabling the identification of salient themes emerging from the empirical material. The coding process unfolded iteratively across multiple phases: initially, open coding integrated "in vivo" codes, preserving participants' authentic language, with theoretically constructed codes representing fundamental conceptual dimensions, thereby mapping respondents' initial sense-making frames (Glaser & Strauss, 1967; Charmaz, 2014). Subsequently, through axial coding, first-order concepts were systematically grouped to clarify underlying relationships, progressively abstracting toward second-order themes and higher-order aggregate dimensions. A distinctive feature of the analytical approach involved member validation: case findings were presented to interviewees for scrutiny and corroboration, enabling confirmation of interpretive accuracy while minimising researcher bias.

To deepen contextual comprehension, interview material was systematically triangulated against multiple documentary sources, including organizational codes of conduct, annual financial reports, and sustainability disclosures, thereby strengthening analytical rigour and enhancing interpretive validity. QDA Miner software facilitated the manual coding process, enabling systematic data organisation and comparative analysis (Lewis & Maas, 2007). The complete coding structure is detailed in Table 4.

Table 4: Coding tree.

First-order theme	Second-order theme	Aggregate dimension
Cultural transition explanation	MANAGERIAL FRAMING AND COMMUNICATION	**MANAGERIAL SENSEGIVING**
Strategic vision articulation		
Narrative construction around BI value		
Need for initial training	TRAINING & COACHING	
Ongoing skill development		
Hands-on practice facilitation		
Managerial data oversight	RESOURCE ALLOCATION & GOVERNANCE	
Data integrity verification		
Dedicated resource assignment		
Encouraging dialogue & ideas	INTERPRETIVE DIALOGUE	
Co-creation of meaning		
Contextualising system outputs		
Daily decision velocity	TIME ADVANTAGE & REAL-TIME REACTION	**PERCEIVED USEFULNESS (PU)**
Time as a key competitive factor		
Responsiveness to market changes		
Need for data certification	DATA RELIABILITY AND UNIFORMITY	
Single source of truth		
Elimination of information fragmentation		
Strategic decision-making	DATA-DRIVEN DECISION QUALITY	
Traditional decision-making (negative contrast)		
Solid informational foundation		
Shift to strategic work	SCOPE OF BI/ROLE DESIGN	
Data interpretation focus		
Enhanced analytical capability		
Personal fulfilment from BI mastery	EMPLOYEE SATISFACTION	

Adoption driven by superiority		
"*Success is usage*"	USAGE AS MEASURE OF SUCCESS	
Engagement metrics as validation		
Visual involvement (dashboard effect)	USABILITY AND USER-FRIENDLINESS	**PERCEIVED EASE OF USE (EOU)**
Universal usability		
Intuitive interface design		
SAP inflexibility	INTEGRATION WITH WORKFLOW (ERP)	
System rigidity conflict		
Workflow disruption vs. enhancement		
Performance issues	SYSTEM PERFORMANCE & RELIABILITY	
Response time expectations		
System availability concerns		
Visible management commitment	MANAGERIAL ENDORSEMENT	**SUBJECTIVE NORMS / SOCIAL INFLUENCE**
Leadership role modelling		
Executive expectation setting		
Colleague adoption behaviours	PEER USAGE PATTERNS	
Social proof of utility		
Informal learning networks		
Organizational expectation communication	NORMATIVE PRESSURE	
Performance evaluation linkage		
Cultural norms around data usage		
Extreme scepticism / resistance	ATTITUDE / MINDSET (RESISTANCE)	**EMPLOYEE FACTORS (ATTITUDINAL BARRIERS)**
Preference for comfort zone		
Scepticism towards algorithms		
Fear of Job loss/replacement	JOB FEARS / IDENTITY THREAT	
Threat to professional expertise		
Loss of decision autonomy		
Managerial distrust in BI results	LACK OF TRUST IN BI/AI	
Perceived lack of contextual understanding by systems		
Over-reliance concerns		
Lack of potential perception	COMPETENCIES & DATA LITERACY GAP	
Digital skills deficit		
Generational divide		
System integration challenge	TECHNICAL INFRASTRUCTURE	**FACILITATING CONDITIONS**
Data architecture quality		
Platform interoperability		
IT support availability	ORGANISATIONAL SUPPORT	
Management commitment (visible resources)		
Budget allocation adequacy		
Workflow integration friction	COMPATIBILITY WITH EXISTING SYSTEMS	
Legacy system constraints		
Data flow continuity		
"*Training based on generation*"	TRAINING PROGRAMS	**HRM PRACTICES (FACILITATING CONDITIONS)**
Lack of refresher courses		
Task-based vs. generic training		
Missing feedback loop/incentive	INCENTIVES & FEEDBACK	
Recognition for data quality contributions		
Performance evaluation integration		
Hands-on participation	PROCEDURAL INVOLVEMENT	

Co-creation of reports		
User customisation enablement		
Loss of organizational knowledge	KNOW-HOW RETENTION	
Need for dedicated resources		
Succession planning gaps		
Managerial distrust in BI Results	TRADITIONAL DECISION-MAKING	
Gut-feel vs. data-driven tension		
Hierarchical approval dependencies		
Resistance to change	LACK OF INNOVATIVENESS CULTURE	
Risk aversion		
Incremental vs. transformational orientation		
Paternalistic culture	FAMILY FIRM DYNAMICS	
Long-term employment orientation		
Informal governance structures		
Willingness to adopt	BEHAVIOURAL INTENTION TOWARD USING BI	**BEHAVIORAL OUTCOMES**
Intention to integrate into workflow		
Openness to learning		
Frequency of use	ACTUAL SYSTEM USE	
Breadth of feature adoption		
Continued vs. discontinued use		
Shadow system maintenance	WORKAROUND BEHAVIOURS	
Parallel manual processes		
Selective compliance		
Personal data entry and ownership	INDIVIDUAL BI IDENTITY CONSTRUCTION	**BI IDENTITY**
Psychological ownership of BI outputs		
Self-efficacy development		
Shared understanding of BI scope	ORGANIZATIONAL BI IDENTITY	
Data-driven culture emergence		
Collective commitment to analytics		

3.4 Case results

This section presents the empirical findings derived from the integrated analysis of interview transcripts, observation protocols, and documentary evidence collected throughout two years of fieldwork at Radici Yarn. The analysis reveals several aggregate theoretical dimensions that clearly outline how managerial sensegiving activities mediate the relationship between BIS deployment and employee adoption patterns.

3.4.1 Managerial sensegiving as interpretive mediation

The first aggregate dimension addresses the central mechanism through which BISs transition from mere technical infrastructure to organizationally meaningful decision-support tools. Drawing on Weick's (1995) conceptualization of sensemaking as a social, ongoing process grounded in identity construction, this dimension reveals that managers function as essential interpretive mediators who actively filter, contextualize, and legitimize system outputs to render them plausible and actionable for organizational members. This finding extends prior research by demonstrating that in BI environments characterized by high data volume and growing algorithmic opacity, managerial mediation becomes constitutive of system value. Without deliberate managerial interpretation, BISs remain underutilized despite their technical functionality, as employees struggle to connect abstract data outputs to concrete operational decisions. Managers establish the organizational vision for BI through communication acts that position the technology within broader strategic imperatives. For instance, the Strategic Marketing Manager (I10) articulated this foundational purpose clearly, stating that the goal is:

> "to essentially capture the opportunities that arise in the market, leveraging the synergies that can be activated within a group like ours, which operates across different levels of the value chain, to optimize management, business development, and risk mitigation."

However, the data reveal significant tension between top-down deployment strategies and grassroots adoption realities. Multiple informants described MIS tools as "*dropped from above*", reflecting centralized implementation decisions made without sufficient end-user consultation. As one manager explained, "*having dropped the CRM from above, the goal was also to have a single tool, but the reality is that people keep using Excel*."

This disconnect necessitates what Pratt (2000) terms "*sensebreaking*", which is the deliberate disruption of existing cognitive frameworks to enable new understandings. Effective sense-givers acknowledged this challenge explicitly. A manager emphasized the cultural dimension of implementation, stating "*We also need to make cultural steps to explain that what was there until yesterday is no longer there*." Another elaborated on the supportive role required, noting "*You must help people to receive the change.*" The verb choice, "*help* people to *receive*" rather than "implement" or "execute", reveals recognition that adoption requires active cognitive and emotional processing by individuals.

The perceived trustworthiness of BI outputs emerged as a critical precondition for acceptance, directly connecting to Weick's criterion of plausibility. However, achieving this plausibility demanded continuous managerial oversight of data quality processes. Multiple informants emphasised this governance function: a senior manager articulated, "*there must be someone who verifies that the information is managed, fed, and structured and then utilised*" correctly. Another manager reinforced this point more bluntly, stating, "*It must be overseen by a manager because* *otherwise those things come out*" incorrectly, comparing unmanaged BI outputs to volatile situations where "*stock markets fall*". This scepticism reflects broader organizational anxieties about algorithmic decision-making, particularly in contexts where tacit knowledge and experiential judgement have historically dominated. Especially within family firms, the governance function involves managers acting as translators between algorithmic logic and operational reality, a role requiring both technical competence and contextual expertise. Consistent with sensemaking's fundamentally social character (Weick, 1995), effective managers fostered interpretive dialogue and structured opportunities for collective meaning-making around BI outputs. One manager described this approach explicitly, stating "*my objective, especially if I have to consider the young part, is precisely to encourage them to express ideas*" about what the data reveal and what actions might follow. These dialogic practices build what Namvar and Cybulski (2014) term '*BI identity'*, that is, individuals' cognitive and emotional connections to BI tools as meaningful components of their work identity. However, the data also reveal significant variation in managers' capacity and willingness to engage in such dialogue. From a TAM perspective (Venkatesh & Davis, 2000), these managerial sense-giving activities function as critical facilitating conditions: external factors that moderate the relationship between belief structures and behavioural intentions. Specifically, strategic framing shapes the salience of BI benefits; governance oversight builds trust in system reliability, and interpretive dialogue provides the social proof necessary for normative acceptance. One informant captured the transformative potential when managers successfully frame BI within job redesign, noting that the system "*would allow us to do a different job, less routine, more strategic at any level."* This reframing positions BI not as a threat to employment but as an enabler of higher-value work, directly addressing the identity concerns that constitute significant adoption barriers. By redesigning roles around BI capabilities, managers can enhance job satisfaction while mitigating fears of obsolescence, transforming potential resistance into engaged adoption.

3.4.2 Perceived benefits as pragmatic justification

The second dimension directly addresses the PU construct within TAM. The empirical evidence demonstrates that managerial sensegiving succeeds when it establishes credible linkages between BI usage and concrete performance-relevant benefits: absent such pragmatic justification, even well-functioning systems face adoption barriers.

Critically, the findings reveal that perceived usefulness is socially constructed through the retrospective sensemaking processes described by Weick (1995). Managers who effectively articulate how BI-enabled decision velocity, data reliability, or analytical depth produced favourable past outcomes increase employees' prospective assessments of perceived usefulness.

In the highly competitive chemical manufacturing sector, facing rapid demand fluctuations and shortened production cycles, temporal advantages constituted the most frequently cited benefit. As one commercial director emphasized, "*the winning variable for us is always time. The sooner the information arrives, the sooner you are winning in this market*." One sales manager described this evolution by stating "*before BI, we would receive reports at month-end and adjust strategy for the next month. Now I can change decisions daily based on real-time order intake and inventory positions*". This capability addresses what Weick (1995) identifies as the retrospective property of sensemaking, i.e., the need to continuously reinterpret the recent past to guide present action.
However, data analysis also reveals that decision velocity benefits remain unevenly distributed. Senior managers with broad decision authority reported substantial value from real-time dashboards, while operational personnel with limited permissions reported minimal relevance. This suggests that PU perceptions are moderated by decision autonomy, that is the degree to which individuals can translate information into action, a factor underexplored in standard TAM formulations. Prior to BI implementation, Radici's information environment was characterized by what informants termed "*everyone making their own tables*", fragmented reporting practices that generated interpretive confusion and political disputes. As one controller explained, "*you could have Commercial Dept. saying something based on their Excel files, Operations saying another thing based on theirs, and nobody could agree because the data sources and calculations were different.*" The BIS's centralization addressed this by establishing what Busco et al. (2006) describe as "*shared meanings applicable to truth*". Multiple managers emphasized the value of "*having certified data that everyone accesses from the same source*", functioning as a sensegiving amplifier. Nevertheless, achieving this centralization required significant organizational discipline, including enforcing data entry protocols, managing master data quality, and preventing the reemergence of shadow reporting systems.
Beyond speed and consistency, informants valued BI's capacity to enable more sophisticated analytical practices. One operations manager articulated this as a transition "*from spontaneous decisions based on gut feel to very targeted, very weighted decisions informed by trend analysis and comparative data.*" This analytical enhancement connects to Weick's (1995) concept of extracted cues, i.e. the selective noticing of informational features that trigger sensemaking episodes. BISs effectively pre-extract certain cues through visualisation, aggregation, and exception reporting, thereby shaping what organizational members notice and interpret.

3.4.3 Employee-level adoption barriers

The third dimension addresses the individual-level psychological and competence factors that mediate the translation of organizational sensegiving efforts into personal acceptance decisions.

Drawing on Weick's (1995) proposition that sensemaking is grounded in identity construction, the findings reveal that BI adoption frequently triggers identity threats, including anxieties that the technology will diminish professional relevance or expose competence gaps. These threats manifest as various forms of resistance that cannot be resolved through improved system design alone; rather, they require managerial sensegiving that explicitly addresses identity concerns and repositions BI as augmenting rather than replacing human expertise. This insight extends TAM by demonstrating that behavioural intention is influenced also by the degree to which technology use aligns with individuals' self-concepts.

The most significant barrier to adoption arose from concerns about technological unemployment. As one IT manager observed, "*it might be that employees experience it as 'now I give all the information, and then BI does everything on my behalf, and I lose my job."* These fears were particularly acute among midcareer employees, whose expertise centred on information synthesis and reporting. This existential anxiety aligns with broader sociological concerns about technology-induced job polarization (Spencer, 2018). In family firms like Radici, characterized by high employment stability and paternalistic labour relations, job loss fears violated implicit psychological contracts, generating resentment toward management for introducing "*threatening*" technologies. Thus, effective sensegiving required explicit reframing of BI's role. One director articulated this approach by stating "*we emphasize that BI doesn't replace people. It eliminates the routine parts of jobs so people can focus on strategic work that machines can't do.*" However, such reassurances require tangible role redesign demonstrating how BI-augmented positions offer enhanced status and developmental opportunities. One sales manager acknowledged: "*they simply don't have a complete perception of what the potential might be, because they lack the basic digital skills to even explore the system*". These competence anxieties were strongly age stratified: multiple informants referenced the "*generational divide*", noting that employees over 50 years old exhibited substantially greater resistance due to limited digital fluency developed earlier in their careers. As one HR manager explained, "*the difficulties are generational*". Critically, competence anxieties created self-reinforcing avoidance cycles. Lacking confidence, employees avoided system engagement; in turn, the lack of engagement prevented skill development, and skill deficits reinforced initial anxieties. Breaking these cycles required not only training, as already discussed, but also what might be termed '*competence* sensegiving', that is the managerial efforts to normalize learning struggles and celebrate small capability gains.

Beyond explicit fears and anxieties, adoption faced the more prosaic obstacle of entrenched work habits. As one commercial manager noted, "*people tend to remain in their comfort zone, working as they have always worked, even when better tools exist*". This inertia reflects what Weick (1995) identifies as the ongoing property of sensemaking. In this case, Excel spreadsheets, notwithstanding their constraints, provided familiarity and individual control. Conversely, BISs, despite their benefits, required adaptation to standardised interfaces and centralised data flows, which felt restrictive. To address such an issue, several informants described contexts where employees maintained parallel "*shadow systems*": personal databases and calculations, to preserve autonomy and avoid dependence on corporate IT infrastructure. This behaviour highlights a fundamental tension: organizational sensegiving seeks to establish shared meanings, but individuals retain strong motivations to preserve personal interpretive frameworks that provide cognitive security and political leverage.

3.4.4 System design attributes and usability

The fourth dimension maps directly onto TAM's PEOU construct. The findings demonstrate that technical design features significantly moderate adoption trajectories, with poorly designed interfaces creating friction that neutralizes even high perceived usefulness.

Critically, findings reveal what might be termed the '*performance paradox*': systems offering substantial analytical capabilities but requiring excessive learning effort face lower adoption than simpler tools offering more modest functionality. This pattern underscores that ease of use acts as a gatekeeper variable: unless users can successfully navigate initial interactions, they never engage deeply enough to appreciate usefulness benefits. This dimension also reveals significant tensions between customisation desires and standardisation imperatives, reflecting broader debates in IS literature about whether user-tailorable or administrator-controlled systems generate superior outcomes (Burton-Jones & Grange, 2013).

Visual design emerged as a powerful driver of both initial trial and sustained engagement. Multiple informants emphasised the motivational impact of well-crafted dashboards, with one noting "*the fact of having a screen in front of your eyes that tells you everything is absolutely a reason for involvement and continuous use.*" However, design effectiveness varied substantially across user groups: senior executives valued high-level KPI summaries enabling rapid assessment; operational managers required drill-down capabilities to investigate anomalies, whereas frontline employees preferred task-focused views eliminating irrelevant information. This heterogeneity challenged BI teams to balance competing design priorities, often resulting in interfaces that satisfied none perfectly, a classic compromise failure.

The most significant usability barrier arose from BI's reliance on SAP as the principal data source. Numerous interviewees regarded SAP as "*extremely rigid*", resistant to customisation and sluggish in adapting to changing business requirements. This inflexibility produces further repercussions for BI: as BI frequently showcases data gathered and structured by SAP, any constraint in SAP's data models inevitably restricts BI's analytical capabilities. Interviewees motivated to switch to BI by assurances of "*real-time decision support*" experienced disillusionment when system latency compelled a return to Excel-based workflows. This underscores a vital aspect of use dynamics: performance expectations are aligned with the designated functions of the system.

3.4.5 Organizational enablers and HRM interventions

The final aggregate dimension addresses the structural and procedural mechanisms, largely under the HR jurisdiction, that operate as facilitating conditions for BI adoption (Venkatesh et al., 2003). Drawing on HRM literature concerning technology-enabled organizational change (Bondarouk et al., 2017), this dimension reveals that successful BI integration requires systematic HR interventions encompassing training, incentive systems, role redesign, and KM. Critically, the findings demonstrate that HRM practices interact synergistically with managerial sensegiving: while sensegiving establishes the interpretive foundation for BI acceptance (clarifying why BI matters), HRM practices provide the operational infrastructure enabling enactment into daily work (how to use BI effectively). Despite this strategic potential, the dimension also reveals notable discrepancies between HRM philosophies and their actual implementation, a recurring theme in implementation research (Khilji & Wang, 2006). The most visible HRM shortcoming concerned training provision: despite substantial BI investment, training is typically limited to brief introductory sessions, with few ongoing support. As one employee explained, "*there were small courses when we started, maybe refresher courses in the first year, but after that nothing. You're on your own*." This disparity forced employees to pursue self-directed learning, favouring digitally proficient individuals while marginalising those lacking essential skills. Since the adoption of BI requires specific digital and analytical skills, training is an essential prerequisite for successful implementation. Furthermore, training must be specifically customised (Bondarouk & Looise, 2005), surpassing traditional technical manuals to deliver task-oriented and job-relevant instruction on the rationale, timing, and methods for utilising system features.

While all employee cohorts require BI training, the findings reveal that the nature and intensity of required support vary substantially. Younger employees generally need help translating technical capabilities into business insights, whereas older employees require foundational digital literacy development before domain-specific BI training becomes meaningful. Interviewees described training approaches that failed to acknowledge these differences, recognising that "*we should design age-differentiated training tracks.*" In this regard, recent studies support AI-driven adaptive learning systems that customise educational trajectories according to individual cognitive styles and digital competencies (Bharathi et al., 2024).

Incentives pertaining to data quality were a substantial yet unacknowledged barrier to adoption: the efficacy of BI essentially depends on timely and accurate data entry by frontline staff. Nevertheless, as one IT manager explained, "*if a tool requires a lot of data entry work, but then the feedback isn't there, the person who enters the information has no stimulus to continue doing it carefully*." This dynamic generated a vicious cycle: poor data quality undermined BI credibility, reduced usage, diminished political support for BI investment, and further demotivated data contributors. Addressing this requires reconceptualising data entry as a contributory behaviour deserving recognition and reward. Several informants proposed solutions, including formal acknowledgement of data quality leaders, incorporating data contributions into performance evaluations, and providing analytical access to employees whose inputs enable others' decisions. However, the actual implementation of these incentives highlights a significant gap in HRM.

The unique characteristics of family firms (such as employment stability, paternalistic culture, and accumulated tacit knowledge) may become vulnerabilities during technological transitions that demand swift development of competencies. Experienced employees possess contextual understanding necessary to interpret BI outputs meaningfully, recognizing when data patterns represent genuine trends versus statistical noise. However, several informants expressed apprehension regarding upcoming retirements, with one noting: "*If four experienced people leave, the company will lose all the accumulated know-how about how things really work, not how they're supposed to work according to SAP*". Furthermore, these same employees frequently demonstrate the greatest resistance to BI, preferring familiar tacit knowledge over formalised analytical methods. Effective KM systematically captures experiential insights and encodes them as interpretive heuristics to support BI usage, thereby establishing an organisational memory that endures beyond individual departures. Furthermore, the incorporation of AI has the potential to act as a catalyst for knowledge sharing, facilitating organisations in capturing and formalising tacit expertise before its possible loss resulting from retirement (Olan et al., 2022). Within the realm of Radici Yarn, this transition holds significant importance.

Only few informants questioned the efficacy of the commitment to this technological shift: resource constraints indicate that, despite rhetorical emphasis, BI remains marginal to organisational priorities. This pattern corresponds with extensive research on implementation failures, which consistently highlights visible management commitment as a solid determinant of success (Nah et al., 2001). From a sensemaking perspective, the findings reveal that HRM practices function as institutionalized sensegiving mechanisms, continuously reinforcing managerial messages about technology importance and appropriate usage. More in detail, training develops the cognitive schemas enabling BI sense-reading; incentives reward behavioural alignment with promoted interpretations; role design structures opportunities for BI identity development, and visible resource commitments signal genuine organizational values. When HRM and managerial sensegiving align, they create mutually reinforcing signals from multiple organizational levels establishing clear expectations. Conversely, when HRM practices contradict managerial rhetoric, they generate sensegiving dissonance. Furthermore, proper HR practices are instrumental in hiring and retaining employees with the necessary innovative capabilities and skills to manage these resources for competitive advantage (El-Kassar & Singh, 2019). Crucially, addressing the generational challenge and the risk of organizational know-how loss, often exacerbated by retirements, requires the allocation of dedicated resources and appropriate mentorship to ensure knowledge transfer and continuity.

3.5 Conclusion

By conducting a case study within a family firm undergoing a technological transition and promoting supportive HR practices, this research illustrates that technology alone is inadequate for ensuring successful adoption: even advanced systems lead to limited progress when employees find it challenging to integrate technological outputs into the practical realities of their daily operations. To ensure effective integration, managers serve a strategic intermediary function by interpreting abstract metrics provided by BI and translating technical outputs into a language that aligns with operational realities and strategic goals. The evidence demonstrates a notable trend: the level of technological sophistication is significantly less important than managers' ability to develop coherent narratives around technology outcomes: when managers effectively present analytical insights, incorporate relevant business context, and corroborate interpretations with domain expertise, they convert unstructured data into a common understanding. Equally important, HRM practices serve as essential facilitators of such socio-technical process: training initiatives, collaborative communication strategies, and deliberate role redesign establish an environment where employees can actively participate in BI rather than perceive it as a source of potential disruption. These practices uphold the human-centred approach throughout digital transformation, in accordance with the Industry 5.0 paradigm (Breque et al., 2021), by aligning technological capabilities with individual skills and organisational values. These initiatives improve perceived advantages, especially when managers explicitly link BI skills to key performance outcomes such as decision-making efficiency, information accuracy, and analytical complexity. Simultaneously, individual-level factors influence the relationship between perception and intention: concerns regarding professional identity, anxieties related to competence, and entrenched resistance serve as mediators in this connection. Consequently, HRM practices establish the institutional framework that either enhances or hinders managerial sensegiving initiatives: well-designed programs, encompassing thorough training, significant incentives, and transparent resource allocation, diminish adoption obstacles and promote routinisation of usage.

Theoretical implications

This research advances several theoretical contributions to the literature on ISs adoption and organizational sensemaking. First, it extends sensemaking theory beyond its traditional applications in strategic change contexts into the domain of technology adoption. While sensemaking scholarship has extensively examined how organizations handle environmental uncertainty and strategic transformation (Maitlis & Christianson, 2014), comparatively little research has investigated how managers construct meaning. The findings reveal that managers engage in prospective sensegiving that actively shapes how employees interpret BISs, thereby transforming algorithmic recommendations into strategically meaningful resources embedded within existing business narratives.

The second contribution addresses a persistent theoretical gap in technology acceptance research. Despite extensive elaboration of the TAM, scholars have consistently noted the model's limited attention to social and organizational antecedents of PU and PEOU (Venkatesh & Davis, 2000). The dominant approach treats these constructs as individual cognitive assessments of objective system attributes, underspecifying the social processes through which perceptions actually form. This study identifies managerial sensegiving as a concrete mechanism that systematically influences both dimensions. In fact, managers shape usefulness perceptions through narrative constructions that articulate how technological capabilities address organizationally salient problems. Perceptions of ease emerge partly from interface design but substantially from managerial efforts to reduce interpretive ambiguity, provide contextual scaffolding, and establish legitimacy for algorithmic outputs. Thus, this study reinterprets the micro-foundations of the TAM by demonstrating that PU and PEOU are collectively constructed interpretations influenced by managerial sensegiving and HRM infrastructures. This reconceptualization transforms TAM from a primarily psychological model into a socially grounded theory of technology acceptance.

The third contribution reconceptualizes BI implementation as a strategic HRM challenge rather than a technical deployment issue. While prior research has acknowledged HRM's supportive role in technology implementation (Marler & Fisher, 2013), these practices are typically positioned as peripheral facilitators rather than central determinants of adoption outcomes. The empirical evidence demonstrates that strategic HRM practices constitute critical organizational infrastructure through which technical capabilities translate into sustained usage. Training programs, communication architectures, incentive alignment mechanisms, and deliberate role redesign create enabling conditions that either amplify or undermine managerial sensegiving effectiveness. Thoughtfully designed HRM practices lower adoption barriers and institutionalize usage norms, whereas absent or poorly executed interventions prevent even highly effective sensegiving from overcoming structural obstacles to meaningful engagement.

This research additionally provides several contributions to the field of family business research. In fact, it broadens the relationship between Social Identity Theory and sensemaking (Diaz-Moriana et al., 2024). Previous research indicates that family members derive substantial value from their identification with the firm, and reputational threats are perceived as personal threats (Deephouse & Jaskiewicz, 2013; Zellweger et al., 2013). Employees frequently show a strong sense of identification with the organization, viewing it as an extension of the family's values rather than a mere economic entity. The introduction of opaque algorithms induces cognitive dissonance, which threatens this identification by imposing a calculative logic that is at odds with the relational culture of the firm (Berrone et al., 2010). Our findings reveal that managers play a role in reframing the technology as a protector of the family's reputation and binding social ties, rather than as a threat to traditional craftsmanship (Berrone et al., 2012). Consequently, the effective implementation of digital tools in family firms is contingent upon the alignment of technological capabilities with the preservation of the family's socioemotional integrity and external legitimacy, rather than merely on their technical utility (Cennamo et al., 2012).

A particular form of sensegiving that we could refer to as "*Identity bridging*" can be essential for the successful adoption of BI. The "black box" of AI is aligned with the transparent values of the family when managers demonstrate that BI data safeguards the firm's reputation, such as through quality control and sustainability reporting. Additionally, managers function as human interfaces for the algorithm, drawing on the principles of XAI (Asif et al., 2025), to prevent data-driven accountability from undermining the Binding Social Ties that define the firm's distinctive social capital.

Practical contributions and managerial implications

The findings offer several actionable insights for practitioners dealing with the complexities of BI implementation. First, successful adoptions primarily rely on proactive sensegiving processes: managers must look beyond technical deployment to actively construct interpretive frameworks that establish the credibility and efficacy of analytical outputs. Such sensegiving is paramount during early adoption phases, when employees may question system reliability or relevance owing to unfamiliarity with data-driven outputs. Furthermore, building upon recent advancements in XAI, managers are expected to employ interpretability tools to ensure that algorithmic results are transparent and easily understandable. By clarifying the mechanisms of the ‘black box’, managers act as intermediaries that harmonize technological innovation with the core principles of the organization, thereby preserving the firm's SEW.

Second, the research highlights that strategic HRM practices are the essential infrastructure of digital transformation: technical implementation must be accompanied by comprehensive training that develops both functional skills and analytical reasoning. Organizations should foster communication architectures and job designs to ensure authentic engagement, allowing employees to see how their interaction with the system directly informs consequential firm decisions, thereby fostering psychological ownership and acceptance.

Third, the study advocates an iterative approach to platform development, emphasising the importance of tailored prototyping and ongoing user feedback mechanisms. This incremental approach ensures that the system evolves in alignment with evolving organisational needs, thereby minimising the risk of investing in unnecessary or misinterpreted functionalities. Additionally, the integration of sensemaking theory into the TAM provides a robust diagnostic framework. When adoption delays occur, managers can systematically identify whether the obstacle is technical (impacting EOU), narrative (failing to establish PU through sensegiving), or structural (insufficient HRM support).

These findings are especially beneficial for family-owned businesses operating within mature sectors. In environments dominated by tacit knowledge and experience-based norms, BI should be regarded as additional organisational support rather than a substitute for human judgement. This research ultimately advocates a paradigm shift, viewing BI implementation as a whole organisational change initiative. A sustainable competitive advantage is established through the effective integration of technological infrastructure with managerial expertise and employee empowerment, fostering a human-centric capability for digital excellence.

Limitations and future avenues for research

Despite this study's solid methodology and depth of insights, many limitations should be acknowledged to open new research pathways. First, the single-case design gives contextual depth but limits generalisability beyond the research environment. Radici Yarn has family ownership, average worker tenure of 15 years, and incremental change approach anchored in 80 years of manufacturing tradition. These characteristics tend to feed adoption dynamics that may not replicate in contexts where employees have shorter tenure and weaker institutional identification, where governance structures prioritise financial metrics over relational stability, or organisational culture values quantitative analysis. Comparative research on BIS adoption across organisational archetypes will show how ownership structures, sectoral features, and institutional settings affect these linkages.

Second, research on initial deployment dynamics and brief post-implementation adjustment periods may have missed longer-term stabilisation processes. Several years of longitudinal research would show if discovered pathways evolve with organisational learning and competitive adaptations. Furthermore, action-research provided organisational access but raised validity issues that needed careful evaluation. As a detached observer documenting adoption processes and an active organisational member contributing to training design and user assistance, the researcher might identify biases. For instance, participants aware of the researcher's role in system adoption may have filtered critical perspectives to avoid disappointing someone involved in implementation success. Systematic triangulation of interview reports and field notes reduced these hazards; however, future ethnographic research with a more detached perspective would validate methods.

Finally, this study paves the way for several avenues of future research at the intersection of AI, SEW, and transgenerational governance. Our findings highlight the importance of BI in formalising reasoning; nonetheless, the rapid development of predictive and generative AI introduces new theoretical challenges that warrant further investigation. For example, researchers should investigate how the deployment of automated decision-making impacts the family control (F) component of the FIBRE model when algorithms propose activities that conflict with traditional family values. As family enterprises increasingly implement data mining systems and AI within their structures to secure a competitive advantage, comprehending the interaction between these technologies and the safeguarding of SEW will be a critical prerequisite for directing the development of family business strategies.

Chapter 4. Closing the production-to-R&D loop

As markets become saturated, understanding customer needs becomes increasingly challenging, competitive opportunities diminish, and the necessity for swift cross-functional integration grows more urgent. When your competitors launch innovation initiatives four years after your organization and reach the market first, the constraint lies not in ideation capacity but in execution capability. This paradox was investigated throughout a three-year longitudinal study at Radici Yarn, a prominent European synthetic fibre manufacturer, examining why technically proficient organizations within mature industries often struggle to translate knowledge into innovation outcomes despite possessing substantial domain expertise and manufacturing capabilities. Drawing upon Organisational Information Processing Theory (OIPT), we address this strategic challenge starting from the primary constraint: a structural mismatch between increasing information processing demands and unchanged organisational capacity. We introduce a comprehensive Polymer Informatics (PI)-MES-BI framework that bridges the production-to-R&D divide through the concurrent deployment of multiple capacity-enhancement mechanisms. Four theoretical propositions formalise these relationships: requirements escalate non-linearly in mature markets; fragmentation explicitly hinders cross-functional integration; the absence of feedback loops obstructs organisational learning; and integrated platforms produce multiplicative gains in capacity.

4.1 Introduction

Mature industries encounter a structural paradox: innovation becomes increasingly challenging while concurrently growing more necessary as markets reach saturation. In sectors where demand growth is stagnating and competitive differentiation diminishes, the ability to identify opportunities and swiftly convert them into products or services is mandatory for maintaining competitive resilience (Cooper, 2011; Onufrey & Bergek, 2021). The chemical manufacturing industry exemplifies this challenge most markedly: global capacity expansions significantly surpass demand growth, foundational innovation seems to have stagnated, and products are becoming commoditised at an unprecedented rate (Lager, 2010; McKinsey, 2024). Furthermore, patent analysis indicate that advancements are predominantly incremental rather than revolutionary (Pavitt, 1984), while reductions in time-to-market have transitioned from a competitive advantage to an imperative to avoid obsolescence and decline (Chen & Chang, 2010).

Organizations competing in saturated markets face a multidimensional information processing challenge that conventional management structures struggle to address. Successful innovation requires coordinating knowledge distributed across organizational silos (Grant, 1996), converting manufacturing intelligence into actionable R&D insights (Leonard-Barton, 1992), and achieving rapid decision-making while preserving analytical depth (Eisenhardt, 1989b). As markets mature and competitive pressure intensifies, these demands grow more acute, but the critical knowledge enabling effective execution remains fragmented. Manufacturing generates rich data revealing process-performance relationships, but this intelligence typically remains locked within operational systems rather than flowing back to inform product development priorities and accelerate learning cycles.

Nevertheless, organisations within established industries typically operate with information processing structures aimed primarily at maximising operational efficiency rather than promoting innovation agility (Benner & Tushman, 2003). Manufacturing data remains confined within production systems, R&D functions are disconnected from every-day operations occurring at the shop floor, and feedback mechanisms that connect production outcomes to product development are either hindered or completely lacking (Nonaka, 1994; Brown & Duguid, 2001). This structural mismatch between the requirements of information processing and organisational capabilities results in a bottleneck that cannot be addressed solely through enhanced algorithmic complexity (Davenport, 2018).

The OIPT offers a compelling theoretical lens for understanding this phenomenon. Since Galbraith's (1973, 1974) seminal work, OIPT has demonstrated that organizational effectiveness depends on aligning information processing requirements and information processing capacity (Egelhoff, 1991). The theory identifies four strategic mechanisms: creating slack resources, designing self-contained tasks, investing in vertical information systems, and establishing lateral relations (Premkumar et al., 2005). These mechanisms have demonstrated robustness over five decades of research, with recent applications affirming their ongoing relevance for the adoption of big data analytics (Cao et al., 2015), digital transformation initiatives (Vial, 2021), and Industry 4.0 supply chains. Nonetheless, despite OIPT's theoretical robustness, three main research gaps limit our understanding of how organizations can leverage information processing architectures for product innovation in mature industries. First, systematic analysis indicates that despite OIPT applications are primarily focused on operational contexts, such as manufacturing process optimisation (Flynn & Flynn, 1999), organizational structure design (Burton & Obel, 2004) and ERP implementation (Karimi et al., 2007), innovation is perceived as a matter of task completion rather than as a strategic capability that requires knowledge integration for the exploiting opportunities.

Second, a closely related gap emerges within the BI and MES literature. Ismail et al. (2019), in their survey of 38 manufacturing-oriented big data platforms, show that current solutions overwhelmingly target operational domains such as process monitoring, quality control, predictive maintenance, and production optimisation, but none support feedback loops toward R&D or mechanisms that link operational insights to product innovation. Moreover, the integration architectures described in academic studies typically enable data to flow from design and planning toward the shop floor, but not in the opposite direction (Xu et al., 2018). As a result, organisations lack systematic means to capture experiential knowledge from production, relate it to product outcomes, and channel these insights back into R&D: capabilities that are essential for improving predictive models and accelerating iterative development cycles (Kusiak, 2018; Tao et al., 2018).

Ultimately, despite PI and computational materials methodologies hold the potential to accelerate innovation by predicting material properties based on molecular structure (Ramprasad et al., 2017; Butler et al., 2018), these models exhibit a notable *'process gap'* that has been explicitly documented in the literature. According to Wu et al. (2019), their failure to adequately address observed fluctuations within polymers may mostly result from insufficient data regarding processing parameters. The Process-Structure-Property-Performance (PSPP) paradigm acknowledges that manufacturing conditions substantially influence final characteristics (Olson, 1997); nonetheless, most models primarily emphasize Structure-Property linkages. This disparity establishes a divide between synthesis and application, constraining practical implementation; even precise molecular predictions are insufficient if manufacturing circumstances are overlooked (Kim et al., 2018; Hatakeyama-Sato, 2023). The primary concern is data availability, as processing conditions are generally proprietary and private data is occasionally restricted from distribution (de Pablo et al., 2019).

To date, no research has investigated the potential integration of these aspects to improve an organization's information processing about product innovation. For such a reason, we conducted a comprehensive three-year longitudinal case study at Radici Yarn. In industries like this one, characterised by deeply rooted processes and mature competitive structures, structural and cultural constraints on innovation remain widespread (Hutcheson et al., 1995; Lager, 2010). As several interviewees observed, their competitive landscape resembles the "*Jurassic of industry*": an expression that captures a highly conservative customer base, diminishing market dynamism, and a gradual erosion of innovative momentum. By integrating PI for computational forecasting and molecular design, MES for real-time process parameter collection, and BI for collaborative information exchange, we aim to clarify the organizational requirements for enhancing innovation in environments where traditional methods have proven ineffective.

4.2 Theoretical background

4.2.1 Organizational Information Processing Theory

The OIPT originated from Galbraith's (1973, 1974) foundational observation that organisations operate as information processing systems, with their effectiveness reliant on aligning information processing demands with capabilities. The core proposition is that greater task uncertainty generates greater information processing requirements, which must be satisfied by a corresponding organizational information processing capacity (March & Simon, 1958; Thompson, 1967). When requirements exceed capacity, performance deteriorates due to delays, errors, or suboptimal decisions (Galbraith, 2014). Galbraith's work, with over 5,000 citations, characterised organizations as entities that must process information to coordinate activities under uncertainty, so establishing a framework that has guided organizational design research for five decades.

Task uncertainty, the theory's central antecedent, refers to the difference between information required to perform a task and information already acquired (Daft & Lengel, 1986). Uncertainty increases with the complexity, variability, and interdependence of tasks (Van de Ven et al., 1976). Thus, to manage uncertainty, Galbraith identified four mechanisms: slack resources, which serve as buffers that reduce the need for tight coordination (Bourgeois, 1981); self-contained tasks, which consolidate resources to minimise cross-unit dependencies; vertical information systems, which are technologies that enhance information flow within hierarchical structures (Huber, 1990); and lateral relations, encompassing direct contact, liaison roles, task forces, and integrating managers that promote horizontal coordination (Lawrence & Lorsch, 1967). Tushman and Nadler (1978) extended this framework to subunit levels, introducing the congruence concept, which underscores that requirements arise from task characteristics, task environment, and task interdependence.

Recent applications demonstrate OIPT's sustained theoretical relevance in digital contexts. For instance, Fan et al. (2017) utilise OIPT for Industry 4.0 supply chains, demonstrating how IoT sensors, real-time data streams, and cyber-physical systems generate both novel information processing requirements and capacity-building opportunities. Such renewed interest confirms OIPT's ability to clarify how organisations manage the increased information volumes that accompany digital transformations (Bharadwaj et al., 2013).

4.2.2 BISs

Building upon the conceptual foundations established in the previous chapters, this section examines how BI functions as an organizational information processing mechanism specifically enabling innovation in mature manufacturing contexts through alignment with OIPT's theoretical framework. While earlier chapters positioned BI as a socio-technical infrastructure encompassing technologies and strategic applications for collecting, integrating, analysing, and presenting organizational data to support evidence-based decision-making (Davenport & Harris, 2007; Yeoh & Koronios, 2010), the analysis here explicates the specific capacity-building mechanisms through which BI addresses information processing constraints limiting product innovation.

BI platforms differ fundamentally from AI and ML systems in their primary function: rather than automating pattern recognition and prediction, BI operates as an integrative architecture facilitating cross-functional information flows (Shollo & Galliers, 2016; Seddon et al., 2017). These platforms consolidate disparate data streams from operational systems, process them through ETL pipelines (Chaudhuri et al., 2011; Kimball & Ross, 2013), and deliver synthesised outputs via interactive dashboards and analytical tools (Few, 2006; Popovič et al., 2012). This integrative capacity directly addresses the architectural fragmentation identified as a critical constraint in mature industries: BI creates connections between previously isolated information domains, enabling organizations to bridge functional silos that otherwise obstruct knowledge flow between production operations and R&D functions (Popovič et al., 2012; Fink et al., 2017).

From an OIPT perspective, BI operates through multiple capacity-building mechanisms simultaneously. First, it generates slack resources by automating routine analytical tasks that typically consume substantial analyst time in manual environments, sometimes exceeding eighty percent of available effort (Davenport & Patil, 2012). Freed from repetitive data manipulation and report generation, analytical personnel can redirect attention toward higher-value interpretation, hypothesis generation, and strategic insight development (Vidgen et al., 2017). Second, BI establishes vertical information systems that accelerate data flow from operational levels to strategic decision-makers, compressing the temporal lag between event occurrence and managerial awareness (Wieder & Ossimitz, 2015). Third, shared BI platforms implement lateral relations by providing common data foundations accessible across functions, enabling coordination through mutual visibility rather than requiring formal hierarchical communication channels.

The strategic potential of BI for facilitating innovation has gained scholarly recognition, though empirical validation remains less developed compared to research examining AI and ML applications (Haefner et al., 2021; Mariani & Dwivedi, 2024). Existing evidence demonstrates positive relationships between BI deployment and firm innovativeness, attributing this connection to enhanced capabilities for knowledge transformation and exploitation that enable new problem-solving approaches and accelerated product development responding to market demands (Eidizadeh et al., 2017; Martíinez-Martínez et al., 2025). Beyond automating analysis, BI generates innovation-enabling slack by identifying and eliminating operational inefficiencies, monitoring performance against benchmarks, and surfacing production bottlenecks or supply chain constraints that consume organizational resources (Mithas et al., 2012). These resources can be reallocated to more ambitious R&D initiatives, proving particularly valuable for risk-averse mature firms seeking to accelerate innovation cycles (Voss et al., 2008).

However, realising these innovation benefits proves contingent upon addressing substantial implementation challenges spanning technical and organizational dimensions (Yeoh & Koronios, 2010). Data governance constitutes a primary technical constraint, encompassing provenance verification to establish data lineage, reliability assurance to validate measurement accuracy, quality maintenance to prevent degradation through processing stages, and validity confirmation to ensure alignment between measured variables and intended constructs (Khatri & Brown, 2010; Tallon, 2013). Manufacturing environments intensify these governance challenges through characteristics distinguishing them from transactional business contexts. Production processes generate high-velocity data streams from sensors, control systems, and quality instruments that often lack standardised schemas, while quality control systems produce heterogeneous outputs combining numerical measurements, operator observations, and visual inspection results resistant to structured integration (Sivarajah et al., 2017; Ismail et al., 2019). This architectural gap between manufacturing data characteristics and conventional BI platforms designed for structured transactional data prevents organisations from systematically establishing production-to-R&D feedback loops. Without mechanisms to capture process parameters during manufacturing trials, associate them with product performance outcomes, and feed this intelligence back to R&D teams, organisations cannot accelerate learning cycles or reduce the number of experimental iterations required for product development. More fundamentally, BI adoption confronts cultural rather than purely technical obstacles, requiring transformation in how organisations conceptualize and practice data-driven decision-making (Kiron et al., 2014). As demonstrated in Chapter 3, successful implementation critically depends on managerial sensegiving, which constructs credibility for analytical outputs, and on HRM practices that develop organisational capacity for interpretation. Training investments must cultivate data literacy as a core competency distributed across organisational levels rather than concentrated in specialized analytical roles (Davenport & Patil, 2012; Wolff et al., 2016). Without these complementary organizational capabilities, even technically sophisticated BI platforms fail to generate meaningful innovation outcomes.

4.2.3 Manufacturing Execution Systems

MESs comprise ISs that monitor, control, and document the transformation of raw materials into finished products on the manufacturing floor (Saenz de Ugarte et al., 2009). Within the ISA-95 enterprise architecture standard, MES occupies Level 3, functioning as the intermediary layer between ERP systems at Level 4 and operational process control systems at Levels 0-2 (ISA, 2010). MES functionality encompasses real-time production monitoring, resource allocation optimisation, Overall Equipment Effectiveness (OEE) tracking, quality management protocols, and increasingly predictive maintenance capabilities enabled through the integration with IoT sensor networks and AI/ML algorithms (Jaskó et al., 2020; Moeuf et al., 2018). These systems continuously capture granular process parameters at high temporal resolution: temperature profiles across heating and cooling cycles, pressure variations within reaction vessels, material flow rates through processing equipment, production cycle times, raw material specifications, and quality control measurements sampled at millisecond intervals. This data acquisition intensity generates substantial operational datasets, often reaching gigabyte scale daily even within single production facilities (Kang et al., 2016).

The evolution of MES within Industry 4.0 contexts has been substantial, transforming these systems from basic production tracking tools into intelligent cyber-physical infrastructures. Shojaeinasab et al. (2022) provide the most comprehensive recent systematic review, analysing 1,383 papers and proposing an Intelligent MES framework incorporating five intelligence levels that progressively integrate IoT connectivity, AI algorithms, ML capabilities, digital twin representations, and blockchain-based traceability. Lee et al. (2015) establish foundational architecture through a unified five-level cyber-physical systems structure enabling comprehensive monitoring and synchronisation between physical factory operations and cyber computational spaces. This architecture enables MES evolution from reactive control systems responding to deviations into self-aware systems monitoring their own performance, self-predicting systems forecasting future states, and self-configuring systems autonomously adjusting parameters to optimise outcomes.

Despite these technological advances, MES research concentrates overwhelmingly on production optimisation rather than innovation support. Systematic literature reviews consistently reveal that dominant applications address operational control challenges: real-time monitoring of equipment status, resource optimisation balancing throughput and efficiency, quality management detecting and preventing defects, and predictive maintenance minimising unplanned downtime (Zhong et al., 2017). Leng et al. (2021) present an integrated Function-Structure-Behavior-Control-Intelligence-Performance framework demonstrating how digital twins enable simultaneous engineering wherein development phases overlap and execute in parallel, with real-time feedback from production to design allowing continuous refinement of manufacturing processes. However, these applications focus on optimizing how to manufacture existing designs more efficiently rather than informing what new designs to create based on manufacturing intelligence (Zhong et al., 2017). Critical examination of the literature reveals a fundamental conceptual gap: MES are conceptualized as operational execution systems supporting current production rather than strategic innovation resources enabling next-generation product development.

From an OIPT perspective, MES function as information processing capacity enhancements addressing uncertainty inherent in complex manufacturing environments. Flynn and Flynn (1999) empirically validate Galbraith's framework within manufacturing contexts, examining how 354 plants cope with environmental complexity through practices that either reduce information processing requirements or increase organizational processing capacity. Their findings demonstrate that manufacturing organizations face the same fit imperatives between task uncertainty and information processing capacity that OIPT predicts for organizational design generally. Gattiker and Goodhue (2005) extends this analysis demonstrating that cross-functional information systems provide greater performance benefits when task interdependence is high, though realizing these benefits requires appropriate organizational contexts including supportive cultures and aligned incentive structures.

However, implementation challenges significantly limit MES potential for innovation support beyond operational efficiency. Almada-Lobo (2015) provides critical analysis identifying that traditional MES architectures fall short of providing decision-making capabilities required in dynamic organizations where adaptive execution strategies are necessary, concluding that conventional MES prove insufficient for innovation-oriented environments demanding flexibility and experimentation. While system integration is designed to optimise operational efficiency, it can paradoxically result in structural inflexibility that impedes an organization's dynamic capabilities (Gebauer & Schober, 2006). Managers frequently report that the costs and time required for system reconfiguration act as a barrier to innovation in manufacturing contexts, where this is particularly evident within legacy MES architectures. Saenz de Ugarte et al. (2009) emphasise the necessity of more modular and interoperable digital frameworks, as this "*integration trap*" frequently results in the circumvention or complete replacement of systems that are too rigid for volatile business environments. Cottyn et al. (2011) argue that standard MES implementations may conflict with lean manufacturing principles, creating procedural rigidity that contradicts flexibility requirements essential for continuous improvement and innovation. Thus, despite substantial theoretical foundations supporting MES applications, the organizational learning potential embedded within these platforms remains largely unexplored. Argote and Miron-Spektor (2011) provide a foundational framework explicating how organizational experience interacts with contextual factors to create knowledge through both latent components embedded in routines and active components requiring deliberate reflection. Their framework applies directly to understanding how manufacturing data captured by MES could enable organizational learning if systematically analysed and fed back into decision processes. Notwithstanding these theoretical foundations, empirical research investigating MES data utilization for product innovation and R&D processes remains absent from the literature. This gap proves particularly consequential for mature manufacturing industries where production systems accumulate significant operational experience over extended timeframes. Established facilities continuously generate performance intelligence with direct innovation relevance: systematic yield variations across material formulations expose which compositions transition successfully from laboratory conditions to industrial-scale processing, recurring process deviations reveal the operational boundaries constraining feasible product specifications, and equipment behaviour during production trials signals manufacturing constraints that should inform next-generation product architectures. Manufacturing operations function as continuous experimental environments generating insights about process-performance relationships under authentic operational conditions, yet this accumulated intelligence rarely flows systematically back to R&D functions developing subsequent product generations. The literature provides no established frameworks for institutionalizing such feedback mechanisms, creating a fundamental gap: organizations invest substantially in MES infrastructure capturing granular production data while simultaneously allowing the strategic innovation value embedded within this data to remain unexploited. R&D teams developing new formulations operate with incomplete knowledge of manufacturing realities, frequently rediscovering through costly experimental iterations the same process constraints and performance limitations that production experience already revealed.

4.2.4 Polymer Informatics and the process gap

PI represents the systematic application of ML and data science to polymer property prediction and molecular design, constituting part of the broader Materials 4.0 movement positioned as the fourth paradigm of materials research (Agrawal & Choudhary, 2016; Ramprasad et al., 2017; Chen et al., 2021b). PI models employ ML algorithms to predict material properties directly from molecular structure, ranging from traditional methods such as Random Forests operating on molecular fingerprint representations to more advanced Graph Neural Networks treating molecular structures as interconnected networks of atoms and bonds. Recent applications demonstrate substantial predictive accuracy, with models achieving R^2 values approaching 0.9 for properties such as glass transition temperature (St. John et al., 2020), indicating that approximately ninety percent of property variation can be explained by structural features alone. These predictive capabilities fundamentally transform the innovation process through inverse design: instead of the traditional approach of synthesizing candidate materials and measuring their properties through laboratory experimentation, researchers can specify target performance requirements and employ computational models to identify molecular structures predicted to meet those specifications. This reversal of the discovery

workflow holds potential to compress development cycles that traditionally require years of iterative experimentation into months of computationally guided exploration (Sanchez-Lengeling & Aspuru-Guzik, 2018).
Nonetheless, PI models suffer from a critical limitation explicitly documented as the '*process gap'*. As observed by Wu et al. (2019), current models fail to account for property variations within nominally identical polymers due to insufficient data on processing parameters and manufacturing-induced molecular structures. The PSPP framework recognizes that manufacturing conditions profoundly influence final material properties even when chemical composition remains constant (Olson, 1997, 2000), including temperature profiles during polymerization, cooling rates affecting crystallization, shear conditions determining molecular orientation, and annealing protocols all fundamentally shaping microstructure and performance (Kalidindi & De Graef, 2015). Yet most PI models prioritize Structure-Property relationships while systematically excluding processing parameters from predictive frameworks (Himanen et al., 2019). This creates a disconnect between computational predictions based on idealized molecular structures and actual performance emerging from real manufacturing processes. Even highly accurate structure-based predictions often fail in industrial contexts where processing variables introduce performance variations that composition-trained models cannot anticipate. For manufacturers like Radici Yarn possessing decades of embedded process expertise, this gap represents both a constraint on PI utility and an opportunity: MES-captured manufacturing data could provide precisely the processing parameter information required to close the gap, transforming PI from computational tool into practical innovation accelerator.

4.2.5 An integrated PI-MES-BI framework

Based on these premises, we propose that integrating PI, ME, and BI creates an information processing architecture that addresses the documented gaps while extending OIPT to product innovation. This integrated framework, synthesized in Figure 12, increases organizational information processing capacity through mechanisms that map directly onto Galbraith's original formulation, repositioned for innovation rather than operational efficiency.

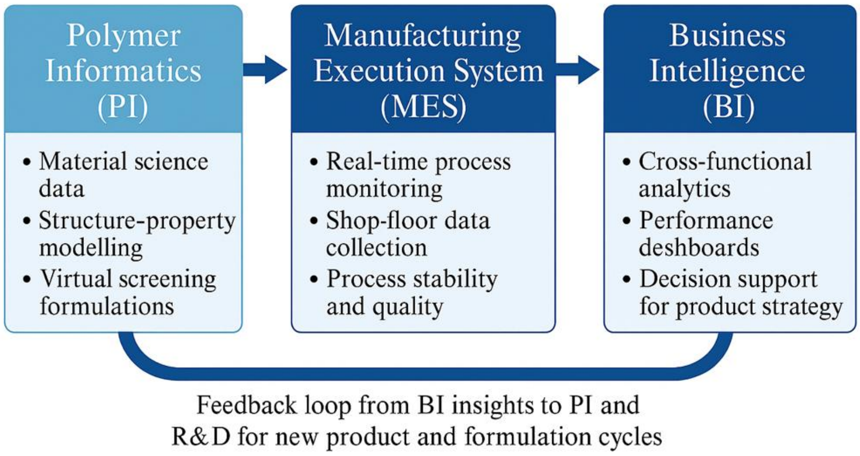

Figure 12: Integrated PI-MES-BI framework for product innovation

Within OIPT's theoretical architecture, PI constitutes a self-contained task mechanism because molecular screening proceeds computationally without necessitating coordination dependencies across organizational units (Gómez-Bombarelli et al., 2018). Computational exploration of chemical space enables researchers to evaluate thousands of molecular candidates in silico, substantially reducing reliance on resource-intensive physical synthesis and experimental characterization that would otherwise generate coordination bottlenecks.

MES infrastructure addresses the documented process gap through systematic capture of manufacturing parameters. When computationally optimised formulations advance to production trials, MES documents precise operational variables: thermal histories during polymerisation, pressure profiles affecting molecular architecture, conditions determining morphology development, and equipment-specific phenomena influencing microstructure. This data acquisition establishes explicit mappings between three traditionally disconnected domains: molecular composition specified through R&D protocols, manufacturing conditions governed by process parameters, and performance attributes quantified through quality measurements. From an OIPT perspective, this represents slack resource generation through institutional memory formation (Cyert & March, 1963). Organisations construct retrievable knowledge repositories encoding validated process-performance relationships, eliminating dependence on tacit knowledge retention and obviating redundant experimental iterations.

BI platforms function as architectural integrators synthesising these discrete capabilities into unified information processing infrastructure. Through vertical information system mechanisms, BI aggregates heterogeneous manufacturing data streams and delivers consolidated analytical intelligence to R&D decision makers via interactive visualisation tools (Allen, 1977; Hansen, 1999). More fundamentally, BI instantiates lateral relations by establishing shared informational environments wherein production specialists and R&D scientists access unified datasets, conduct collaborative analysis, and coordinate activities through informational transparency rather than hierarchical protocols. This bidirectional architecture operationalises the production-to-R&D feedback mechanism systematically absent from conventional organizational structures.

Framework effectiveness depends critically on Expert-in-the-Loop (EIL) governance aligned with Industry 5.0's anthropocentric design principles (Nahavandi, 2019; Breque et al., 2021). Domain experts establish screening parameters reflecting strategic priorities and manufacturing constraints, interpret algorithmic recommendations by synthesising computational outputs with tacit procedural knowledge (Polanyi, 1966) and validate predictive outputs against practical considerations before resource allocation. This philosophy addresses epistemological concerns regarding algorithmic opacity constraining ML deployment (Rudin, 2019) while acknowledging that purely algorithmic approaches cannot access experiential knowledge embedded in specialists who comprehend process subtleties and boundary conditions that datasets fail to encode comprehensively (Nonaka & Takeuchi, 1995). The framework positions computational intelligence as augmentation rather than substitution, combining algorithmic capabilities with human judgement grounded in contextual understanding.

4.3 Methodology

This study emerged from a three-year collaborative engagement with Radici Yarn, during which the researcher maintained continuous presence within the organisation as part of an industrial doctorate program. The genesis of this investigation traces directly to a strategic question posed by the company's general director:

RQ6. How can an established manufacturer sustain product innovation within a saturated market characterised by declining organic growth, commoditisation pressures, and accelerating competitive velocity?

This fundamental challenge, articulated repeatedly throughout executive discussions and strategic planning sessions, revealed a persistent gap between technical capabilities and innovation outcomes that existing management frameworks struggled to explain. Despite possessing substantial technical competence, advanced production capabilities, and decades of accumulated manufacturing expertise, the organization experienced persistent challenges translating knowledge into market innovations at a pace sufficient to sustain its competitive advantage.

4.3.1 Research design

The research adopts a qualitative single case study design (Eisenhardt, 1989a; Stake, 1995; Yin, 2018) to investigate how integrated PI-MES-BI platforms can increase organizational information processing capacity for product innovation in mature industries. Single case studies prove appropriate when the phenomenon under investigation is revelatory, providing access to situations previously inaccessible to scientific inquiry (Yin, 2018), and when research aims to extend theory into new domains (Lee & Liebenau, 1999; Siggelkow, 2007). This case satisfies both methodological criteria: production-to-R&D feedback loops represent a revelatory phenomenon that remains empirically underexplored in scholarly literature despite practitioner evidence suggesting substantial innovation impact, while the theoretical contribution extends OIPT application beyond its conventional focus on operational efficiency toward understanding strategic product innovation capabilities.

The longitudinal nature of the study enables observation of information processing challenges as they evolve organically rather than through isolated snapshots (Van de Ven & Huber, 1990; Langley, 1999). Following Dyer and Wilkins (1991), we prioritise depth over breadth, seeking rich contextual understanding of how information processing constraints manifest in practice and how organizational actors interpret these challenges.

Radici Yarn exhibits characteristics that make information processing challenges for innovation particularly acute and theoretically illuminating. First, it operates within a mature, saturated market where organic demand growth has stalled and competitors face declining performance (Porter, 1980), creating the precise environmental conditions where information processing requirements escalate while resources remain constrained. Second, as a process industry manufacturer, it confronts complex PSPP relationships where manufacturing conditions profoundly influence product properties (Lager, 2010), necessitating systematic feedback loops between production and R&D that conventional organizational architectures fail to support. Third, as a family-owned enterprise, it must balance operational scale with customization agility (Carney et al., 2015), introducing distinctive governance dynamics that influence technology adoption and KM practices. Fourth, despite possessing decades of technical expertise, advanced production systems, and substantial R&D investment, the organization consistently identifies innovation velocity as its primary competitive constraint, creating a paradox between resource endowments and innovation outcomes that information processing theory can illuminate.

The extended temporal engagement fundamentally shaped the research approach and data collection strategy. Rather than conducting interviews at a single point in time, the researcher participated in ongoing organizational discussions spanning multiple strategic cycles, technological implementation phases, and market condition shifts. This sustained presence provided access to naturally occurring conversations about ISs, innovation challenges, cross-functional coordination difficulties, and strategic priorities. Informal discussions during daily operations, observations of management meetings addressing digital transformation initiatives, participation in project teams evaluating BI platform requirements, and continuous dialogue with personnel across organizational levels generated cumulative understanding of how information processing constraints actually operate.

4.3.2 Data collection

Data collection focused on managers and professionals across organizational functions involved in innovation processes and information flows: Commercial and Sales, Technical Assistance, Quality Management, Production, R&D, Strategic Procurement, Marketing, Market Analysis, and CSR. This cross-functional sampling strategy ensures representation of diverse perspectives on information processing challenges, capturing how coordination failures manifest differently across organizational boundaries and how various functions perceive barriers to knowledge integration (Patton, 2002).
Beyond formal interviews, the three-year engagement with the firm generated substantial secondary evidence: internal documentation accessed throughout the research period provided essential context for understanding organizational information architecture and strategic priorities; systems architecture diagrams illuminated how data flows across platforms and where integration challenges emerged; organizational charts clarified reporting relationships and functional boundaries affecting cross-unit collaboration; strategic planning documents articulated innovation priorities and competitive positioning concerns, and project proposals for digital infrastructure investments revealed technological investment trajectories and implementation challenges. These materials proved invaluable for comprehending the organizational context within which information processing constraints operated. Complementing this analysis, the intricacy of polymer processing was revealed through the observation of manufacturing operations. This included the precise control of temperatures during polymerisation and the adjustment of parameters in response to subtle warning signs. Participation in cross-functional meetings exposed the interpretive work required to translate between domains. These interactions demonstrated how knowledge remains distributed across functional boundaries and how coordination emerges through ongoing negotiation rather than through formal information systems. Informal conversations during shop floor visits and coffee breaks often surfaced concerns that formal interview settings might not have elicited. Witnessing actual decision-making processes illustrated the gap between prescribed workflows depicted in organizational charts and the improvisational problem-solving characterising daily operations.
Such a methodological approach, facilitated by the industrial doctorate model, created distinctive epistemic advantages for studying phenomena requiring both insider access and analytical distance. The dual positioning as an organisational participant contributing to practical problem-solving and an academic observer maintaining a theoretical perspective enabled access to tacit organizational knowledge while preserving the analytical rigour necessary for systematic interpretation.

4.3.3 Data analysis

Data analysis employed the systematic qualitative research procedures outlined by Gioia et al. (2013), moving iteratively between empirical data and theoretical constructs (Strauss & Corbin, 1998). The coding methodology and data structure development followed the approach detailed in Chapters 2 and 3, where the complete analytical process is documented. Since the empirical material for this chapter derives from the same organizational investigation as previous studies, the coding procedures, including open coding generating first-order concepts, axial coding consolidating themes, inter-rater reliability protocols, and member validation processes are not reiterated here to avoid redundancy.

Interviews and informal conversations with organizational members addressed four thematic domains aligned with the theoretical framework guiding this investigation (Rubin & Rubin, 2011). First, current information acquisition and processing practices, including sources accessed, systems utilized, perceived gaps between information needs and availability, and workarounds developed to compensate for architectural limitations. Second, digital technology adoption experiences, encompassing BIS platforms, MES, integration challenges, cultural resistance patterns, and success factors identified by early adopters. Third, innovation processes and production-R&D relationships, exploring how manufacturing knowledge currently informs product development, where feedback loops break down, and what organizational mechanisms might strengthen cross-functional learning. Fourth, barriers and enablers of information-driven decision making, examining both technical obstacles such as data quality and integration complexity, and organizational obstacles such as analytical skill deficits and managerial scepticism regarding algorithmic recommendations.

4.4 Results

Drawing upon three years of sustained organizational immersion, the findings document how escalating information processing demands characteristic of mature industries encounter architectural and organizational constraints that systematically limit innovation performance. This capacity-requirement misfit manifests through three interrelated mechanisms: architectural fragmentation preventing seamless cross-functional information integration, disrupted production-to-R&D feedback loops obstructing organizational learning from manufacturing experience, and decision cycle durations that is incompatible with competitive velocity imperatives.

Analysis of empirical evidence collected through interviews, observational fieldwork, and archival documentation demonstrates strong alignment with OIPT's theoretical predictions regarding the consequences of information processing capacity constraints. These empirical patterns provide robust support for the four theoretical propositions extending OIPT from operational efficiency contexts to strategic product innovation domains. Simultaneously, the findings illuminate organizational preconditions and implementation considerations necessary for integrated PI-MES-BI platforms to function effectively as capacity-enhancement mechanisms within mature manufacturing environments. The subsequent sections present empirical evidence organized according to the four propositions structuring the theoretical framework, followed by analysis of barriers and enablers affecting framework implementation.

4.4.1 Escalating information processing requirements

The interview data provide compelling evidence that information processing requirements for product innovation increase non-linearly as markets mature. Informants consistently characterized their competitive environment through three interconnected dimensions: market saturation with declining organic growth, accelerating competitive velocity demanding rapid response, and customer passivity requiring active downstream signal processing.

Market saturation emerged as a fundamental contextual factor shaping information processing demands. As the commercial director articulated: "*The textile industry is not innovative, we have completely lost the know-how we once had*". This capacity erosion occurs despite continued technical competence, indicating that the constraint lies in information processing architecture rather than knowledge availability. A sales manager emphasized the existential nature of competitive pressure: "*competitors continue to die*", illustrating consolidation dynamics that reward firms capable of processing market information and translating it into innovation rapidly. The urgency of this situation was reinforced by multiple informants, such as the quality manager who identified innovation acceleration as an imperative rather than an advantage: "*The variation that has occurred in the last five years is much more pronounced than that which occurred in the previous twenty-five years*", quantifying the non-linear acceleration in environmental velocity that OIPT predicts will increase requirements.

The temporal dimension of competitive dynamics emerged as the critical performance variable, directly supporting the theoretical proposition that mature markets demand faster information processing. A commercial manager stated: "*It is no longer possible to stay on the market with these reaction times*"; indeed, this temporal compression transforms innovation from a capability that can be developed over months to one requiring day-scale responsiveness.

Consistent with findings presented in previous chapters, the temporal dimension emerged as transcending operational efficiency to constitute a strategic imperative. As the sustainability manager articulated: "*The time factor is the only one that can allow the company to excel*". These statements align precisely with OIPT's prediction that task uncertainty increases information processing requirements through both the volume of information that must be processed and the speed at which processing must occur.

Customer passivity fundamentally alters information processing requirements by forcing organizations to generate weak signals from downstream markets rather than responding to articulated needs. A sales manager explained this dynamic: "*Our (direct) customers are passive. We must look for them in the downstream market, going to the consumer or the brand*". This passivity increases information processing requirements in multiple ways. First, organizations must monitor not only their direct customers but also customers' customers and end-consumers, expanding the information environment that must be surveyed. Second, the information available is inherently weaker and more ambiguous than explicit customer requirements would be, requiring more sophisticated interpretation. Third, the organization must actively construct demand intelligence rather than reactively responding to stated needs, imposing additional analytical burden. A technical manager reinforced this point: "*We must get closer to the final consumer, which for us is particularly critical and important because we do not know what decisions influence the production chain*". The extended value chain creates informational distance that must be bridged through active processing mechanisms.

The gap between idea generation capacity and market implementation speed provides the most direct evidence: as one sales manager articulated: "*our company is very innovative in terms of upstream projects but compared to our direct competitors we are much slower in transmitting these projects downstream. So, we usually move before others, but we don't exploit our time advantage, and in the end, others arrive four years later but are much more incisive than us.*" This statement reveals that the constraint is not ideation but information processing: the organisation possesses ideas but cannot process the information required to convert them into market innovations rapidly enough to maintain first-mover advantages. The fact that competitors "*four years later*" can surpass initial innovators demonstrates that information processing capacity, not technical knowledge, determines competitive outcomes in mature markets where windows of opportunity close rapidly.

The market analysis manager synthesized this misfit: "*The real problem is the step from the availability of innovations to the decision to industrialise the innovation."* This "*step*" is essentially an information processing challenge, involving the integration of technical feasibility data, market opportunity assessment, manufacturing capability evaluation, and commercial viability analysis to make informed decisions. When this processing takes months in markets where competitors can execute their strategies in weeks, it results in persistent underperformance in innovation, even when technical competence is present.

4.4.2 Architectural fragmentation as a capacity constraint

The empirical evidence also strongly supports another proposition: architectural fragmentation reduces information processing capacity for innovation more severely than for operations because innovation requires integration across functional boundaries that fragmentation specifically impedes. Informants provided detailed descriptions of how systems fragmentation creates bottlenecks that particularly constrain innovation processes.

The most direct characterisation came from a senior commercial director: "*From an IT perspective, from a systems perspective, we deal every day with their heterogeneity*". This assessment captures the theoretical construct precisely: heterogeneous systems create integration friction that consumes organizational capacity. The statement that these problems are encountered "*every day*" indicates that the friction is not occasional but systematic, imposing continuous overhead on information processing activities.

As already pointed out in Chapter 2, the fragmentation is particularly critical across functional boundaries, which are precisely the boundaries that innovation processes must span. One technical manager described the challenge of integrating manufacturing and R&D information: "*If we have to reconstruct a history, where obviously at this moment we are managing with emails, there we lose time because we have to search*". The reliance on email for cross-functional information transfer represents a failure of architectural integration. Email is inherently unstructured, lacks systematic capture mechanisms, and depends on individuals' memory of past exchanges. When manufacturing needs to inform R&D about process outcomes, or when R&D needs to understand production constraints, the email-based approach imposes substantial friction.

Multiple informants identified the need to access multiple systems as a persistent friction point: each system transition imposes cognitive switching costs, requires separate authentication and interface learning, and creates opportunities for inconsistency when the same information appears differently across systems. For innovation processes that require synthesising information from production, quality, commercial, and R&D systems, these costs compound. Without a single certified source, different functions may work from inconsistent data, leading to coordination failures that are particularly damaging for innovation where technical, market, and manufacturing constraints must align precisely.

The architectural fragmentation manifests most critically in disrupted production-to-R&D feedback loops; that is the specific informational linkage that the theoretical framework identifies as essential for accelerating innovation cycles. A technical manager articulated an aspiration, revealing the current organizational gap: "*This would remain clearly in the company: in ten years a customer reports the same thing, but I don't do the analysis anymore, because I've already done it*". This statement expresses a desired future state wherein past problem-solving efforts become retrievable organizational memory rather than individual experiences. The aspiration describes precisely what OIPT terms slack resource creation: if the organization systematically captured and codified process-performance relationships discovered during previous production trials and quality incidents, subsequent similar situations could be resolved by accessing stored knowledge rather than requiring fresh analytical work. The absence of such systematic capture mechanisms forces repeated rediscovery of the same constraints. As the same manager acknowledged, without institutional memory systems "*we make the same mistake again*", consuming analytical capacity addressing recurring problems instead of dedicating resources to novel innovation challenges. Manufacturing personnel repeatedly invest effort understanding why specific formulations fail under certain processing conditions, quality teams analyse defect patterns whose root causes were previously identified, and R&D scientists rediscover process boundaries that production experience already revealed. This knowledge fragmentation creates a vicious cycle: constrained capacity gets consumed by repetitive problem-solving, leaving insufficient resources for the systematic analysis that would build the knowledge repositories preventing such repetition.

The fragmentation creates specific challenges for data-driven innovation approaches that require integrating manufacturing parameters with product performance. As one manager explained, when product performance issues emerge in the field, understanding their root causes requires tracing back through manufacturing conditions, but the lack of systematic linkage between production data and quality outcomes prevents this analysis. In some cases, the organization cannot learn from manufacturing experience because the information architecture does not create the necessary linkages.

4.4.3 The integrated PI-MES-BI framework

The empirical evidence substantiates two central theoretical arguments. First, disrupted production-to-R&D feedback loops systematically prevent organizations from learning from accumulated manufacturing experience, forcing repeated problem-solving that consumes capacity better allocated to innovation. Second, integrated PI-MES-BI platforms generate capacity increases through mutually reinforcing OIPT mechanisms, producing multiplicative rather than additive benefits. Informants articulated clear understanding of how individual framework components address specific capacity constraints while recognizing that architectural integration creates synergistic effects.

MES as slack resources

MES implementation emerged as essential for creating the slack resources that buffer against repeated problem-solving. Multiple informants identified process parameter capture as foundational: by systematically capturing manufacturing conditions, the organization creates an information buffer that can be accessed when needed rather than requiring new data collection for each decision. One technical manager emphasized the repository function: "*I believe that the man sending an email with information is truly obsolete. I believe instead that there should be a digital platform for traceability*". The shift from person-dependent knowledge transfer to system-captured information transforms organizational learning from a fragile process dependent on specific individuals' memory to a robust process supported by systematic data infrastructure.

The knowledge loss risk was articulated explicitly by multiple informants. As one manager warned: "*If four people leave, the company loses all the know-how*". In OIPT terms, this describes an organization operating without slack resources, where all critical information resides in individuals' know-how rather than in accessible repositories. MES addresses this concern by capturing process parameters, quality outcomes, and production conditions in real-time, creating what one manager called "*a digital platform that traces everything*".

BI as vertical IS and lateral relations

BI emerged in the interviews as a critical integrator, implementing both vertical IS and lateral relations. The vertical information system function was described by the sustainability manager: "*BI helps me to make informed decisions based on data*". This function addresses the fragmentation documented in Section 4.2 by aggregating information from disparate operational systems and presenting it in forms appropriate for strategic decision-making. Several informants emphasized the temporal dimension: "*the possibility to check on a daily basis*" rather than monthly. This acceleration of information flow from operations to strategy represents the vertical IS mechanism, enabling decisions at a pace aligned with market velocity.

The lateral relations function emerged through descriptions of shared information spaces that enable cross-functional coordination without hierarchical channels. One manager characterised this capability as "*data that can be the same primary base data used for different purposes*". When production, R&D, commercial, and quality functions can access common data sources, they can coordinate activities through shared understanding rather than formal meetings or hierarchical information requests. Another informant emphasised the certification function: "*having information that is substantially certified*", which enables different functions to trust that they are working with consistent data. This shared and certified data foundation creates lateral relations by reducing the transaction costs of cross-functional information exchange.

Multiple informants emphasised that BI's integrative function differentiates it from fragmented operational systems. One manager noted: "*when it is necessary to go and search for information, everything becomes more complicated*", contrasting this with a unified platform where "*the exchange favoured by a system removes complications*." The elimination of search friction represents capacity enhancement: time spent locating and reconciling information is time unavailable for analysis and decision-making. A technical manager articulated the efficiency gain: "*avoid sending 10 emails and trace the entire path on a platform."* When cross-functional coordination can occur through shared platform visibility rather than email chains, the capacity consumed by coordination diminishes, freeing resources for innovation activities.

PI as self-contained task

Although the PI component remains aspirational at Radici Yarn, informants recognized the theoretical necessity for computational approaches to handle the complexity that overwhelms human analytical capacity. The sustainability manager articulated this necessity: "*the capacity to synthesize both numbers and experience, that's the difference between a computer and a human being*". This statement acknowledges that while human expertise remains essential for interpretation, the volume and complexity of data exceed unaided human processing capacity. The recognition that big data with AI represents a necessary capacity multiplier indicates understanding of the self-contained task mechanism: PI can explore vast molecular design spaces autonomously, reducing dependencies on iterative physical experimentation that consumes time and resources across multiple organizational units.

Multiple informants emphasized the need for computational support without displacing human judgment, describing what the framework terms Expert-in-the-Loop (EIL) architecture: "*You must provide the suggestion, while leaving the final judgment to the domain expert*". This design principle addresses scepticism about algorithmic decision-making: "*If we delegate the decision to the machine I do not agree… it limits the analytical capacity of the human being*". The EIL architecture resolves this tension by positioning PI as augmentation rather than replacement: computational models screen large possibility spaces and provide recommendations, but domain experts set criteria, interpret results against tacit knowledge, and make final decisions. This governance principle emerged consistently across informants as essential for adoption.

4.4.4 Production-to-R&D feedback loop: closing the gap

The empirical evidence directly substantiates the theoretical argument that absent systematic production-to-R&D feedback mechanisms prevent organizational learning and force repetitive problem-solving: when manufacturing experience fails to systematically inform R&D decision-making, organizations cannot extract learning from past development attempts. Each innovation cycle necessitates rediscovering process constraints and performance relationships rather than leveraging accumulated organizational knowledge.

The integrated PI-MES-BI framework establishes this feedback mechanism by linking the three components in mutually reinforcing configurations. MES infrastructure captures process parameters and quality outcomes generated during production trials, BI platforms aggregate these manufacturing data streams with commercial performance metrics and R&D specifications, creating informational linkages across functional boundaries previously operating in isolation, whereas PI models trained on this integrated dataset can predict how molecular structure and manufacturing conditions jointly determine product performance, enabling R&D teams to design process protocols that manufacturing can execute reliably at scale. As one manager explained regarding integration value: "*having a digital platform that traces everything from the request phase to the utilization phase*" enables organizational learning because the complete development trajectory becomes captured and accessible for future reference rather than remaining fragmented across individual memories and disconnected systems.

Multiple informants recognized that architectural integration creates multiplicative rather than additive capacity gains, supporting the theoretical claim that integrated platforms generate synergistic effects. The sustainability manager articulated this multiplier dynamic: "*The introduction of BI enables development, both in terms of margins and in terms of breadth and depth of the market*", thus extending benefits beyond operational efficiency improvements to strategic capability enhancement. Another manager emphasized that integration value exceeds component summation: "*integration with a bit of all company functions is the only thing that can give real success for an activity of this type*". This statement captures the theoretical mechanism underlying the framework: integrated platforms implement multiple OIPT capacity-enhancement mechanisms simultaneously, and these mechanisms reinforce one another rather than operating independently with merely additive effects.

4.4.5 Implementation barriers and enablers

The interview data reveals that the greatest challenges to integrated platform deployment are organizational and cultural rather than technical: a finding with important implications for implementation strategy. Multiple informants identified resistance among senior personnel as the dominant barrier. A sales manager stated: “*The issue is that many people still don’t see the potential* *of these tools, and many times the ones who make the decisions are actually the more senior, the older ones*." This demographic pattern creates notable challenges, already previously evidenced, because decision authority concentrates precisely where technological scepticism is highest. Adoption requires that established personnel "*question their role and their competencies*", which threatens professional identity and may be resisted even when objectively beneficial.

Several informants emphasised that overcoming resistance requires concrete demonstration rather than abstract argument. As one manager explained: "*You must make them see something that they cannot even imagine*". This necessity for visualisation suggests that implementation strategies must include proof-of-concept demonstrations showing specific value in organizational contexts that resonate with sceptics.

The interview data also revealed that not all informants shared the critical assessment of organizational capacity. As a manager noted, "*top management is absolutely supportive and the senior management supports with a strong initial commitment*": this leadership support creates an enabling condition that may differentiate successful from unsuccessful implementations, suggesting that top management commitment represents a critical boundary condition for the theoretical relationships. The contrast between this statement and the earlier suggests that support varies by organizational level or function, with strategic leadership potentially more receptive than middle management.

Scepticism about algorithmic approaches emerged consistently and should be considered theoretically important because it identifies a boundary condition: platforms must augment rather than replace human judgment to achieve adoption. Multiple informants emphasized that automation must provide "*the suggestion*" while preserving expert authority: "*the final judgment must remain with the domain expert, whose experience is deemed irreplaceable*". This requirement for flexible integration rather than rigid automation emerged across informants and represents a design constraint that implementations must satisfy.

The implementation challenge extends beyond individual scepticism to systemic organizational change requirements. One manager characterized current systems as suffering from "*rigidity and user-unfriendliness of standard enterprise systems that have previously created more problems than anything else*". This history of problematic implementations creates legacy scepticism that new initiatives must overcome. Multiple informants emphasized that platforms must be "*tailor-made*" rather than forcing processes to conform to standardized software. This customization requirement, while potentially costly, may be essential for achieving the flexible integration that preserves expert authority while providing analytical support.

Table 5 summarizes how each component implements distinct OIPT mechanisms that address complementary information processing challenges, collectively transforming organizational innovation capacity.

Table 5: Integrated PI-MES-BI framework: OIPT mechanisms and innovation impacts

Core component	OIPT mechanism	Challenge addressed	Strategic impact on innovation
Polymer Informatics (PI)	Self-contained task	Reduces the necessity for physical experimentation across a vast molecular space.	Enables inverse design and front-end screening, shifting R&D focus from trial-and-error to computationally guided hypothesis generation.
Manufacturing Execution System (MES)	Slack resources	Overcomes "process gap" uncertainty by capturing real-time operational parameters.	Creates a Process-Performance repository, transforming shop-floor data into systemic organizational memory to buffer against repeated problem-solving.
Business Intelligence (BI)	Vertical IS	Mitigates data fragmentation ensuring aggregated data flows efficiently to hierarchical decision-makers.	Supports evidence-based strategic decision-making by providing management with unified and real-time metrics on innovation portfolio performance.
	Lateral relations	Addresses functional siloing by bridging the operational-strategic divide between R&D and production.	Facilitates cross-functional integration and joint sensemaking, enabling rapid coordination and interpretation of results without formal hierarchical channels.
Production-to-R&D feedback loop (Integrated)	Multiplicative capacity gain (by reinforcing configuration of all four mechanisms)	Tackles asymmetric organizational learning by closing the loop from manufacturing experience back to R&D design.	Accelerates time-to-market by replacing manual integration with parallel, data-driven learning, thereby enhancing the firm's strategic capability.

4.5 Discussion

This study investigated organizational information processing challenges constraining product innovation in mature industries through an in-depth longitudinal case analysis. The findings reveal a fundamental misalignment between escalating information processing requirements and constrained organizational capacity within saturated market contexts. Interpreting these empirical patterns through OIPT's theoretical lens, the analysis generated four theoretical arguments extending the theory from operational efficiency domains into strategic product innovation contexts.

The empirical evidence demonstrates strong convergence with these theoretical expectations across multiple dimensions. First, organizational members consistently characterized temporal performance as the overriding competitive imperative, describing how the competitive environment demands radical compression of decision cycles from months to days. As articulated by one manager, "*the time factor*" has become the critical strategic variable. This temporal pressure intensifies as market ambiguity increases: customers described as "*very passive*" force organizations to actively construct demand intelligence by processing "*weak signals*" from downstream brand partners and end-users rather than responding to articulated requirements. These dynamics empirically instantiate the theoretical prediction that mature markets generate escalating information processing requirements through accelerating competitive velocity, increasing environmental ambiguity, and customer passivity shifting information processing burdens onto suppliers.

Second, the data expose significant organizational capacity constraints resulting primarily from architectural fragmentation across legacy information systems. This fragmentation prevents the cross-functional knowledge integration essential for innovation, forcing personnel to rely on uncontrolled communication channels including email for critical data transfer and validation, thus resulting in practices that informants characterized as problematic and inefficient. These empirical patterns align with the theoretical expectation that architectural fragmentation systematically constrains innovation capacity by impeding cross-functional integration more severely than it constrains routine operational activities.

Third, the empirical evidence directly illuminates how disrupted production-to-R&D feedback mechanisms prevent systematic organizational learning from accumulated manufacturing experience, forcing repeated problem-solving that consumes capacity better allocated to novel innovation challenges. Informants articulated clear recognition of this learning deficit and its consequences for innovation performance.

Fourth, organizational members demonstrated mature understanding that integrated PI-MES-BI platforms would generate capacity increases through mutually reinforcing OIPT mechanisms rather than through simple additive effects, recognizing that architectural integration creates synergistic benefits exceeding isolated component deployment.

Beyond validating these theoretical expectations, the case investigation exposed critical implementation considerations conditioning whether integrated platforms can effectively enhance innovation capacity in practice. Cultural resistance to algorithmic decision-making emerged as a primary adoption barrier, necessitating EIL governance architectures that position computational intelligence as augmenting rather than replacing human expertise. Informants emphasized that demonstrating tangible value through pilot implementations and securing visible senior management commitment constitute essential preconditions for overcoming organizational inertia. These implementation insights provide practical guidance for translating theoretical frameworks into organizational interventions within mature manufacturing contexts characterized by established routines, embedded legacy systems, and cultures privileging experiential over analytical knowledge.

Figure 13 depicts the integrated framework resulting from empirical analysis: this architecture combines technological capabilities with organizational processes and learning mechanisms, revealing how PI computational screening, BI data integration, and MES process capture collectively enable systematic feedback from manufacturing to R&D, thereby enhancing innovation capacity.

INFORMATION PROCESSING REQUIREMENTS

(e.g., market speed, competitive pressure)

↓

POLYMER INFORMATICS	**BUSINESS INTELLIGENCE**	**MANUFACTURING EXECUTION SYSTEM**
Computational prediction molecular design candidate screening	Data integration dashboards & analytics shared information spaces	Process parameters capture real-time monitoring quality data
OIPT: Self-contained task	*OIPT: Vertical systems + Lateral relations*	*OIPT: Slack resources*
↓	↕	↑

PRODUCTION-TO-R&D FEEDBACK LOOP

Structure → Process → Property → Performance → Learning

↓

EXPERT-IN-THE-LOOP

(e.g., domain expertise, interpretation, validation, decision authority)

↓

INNOVATION OUTCOMES

(e.g., reduced time-to-market, increased processing capacity, organizational learning)

Figure 13: The multi-layer information-processing framework

4.6 Conclusion

This investigation examined organizational information processing constraints limiting product innovation performance in mature industrial contexts. The three-year longitudinal case analysis at Radici Yarn documented a fundamental misalignment between escalating information processing requirements, characteristic of saturated markets, and organizational capacity constrained by architectural fragmentation and absent feedback mechanisms. Addressing this capacity-requirement gap, the research developed an integrated PI-MES-BI framework implementing multiple OIPT capacity-enhancement mechanisms in mutually reinforcing architectural configurations.

The study advances theoretical understanding along three dimensions. First, it extends OIPT application from traditional operational efficiency domains into strategic product innovation contexts, demonstrating how Galbraith's foundational mechanisms operate within mature manufacturing environments confronting innovation imperatives. Four theoretical arguments formalize these relationships, repositioning OIPT as a theory capable of explaining strategic capability deployment rather than solely operational coordination.

Second, the research provides systematic empirical investigation of organizational preconditions and implementation contingencies affecting integrated PI-MES-BI platform effectiveness. This addresses a documented gap in manufacturing informatics literature wherein technological capabilities receive extensive attention while organizational and cultural enablers remain underexplored.

Third, the findings generate actionable frameworks for practitioners in mature industries navigating digital transformation initiatives, specifying diagnostic approaches for identifying capacity constraints, design principles for architectural integration, and implementation guidance addressing cultural adoption challenges.

Empirical evidence substantiates the framework's capacity-enhancement potential while simultaneously exposing critical implementation requirements. Organizational members recognized MES infrastructure as essential for systematic process parameter capture, creating the slack resources and institutional memory necessary to prevent repetitive problem-solving. BI platforms emerged as architectural integrators enabling both vertical information flows from operations to strategic decision-makers and lateral coordination across functional boundaries. Informants valued BI's provision of unified and certified data sources supporting daily monitoring rather than monthly retrospective analysis, directly addressing the temporal compression characterizing competitive dynamics. Cross-functional data accessibility implements lateral relations, facilitating coordination through informational transparency rather than hierarchical protocols.

The aspirational PI component received justification through recognition that analytical complexity exceeds unaided human processing capacity, positioning computational intelligence as necessary augmentation for managing high-dimensional chemical spaces. However, the investigation exposed cultural and organizational challenges as primary implementation obstacles, centred specifically on EIL governance requirements. This governance architecture addresses both epistemological concerns about algorithmic opacity and practical recognition that experiential knowledge embedded in senior personnel remains organizationally invaluable.

Consistent with the findings of the previous chapters, implementation requirements extend beyond technological deployment to encompass comprehensive organizational change initiatives. Informants explicitly demanded customized solutions addressing specific organizational contexts rather than standardized enterprise systems whose rigidity previously generated more obstacles than benefits. This customization imperative reflects the need for flexible integration accommodating established workflows, legacy system constraints, and organizational cultures privileging experiential over purely analytical reasoning. Successfully deploying the PI-MES-BI framework therefore requires simultaneous attention to technological architecture, cultural transformation fostering data-driven practices, training programs developing analytical competencies and governance structures preserving human expertise at critical decision nodes. The framework's effectiveness ultimately depends on organizational capacity to integrate computational capabilities with accumulated domain knowledge, creating hybrid intelligence combining algorithmic pattern recognition with contextual human judgment.

While the PI-MES-BI framework was inductively derived from empirical industrial evidence, its analytical robustness can be further strengthened by explicitly aligning it with the conceptual architecture and governance principles articulated in Regulation (EU) 2024/903, the so-called *Interoperable Europe Act*. The Regulation conceptualizes cross-border interoperability as the capacity of public and private entities to interact through the structured exchange of data, information, and knowledge, in compliance with legal, organisational, semantic, and technical standards.

This perspective provides a powerful interpretative lens for repositioning the PI-MES-BI architecture as an *interoperability-by-design* infrastructure. Within this framing, the platform institutionalizes structured coordination across technological and organizational domains. Specifically, the architecture operationalizes: (i) *technical interoperability*, through structured and bidirectional data exchange across manufacturing execution systems, laboratory and R&D modules, and Business Intelligence layers; (ii) *semantic interoperability*, by harmonizing data definitions, taxonomies, and metadata across production, quality, and R&D functions, thereby ensuring interpretative consistency of operational signals; and (iii) *organisational interoperability*, via explicit governance mechanisms defining responsibilities, data ownership, validation procedures, and cross-functional coordination routines. The Regulation underscores the necessity of evaluating these dimensions in conjunction with a governance layer, which functions as the supervisory and accountability foundation of interoperability frameworks. In addition to serving as a technical enabler, the PI-MES-BI model facilitates the conceptualisation of the interoperability platform as a formalised governance and documentation infrastructure. In this respect, integration decisions are rendered auditable, traceable, and transferable across organisational contexts.

Limitations and future research avenues

The limitations of this study open several promising avenues for future research that merit systematic investigation. Arguably most importantly, the theoretical propositions developed here require rigorous quantitative validation across diverse organizational and industry contexts. While our longitudinal case study provides rich insights, the generalizability of these relationships demands systematic empirical testing through large-scale survey research.

The moderating role of ownership structure on information processing dynamics represents a particularly intriguing extension of our framework. Family firms, which predominate in many mature manufacturing sectors, often exhibit distinctive decision-making patterns characterized by longer time horizons, greater risk aversion and stronger emphasis on tacit knowledge transmission. It appears evident that the integration of the PI-MES-BI architecture in a mature sector is a theoretical anomaly when viewed from the perspective of conventional risk aversion. Our findings, however, present a counter-narrative that corresponds with the Behavioural Agency Model (BAM) (Wiseman & Gomez-Mejia, 1998). This research challenges the view of family firms as technologically conservative, suggesting that they become "risk-willing" innovators when their familial legacy is threatened. In alignment with the mixed gamble theory (Gomez-Mejia et al., 2014), our findings posit that the family shown a propensity for risk in technological deployment to mitigate the significant performance threat. In this context, the PI-MES-BI system serves as both a functional instrument and a strategic protection for the family's heritage. By formalising the "production-to-R&D" feedback loop, the company effectively distinguishes its innovative capability from the implicit knowledge of individual family members, hence ensuring the firm's long-term sustainability against the biological constraints of the founding generation (Tan et al., 2024).

Industry characteristics likely constitute another important boundary condition warranting systematic investigation. Process industries such as polymers, pharmaceuticals, and specialty chemicals face acute PSPP relationships where manufacturing conditions critically affect outcomes. Discrete manufacturing industries or service sectors might exhibit different information processing dynamics. Furthermore, the network and ecosystem dimensions of information processing extend our framework beyond the intra-organizational focus of the current study. Innovation increasingly occurs through inter-organizational collaboration involving suppliers, customers, research institutions, and even competitors. The production-to-R&D feedback loop might need to span organizational boundaries when, for instance, a polymer manufacturer must integrate process data from customer manufacturing operations to understand how its materials perform in downstream applications. Research on open innovation architectures could examine how integrated platforms enable or constrain information flows across organizational boundaries, how intellectual property concerns influence the willingness to share production data with external partners, and how ecosystem-level information processing capacity emerges from interactions among multiple organizations.

Finally, the sustainability implications of enhanced information processing capacity represent another promising research direction: the accelerated innovation cycles enabled by integrated platforms could be directed toward environmental objectives rather than purely commercial goals. Such work would be timely given regulatory pressures for circular economy (CE) transitions and corporate commitments to carbon neutrality that require fundamental materials innovation.

Conclusions

This doctoral dissertation investigates the adoption, implementation and strategic use of BISs in mature and process-intensive manufacturing environments. The empirical foundation of the work is a three-year longitudinal case study conducted at Radici Yarn, an Italian manufacturing family firm operating as one of the leading European producers of synthetic fibres and polymers.

The research confronts a central paradox that characterises many contemporary organisations: although firms have access to increasingly integrated and extensive datasets, they often struggle to convert this informational abundance into meaningful strategic insight and stronger managerial capability. Reported BIS failure rates, which in several studies remain between seventy and eighty percent (Pham et al., 2016; Williams et al., 2023), highlight the importance of understanding the organisational and technological conditions that support effective BI assimilation.

The dissertation is structured around a systematic literature review and three empirical studies, each informed by a distinct theoretical perspective. The first research draws on Diffusion of Innovation (DOI) theory, the second mobilises KM perspective that combines the Knowledge-Based View (KBV) with the Resource Orchestration Perspective (ROP), the third engages with sensemaking theory, and the fourth applies the principles of Organizational Information Processing Theory (OIPT). Together, these studies offer a composite view of how organisations interpret, embed and operationalise BI technologies to strengthen organisational capabilities and support strategic decision-making in data-intensive settings.

This concluding chapter synthesizes the main empirical findings and articulates their broader theoretical and practical implications through three interrelated analytical lenses reflecting the very structure of the doctoral path within which this research was developed: *Technology*, *Innovation*, and *Management*. The technological lens addresses the design and governance of digital infrastructures, in line with the program's focus on digital transformation and advanced industrial systems. The innovation perspective examines how mature manufacturing firms translate technological potential into organizational renewal, coherently with TIM's mission of training researchers capable of managing complex innovation processes across industrial contexts. Finally, the managerial lens investigates the organizational, cultural, and human mechanisms that enable, or constrain, the effective use of BI, embodying the program's emphasis on integrating technical, economic, and social competences in the analysis of industrial systems. In this sense, the dissertation operationalizes the TIM framework: it connects digital technologies, innovation dynamics, and managerial governance within a single, empirically grounded research trajectory.

Technological perspective

The first pillar of this research focuses on the technological foundations requisite for BI success. The systematic literature review presented in Chapter 1 synthesized 158 publications spanning multiple disciplines to identify key factors influencing BI adoption in organizations. Among them, the critical function of architectural integration and IT infrastructure sophistication plays a central role. Indeed, architectural fragmentation, characterized by isolated data silos, incompatible system interfaces and lack of enterprise-wide data standards, emerges as the primary technological barrier to successful BI deployment. Organizations characterized by legacy systems operating independently across functional areas face substantial challenges in establishing the integrated data environments that BISs require to generate strategic insights. This finding aligns with extensive prior research documenting the difficulties organizations encounter when attempting to integrate disparate ISs (Quattrone, 2016). However, the present research extends this body of literature by demonstrating how architectural fragmentation specifically impedes BI capability along three dimensions: data extraction complexity, semantic inconsistency and real-time synchronization challenges. At Radici Yarn, the transition from fragmented legacy systems to an integrated PI-MES-BI architecture proved foundational for enabling advanced analytics and cross-functional performance management.

Over these three years, the architectural evolution observed at Radici Yarn mirrors the vision of BI and Knowledge Management (BIKM) proposed by Cody et al. (2002). According to the Authors, strategic value no longer resides solely in the analysis of structured data (like MES records) but in their fusion with the enterprise's unstructured knowledge assets. In this context, the integrated platform becomes a mechanism for correlating quantitative efficiency metrics with the qualitative insights necessary to explain the root causes of production phenomena. Such a technological convergence is what transforms mere data availability into the timely and accurate knowledge essential for competitive performance.

Furthermore, the study responds to the dichotomy noted by Chen et al. (2012), who distinguish between Big Data’s emphasis on the technological aspects of collection and storage versus BI’s focus on transforming such data into business decisions. The implemented architecture bridges this functional divide: the MES acts as the Big Data collector, handling the volume and velocity of high-frequency process parameters, while the BI layer serves as the managerial interpreter. This configuration avoids the common risk documented in literature of creating technologically advanced data repositories that remain disconnected from strategic decision-making processes.

An often underappreciated dimension of technological preparedness for BI adoption concerns the identification, assessment and preparation of data sources. Olszak and Ziemba (2007) emphasize that organizations must specify sources of data capable of supporting business needs, verify reliability of these sources and determine appropriate transformations required to enable analytical use. This preparatory work demands collaboration among decision makers, operational workers, IT departments and KM centres, requiring organizational capabilities extending beyond technical data processing competence. At Radici Yarn, extensive data quality initiatives preceded successful BI deployment, including standardization of product codes across manufacturing sites, reconciliation of discrepancies between production and financial reporting systems, and establishment of master data governance processes ensuring ongoing data integrity. The challenge of data preparation proves particularly acute when organizations seek to integrate internal transaction data with external sources such as market intelligence, competitive benchmarking, or regulatory databases. Organizations must develop capabilities not only for technical data extraction but also for assessing reliability, precision, and consistency of diverse information sources. These capabilities are prerequisites for effective BI operations, although they frequently receive insufficient consideration during implementation planning, as organisations predominantly concentrate on analytical tools rather than essential data infrastructure.

Rapid implementation pressures conflict with customization requirements: platform independence may limit exploitation of proprietary vendor capabilities, scalability investments may exceed immediate needs, and organizations must make deliberate trade-offs informed by strategic priorities, resource constraints and risk tolerance. At Radici Yarn, leaders prioritized architectural flexibility over rapid deployment, accepting longer implementation timelines in exchange for a foundation supporting future evolution. This strategic perseverance was rewarded as the flexible architecture enabled subsequent expansions to proceed rapidly. The decision between creating individual data marts subsequently integrated into an enterprise DW versus immediately building an integrated warehouse represents another critical trade-off. Data mart approaches offer less demanding project scopes and faster results but create future integration challenges and potential inconsistencies. Integrated warehouse approaches demand greater upfront investment but provide superior foundation for enterprise-wide analytics.

Innovation perspective

The second pillar examines how BISs, once technologically established, serve as engines for product innovation and organizational learning, shifting the focus from operational efficiency to strategic capability. More in detail, the study illustrated in Chapter 4, applied Galbraith's (1973, 1974) OIPT to examine how integrated PI-MES-BI systems can accelerate product innovation in polymer manufacturing contexts. OIPT posits that organizations face varying levels of uncertainty and information processing requirements depending on task characteristics, environmental volatility, and strategic objectives. Organizations can respond to increased information processing demands through three primary mechanisms: creating slack resources, implementing vertical ISs, or establishing lateral relations across organizational boundaries. Traditional conceptualizations of MESs position these technologies primarily as operational efficiency tools, focused on reducing production costs, minimizing waste, and optimizing throughput. The study challenges this view by demonstrating how integrated PI-MES-BI architectures can support strategic innovation processes by enhancing organizational information processing capacity along non-routine dimensions. Specifically, the integrated architecture enabled production-to-R&D feedback loops that accelerated polymer formulation optimization, reduced time-to-market for new fibre variants, and enhanced organizational learning about material property relationships. A significant theoretical contribution involves extending OIPT from its traditional domain of operational efficiency toward strategic innovation support. This research demonstrates OIPT's applicability to strategic innovation processes characterized by high uncertainty, equivocality, and non-routine information processing demands. Four theoretical propositions emerged from the OIPT analysis:

(P1) Product innovation processes in mature industries are characterized by non-linear information processing requirements that traditional MES configurations inadequately support;

(P2) Architectural fragmentation between MES, R&D, and BISs constrains innovation capacity by limiting cross-functional information flows;

(P3) Production-to-R&D feedback loops, enabled by integrated PI-MES-BI architectures, serve as critical mechanisms for organizational learning and innovation acceleration;

(P4) Integrated platforms yield multiplicative capacity gains across efficiency and innovation objectives simultaneously.

On the other hand, the study presented in Chapter 2 examined BI adoption through a KM lens, investigating how BISs facilitate organizational knowledge creation, integration, and application processes. This perspective shifts analytical focus from BI as a technological artifact to BI as an organizational capability that enhances strategic decision-making through improved knowledge flows. Building on Nonaka et al.'s (1996) SECI model and Zack's (1999) KM framework, the study demonstrated how BISs support knowledge integration across three dimensions: tacit-to-explicit conversion, explicit-to-explicit recombination, and explicit-to-tacit internalization. At Radici Yarn, BI-enabled dashboards and analytics facilitated externalization by capturing previously tacit production expertise in formalized metrics and KPIs. Combination processes were enhanced through cross-functional reporting that integrated financial, operational, and commercial data into unified strategic views. Internalization occurred as managers developed intuition and pattern recognition capabilities through repeated interaction with BI-generated insights. This dynamic confirms the critical distinction posited by Herschel and Jones (2005): while BI excels in managing explicit knowledge, product innovation requires the mobilization of tacit knowledge residing in expert intuition and experience.

The implemented architecture, therefore, must not be understood as a substitute for human judgment but as a catalyst for knowledge socialization and internalization processes. As argued by the authors, BI is effective only when integrated into a broader KM strategy that values human interaction; without this bridge to tacit intellectual capital, analytical tools risk providing technically correct but strategically sterile answers. The evolution observed in Radici Yarn also reflects a macroscopic trend identified in the study conducted by Liang and Liu (2018): the progressive convergence between Big Data Analytics and KM.

A central theoretical contribution concerns the identification and characterization of misfit between organizational information processing requirements and existing information processing capacity. In many mature manufacturing firms, product innovation processes generate information processing demands that substantially exceed the capacity provided by Management Control System (MCS) configurations. This misfit manifests in several problematic ways: delayed feedback on production trials limits rapid experimentation cycles, fragmented data across R&D and manufacturing silos impedes learning transfer, and inadequate analytical capability constrains pattern recognition in complex material property relationships. The integrated PI-MES-BI framework examined at RadiciGroup directly addresses this misfit by expanding organizational information processing capacity along both volume and complexity dimensions. Volume expansion occurs through automated data capture, reducing manual reporting burdens and enabling real-time visibility into production processes, whereas complexity expansion occurs through advanced analytics that reveal non-obvious relationships between process parameters and product properties, supporting more sophisticated causal reasoning about innovation outcomes. This architectural integration addresses a critical epistemological challenge that Mariani et al. (2018) have identified, which is the importance of resisting the "*end of theory*" temptation in the presence of an abundance of data (Mazzocchi, 2015). In the context of the analysis, the sheer accumulation of Big Data (e.g., high-frequency MES process parameters) has the potential to produce spurious correlations if it is not guided by robust theoretical frameworks. Instead, value is generated by the complementarity between automated Big Data and "small data”, such as laboratory validations and chemical expertise. The variety and velocity of the former are balanced by the veracity and value of the latter. The integrated platform, therefore, does not replace the scientific method with computational brute force but enables the reconciliation between data science and management science essential for navigating mature market complexity.

Perhaps the most novel empirical finding concerns the identification of production-to-R&D feedback loops as a critical mechanism through which integrated BISs accelerate product innovation. In polymer manufacturing contexts, successful innovation depends on rapid iteration between formulation design (R&D domain) and production validation (manufacturing domain). Traditional organizational structures and ISs create substantial barriers to efficient iteration: R&D teams may lack real-time visibility into production outcomes, manufacturing teams may lack understanding of scientific hypotheses driving formulation changes, and knowledge generated during production trials often remains localized rather than being systematically fed back to inform subsequent R&D decisions. The integrated PI-MES-BI architecture examined in this research specifically addressed these barriers by institutionalizing systematic feedback mechanisms. Production trial data captured by MES automatically populated BI dashboards accessible to R&D scientists, enabling rapid assessment of formulation performance. Statistical analytics within BI identified process parameter effects on product properties, revealing optimization opportunities. Collaborative workspaces supported joint R&D-manufacturing review of trial outcomes, facilitating shared sensemaking and organizational learning. The integrated architecture has the capacity to condense feedback cycles to days or even hours, whereas traditional approaches require weeks or months for production trial results to inform subsequent R&D decisions. This acceleration enables more experimental iterations within constrained development timelines, increases learning rates, and ultimately enhances innovation productivity.

Managerial perspective

The third pillar addresses the managerial dynamics required to govern BI adoption, emphasizing that technology is insufficient without human agency, organizational culture and strategic alignment. While technological and architectural factors undeniably influence BI adoption outcomes, the research consistently demonstrates that managerial and human factors constitute primary determinants of BI success or failure.

The third study, reported in Chapter 3, employed Weick’s (1995) sensemaking theory to examine how organizational members interpret, rationalize, and ultimately embrace or resist BI adoption. This analysis revealed that technical capability and potential value are insufficient for successful BI deployment; rather, adoption outcomes depend critically on managers’ ability to construct coherent narratives explaining why BI matters, how it aligns with organizational objectives, and what behavioural changes it requires. These finding challenges technology-deterministic views that implicitly assume organizational adoption follows naturally from technical installation. TAM frameworks, which have dominated IS adoption research for decades, focus primarily on PU and

PEOU as adoption drivers. While these factors certainly matter, the sensemaking perspective adopted in this research reveals their insufficiency: managers and employees do not simply calculate utilitarian value when deciding whether to embrace new systems; rather, they engage in complex interpretive processes shaped by organizational identity, professional norms, power dynamics, and anxiety about technological change. The concept of "expert-in-the-loop" emerged as particularly salient during the BI and MES implementations within Radici Yarn. Rather than positioning BI as autonomous intelligence that replaces human judgment, successful adoption narratives framed BI as augmented intelligence that enhances expert decision-making. This framing proved critical for overcoming resistance from family firms experienced managers who initially perceived BI analytics as threatening their professional status and accumulated domain expertise. These findings resonate strongly with the evidence from Guarda et al. (2013), demonstrating that organizational absorptive capacity is fundamental to both the readiness of the technology infrastructure for supporting BI integration and the successful assimilation into the overall MCS.

The systematic literature evaluation, which is summarised in Chapter 1, revealed a substantial research gap regarding BI adoption in family firms. This discrepancy is significant because family firms exhibit unique characteristics, including a long-term orientation, concentrated ownership and decision authority, strong organisational cultures and the prevalence of tacit knowledge, that may have a different impact on the adoption of technology than non-family firms. The findings at Radici Yarn reveal that these organisations may possess structural advantages for BI adoption under certain conditions; indeed, concentrated decision authority reduces coordination complexity and shortens approval cycles for strategic initiatives, long-term orientation aligns well with BI investments that require sustained commitment and deliver value over extended timeframes, and strong organizational cultures facilitate shared sensemaking and collective adoption narratives. However, as highlighted by Herschel and Jones (2005), the success of such initiatives is deeply rooted in organizational culture: BI technology cannot compensate for the absence of a propensity for knowledge sharing. In the context of a family firm, where trust and relationships are central, the managerial challenge is cultural. Leadership must promote an environment where data sharing is not perceived as a loss of personal power but as a contribution to the collective intellectual heritage. Ultimately, BI must be governed not as a standalone IT project but as a central subset of corporate KM.

The findings of this research can be further strengthened by considering the iterative and cyclical nature of BI implementation evidenced by Olszak and Ziemba (2007), which suggest a distinction between BI *"creation*" and BI "*consumption*" phases, underscoring how assimilation is not a linear process but requires continuous cycles of organizational learning. As Olszak and Ziemba (2007) emphasize, successful BI utilization requires users to continually identify and model knowledge, monitor and modify data repositories, create their own analyses and reports, learn how to interpret results and ask sophisticated questions, and improve business and decision making on an ongoing basis. The interactive nature of these two phases suggests that organizations must view BI implementation as an ongoing process of refinement and adaptation.

The research identified strategic HRM practices as critical enablers of successful BI adoption, operating through multiple mechanisms. First, training and development programs provide technical skills necessary for effective BI utilization, reducing competence anxiety and building confidence. Second, recruitment and selection processes can prioritize analytical competencies and technology orientation. Third, performance management and compensation systems that incorporate BI utilization metrics incentivize adoption and signal organizational commitment.

To conclude, the dissertation's primary contribution lies in the resolution of the theoretical tension between explicit data, which is peculiar to the digital era, and tacit knowledge, which has historically been the source of family firm advantage. This research demonstrates that BI functions as a mechanism for SEW formalisation, securing the family's legacy against the erosion of time and market volatility, even though extant literature has frequently viewed formalisation as opposed to the character of family governance. The integration of digital systems serves distinct socioemotional functions that correspond to the FIBER dimensions, as is evident throughout the longitudinal analysis. First, the PI-MES-BI framework (Chapter 4) transcends operational efficiency in its application to the Renewal (R) of family connections through dynastic succession. It functions as a container for the codification of individual expertise into a permanent organisational asset. Second, the research illustrates that data transparency safeguards the family's reputation in the context of Identification (I) and Binding Social Ties (B). As demonstrated in Chapter 2, the family can transform its normative commitment into verifiable metrics by utilising a reliable BI infrastructure. This reputational certification protects the family name from the possibility of operational failure or greenwashing in a global market where trust demands empirical substantiation. This strengthens the social contract with both internal and external stakeholders. Finally, this dissertation contests the notion that the influence of families in the context of Family Control (F) is diminished by AI and automation. Family proprietors can preserve control while still embracing modernisation through the implementation of managerial identity bridging and explainable AI, as demonstrated in Chapter 3 through the lens of sensemaking. The demystification of the "*black box*" of technology is achieved by transparently rendering algorithmic decisions in accordance with the family's stewardship values. This process paradoxically reinforces the family's legitimacy and authority by substituting the opacity of traditional nepotistic control with the transparency of data-driven accountability and transparency. In this regard, the integration of the "Family DNA" into the digital infrastructure of family firms should be viewed as a sophisticated preservation strategy. In accordance with recent research, family firms' digital engagement is driven by internal motivations for preserving SEW, including family identity and long-term legacy, in addition to external competitiveness (Wu, 2025).

Concluding reflections

This dissertation set out to understand how organizations in mature and process-intensive industries can successfully adopt and leverage BISs to enhance management capabilities and support strategic decision-making objectives. Through intensive longitudinal examination of BI implementation at RadiciGroup, complemented by systematic literature synthesis, the research identifies critical technological, innovation-oriented, and managerial factors influencing adoption outcomes.

Several overarching themes emerge from this inquiry. First, successful BI adoption requires viewing these systems as organizational interventions rather than mere technical implementations. BISs are not self-executing technologies that automatically generate value upon installation, but rather enablers whose effectiveness depends entirely on organisations developing complementary capabilities to interpret insights and inform decisions.

Second, the research challenges deterministic technology adoption models assuming linear progressions from awareness to progressive implementation to full integration to benefit realization. Actual adoption trajectories exhibit non-linear, iterative characteristics, including contested interpretations, gradual convergence and emergent learning.

Third, the findings highlight that successful BI implementation requires holistic approaches addressing multiple dimensions simultaneously. Isolated implementations focused narrowly on specific metrics or decision contexts achieve limited value compared to integrated deployments supporting planning, cybernetic, administrative, and reward controls comprehensively. This integrated perspective aligns with recent literature emphasizing ISs packages rather than isolated techniques and suggests productive directions for future theory development and practical innovation.

Finally, positioning this work within the four-phase research framework proposed by Liang and Liu (2018), i.e., Technology, Application, Management, and Impact, the dissertation demonstrates that true competitive advantage emerges from the simultaneous orchestration of these dimensions. While much prior literature has limited itself to isolating the technological or applicative components, Radici experience highlights that real impact, measured in the acceleration of innovation, is achieved only by resolving the management challenges of adoption and culture that act as the transmission belt between IT infrastructure and business application.

Ultimately, the transition toward data-driven processes must not obscure the need for a "*theoretical narrative*" that makes sense of data (Mariani et al., 2018), especially in contexts like family firms, where expert intuition and tacit knowledge remain inimitable assets. The journey from data to decisions remains complex, context-dependent, and irreducibly social. Technologies like BISs provide powerful enabling infrastructures, but organizational capabilities, managerial wisdom and human judgment remain central to converting information into competitive advantage.

Our findings contribute to the ongoing discussion that family firms demonstrate a diverse propensity to engage in digital transformation (De Massis et al., 2016; Appleton et al., 2025). Recent research on family businesses indicates that familial character traits, including risk tolerance, generational aspirations, and identity congruence, determine unique digital pathways, contrary to classical innovation theory, which predicts a consistent response to competitive pressures. As a result, this dissertation contributes to the body of existing research by demonstrating that digital tools, such as BI, are not neutral agents of change; rather, they are interpreted, legitimised, or contrasted in accordance with the interaction between familial objectives and governance structures.

Implications for managers: from industrial research to organizational practice

Industrial doctoral research occupies a distinctive epistemic position at the intersection of academic rigor and organizational reality. This dissertation acknowledges that scholarly inquiry into contemporary organizational phenomena cannot remain sequestered within academic boundaries but must demonstrate its capacity to generate actionable insights, inform strategic decision-making, and ultimately enhance competitive performance in industries facing unprecedented technological and market pressures. This dual orientation proves essential for addressing complex contemporary phenomena where purely academic perspectives risk losing practical relevance while purely practitioner perspectives may lack conceptual depth necessary for generalizable insight.

Radici Yarn, with its deeply rooted presence in the Bergamo territory since 1941 and its current global footprint spanning three continents, represents an exemplary context for examining how process-intensive manufacturers navigate digital transformation while preserving organizational identity and competitive advantage. At the same time, it embodies the enduring strength of *Made in Italy* as a distinctive model of industrial excellence.

The company reflects a manufacturing tradition shaped within Italy's industrial districts, where technical expertise, craftsmanship, and entrepreneurial vision have historically converged. This model is grounded in territorial embeddedness, intergenerational continuity, and the cumulative development of tacit knowledge (Cucculelli & Storai, 2015). It combines artisanal precision with industrial scalability, engineering depth with production flexibility, and a persistent commitment to quality and sustainability. Competitive advantage, in this tradition, is not built on cost minimization but on the capacity to generate value through design sensitivity, process refinement, and technical reliability. This is consistent with the evidence that *Made in Italy* is perceived as a quality signal and elicits a quantifiable willingness-to-pay premium (Cappelli et al., 2017). Italy's industrial history demonstrates a unique ability to integrate technological innovation with cultural identity and aesthetic awareness: this synthesis has positioned Italian firms among the most competitive actors in high-value, design-intensive, and technologically sophisticated global markets. Within this broader framework of national excellence, Radici Yarn can be interpreted as a contemporary expression of the Italian manufacturing *ethos*: a production culture capable of aligning advanced engineering capabilities with systemic supply-chain integration, knowledge accumulation, and long-term strategic orientation. The firm's strategic architecture, centred on knowledge integration, cross-functional collaboration, and innovation acceleration, strengthens its adaptive capacity in data-intensive environments while preserving the distinctive qualities associated with *Made in Italy*. Quality, reliability, sustainability, and industrial continuity remain central pillars. Digital transformation becomes a means to reinforce these attributes, ensuring that Italian manufacturing excellence evolves without losing its identity.

The findings emerging from the four empirical studies that compose this dissertation converge into a coherent set of managerial implications. These implications are grounded in rigorous empirical analysis while remaining explicitly oriented toward practical applicability. They extend beyond the strategic relevance of BI adoption to address a deeper issue: the organizational transformation required to translate data-driven capabilities into sustained competitive advantage. The following sections articulate these implications, recognizing that effective knowledge transfer between academic research and managerial practice requires both conceptual precision and contextual sensitivity.

The first and perhaps fundamental implication concerns how managers conceptualize BI within the context of increasingly demanding environmental, social, and governance (ESG) requirements. This research shows clearly that BI effectiveness depends on intricate alignment among technological infrastructure, user competencies, organizational culture, data governance frameworks, cross-functional integration mechanisms, and strategic vision. Radici's commitment toward sustainability, formalised through its comprehensive plan targeting 2030, exemplifies how BI capabilities must extend beyond traditional performance monitoring to actively support environmental and social objectives. The plan's ambitious targets including 80 percent energy from renewable sources, 25 percent reduction in water consumption intensity, 35 percent reduction in carbon emissions intensity, and systematic measurement of Scope 3 emissions across all operations represent information-intensive goals requiring sophisticated data integration mechanisms that BI platforms uniquely enable. For Radici specifically, this manifests in the capacity to monitor real-time energy consumption patterns across geographically dispersed sites, integrate production data with environmental metrics, and identify optimization opportunities that simultaneously improve operational efficiency and reduce environmental footprint. Recent scholarship demonstrates that organizations successfully integrating sustainability metrics into BI frameworks achieve superior environmental performance while maintaining competitive positioning (Chalmeta & Ferrer Estevez, 2023). Cheng et al. (2023) provide empirical evidence that BI combined with Big Data analytics capabilities positively influences sustainable development management through enhanced analytical capabilities supporting strategic CSR information processing (Cerchione et al., 2026a). For manufacturers in mature industries like synthetic polymers, where incremental efficiency gains translate directly into reduced resource consumption and emissions, this integration proves particularly consequential.

Managers must therefore resist the allure of technological determinism that positions BI platforms as turnkey solutions capable of transforming decision-making through deployment alone. Instead, BI should be understood through the lens of dynamic capabilities theory as a higher-order organizational capacity that enhances information processing capabilities necessary for both competitive responsiveness and sustainability performance (Teece, 2007; Watson & Wixom, 2007b). The systematic literature review conducted in Chapter 1 reveals that organizations achieving sustained BI value creation invariably invested in parallel capability development encompassing analytical skill formation, change management processes, data literacy programs, and cultural transformation initiatives that normalized data-driven decision-making while preserving space for professional judgment and experiential knowledge (Popovič et al., 2012; Ain et al., 2019). For Radici Yarn specifically, this implies that BI maturity represents a multi-year developmental trajectory requiring patient investment, iterative learning, and organizational commitment extending beyond initial system deployment. The progressive implementation of SAP ERP systems across Business Areas demonstrates systematic architectural development enabling enterprise-wide data integration. However, technological deployment represents merely the foundation: true capability maturation requires parallel development of analytical competencies among polymer chemists, production engineers, and commercial managers enabling them to leverage integrated data for hypothesis generation, experimentation design, and continuous optimization. Managers should establish realistic expectations regarding timelines, recognizing that capability maturation follows non-linear pathways characterized by experimentation phases, consolidation periods, and occasional setbacks as documented in DOI literature (Rogers et al., 2014).

Research findings repeatedly emphasize that BISs generate value through enhancement of organizational absorptive capacity, defined as the ability to identify, assimilate, transform, and exploit knowledge for competitive purposes (Zahra & George, 2000). This theoretical insight carries profound practical implications for organizations like Radici pursuing aggressive CE strategies where knowledge integration across traditional functional boundaries becomes essential. The firm's comprehensive approach to circularity, encompassing eco-design principles emphasizing monomateriality, intrinsically recyclable nylon formulations enabling thermomechanical recycling with limited energy requirements, bio-based alternatives and systematic optimization of recovery systems differentiating between closed-loop and open-loop applications, represents knowledge-intensive innovation requiring seamless information flows between R&D, production, commercial, and supply chain functions.

Empirical evidence from Chapter 2 demonstrates that BI effectiveness in supporting KM depends critically on both potential absorptive capacity (knowledge acquisition and assimilation) and realized absorptive capacity (knowledge transformation and exploitation). Furthermore, realized absorptive capacity demands institutional mechanisms ensuring analytical insights inform actual decisions rather than accumulating in unused reports. This requires establishing cross-functional committees reviewing BI outputs regularly, integrating BI metrics into performance evaluation frameworks, creating feedback loops demonstrating how analytical findings influenced strategic choices, and developing communities of practice where BI users share interpretive strategies and application experiences. At Radici Yarn, this might involve regular technical-commercial meetings where production data from MES informs product development priorities within the company's fibre innovation roadmap. The recently implemented SuccessFactors HRM system demonstrates how digital platforms can formalize and enhance knowledge flows related to career development and competency building, creating transparency and accessibility previously unavailable through informal mechanisms.

Chapter 3 reveals a subtle but consequential tension inherent in BI-enabled decision environments: while BISs enhance analytical capabilities by processing vast data volumes and identifying patterns invisible to unaided cognition, they simultaneously introduce interpretive challenges requiring active managerial intervention. Algorithmic outputs do not speak for themselves: they require translation into organizational language, contextualisation within strategic frameworks, and legitimation through narrative construction rendering them meaningful and actionable for diverse stakeholders (Weick, 1995). This sensemaking imperative proves particularly acute when analytical insights concern sustainability performance, where technical metrics must be translated into meaningful narratives accessible to internal and external stakeholders possessing varying levels of technical sophistication. Radici's comprehensive sustainability reporting, providing detailed disclosure across ESG dimensions, demonstrates sophisticated external sensegiving translating complex operational data into stakeholder-comprehensible narratives. However, external communication represents only one dimension. Equally critical remains internal sensemaking where managers interpret BI outputs to guide operational decisions while maintaining organizational coherence with established values and long-term strategic vision. This research reveals that effective BI utilisation depends fundamentally on managers functioning as sensemakers and sensegivers who bridge technical analytics and organizational understanding (Maitlis & Christianson, 2014). Sensemaking involves interpreting BI outputs by integrating them with tacit knowledge, historical experience, industry expertise, and strategic context. This interpretive work demands asking serious questions: *what do these patterns really mean? Do findings align with what we already know, or challenge it? What other explanations might account for what we observe?*

This interpretive activity appears particularly important in manufacturing contexts where operational data may contain noise from equipment variations, measurement inconsistencies, or transient process disturbances that algorithms cannot automatically distinguish from meaningful signals. For polymer manufacturing specifically, where molecular structure, process conditions, and end-use performance interact through complex non-linear relationships, purely data-driven pattern recognition risks identifying spurious correlations lacking physical explanatory mechanisms. The process gap identified in the PI literature (Wu et al., 2019; Tran et al., 2024), where predictive models trained exclusively on molecular descriptors fail to forecast performance accurately because processing conditions determine morphology and mechanical behaviour, underscores the necessity of expert interpretation validating algorithmic predictions against scientific understanding. When MES data from Radici Yarn's manufacturing systems suggest unexpected yield variations across similar formulations, managers must work collaboratively with polymer chemists and process engineers to determine whether patterns reflect meaningful process changes requiring investigation or merely statistical noise arising from measurement variability or temporary environmental fluctuations.

Managers must therefore craft narratives positioning BI as augmented intelligence complementing *rather than* replacing human judgment. This framing proves particularly important in family firms where senior leadership may possess decades of accumulated wisdom commanding organizational respect.

The fourth study's central contribution reveals that strategic value emerges through systematic integration enabling cross-functional information flows supporting innovation processes. This finding carries direct implications for managerial decisions regarding IS investments and governance structures, particularly relevant for organizations like Radici Yarn pursuing simultaneous operational excellence and innovation acceleration. Traditional approaches emphasize functional optimization, deploying BISs for commercial intelligence, MES platforms for production control, laboratory information management systems for R&D support, and ERP systems for financial and supply chain management, with each system optimized independently according to departmental requirements. This functional logic generates architectures where systems cannot communicate effectively, creating information silos preventing knowledge integration necessary for innovation. Production data remains trapped in MES inaccessible to R&D teams who could leverage it for product development, customer feedback analysed in BI dashboards never reaches production managers who might adjust processes accordingly, laboratory characterization results remain isolated from commercial teams making sales commitments and quality incident patterns documented in manufacturing systems fail to inform material design priorities. Radici systematic implementation of MES across production sites, ongoing throughout 2024, creates potential for production-to-R&D feedback loops but realization requires deliberate architectural integration. The improvements in defect detection timeliness and accuracy achieved through MES deployment provide immediate operational value through reduced waste and improved quality consistency. However, strategic value multiplication occurs when these defect patterns, correlated with specific process parameter combinations, material characteristics, and environmental conditions, inform R&D hypotheses about structure-property-process relationships enabling more robust product designs. Similarly, when unexpected superior performance emerges in specific production lots, systematic capture and analysis of the associated process conditions enables deliberate replication and potential formalization into improved standard formulations. The concrete evidence of the strategic relevance of modular and open system architectures is provided by the proven effectiveness of Radici's traceability platforms, which incorporate inorganic tracers embedded directly into nylon fibres with a digital tracking infrastructure accessible through QR codes (RadiciGroup, 2023). The initiative integrates physical product authentication with blockchain-enabled digital certification and was developed in collaboration with industrial and technological partners within an open innovation framework. The platform guarantees end-to-end traceability, transparency, and data integrity throughout the supply chain by connecting material-level identification technologies to distributed digital ledgers. In addition to its technical functionality, the project highlights the importance of designing organisational and digital infrastructures that can accommodate emergent specialised technologies without requiring disruptive systemic redesign.

From a sustainability perspective, for organizations like Radici Yarn requiring sophisticated performance monitoring across ESG dimensions, maturity assessment must explicitly consider sustainability-specific capabilities. The systematic measurement of Scope 3 emissions across all operations for the first time in 2024 demonstrates maturity progression requiring both enhanced data collection mechanisms capturing upstream and downstream value chain activities and sophisticated analytical capabilities allocating indirect emissions appropriately. The firm's comprehensive LCA portfolio, maintaining scientifically rigorous methodologies with third-party verification for strategic products, reflects advanced sustainability analytics maturity enabling both compliance reporting and strategic decision support comparing alternative materials, processes, and product configurations on environmental performance dimensions. However, some room remains for further integration. For instance, connecting LCA insights more systematically with commercial pricing decisions, R&D portfolio prioritization, and supplier qualification criteria would represent progression toward integrated sustainability-business intelligence supporting value creation rather than merely risk mitigation and compliance.

In conclusion, the DOI framework applied in Chapter 1 reveals that BI adoption unfolds through sequential stages characterized by distinct organizational challenges requiring stage-appropriate managerial responses (Rogers, 1995; Puklavec et al., 2014). During awareness stages, the primary challenge involves building organizational understanding of BI potential while managing expectations regarding timelines and investment requirements. Managers must resist pressure to overpromise, acknowledging that BI value realization requires time, patience, and sustained commitment. Communicating realistic expectations, supported by evidence from peer organizations, helps build psychological readiness while preventing premature disillusionment.

Experimentation stages present different challenges centred on pilot implementation, user learning, and iterative refinement. Managers should resist temptations to scale prematurely before demonstrating value in controlled contexts. Pilot projects provide opportunities for organizational learning about data requirements, analytical capabilities, user needs, and integration challenges inevitably requiring system adjustments. Successful pilots generate organizational confidence, develop internal expertise, and produce concrete evidence supporting broader investment. Failed pilots, when approached as learning opportunities rather than catastrophes, reveal implementation barriers requiring attention before enterprise-wide deployment (Isik et al., 2013). Radici's experimentation with blockchain-based digital product passports exemplifies controlled piloting enabling feasibility assessment before committing to enterprise-wide implementation. The proof-of-concept focused on a single apparel item, mapping the complete production cycle and validating the platform for future Digital Product Passport implementation guaranteeing traceability, data transparency, and environmental impact measurement. This bounded experimentation enables evaluation of technological feasibility, user interface intuitiveness, data integration requirements, and value proposition clarity before expanding to broader product portfolios.

Transition stages, where BI becomes embedded in organizational routines, demand sustained change leadership addressing cultural resistance, power dynamics, and psychological threats that analytical systems often provoke. Long-tenured employees whose authority derived from experiential knowledge may perceive BI as threatening their organizational position. Functional departments may resist transparency that BISs create, fearing exposure of inefficiencies or performance gaps. Managers must acknowledge these concerns explicitly while constructing narratives positioning BI as complementary to existing expertise rather than threatening it (Shollo & Galliers, 2016).

Throughout all stages, top management commitment proves essential. BI initiatives lacking visible executive dedication struggle to secure necessary resources, coordinate across functional boundaries, and maintain organizational priority when competing demands emerge (Yeoh & Koronios, 2010). Senior managers must demonstrate personal engagement with BISs, reference analytical findings in strategic communications, and hold subordinates accountable for evidence-based decision-making. This visible commitment signals organizational seriousness while legitimizing the investment of time and effort that BI adoption requires. Radici's incorporation of BI-derived sustainability metrics into corporate reporting, with detailed disclosure in the comprehensive Sustainability Report following GRI standards and external assurance verification, signals long-term executive commitment to data-driven sustainability management while creating accountability mechanisms reinforcing systematic performance monitoring (RadiciGroup, 2024).

The findings shed light on the need for interpreting maturity models as dependent upon contextual factors, including industry dynamics, competitive positioning, organizational size, governance structures, and strategic priorities legitimately generating diverse maturity trajectories (Popovič et al., 2012). Managers should employ maturity frameworks as diagnostic and planning tools, adapting developmental sequences to organizational circumstances while maintaining focus on balanced capability growth across multiple dimensions simultaneously.

Perhaps the most strategically consequential finding concerns BI's potential for accelerating innovation in mature industries traditionally characterized by incremental improvement rather than radical transformation. Chapter 4 demonstrates that systematic integration of production data, laboratory characterization, and computational modelling through BI platforms enables closing production-to-R&D feedback loops that previously remained open, constraining innovation velocity. This capability proves particularly valuable for process-intensive manufacturers where product performance depends critically on manufacturing conditions that must be discovered through systematic experimentation rather than pure computational prediction. For Radici Yarn, BI-enabled innovation acceleration addresses multiple simultaneous imperatives.

Radici's openness to sustained academic engagement, providing access to internal processes, personnel, and data while maintaining transparent dialogue about implementation challenges and organizational constraints, created conditions enabling research that is both theoretically sophisticated and practically relevant. The implications that have been previously articulated are intentionally designed to motivate action. Indeed, they recognise the complexity of the context while simultaneously identifying principles that are applicable to similar organisational environments. They recognise patterns that are more generally applicable to organisations that are navigating digital transformation amid sustainability imperatives while also respecting the distinctive characteristics of family-owned, process-intensive, and mature manufacturing firms. As RadiciGroup navigates the organizational transition following Lone Star Funds' acquisition of Specialty Chemicals and High Performance Polymers Business Areas while the Radici family continues guiding Advanced Textile Solutions, the organizational learning and capability development investments documented in this research constitute valuable assets transferable across the evolving organizational configuration. BI capabilities, analytical competencies, sustainability management systems, and innovation processes developed through years of deliberate investment remain relevant regardless of ownership structures, representing organizational knowledge embedded in systems, routines, and personnel competencies rather than merely formal structures. The principles articulated in this concluding chapter, grounded in both empirical observation and theoretical synthesis, provide guidance applicable not only to Radici's current configuration but to the evolving entities that will emerge from the organizational restructuring, ensuring that collaborative research insights continue generating value as organizational forms adapt to changing strategic and competitive circumstances.

Ultimately, *weaving data into strategy* is not merely a technological exercise. It is an act of organizational continuity. It means interlacing accumulated tacit knowledge with analytical capability, integrating sustainability commitments with digital architectures, and aligning historical identity with forward-looking competitiveness. In this sense, *weaving data into strategy* becomes the disciplined craft of transforming chemical expertise and textile mastery into enduring competitive strength, ensuring that the family's industrial heritage is not carried forward unchanged but consciously rewoven into the fabric of its digital future.

List of Figures

Figure 1: Two-dimensional framework 22

Figure 2: Number of collected articles..25

Figure 3: Percentage of articles taking into account both BI and digital technologies......................25

Figure 4: Number of articles per DOI dimension 26

Figure 5: Number of articles per BI dimension 26

Figure 6: BI dimensions distribution per DOI theory stages during the period 2018-2023 27

Figure 7: Literature map on BI per DOI theory stages by crossing drivers, barriers, success factors and impacts 38

Figure 8: The conceptual framework 48

Figure 9: The information flow of the firm under investigation..56

Figure 10: Firm’s main bottlenecks of information 58

Figure 11: The sense-making theoretical framework 75

Figure 12: Integrated PI-MES-BI framework for product innovation..105

Figure 13: The multi-layer information-processing framework 120

List of Tables

Table 1: Participants details 53

Table 2: Coding tree...55

Table 3: Participants details 78

Table 4: Coding tree...80

Table 5: Integrated PI-MES-BI framework: OIPT mechanisms and innovation impacts 118

References

Abbate, S., Centobelli, P., & Cerchione, R. (2023). The digital and sustainable transition of the agri-food sector. *Technological Forecasting and Social Change*, *187*, 122222. https://doi.org/10.1016/j.techfore.2022.122222

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