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An emergent grounded theory of AI-driven digital transformation: Canadian SMEs' perspectives

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ABSTRACT
Artificial intelligence (AI) empowers traditional firms to transform into Industry 4.0, enabling them to compete in an era of rapid technological advancements. However, AI adoption remains limited among Canadian firms. This research aims to identify the key dimensions of AI-driven digital transformation (AIDT) and develop a grounded theory that provides a rich and nuanced understanding of how the AIDT process unfolds within Canadian SMEs. The study reveals that the AIDT process is shaped by the interplay of five core dimensions: *evaluating transformation context*, *auditing organisational readiness*, *piloting the AI integration*, *scaling the implementation*, and *leading the transformation*. The first four dimensions follow a sequential, stage-like progression, while the fifth dimension is recurring and omnipresent, exerting a continuous impact on the other phases. AIDT is characterised as a path-dependent, slow evolutionary change spectrum that demands firms adapt by developing their sensing, seizing and reconfiguration capacities to evolve and sustain their evolutionary fitness. The study explores several theoretical and managerial implications that arise from the findings.

KEYWORDS
Artificial intelligence; digital transformation; dynamic capability; grounded theory; industry 4.0; technological innovation

JEL CLASSIFICATION
C80; D20; L60; O30

1. Introduction

Technical change has long been considered an imperative for organisational transformation. With proliferation of modern digital technologies (e.g. AI and big data analytics), organisational transformation has gained renewed momentum under the term Digital Transformation (DT). DT refers to 'a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies' (Vial 2019, 118). It is an emerging, recurring, and evolving research theme among scholarly researchers and practitioners (Appio et al. 2021; Hanelt et al. 2021). As DT is a multidimensional phenomenon, the literature is diverse, fragmented, divergent in views and lacking consensus on its nature (Vial 2019) and nuances (Gray and Rumpe 2017).

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The renewed interest in DT can be attributed in part to the very nature of modern technologies and in part to their significant impacts on both organisation performance and 'consumers' expectations and behaviours' (Verhoef et al. 2021, 889). Further, modern technologies are qualitatively different from earlier firm-level efficiency-enhancing enterprise systems in that they are modular, distributed, cross-functional, generative, and interactive (Bharadwaj et al. 2013; Kallinikos, Aaltonen, and Marton 2013). They also offer firms new functional capabilities and affordances (Iansiti and Lakhani 2020), thereby impacting the highly competitive business landscape and increasing the pressure on firms to transform their business models (Porter and Heppelmann 2014). Recent studies have underlined the departure of DT from classic IT-enabled organisational transformation, as DT propels a firm towards a new organisational identity and redefinition of its value proposition (Wessel et al. 2021).

The existing literature on DT clarifies its concepts and importance (Hess et al. 2016; Sawy et al. 2016). It highlights the role of DT in SME business model innovation and value creation (Matarazzo et al. 2021) and frames DT strategy as something that is 'continuously in the making, with no foreseeable end' (Chanias, Myers, and Hess 2019, 17). However, there are caveats regarding phase transitions, platform change, and the relationship between DT and dynamic capabilities (Appio et al. 2021; Vial 2019). What's more, research on AI-driven DT among manufacturing SMEs remains at an embryonic stage.

Furthermore, AI – the most prominent of Industry 4.0 technologies – has the strongest pervasive impact, compared to other many forms of digital technologies (Leone et al. 2021). Considered a general-purpose technology or GPT (Agrawal, Gans, and Goldfarb 2019), AI systems are increasingly being integrated into the fabric of our business processes. These have the potential to exert great influence on innovations in a multitude of industries; and consequently, to significantly impact the economic landscape. To illustrate, machine learning is a key enabler for transformation of traditional manufacturing systems into Industry 4.0 (Lu 2017; Xu, Xu, and Li 2018), with applications such as predictive maintenance and planning as well as defect detection and classification (Bertolini et al. 2021; Susto et al. 2015).

Recent years have seen substantial growth in AI research, primarily in the area of AI technologies, with comparatively less emphasis on firm-level AI adoption, particularly in the manufacturing sector (Kinkel, Baumgartner, and Cherubini 2022). Successful execution of AI initiatives requires firms to possess a certain level of AI readiness. However, AI readiness is a complex concept that encompasses organisational, technological, financial, and cultural dimensions within a firm (Castrounis 2019). This complexity has created a gap in the literature, particularly in the context of manufacturing SMEs in Canada.

In Canada, much like other OECD nations, a limited number of frontier firms[1] drive productivity growth through technology adoption and research and development (R&D) efforts (Andrews, Criscuolo, and Gal 2015; Mullin 2020). However, even frontier firms experienced a decline in the pace of innovation during the 2000–2015 period, contributing to an overall slowdown in aggregate productivity (Gu 2020). Surprisingly, adoption and integration of AI into production and manufacturing processes across various industries remains relatively low, as indicated by surveys and academic research (Kinkel, Baumgartner, and Cherubini 2022). This low adoption rate has resulted in only a small cluster of

[1]Frontier firms are defined as the top 10% most productive firms in an industry (Gu 2020).

international firms implementing AI in industrial applications (Bertolini et al. 2021).

Given that technology-driven growth has become the primary driver of new economic activity worldwide (Mullin 2020), it is crucial to bridge the gap between the potential of AI and its actual adoption rate. Therefore, we aim to investigate and elucidate the phenomenon of AI-driven digital transformation (AIDT) in Canadian manufacturing SMEs by addressing the following questions: What are the primary dimensions of AIDT observed among a sample of Canadian SMEs? How does the process of AIDT unfold within this specific context?

Following an inductive qualitative methodology, we collected data through 27 interviews with participants from 17 organisations as well as attending five AI-focused events. We then followed grounded theory (GT) techniques and guidelines (Strauss and Corbin 1990) to analyse the data and develop a conceptual model of the AIDT process.

From a theoretical standpoint, the emergent GT model offers valuable insights into understanding AIDT. This model delineates the scope of the DT process by explicitly identifying and elucidating five core dimensions that underpin AIDT: *evaluating the transformation context*, *auditing organisational readiness*, *piloting AI integration*, *scaling AI implementation*, and *leading the transformation*. The first four dimensions correspond to the fundamental phases of AIDT identified in this study, occurring in a sequential and stage-like manner. The fifth dimension, *leading the transformation*, is recurrent and omnipresent, exerting a continuous impact on the other four phases. The GT model not only presents these phases but also provides an overview of the nature of the AIDT process. The AIDT process represents a multifaceted digital innovation process, the outcomes of which enhance firm efficiency and productivity, with the potential to generate further innovations through its ripple effects. Consequently, this process contributes to the literature on digital innovation management, which seeks fresh perspectives on the relationship between innovation processes and outcomes (Nambisan et al. 2017) and advances our understanding of DT as a strategic renewal process for firms (Agarwal and Helfat 2009).

Furthermore, we extend the explanatory boundary of our model by integrating key insights from dynamic capabilities or DC (Teece, Pisano, and Shuen 1997). We characterise AIDT as a slow evolutionary innovation process susceptible to path dependencies. We further identify how sensing, seizing and reconfiguring capacities (Teece, Pisano, and Shuen 1997) are leveraged in each phase of the AIDT process. To enhance the understanding of DC, we break down sensing into inward and outward-looking components, providing greater clarity and granularity in explaining AIDT through a DC lens. Moreover, the five dimensions of our model can serve as inputs for the development of a deductive taxonomy, derived not from empirical cases but based on theory or conceptualisation (Nickerson, Varshney, and Muntermann 2013).

Our proposed model presents a comprehensive and nuanced narrative, highlighting crucial details within each phase of AIDT. This model can serve as a strategic navigation tool for practitioners, assisting them in defining their roles and establishing realistic expectations during each stage of the transformation process. For instance, recognising the enduring significance of leadership throughout the DT journey, top management will understand that their involvement is not limited to an initial phase but requires a long-term and continuous commitment.

Moreover, decision-makers, often concerned with return on investment (ROI) as a primary criterion for approving DT initiatives, will recognise the peril of placing excessive emphasis on this requirement during the early phases. Premature expectations regarding immediate ROI can potentially undermine the success of AIDT right from the start. Therefore, managers can benefit from our findings to navigate their AIDT process more prudently.

The remainder of this paper is organised as follows: Section 2 briefly surveys the relevant literature. Section 3 explains the research methodology. Section 4 presents the findings, providing the narratives around AIDT, organised into five dimensions and their underlying themes (i.e. the answer to question 1). Section 5 introduces the emergent model (i.e. the answer to question 2). Section 6 discusses the findings, and concludes.

2. Literature review

2.1. Digital transformation in the age of AI

IT strategy has been increasingly fused into firm business strategy (Bharadwaj et al. 2013). So much so, that a firm's DT strategy now goes well beyond the bounds of the technology-centric IT strategy (Matt, Hess, and Benlian 2015), supporting its innovation process (Appio et al. 2021) and making strategic contributions to its financial, strategic and innovation performance (Vial 2019). Consequently, researchers have emphasised the role of management in formulating a sound DT strategy that considers technology deployment in tandem with changes in structures, value creation processes and ways to finance DT initiatives (Matt, Hess, and Benlian 2015). However, such strategy formulation relies on delineating DT process and its constituents. We need to consider the role of digital technologies in closing the competition gap (Grover and Kohli 2013) while also exploring issues related to leadership (Sia, Soh, and Weill 2016), skill gaps, corporate culture (Kohli and Johnson 2011), and the ambidexterity of management in analogue and digital capabilities (Sebastian et al. 2017). More importantly, a firm's DT decision requires its top management to work with a complex and multifaceted process (Vial 2019) which impacts a firm's business model and its underlying structures and processes (Hess et al. 2016). Such processes are often heavily contextual and may differ from firm to firm.

With the advent of Industry 4.0, propelled by digital technologies, firms can expand and extend their operational efficiency beyond their boundaries for a stronger market impact (Cenamor, Parida, and Wincent 2019). Compared to other many forms of digital technologies, AI is perceived as having the strongest pervasive impact (Leone et al. 2021), greatly transforming organisations (Davenport 2018). Organisations harness AI technologies to cut costs, increase the quality of their products and services, be more productive, and gain efficiency (Iansiti and Lakhani 2020).

Unfortunately, many firms still find it overwhelming to implement smart technologies and successfully transform (Correani et al. 2020). Given the technical features and knowledge requirements of AI, its implementation can be quite complex (Gallivan 2001). This sets AI apart from other digital technologies, which are generally simpler to use and deploy (Lokuge et al. 2019). Significant barriers remain, as most firms do not go beyond a single-pilot AI deployment, with only 8% succeeding in AI adoption in their core business practices (Fountaine, McCarthy, and Saleh 2019).

In general, researchers have attributed the challenging nature of implementing complex systems to impediments such as knowledge barriers (Attewell 1992), inertia imposed by existing infrastructure (Hanseth and Lyytinen 2010), inconsistencies between strategy formulation and implementation (Chanias, Myers, and Hess 2019), and insufficient top management actions in which management's involvement, leadership and support remain the most critical success factors (Loonam and McDonagh 2005). However, more recently, researchers have emphasised the importance of the issue of AI readiness to reduce the risk of failure and enhance the likelihood of AI initiatives (Castrounis 2019; Holmstrom 2022; Jöhnk, Weißert, and Wyrtki 2020).

2.2. AI readiness as an integral part of the digital transformation process

Having adopted an organisational readiness lens (Lokuge et al. 2019), researchers have emphasised the firm's readiness state as an important precursor to successful implementation of AI (Jöhnk, Weißert, and Wyrtki 2020). By developing AI readiness models and maturity frameworks, researchers have assumed a demarcation between AI readiness and AI adoption. AI readiness refers to 'an organisation's abilities to deploy and use AI in ways that add value to the organisation' (Holmstrom 2022, 330). It has been differently operationalised by different authors and in different contexts, with some degree of overlap. Castrounis (2019) conceptualised AI readiness through organisational, technological, cultural, and financial categories. AI readiness is differentiated from the AI maturity concept, with the latter being more associated with successfully developing and executing an AI vision and strategy. AI maturity is further broken down into the subcategories of data maturity and analytics maturity, on the ground that data-specific and analytics-specific roles, processes, and tools can differ, as can their corresponding levels of maturity (Castrounis 2019). Jöhnk et al. (2020) identifies strategic alignment, resources, knowledge, culture, and data as major categories of AI readiness. Finally, Holmstrom (2022) breaks AI readiness into the four dimensions of technologies, activities, boundaries, and goals.

It is imperative to note three points regarding the AI readiness framework. First, research on AI readiness has just begun (Jöhnk, Weißert, and Wyrtki 2020), with little consensus on its underlying factors. This lack of consensus may be because readiness models are highly context specific, meaning that they need to adapt to account for a firm's specific context such as its industry, organisational particularities, or specific technology domain (Jöhnk, Weißert, and Wyrtki 2020; Molla and Licker 2005). Second, research on AI readiness framework – for example, the scorecard proposed by Holmstrom (2022)—offers a static view of a firm without necessarily integrating the adoption stage, thus treating readiness and adoption as separate states. Conversely, research on DT has portrayed the whole process to be dynamic and in flux (Vial 2019). Third, recent research on AI readiness has shown that readiness is not just a prerequisite for technology adoption, but an essential factor throughout the entire process. Rather than being a one-time condition that is established before adoption, readiness and adoption are highly interdependent and mutually reinforcing concepts (Jöhnk, Weißert, and Wyrtki 2020). Given the interdependence of AI readiness and adoption, it is essential to study and discuss these concepts in conjunction with each other as part of the broader process of AIDT. This holistic approach can help organisations to better understand and address the challenges and opportunities of implementing AI technology and ensure that readiness is continuously evaluated and improved throughout the adoption process.

In a nutshell, taking a more holistic approach to understanding AIDT allows for a dynamic explanation of the model that considers the interrelationships between all its underlying elements. By viewing the AIDT in its entirety, organisations can gain a more comprehensive understanding of how AI technology can be integrated into their operations, and how readiness and adoption can be optimised to achieve the desired outcomes. Thus, in this study, our focus is on the entire AIDT process including AI readiness.

2.3. AI, SMEs, and digital transformation in Canada

Researching AIDT in the context of Canadian manufacturing SMEs is both significant and timely. Canada has demonstrated its commitment to AI development through initiatives such as the Pan-Canadian AI strategy, as well as its dedication to fundamental R&D (Vector Institute 2021; Zhang et al. 2021). Despite Canada's prominent position in AI development and policy, there remains a critical disparity between the potential of AI and its widespread adoption across industries. Canadian firms, including manufacturing industries, face challenges in understanding the business case for AI and its practical applications (NGen Canada 2021a). This is particularly noteworthy considering that manufacturing sectors can significantly benefit from productivity gains facilitated by AI. However, the adoption rate of AI projects in Canadian manufacturing sectors is alarmingly low, with about only 10% of manufacturers having implemented at least one fully operational AI project (NGen Canada 2021b), as compared to 28% in the US, 30% in Japan, and 25% in Korea (Capgemini Research Institute 2019).

Moreover, SMEs play a significant role in the Canadian business landscape. With an overwhelming majority comprised of 99.8% of all Canadian firms, they contribute significantly to the country's gross domestic product (GDP). Over the 2015 – 2019 period, SME contribution to GDP was 53.2% on average in the goods-producing sector, as compared to 51.8% in the services-producing sector (ISEDC 2022). These statistics not only underscore the economic importance of SMEs but also highlight the potential impact that AI implementation in this sector can have on overall economic growth and productivity.

Prior research has emphasised the significance of DT for SMEs, as it enhances their entrepreneurial performance (Li et al. 2018) and provides strategic opportunities for global competitiveness. However, statistics reveal that most DT projects fail (Correani et al. 2020), and the transformation to smart manufacturing remains a significant hurdle for SMEs (Kane 2017). Industry reports further reveal an alarmingly low adoption rate of advanced technologies among SMEs (Klitou et al. 2017). As a result, SMEs have not been able to fully exploit digital technologies, leading to a widening gap with larger firms (Scuotto et al. 2021).

Our understanding of DT remains incomplete due to the broad and imprecise nature of its nuances (Gray and Rumpe 2017; Vial 2019). Despite conceptual research proposing a general framework, the common elements within the proposed dimensions lack empirical identification and testing (Matt, Hess, and Benlian 2015). Important aspects, including clarification of ROI, cultural transformation elements, and assessing readiness, still pose challenges and are marked by inconclusive findings. Therefore, there has been a call for 'a critical need for novel theorising on digital innovation management' (Nambisan et al. 2017, 223). Through GT research, we endeavour to inductively identify and uncover implicit concepts associated with the AIDT process and provide a comprehensive explanation of its essential phases. This approach allows us to offer detailed descriptions of micro elements and interweave them to present a holistic picture of AIDT within the context of the Canadian SMEs under study.

2.4. Digital transformation as a dynamic and evolutionary firm behaviour

To respond to rapid technological and market changes, firms must adopt new capabilities and innovate. Firms that have transformed successfully, particularly through AI integration, have been able to innovate their business models and improve their strategic position (Iansiti and Lakhani 2020). Consequently, DT is seen as a way to achieve or sustain a competitive edge and dynamic capability (DC) framework is adopted as a fitting lens to further explain DT process (Vial 2019; Warner and Wäger 2019). DC recognises the role of routines and the 'capacity to renew competencies' (Teece, Pisano, and Shuen 1997, 515) in organisations. DC enables firms to create capabilities to sense opportunities and threats, to respond through innovations, and to reconfigure routines to maintain evolutionary fitness (Teece, Pisano, and Shuen 1997).

In DC framework, sensing represents an exploratory activity. It involves identifying what lies on the surface and understanding latent demands. Shaping an opportunity is a more interpretive part where a firm, for instance, needs to choose its technology trajectory and decide how to shape the rules of the game in a broader environment – thus impacting ecosystem participants. Seizing opportunities involves addressing the sensed opportunity through new products, processes, or services. However, if the sensed business opportunity calls for a radical competence-destroying innovation, the firm may opt for a more incremental competence-enhancing improvements, thereby emphasising reliance on path-dependent routines, assets, and strategies. Finally, reconfiguring capacity is 'to maintain evolutionary fitness and, if necessary, to try and escape from unfavourable path dependencies' (Teece 2007, 1335). This dynamic state works towards achieving continual firm renewal through redesigning routines and business models. Overall, DC represents a general framework for better understanding firm-level competitive advantage in the context of fast-paced technological change.

The extant research at the intersection of DC and DT has dominantly conceptualised sensing as a firm-level capability to scan the external environment for unexpected trends that could disrupt the organisation (Birkinshaw, Zimmermann, and Raisch 2016; Giudici, Reinmoeller, and Ravasi 2018; Helfat and Raubitschek 2018). For instance, sensing capability is viewed as 'digital scouting' (Warner and Wäger 2019, 327) – thus incorporating a rather outward-looking perspective to sensing opportunities. However, we believe that the firm's endogenous knowledge of its transformational context is equally important and should be given the same level of consideration as external sources of opportunities. As emphasised by Schumpeter (1934), a firm can sense and shape opportunities by using both endogenous and exogenous knowledge and information.

Through GT development, we can determine whether firms that have faced difficulties with AIDT would benefit from an inward-looking approach to sensing opportunities.

3. Research methodology

3.1. Research design

In line with this study's research questions, we adopted an empirical qualitative methodology to explain AIDT as a complex, dependent, real-world phenomenon, in its socio-organisational embedded context (Yin 2011). The AIDT process is the unit of analysis embedded in an organisational context which is chosen as the level of analysis. We further adhere to the Straussian GT method which does not necessarily favour 'abstinence from existing literature' prior to data collection (Dunne 2011, 114). We follow GT methodology for two main reasons. First, it stresses 'dynamic interplay between data collection and analysis' (Payne 2007, 68) realised through constant comparative analysis and theoretical sampling (Strauss and Corbin 1990). This enables us to systematically follow an emic or inductive approach to data analysis and theory building. Further, GT methodology, irrespective of historical debates on when the literature review step should take place (Dunne 2011), emphasises the insights (in form of concepts and their interrelationships) that emerge from data analysis over the *a priori* knowledge of researchers regarding the phenomenon under investigation. By avoiding imposition of *a priori* constructs, we remain open to the possibility of new constructs emerging through the process of field learning (Strauss and Corbin 1990).

3.2. Data collection

We collect primary data through in-depth semi-structured interviews. We use open-ended and semi-structured questions such as: 'How did your firm go about integrating machine learning into its work processes?' In so doing, we are able to adapt and change as the research progresses, respecting the notion of 'designed-in flexibility' in interpretive research (Gioia, Corley, and Hamilton 2012, 19–20) or the recursive nature of the design process (Yin 2011).

To choose interviewees, we followed purposeful sampling strategy coupled with the snowball sampling technique (see Lincoln and Guba 1985). We focused on the perspectives, experiences and opinions of individuals who had been directly involved in an AIDT process in Canada. The provinces of Ontario, Quebec, British Columbia, and Alberta are at the forefront of the Canadian AI industry, with a significant concentration of AI firms (see Boulet et al. 2020). These four provinces are also home to the majority of manufacturing firms (more than 90% of the total number; ISEDC 2021). More than 70% (12 out of 17) of our sampled firms, and about 80% (21 out of 27) of our interviews are from the provinces of Quebec and Ontario (for an industry breakdown see Table 1).

We expanded our research beyond the two specified regions using the snowball sampling technique, reaching out to participants in various Canadian provinces. The selection of participants was based on the following specific criteria: a) advanced knowledge of AI and/or its implementation within organisational contexts; and b) involvement in the DT process either as an AI expert, a decision maker within a firm undergoing

Table 1. Profile of interviewees.

Interviews			Interviewees		Firm characteristics		
Code	Number	Duration (min.)	Position	Education level	Industry	Firm Size[a]	HQ[c]
IC01	2	73	Co-founder & technical lead	Ph.D.	Consumer electronics	2–10	QC
IC02	1	61	Lead engineer	M.B.A.	IT & Services	2–10	IL
IC03	1	60	Project manager	M.Sc.	Aviation & Aerospace	11–50	QC
IC04	1	15	Director of Research	Ph.D.	Computer software	51–200	QC
IC05	2	80	Technical Research Manager	Engineer	Computer software	10,000+	CA
IC06	7	434	Chief Strategy & Partnership Officer	M.Sc.	IT & Services	11–50	QC
IC07	1	45	Chair of Advisory Board	Ph.D.	IT & Services	11–50	ON
IC08	1	46	AI Chair	Ph.D.	Research	51–200	ON
IC09	1	64	President	M.B.A.	Aviation & Aerospace	51–200	QC
IC10	1	37	Researcher	Ph.D.	Education Institution	5,001–10,000	ON
IC11	1	30	Control & Automation Software Developer	Ph.D.	Aviation & Aerospace	10,001+	QC
IC12	1	49	Sr. Data Scientist	MSc.	Computer Software	1,001–5,000	DC
IC13	3	229	CEO	M.B.A.	IT & Services	2–10	ON
IC14	1	18	Executive Director	M.B.A.	Financial Services	2–10	QC
IC15	1	35	Research Assistant Professor	Ph.D.	Computer Research Institutes	11–50	CA
IC16	1	20	Sales Dept.	N.D.[b]	Machinery	51–200	SK
IC17	1	41	Industry Training Manager	M.B.A., M.S.	Industrial Machinery Manufacturing	11–50	ON
TOTAL	**27**	**1,337**					

[a]Size based on fulltime employees.
[b]Not disclosed. This interviewee has decades of experience with farming industry and machinery in SK, Canada and knows about the state-of-the-art AI tools used in farming supply chain activity.
[c]CA: California; DC: District of Columbia; IL: Illinois; ON: Ontario; QC: Quebec; SK: Saskatchewan.

transformation, or a decision maker within an AI consultancy firm guiding the DT process. The second criterion enabled us to document the perspectives of AI consultancy firms, including their discussions, rationale for actions, and approaches towards AIDT. Additionally, we were able to gather insights from firms that had integrated AI into their work processes in order to better understand their perceptions and experiences. In essence, we captured and analysed the dual-sided AIDT dialogue, unpacking its various components for a comprehensive understanding.

Each interview was digitally recorded and then transcribed, with an average duration of about 49 minutes. In total, 27 interviews with 17 organisations were completed, amounting to 1,337 minutes of recorded data (see Table 1). To add further clarifications to our thought process, we attended AI-focused webinars, round tables, and panel discussions (i.e. events; see Table 2).

Table 2. Event data sources.

Event Code	Event Type	Secondary sources referred by informants	Year	Mode	Duration (min.)
EC1	Webinar	Creating Value for Business through AI	2021	Online	60
EC2	Follow-up Round Table	Using AI to Drive Manufacturing Success	2021	Online	60
EC3	Webinar	Additive Manufacturing Ecosystem	2021	Online	60
EC4	Follow-up Round Table	Additive Manufacturing in Canada	2021	Online	60
EC5	Webinar	Adopting AI: Ensuring Technical Readiness (MIT)	2021	Online	58

3.3. Data analysis

To conduct data analysis, we adhered to the techniques and guidelines proposed by Strauss and Corbin (1990) and Gioia et al. (2012). We employed a systematic coding approach (constant comparative method), which comprises open, axial, and selective coding techniques. Our interpretive methodology uses an iterative process involving simultaneous data collection and analysis. Additionally, we actively sought new informants based on the information deemed significant by previous informants. This approach allowed us to work with a continuously evolving and increasingly relevant sample until we reached a point where no additional themes emerged – a stage referred to as theoretical saturation, marking the conclusion of data collection and analysis. During the open coding stage, our preliminary analysis remained faithful, as much as possible, to the terms used by the informants. This process generates first-order concepts at the semantic or explicit level. Subsequently, by examining the logical fit and relevance between and among (chunks of) codes, we establish rich and dense categories known as second-order concepts. These categories represent a series of interconnected codes, allowing us to identify connections and relationships between these concepts through axial coding. Lastly, we developed aggregate dimensions, which represent the highest level of abstraction in our analysis.

4. Findings

Figure 1 illustrates the data structure and ordering of the data from specific (first-order) concepts used by informants to more general (researcher-induced second-order) themes. The second-order themes and aggregate dimensions are the building blocks of our proposed GT (Figure 2). This figure does not establish causal relationships; rather it represents the core concepts and their relationships that serve as the basis for the emergent theoretical model. The first four dimensions – evaluating transformation context, auditing organisational readiness, piloting the AI integration, and scaling the implementation – correspond to four fundamental phases of AIDT. They follow a sequential, stage-like progression, while the fifth dimension – leading the transformation – is recurring and omnipresent, exerting a continuous impact on the other phases. Together, these sequential and recurrent dimensions lead to the development of the emergent GT, articulated based on the narrative that emerges from the findings.

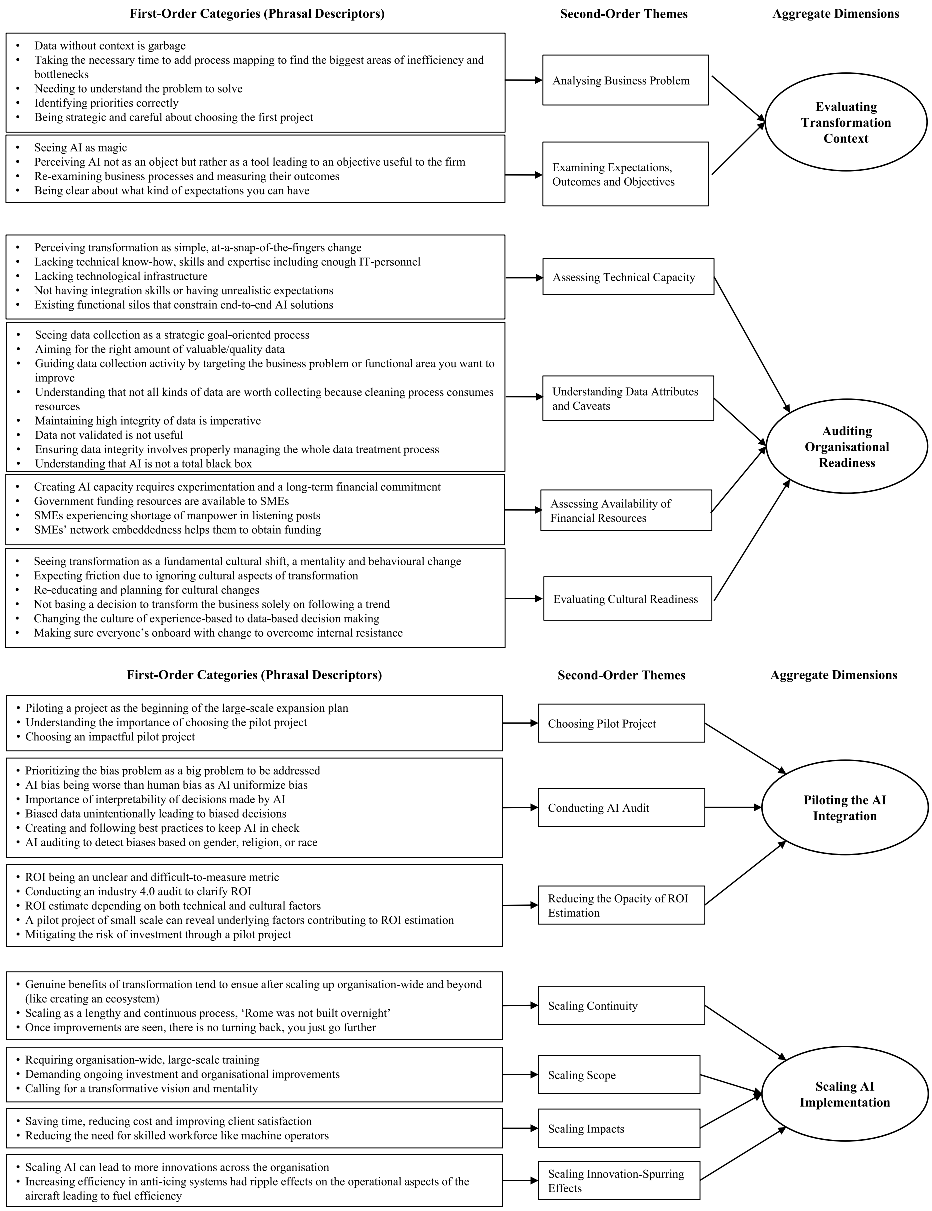

Figure 1a. Data structure. Source: Compiled by the authors based on interview data.

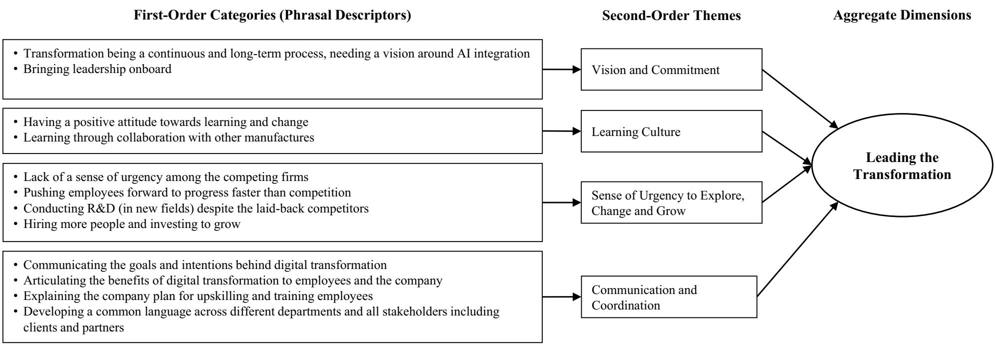

Figure 1b. (Continued).

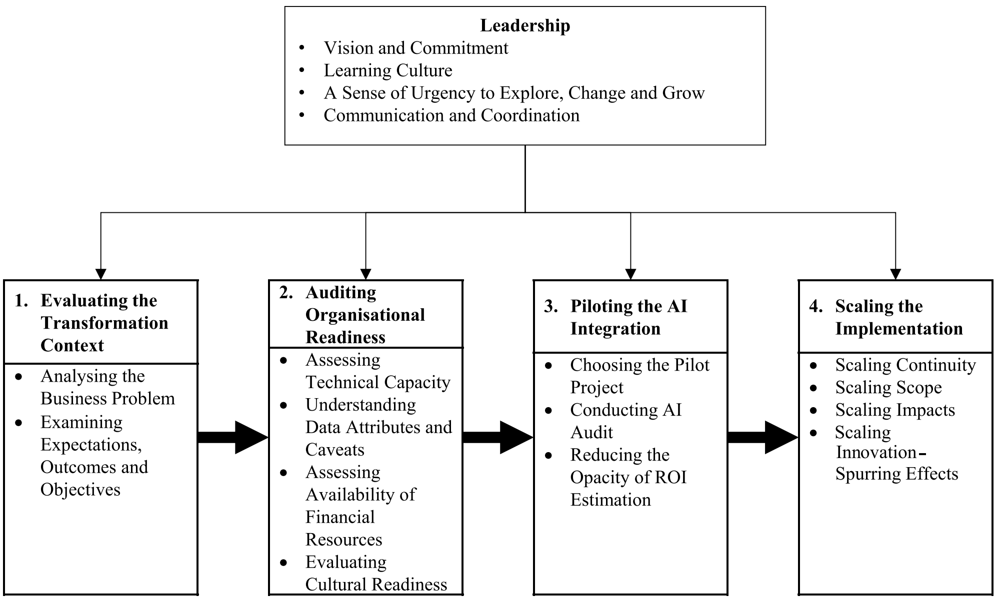

Figure 2. An emergent grounded theoretical model of AI-Driven digital transformation.

4.1. Dimension 1: evaluating the transformation context

The first dimension includes two themes: analysing the business problem; and examining expectations, outcomes, and objectives. The first step in an AIDT process is to understand and evaluate the context into which the AI solution will be integrated. AI integration cannot happen in a vacuum, nor does it need to be motivated by keeping up with the Joneses, or as a discussant puts it, ‘don’t just follow the trend!’ (EC1). AI’s value lies in its capacity to solve an organisational problem towards a ‘business destination’ which should be customer centric (IC17). Put squarely by a discussant, we should consider AI ‘a means to an end’ (EC2). ‘We need to focus on the context of the problem, process requirement and objectives. We do not have screwdriver initiative, we have process initiatives. We digitalise in the context of problems' (EC2). Before embarking on data collection, a firm needs to survey its work processes to identify the bottlenecks and prioritise the projects that would benefit from AI. They need to set clear objectives through implementation of AI into a work process. For example, is the objective to create a new product, to enhance the efficiency of a process or to increase the productivity of a production line? At this stage, it is very tempting to shape the discussions around ROI, yet to do so is considered premature and can lead to managers getting cold feet about undergoing the transformation. Estimating ROI is crucial to justifying AIDT, however, due to situational opacity at the beginning of the DT journey, it is not quite feasible to produce a realistic estimation of ROI at this stage.

4.2. Dimension 2: auditing organisational readiness

The second dimension includes assessing technical capacity, understanding data attributes and caveats, assessing the availability of financial resources, and evaluating cultural readiness. An interviewee (IC06) emphasises conducting an Industry 4.0 audit to assess a firm's technical and cultural readiness for AIDT, thereby ensuring its successful implementation.

4.2.1. Assessing technical capacity

Integrating AI into an organisation is not a plug-and-play task; rather, it demands a technological transformation of the firm. This requires building integrated technical capacity and know-how. The former implies putting in place the supporting IT infrastructure (technologies such as sensors, software, networks, cloud computing); the latter refers to learning how to integrate the technologies underlying AI around the work processes, as well as developing new skills to use them. The following quotes shed light on these views.

> And they think they can do it, like, at the snap of the fingers. [. . .] But they don't necessarily know how, or how the process works. They often lack the expertise and skills to integrate AI into their organisations' work processes. [. . .] Often lack the skills to integrate AI which sometimes can create some friction, when we have to integrate AI in the company, because they have some expectations. They think that you can integrate AI like you would add a new computer in the company, which is absolutely wrong (IC06).

However, finding talent is described as 'one of the most difficult parts of this job' (IC01). When we asked why, the interviewee (IC01) brought up the oxymoronic request made of candidates to be 'motivated, knowledgeable, but at the same time are not so costly'. They further expressed their concern about the exodus of the workforce to rival firms with better offers. This shows how cumbersome it is for small firms to build up their technical know-how. SMEs often lack the crucial skills and expertise for AI integration and implementation, even at the level of proof-of-concept development and prototyping. Even for those who dare to try, the road to integration is fraught with friction due to unrealistic expectations and lack of proper understanding of AI at both the technology and integration levels. This can lead to managers getting cold feet right from the beginning: 'they can be a bit cold footed with integrating AI [. . .] because they don't necessarily know what it does, but instead of being optimistic, they're kind of sceptical' (IC06).

Furthermore, 'there might be a lot of cases where people are kind of pigeonholed into specific silos' (IC12). Enterprise systems and industrial and/or production systems have been traditionally set up to work in silos. This implies that each system must have its own dedicated IT team to manage the underlying network, security, and data management processes, often with strong separations of security and data management functions, even within the same network, once the overall architecture is up and running.

Throughout an AIDT, there is a need for not only internal IT competencies but also for supporting systems that are well integrated with one another so that machines can seamlessly engage with other machines. The integration of machine learning which comes with climbing up the ladder of efficiency, further demands increasing an organisation's integration of IT systems and the teams that manage them. Thus, both human actors and technologies must work in an integrated fashion: 'In the past 8, 9 years we created integration systems that connect to all machines, cams, humans, and robots; and it communicates information with all those systems' (IC09). This calls for 'the design of a new systems architecture [and the setup of a] function to coordinate these teams' (IC06) to reach this target, to ensure the new system works and communicates smoothly, and to engage the organisation to move from a culture of data exploitation to one of data exploration.

4.2.2. Understanding data attributes and caveats

Data availability is a necessary condition and critical part of the AIDT process. It is viewed as a precursor to the application of machine learning and the benefits that ensue. In this context, data quality and integrity are essential.

The quality of the collected data corpus, including its cleanness and relevance, as well as the different data sets, is crucial. Gathering excessive amounts of data without a proper data collection and treatment strategy (i.e. data governance) can significantly increase the challenges and costs associated with working with the collected data.

> Start collecting valuable data, now! [. . .] So that's why it's important to start thinking today strategically of what you want to improve in your company, start collecting data on that area, that specific business activity. [. . .] What's really important is to collect valuable data on a specific project that will be useful for your company (EC1).
>
> If you don't have that very nicely cleaned dataset, how do you go about building something like that? What's your strategy for taking the rawest level data that you have and getting towards that sort of nice pretty picture which you can then start making predictions of? (IC12).

Data integrity must also be ensured: 'data not validated is not useful' (EC2). This involves the whole process of data collection, storage, analysis, and the systems supporting these tasks.

4.2.3. Assessing the availability of financial resources

Investing in an AI project is perceived as an inevitable experimentation. A firm funds the development process of its technical capacity, including building the data infrastructure, because it is seen as an inevitable financial investment, as shown in the following quotes:

> Sunk cost happens, and you should be willing to experiment. Information systems are not like investment in buildings. In our recent time, value has moved from tangibles to intangibles . . . So, value is the value of data (IC09).

> You need to find funding sources, and there are a couple of organisations that can help you finance your initiative (EC01).

Moreover, this is not a one-shot investment, but rather a continual one. AIDT falls under the overall corporate strategy in that a firm's top management must decide if they are going to make fundamental changes to their business model. Once a firm embarks on a DT journey, data becomes an important asset and a basis for the firm's decision-making process. Consequently, the firm must evolve alongside its underlying technological trajectory to maintain its momentum. This requires a longer-term financial commitment at the strategy level.

At the operational level, Canadian SMEs can enhance their access to additional financial resources by leveraging government funding. While there are numerous provincial and federal consortia, funding sources, and clusters available to support AIDT, it has been observed that many small firms are unaware of how to utilise these funding supports. This knowledge gap primarily stems from a lack of human resources dedicated to actively seeking out and compiling relevant funding opportunities within a reasonable timeframe.

In addition, for those opportunities that require joint applications between a small or medium-sized firm and a partnering larger firm to meet funding requirements, SMEs face considerable challenges. Large firms possess greater resources and extensive networks, enabling them to capitalise on these opportunities more effectively. Consequently, the establishment of a partnership alone can act as a significant barrier for SMEs in realising their AI transformation projects. One interviewee views the process of identifying and applying for funding opportunities specifically tailored to AIDT projects as a 'technical obstacle' (IC06).

> One involuntary negative impact of partnership requirements for AI funding opportunities is that those small firms that are already embedded in a supply chain of large companies will be in a more favourable position than those who are not (IC06).

4.2.4. Evaluating cultural readiness

Realising AIDT process necessitates and drives cultural shifts that influence the daily routines, habits, mental frameworks, emotions, and expectations of employees across different organisational levels. This underscores the significance of fostering 'human readiness' (EC05).

While most firms are accustomed to 'data exploitation' (IC06), the adoption of a 'data exploration paradigm' (IC06) becomes necessary for AI projects. The objective is to utilise data for exploration, scenario-building, and predictive modelling to drive innovation, rather than solely relying on data for routine operations. This shift is exemplified by managers striving to instil a Silicon Valley culture within their companies (IC09). In the AIDT process, cultural transformation holds equal importance to technological transformation.

> Top executives can be very enthusiastic in adopting AI, but what about those IT technicians and engineers who will actually engage in the whole integration process, upskilling and on-the-job training? (IC06)

> Even if the company wishes to train people, not everybody's going to be ready to go through that learning curve (IC07).

> Sometimes managers have to smooth the integration process and overcome internal resistance to change which takes time, and it costs .... Executives need to build more consensus toward transformation by educating employees about how transformation will happen (IC06).

Cultural transformation affects an entire organisation, including top managers, middle managers, IT department staff, and front-line workers. The challenges of 'resistance to chang[ing] the work process' (IC03) and 'sabotage' (IC06) are not fairy tales or outdated notions, rather, they still impact the success or failure of AI projects. The motivation for employees who have long-established ways of working to embrace change, upskill, and adopt new approaches is a pertinent question. Hence, friction, resistance, and sabotage can arise from employees at various levels, underscoring the cultural aspect of AIDT.

> What is the motivation for an employee who has been to school decades ago to change, to upskill, and to start doing things differently? (IC06)

Moreover, utilising data as a vital component in the decision-making process has implications for the decision-making hierarchy within an organisation. This is described in terms of 'a weather forecast' (IC09) where one no longer looks at the sky or the shapes of clouds to make predictions about the weather, but instead, trusts systems to make predictions based on data and bases decisions upon those predictions. In fact, 'Organisations should remove the power of intuition, the power of experience [...] Then you have to start to implement the culture of data; and to implement a culture of data you have to remove the culture of experience' (IC09).

Despite the apparent simplicity of this logic, implementing it within an organisation with pre-existing established routines is no simple task. However, one of our cases successfully navigated this challenge by developing new competencies, establishing fresh routines, and reshaping the underlying organisational structure. This transformation enabled them to shift from a traditional experience-driven organisation to a data-driven one. Nevertheless, the battle against entrenched managers who rely heavily on experience rather than data for decision-making is far from easy to overcome. Our further investigation uncovers the underlying issue:

> Many enterprises' issue with AI is that there are very small number of top managers who use data. This is mainly because top managers are proud to show they have experience. Top managers are proud to explain that they can make decisions like that. But in reality, what we should do as top managers is to explain to employees how to use the data to make the right decision (IC09).

There are different sides to this debate. For instance, some people believe that 'as a manager, you have to trust the data more than your experience [. . .] even at the expense of becoming less relevant to your organisation' (IC09). It seems that it is not necessarily about data but rather the 'legitimacy of senior managers' (IC09), their mental paradigm and management style.

To be more specific, certain senior managers prefer to be the primary source of experiential knowledge as it grants them legitimacy. They perceive the data-driven decision-making process as a direct competitor to their legitimacy, rather than a complementary element. Consequently, they may not fully cooperate in facilitating the transformation process. Therefore, the organisation must emphasise the advantages of data-driven decision making while also ensuring that the new decision-making paradigm is not perceived as a threat to the perceived value of the experience held by top managers in the decision-making process.

4.3. Dimension 3: piloting the AI integration

This dimension includes choosing the pilot project, conducting an AI audit, and reducing the opacity of ROI estimation. Embarking on a pilot project, according to a round table discussant, 'is like having a bit of fun with AI' (EC2); yet it is also a strategic choice. It is imperative to choose a small project that leads to solving a real business need with a tangible measurable impact.

> Don't just follow the trend! You need to be strategic; you need to be careful on what project to start with [. . .]. And first projects are the ones that should have the greatest ROI, because they are usually the low hanging fruits that you can get from AI (EC1).

A pilot project provides a unique opportunity for hands-on learning and practical experience, as highlighted in the statement, 'there's a trade-off between waiting and learning. . . we do have to probably get hands-on' (EC3). Additionally, a pilot project enables the identification of systematic biases and the implementation of measures to mitigate them. It is important to acknowledge that AI 'systems that were found to be grossly biased, or just morally questionable, weren't developed with ill intent, but the teams involved just did not think about how that system would manifest itself in real life' (E05).

Further, biased data leading to biased algorithms and consequently unfair decisions, is viewed as 'a big problem to be addressed' (IC08). 'It is us who have defined the decision-making algorithm for the machine. So, it's all about us' (IC10). Ignoring this can have detrimental impact on the image of the firm because 'if you put an AI in the decision-making, then you uniformise the [bias] problem' (IC08). Consequently, a firm should cautiously audit the algorithms being deployed 'to prove that AI is not biased according to gender, religion, and race' (IC08).

> What we do is, we try to set rules for ourselves, so we stay within those constraints. That's why we do validation and things like that (IC02).

The audit is especially important, as regulations about AI are still being formed in emerging fields such as autonomous equipment manufactured for farming. To not perform an audit can in fact impose liability on the firm.

> It's an interesting challenge, though, because, obviously, regulations are not really there, because it's new, nobody knows how to handle it, or the liability side of it (IC16).

Many firms further hesitate to integrate AI due to difficulties in accurately estimating the projects' ROI. During the pilot phase, the firm gains valuable insights into key factors and the actual costs they will incur, allowing for a more accurate estimation of the ROI for their AIDT project(s). For example, if the pilot project encounters significant internal resistance, it becomes evident that transforming the entire organisation without setbacks and in a short timeframe is not realistic. Therefore, management should consider the costs associated with setbacks, resistance, and cultural training when assessing the overall ROI. This further mitigates the risks associated with an AIDT process.

4.4. Dimension 4: scaling the implementation

The scaling dimension includes continuity, scope, impacts, and innovation spurring effects. A pilot project is described as 'a low hanging fruit' (EC02). A firm can 'start with a small project and then scale it from one machine to a whole production line' (EC01), and beyond. However, scaling is crucial to fully harness 'the real value of AI' (EC02). While a pilot project necessitates training a few employees to become proficient in the technology and project management, scaling requires the implementation of a companywide training plan. Scaling exemplifies the broader evolving and continuous nature of AIDT, as aptly expressed in the quote: 'Rome was not built overnight! Our AI platform grows with our clients' (IC04).

As an organisation-wide phenomenon, scaling is closely tied to the vision of leadership, as expressed in the quote, 'if a company has dreams, they can always explore further with AI and accelerate their projects by hiring external experts beyond an early-stage deployment' (IC04). It is therefore a planned activity that can be tied to overall firm strategy. It manifests the scope of change – the extent to which a firm intends to integrate AI into its projects and work processes. Through the pilot project, a firm can plan for the extent of changes to effectively support its scaling objective. In one of our cases, a fundamental change was the transformation into a data-enhanced organisation as a prerequisite for becoming an AI-enhanced firm. The AIDT process lasted about a decade, during which time the firm evolved both technically and culturally. In another case, a manufacturer of recycling facilities integrated machine learning solutions into their facilities built for clients to significantly reduce their operation costs while increasing their client satisfaction through predictive maintenance. Through scaling up to more projects, and including more clients, they managed to generate vast amounts of data which consequently added significantly to the effectiveness of their AI models and have led to further productivity gains as well as more effective and efficient service offerings.

While scaling up inevitably adds more continuous investment pressures, it is not seen as wasting resources. A manager says, 'if you work with data, you improve the work processes, and when you improve, you never go back, you only go further' (IC09). Becoming a data-enhanced organisation sets in motion the development of new organisational routines that further trickle down to new path-dependent choices. As the new inertia sets in, going forward makes more sense.

Finally, scaling has significant ripple effects through spurring more innovations. In one project (IC06), a firm decided to deploy AI-based simulations to test the design (aerodynamics) of aircraft wings instead of running costly live wind tunnel tests in international test facilities. Consequently, they improved engineering productivity and reduced the cost of testing. In the process of deploying machine learning algorithms, they also managed to increase the efficiency of anti-icing systems embedded in the aircraft wings – thus reducing the overall energy consumption of the aircraft. As a result, they enhanced the productivity of the aircraft by reducing their operation cost through energy saving. In short, the spring cleaning required to scale up AI implementation can possibly lead to unforeseen productivity and efficiency gains.

4.5. Dimension 5: leading the transformation

Leadership plays a fundamental role in the AIDT process. It unfolds in terms of vision and commitment, elements of learning culture such as willingness to learn, change and collaborate, having a sense of urgency to explore, change and grow, and the ability to openly communicate and coordinate with employees regarding the transformation plan and what it entails. A round table discussant advises, 'bring leadership on board [. . .] it is always important to have a vision around AI integration because it is not just a project that's gonna end after a few months. This is something that you're gonna integrate into your company, that you're gonna maintain, that you have to keep updated' (EC1). This goes back to the very dynamic nature of 'AI algorithms that require constant care and feeding' (EC5). Leadership is therefore a crucial and pervasive role in every step of the AIDT process.

AIDT can be likened to a process innovation that catalyses further innovations, thus requiring leaders who possess a capacity and passion for learning, embracing change, and driving progress – all with a sense of urgency. These leaders play a crucial role in fostering a culture of continuous improvement and adaptability within the organisation.

Learning can happen through modelling the behaviour of success stories through continued (self)education. 'The books that I read about management come from Silicon Valley [. . .] the way they manage, they organise, they think. You have to change completely the way your company thinks' (IC09). Further, the participant mentions that he sees his competitors as indifferent to changes happening around them. 'When I see my competition, I don't see them having the same sense of urgency [. . . and] fun to implement robots, fun to implement technology' (IC09). Sensing the urgency can be impactful because 'whatever decisions we make in the next five to 10 years will have very long-lasting impacts' (IC15). It is also an attribute of leadership and their vision to 'become more rational in all company decision-making' (IC03) and lead their industry; 'We pushed our employees. I said if there is a crisis [referring to the COVID-19 pandemic] we have to go faster. If the others don't want to work and innovate, in the future, I will be in front of them' (IC09).

Lastly, effective communication and coordination play a pivotal role in fostering consensus and alleviating fears associated with change and unemployment. It is essential to disseminate key information, including project goals, training and upskilling road-maps, and contractual changes, to all stakeholders affected by the AIDT process. This communication and coordination should extend across departments within the organisation and encompass external parties such as clients and collaborators.

A few leaders echoed their employees' fear of job loss due to AIDT. This fear stems from a combination of inadequate understanding of how AI works and a lack of communication regarding its impact on work processes. It is crucial to address these concerns by providing clear explanations of the AI technologies and proactively communicating on how 'human and AI integrated systems work better than either of those [...] AI doesn't need to replace people in the workforce, but the combination of AI and the people [...] really makes the whole system that much better' (IC12). To illustrate, AI-powered generative design technology integrates AI algorithms with optimisation schemes such as shape synthesisers and leverages the expertise of designers to provide component designers with a more robust tool that rapidly generates design alternatives. As mentioned by the interviewee, 'AI will ultimately help us decide and find the optimum solution to our problem and make suggestions for further exploration' (IC05). This highlights the concept of 'having the human in the loop as part of the system' (IC12).

Consequently, it falls on leadership to 'communicate on the intentions and the key benefits for the company and the staff [...] to explain to everyone in the team that's going be affected [... and that] it's not something to replace people, it's something there to help them make their life better' (EC01). This communication and coordination effort is crucial in bridging organisational silos by establishing 'a common language' (EC02). As 'each department speaks a different language ... we need to make sure they communicate crisply with one another over tasks, not equipment' (EC02). With AIDT encompassing multiple cross-departmental work processes, 'having that cross-business alignment helps those data modellers a lot as well' (IC12).

5. An emergent grounded theory of AIDT

These findings suggest that AIDT is a complex, multifaceted, adaptive, and evolutionary process that unfolds over an extended period. Figure 2 situates the five dimensions and their embedded themes in the form of a process model that lends the necessary dynamism to the relationships between these key concepts. The model outlines four sequential phases, wherein leadership assumes a critical and pervasive role at each stage of the AIDT process.

The initial phase entails evaluating the transformation context through the lens of the business problem. Firm leadership takes the lead in initiating and overseeing this phase, while department heads and/or middle management are responsible for executing process mapping and identifying areas of inefficiency and bottlenecks. Additionally, priority areas are strategically determined during this phase. Clear expectations and articulated goals must be established for the successful transformation of the selected areas. Leadership plays a vital role at this stage, ensuring alignment between the AIDT and the overall business strategy, as well as demonstrating their commitment to providing support.

In the second phase, the firm conducts a comprehensive evaluation of its technical, financial, and cultural readiness. Rather than viewing AI as an enigmatic black box, management and personnel strive to gain a detailed and realistic understanding of how the AI development and deployment processes will unfold within their specific context.

They assess the organisation's technical capacity at the firm level and delve deeper into their data to identify its essential attributes and potential pitfalls. Additionally, they evaluate the availability of the financial resources required for AI implementation. The firm also re-examines its organisational culture, existing routines, and mental frameworks to identify any cultural gaps and potential sources of friction and resistance. At this stage, leadership initiates communication with all stakeholders, informing them about the forthcoming changes on both cultural and technical levels.

Advancing to the third phase, the firm initiates piloting by embarking on an exploration and experimentation process with a small yet impactful project. This phase typically extends to approximately one year, allowing the firm's leadership to gather valuable insights into the feasibility of their transformation endeavours. As the hidden challenges of the AI development and deployment process start to emerge, they manifest as potential frictions, resistance to change, sabotage, skill and expertise shortages, training needs, and even unrealistic budgeting issues. These challenges provide valuable lessons that contribute to a clearer understanding of the ROI and enable a more realistic cost-benefit analysis of AI integration. The success of the pilot project heavily relies on management's willingness to commit to organisational learning, change, and adaptability.

The final phase, scaling, signifies the ongoing evolution of the integration process as it expands to encompass more projects. This phase is characterised by continuous growth and is influenced by the firm's ambitions and desired position within its industry. Scaling involves sustained investment, improvement, up-skilling, and engagement across various departments, clients, and partners, potentially resulting in the creation of an AI ecosystem. Ultimately, the firm aims to establish an ecosystem where AIDT becomes ingrained in the DNA of all stakeholders. The leadership of the focal firm plays a crucial role in orchestrating interrelationships and coordinating tasks within the ecosystem. As one interviewee states, 'You have to create an ecosystem. We have to develop the ways [processes] to use data, like a water system' (IC09). Data, like water, flows through all work processes within an integrated and interconnected system. Scaling is essential to harness the long-lasting effects of AIDT, impacting critical aspects of the business by improving efficiency gains, enhancing client satisfaction, and potentially leading to further innovations through the ripple effect of AIDT.

The GT model serves as a representation of the dynamic progression of the AIDT process, emphasising key phases that unfold over time. It acknowledges the nuanced nature of each industry, considering factors such as the pace of technological innovation and obsolescence, competition, and other industry-specific characteristics. Our model aims to provide a concise framework that captures the most significant themes that emerged from our study.

6. Discussion and conclusion

Despite the growing interest in DT research, not only is there still a lack of agreement on the precise definition and nature of DT (Warner and Wäger 2019) but there is also a lack of clarity as to how the existing knowledge on organisational change can be used to explain the DT process and its drivers (Hanelt et al. 2021). This is partly because DT is a complex and multifaceted phenomenon that can manifest differently depending on the context. For instance, there are different perspectives on the drivers of DT and characterisation of its process.

Our research has uncovered a critical insight for companies undertaking AIDT: hasty reactions to external pressures and exogenous factors are likely to hinder success. Instead, our findings suggest that a more strategic approach is needed to maximise the chances of a successful AIDT initiative. To achieve this, our proposed GT model advocates for an introspective approach. This involves beginning the AIDT process by conducting a thorough assessment of the internal organisational context, analysing business problems, and mapping business processes to identify bottlenecks. By focusing on the unique needs and goals of the organisation, rather than being swayed by external forces and competition, companies can ensure that their AIDT initiatives are well-aligned and more likely to deliver tangible benefits.

To lay the foundation for a successful AIDT initiative, Phase One (Figure 2) necessitates a more nuanced and context-bound understanding of 'sensing capability' (Teece 2007). This begins with a thorough examination of existing business processes to identify areas that require streamlining. Subsequently, the firm should broaden its exploration to uncover novel AI technological opportunities that extend beyond its immediate boundaries, as highlighted by Warner and Wäger (2019).

By conducting an in-depth analysis of core business processes – the established routines – the firm can identify the underlying factors contributing to performance issues. This step is crucial to prevent engaging in AIDT initiatives solely for the purpose of imitating competitors or succumbing to AI hype. Sensing capability can thus be further categorised into *inward* and *outward-looking* types, both of which play a pivotal role in the early stages. This enables the firm to make well-informed and strategic decisions regarding the most suitable business and technological opportunities that align with its distinct requirements and objectives.

While previous literature has focused on the development of dynamic capabilities underlying DT and proposed processes primarily driven and guided by external factors, our research emphasises the need to consider internal business processes. For example, Matarazzo et al. (2021) emphasised the relevance of sensing and learning capabilities as triggers of DT, while Warner and Wäger (2019) proposed a model that begins with external triggers and follows with digital sensing (digital scouting, scenario building, and mindset crafting). Li et al. (2018) highlighted the gap between the firm and its benchmark companies, and others (Hanelt et al. 2021) underlined the role of the ubiquity of digital business ecosystems. Although these models have significantly improved our comprehension of DT processes, we have also discovered through the successful and failed experiences of senior executives that neglecting to identify the actual problems entrenched in existing routines in favour of prioritising external technological opportunities can signify the start of a failed AIDT initiative. Thus, we recommend a more balanced approach, incorporating both inward and outward-looking sensing capabilities as necessary to increase the likelihood of a successful AIDT initiative. Consequently, we propose the following research proposition:

Proposition 1: A firm's inward-looking sensing capability plays a pivotal role in enhancing the likelihood of success in their AIDT initiative. By effectively leveraging this capability, the firm can foster a stronger alignment between the actual problems deeply rooted in their existing routines, their unique needs and goals, the available external technological opportunities, and the influential exogenous factors.

Phase Two – auditing organisational readiness – focuses on conducting an in-depth analysis of technical, financial, and cultural routines, path dependencies, and competencies. The primary objective is to identify areas requiring modification and novel competencies that need to be developed. It also underlines the firm's ability to assess its data readiness. Our participants place a balanced emphasis on technical and cultural readiness without undermining one at the expense of the other. Furthermore, discussions pertaining to data emerged alongside the exploration of technical and cultural aspects of DT.

Organisational culture plays a pivotal role in the success or failure of new technology assimilation, yet it is often neglected, briefly discussed or mentioned in obscure terms (Hartl and Hess 2017; Hoffman and Klepper 2000). Within DT studies, creating the right culture is seen as an essential element (Li et al. 2018; Warner and Wäger 2019) and an important dimension of Industry 4.0 maturity models. Several studies have examined culture from various perspectives. For instance, Schumacher et al. (2016) linked culture to knowledge sharing and open innovation, while Li et al. (2018) focused on the generation gap between CEOs and employees. Holmstrom (2022) examined the role of a digital mindset in shaping culture, and Warner and Wäger (2019) investigated the impact of digital culture on organisations. In our study, culture is comprised of several components, with one important aspect being adoption of the data exploration mentality. This suggests a shift from experience-based decision making to data-based decision making. The dichotomy between the two approaches may be rooted in the generation gap discussed by Li et al. (2018). In this context, we found that effectively communicating the upskilling and training roadmap is crucial to creating human readiness, particularly among senior decision-makers. This is pivotal in reducing friction, resistance to change, and the likelihood of sabotage, thereby enhancing the chances of success. Within the context of AIDT, cultural and technical readiness are closely intertwined and directly impact the success or failure of the AIDT process.

Aligned with the concept of dynamic capabilities, inward-looking sensing is manifested through a comprehensive examination of both technical and cultural routines and competencies. The firm identifies the technical and cultural gaps as well as internal and external sources of what Hannan and Freeman (1984) call structural inertia to locate the parameters for changes. Phase Two can potentially be conducive to friction and resistance. For example, the scope of change can constrain a firm's behaviour if it involves modifying or creating radically new competencies and routines. Consequently, we propose the following research proposition:

Proposition 2: A firm's balanced approach to evaluating both cultural and technical readiness in the context of AIDT is instrumental in enhancing the likelihood of success in their AIDT initiative by effectively mitigating potential friction, resistance, and the occurrence of sabotage.

Phase Three involves piloting the AI integration. However, piloting and its underlying constructs have received scarce attention in DT studies. Extant research characterises piloting as rapid prototyping to strengthen strategic agility and to improve digital maturity (Warner and Wäger 2019). Our findings contribute to our understanding by highlighting the crucial role of the piloting phase, emphasising the importance of prioritising, and making informed choices that consider business impact, the pitfalls of algorithmic biases, and the challenges associated with accurately estimating the ROI. To examine piloting, particularly in the context of AIDT, is essential for the following reasons. Firstly, algorithms are inherently value-laden and may perpetuate discrimination against stigmatised groups based on their social identity (Dovidio, Major, and Crocker 2000). Secondly, selecting and prioritising a pilot project is a crucial decision-making factor as it should yield the most impactful business results (Andriole 2020). Thirdly, without conducting a piloting initiative, a company cannot accurately nor objectively determine the ROI for their AIDT.

Moreover, piloting phase leverages the firm's DC to seize opportunities by addressing sensed business and technological opportunities through careful selection and execution of the pilot project. The pilot project should aim to solve a real need with the greatest business impact. Reducing the ROI's opacity is achieved through pragmatic evaluation of the pilot's execution. The pilot phase provides this opportunity for the firm to create its own custom to-do list and assess the feasibility of implementing timely changes. The element of timeliness is important as 'learning and adjusting structures enhances the chance of survival only if the speed of response is commensurate with the temporal patterns of relevant environment' (Hannan and Freeman 1984, 151). Based on these insights, we propose the following research proposition:

Proposition 3: The piloting phase plays a critical role in AIDT and significantly impacts the likelihood of success in a firm's AIDT initiative by enhancing the firm's capability to select the right project, measure the ROI, and identify the appropriate scope of timely changes to be undertaken.

Phase Four, scaling the implementation, is contingent upon successful completion of the piloting phase and alignment with the firm's overarching vision. Scaling is a gradual and continuous process that evolves alongside the changing needs of the firm, its clients and partners. DT tends to be 'ad hoc and disjointed' at the onset (Sawy et al. 2016, 155). As our findings show, once the decision to scale is made, the number of AI-related projects increases both internally and externally, connecting a larger network of stakeholders including clients, partners, and suppliers, sometimes even across different industries. This highlights the inherent scalability potential of digital technologies (Warner and Wäger 2019) and AI (Iansiti and Lakhani 2020). Our findings not only support this notion but also shed light on the innovation-spurring nature of AIDT, providing further evidence that AI can serve as a GPT (Agrawal, Gans, and Goldfarb 2019).

The scaling process draws upon a combination of sensing and seizing capacities. It involves a continuous cycle of identifying opportunities, prioritising them, and executing actions to seize those opportunities. As scaling progresses, the firm's sensing capacity expands from an internal capability to an ecosystem-level capacity. This expansion involves the focal firm and other stakeholders making crucial boundary decisions as they strive to refine their business model (see, for example, Teece 2007). This expansion also necessitates a renewed reconfiguration capacity, which directly involves leadership. This is partly because scaling the implementation depends on the leadership's long-term vision for the firm's position in the industry and its role in aligning diverse interests. Provided that the firm intends to play a leading role in its industry and can indeed move as a cohesive unit, this phase extends the firm's boundaries to include a larger ecosystem of partners, clients, and other stakeholders. Additionally, the internal environment of the focal firm and its level of success in earlier phases have a significant impact on the scaling process. Hence, we propose the following proposition:

Proposition 4: The decision to scale a firm's AIDT initiative is contingent upon both the outcomes and results achieved during the preceding piloting phase, as well as the firm's alignment with its long-term vision.

Digital leadership plays a critical role in driving the strategic success of digitalisation within an enterprise and its business ecosystem. However, despite its importance, there is 'no common consensus on the operational aspects of digital leadership' (Sawy et al. 2016, 142). Research indicates that successful DT requires effective leadership at all levels of the organisation, with senior executives playing a pivotal role in driving the change process. Leaders must communicate the transformation widely both internally and externally, set expectations, provide training and empowerment, and create incentives. Additionally, they must drive and reinforce cultural changes to ensure sustainable success (Weill and Woerner 2018). Sawy et al. (2016) have characterised digital leadership in terms of business strategy, business model, enterprise platform, people's mindset and skillset, corporate IT function, and humanised workplace. Our research findings focus on leaders' attributes such as vision, commitment, learning culture, sense of urgency to explore, change and grow, communication, and coordination. Therefore, our research contributes to the existing literature by highlighting the individual and micro-perspectives of leadership in AIDT. Furthermore, leadership plays an impactful and pervasive role in every step of the AIDT process. Thus, we propose the following:

Proposition 5: To enhance the likelihood of a successful AIDT process, it is crucial to maintain a continuous, committed and pervasive leadership presence at every stage, ensuring that leaders exhibit the necessary attributes, provide guidance, and actively drive the necessary cultural and organisational changes.

Our research contributes to theory development by providing a rich and detailed context for understanding DT, particularly driven by the intention to integrate AI technologies into the manufacturing processes of SMEs. We have developed a parsimonious GT model which characterises AIDT in terms of five aggregate dimensions and their constituents. The emergent model further portrays AIDT as a four-phased sequential process during which firm leadership is significant and omnipresent – playing an active, non-symbolic role. This research illuminates how the AIDT process unfolds among the selected Canadian manufacturing SMEs. AIDT is proven to be a slow and evolutionary innovation process taking place over an extended period and susceptible to a firm's path-dependent behaviour and vision.

Our study is subject to certain limitations which call for further research. We acknowledge the limits of our data with regards to the concepts identified and characterised, thus we propose follow-up interpretive research in different industries and regions to provide contradictory or corroborative evidence. Specifically, the relationship between leadership style and DT remains inadequately explored and established. Subsequent studies could investigate the impact of different leadership styles, such as transactional, transformational, and laissez-faire, on DT, with a particular emphasis on the AIDT. The findings would deepen our understanding of the leadership dynamics that drive successful transformation initiatives. In addition, the proposed GT model presents a parsimonious model and set of propositions to guide theory-testing research designs to ensure that our findings can be further generalised (Lee and Baskerville 2003).

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