

AI Governance and the Decentralization of Technology Production:

An Investigation of AI-based IPA Bots[†]

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ABSTRACT

The enduring tension between centralization and decentralization in IT governance takes renewed significance in the age of artificial intelligence (AI). Intelligent Process Automation (IPA) bots combine robotic process automation with AI technologies and process mining based on deep, mindful domain expertise. IPA bots challenge foundational assumptions of the IT governance literature as they represent the decentralization of technology production, their AI components learn and adapt, and business users are involved in how bots are deployed. We accordingly problematize the literature and revisit the centralization–decentralization dichotomy in the context of decentralized technology production at the AI frontier. We collaborate with a Fortune 200 multinational to study how IPA projects yield successful governance outcomes of utilization and repeatability. Using a multi-phase research design integrating hermeneutics, induction, and abduction, we formulate a theoretical framework that categorizes characteristics of IPA projects along the dimensions of Governance, Process, and Technology. Our research yields three distinct governance mechanisms formulated as three propositions that showcase the limits to centralization, pathways to democratization, and limits to democratization of AI deployed in the form of IPA bots. First, centralization, in the form of centrally mandated IPA projects that especially require user involvement after deployment, underperforms despite the advantages traditionally associated with centralization. Second, decentralization, in the form of democratization through business user-led initiation and implementation, yields successful outcomes. Third, boundary conditions where democratization of AI has low performance lie in the combination of business user-led initiation and development, paired with human–AI hybrid bots having a low extent of AI. We thereby reframe the centralization–decentralization tension to include not only who makes technology decisions, but also who produces, implements, and deploys AI systems, how extensive the underlying AI is, and how governance activities interact with post-deployment dynamics, thereby making contributions to the burgeoning literature on AI governance.

Keywords: AI Governance, Artificial Intelligence, IS Project Management, IT Governance, Business Value of IT

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1. INTRODUCTION

The governance of information technology (IT) has been a subject of timeless inquiry in the information systems (IS) literature (Olsen and Chervany 1980, King 1983, Sambamurthy and Zmud 1999). This body of work has a rich history of theorizing how the delineation of decision rights, the delegation of responsibilities, and the design of control mechanisms shape the initiation, implementation, and impact of IT-related activities (Kirsch and Cummings 1996, Weill and Ross 2004). At its core lies the enduring tension between centralization and decentralization. This dichotomy in the governance literature has been examined across various contexts, including system development, system portfolios, IT infrastructure, mobile applications, and platforms (Brown 1997, Tiwana and Konsynski 2010, Tiwana et al. 2010, Karhade et al. 2015, Tiwana and Kim 2015). This research has conceptualized centralization as the concentration of decision-making authority within a small group and decentralization as decision-making occurring across multiple levels of the organization.

This longstanding tension takes on renewed significance in the age of artificial intelligence (AI). Advances at the AI frontier, coupled with the proliferation of low-code/no-code (LCNC) toolkits and robotic process automation (RPA), have given rise to intelligent process automation (IPA). IPA bots combine RPA with AI technologies and process mining based on deep, mindful domain expertise (Butler and Gray 2006, Lacity and Willcocks 2021, Lacity et al. 2021). IPA projects represent *the decentralization of technology production* as they can be not only conceived by, but also implemented and deployed by business users with little to no coding experience using LCNC toolkits (Elshan et al. 2023). We conceptualize the above phenomenon as the *democratization of AI*, which is a form of decentralization, making AI more easily available, implementable, deployable, and reusable across a range of people within an organization (van Giffen and Ludwig 2023).

Despite its rich history (c.f., Saunders et al. 2020), IT governance research remains inadequate for explaining the governance of AI systems deployed as IPA bots. Three foundational assumptions of this literature are increasingly challenged. First, governance research has largely presumed that technical expertise and the agency for technology production reside within specialized IT departments (Applegate et al. 1986, Brown 1997, Sambamurthy and Zmud 1999), with business users primarily playing a role in technology access and consumption (Gregory et al. 2018). LCNC toolkits now enable business users to initiate, implement, and deploy AI systems (Viljoen et al.

2025). This shift blurs the long-standing boundary between users and developers (Elshan et al. 2023). Second, prior work has focused on static, rules-based systems whose behaviors are fixed at deployment. AI systems, such as the AI components of IPA bots, adapt and evolve post-deployment through continuous learning from real-world data (Baird and Maruping 2021). Hence, AI systems can execute tasks characterized by uncertainty (Jarrahi 2018) and complex cognitive demands (Davenport and Kirby 2015, Rai et al. 2019). Third, the functional scope of AI systems increases in step with the expanding frontier (Berente et al. 2021). Governance must now contend not only with initial design choices but with post-implementation dynamics.

These violated assumptions raise fundamental questions about the effectiveness of IT governance - reflected in desirable behaviours and successful outcomes (Weill and Ross 2004) - when technology production is decentralized, systems learn and adapt, and business users are involved in how the AI system is deployed. The IT governance literature is not adequate in addressing these issues that affect the success of IPA projects. This motivates us to thereby frame our research question as follows: *What governance mechanisms (centralization — decentralization) appropriately control business user behavior without constraining the success of technology production (through the democratization of AI deployed) in the form of IPA bots?*

This question is important because the era of decentralization of technology production is enduring and irreversible. IT governance must therefore make space for the democratization of AI (deployed in the form of IPA bots) without muting the role of the user, making this a vital question. Further, though AI is a frontier of expanding performance and scope (Berente et al. 2021), many firms struggle with its governance and desirable performance outcomes (Lacity and Willcocks 2021), focusing instead merely on its dramaturgical potential (Cunha and Carugati 2018). The success of IPA projects lies in their *Utilization* and *Repeatability*, which capture how extensively IPA is adopted and further reused within the firm, respectively (Doll and Torkzadeh 1989, Gamma et al. 1995, Keil et al. 1995, Lacity and Willcocks 2021, Lacity et al. 2021). Overall, IPA projects compel us to holistically rethink the taken-for-granted separateness between human and nonhuman (in this case, AI) that underpinned the governance of traditional technology deployments (Brown 1997). We thus revisit the centralization–decentralization tension in the context of decentralized technology production at the AI frontier, focusing on IPA bots as a salient manifestation of the democratization of AI.

Given the newness and novelty of IPA bots, an in-depth field immersion in the spirit of engaged scholarship is necessary to conceptualize, collect, and curate data. We collaborated with a Fortune 200 US multinational IT services firm with an IPA practice worth over \$200 million. Our multi-phase research design for theory development (Leidner and Gregory 2024) comprises fieldwork and qualitative analysis using a hermeneutic approach, induction of decision trees, and abduction to formulate plausible explanations and propositions (Lindberg 2020).

In the first phase of fieldwork, we *purposefully sample* completed IPA projects in the Banking, Financial Services, and Insurance (BFSI) domain, which defines the scope and boundary conditions of our intended theory development (Berente et al. 2019). We follow up with *theoretical sampling* to curate a dataset of 176 IPA projects using elite informant interviews, semi-structured interviews, and archival documents, including trace data such as emails and other “event-based” records of activities. This fieldwork led to the crystallization of our theoretical framework comprising *Governance*, *Process*, and *Technology* dimensions for characterizing IPA projects, and *Utilization* and *Repeatability* as desirable outcomes constituting IPA project success. In the second phase, the induction of trees serves as the basis for discovering tacit patterns in our curated data (Lindberg 2020). These patterns represent cumulative influences of governance, process, and technology dimensions on IPA project success. Induced trees and the accompanying governance patterns, namely rules extracted from trees, serve as building blocks for theory building. This inductive discovery and theory-building process provides inputs to the third phase. This involves abductive reasoning for making sense of governance patterns to formulate theoretically plausible explanations and propositions. Our research design thus combines manual and computational analysis as complements for *computationally intensive theory development* (Berente et al. 2019). Using such a combination of techniques exemplifies *methodological pluralism* (Miranda et al. 2022), allowing robust theory development through triangulation (Van de Ven 2007).

Our methodologically plural research design, undertaken in the spirit of engaged scholarship, yielded a theoretical framework to categorize characteristics of IPA projects along the dimensions of *Governance*, *Process*, and *Technology*. Governance includes *Genesis*, *Sourcing*, *Implementation*, and *Deployment* of IPA projects. The process dimension includes *Process Dependency* and *Process Intricacy*, while *Extent of Coupling*, *Extent of AI*, and *Extent of Coding* comprise the technology dimension. Characteristics individually and collectively hold rich explanatory power.

Our research yields three distinct governance mechanisms formulated as three propositions. These propositions advance IT governance research into the era of decentralized technology production by showcasing the limits to centralization, pathways to democratization, and limits to democratization of AI deployed in the form of IPA bots. First, centralization, in the form of centrally mandated IPA projects that especially require user involvement after deployment, underperforms despite the advantages traditionally associated with centralization. Second, decentralization, in the form of democratization through business user-led initiation and implementation, yields successful outcomes. Third, boundary conditions where democratization of AI has low performance lie in the combination of business user-led initiation and development, paired with human–AI hybrid bots having a low extent of AI.

Our study makes three contributions to the burgeoning AI governance literature, where theoretical lexicons are underdeveloped (Miranda et al. 2022), ensconced within the broader IT governance literature. First, we contradict findings from the canonical IT governance literature, which holds that centralization yields superior results (Sambamurthy and Zmud 1999, Weill and Ross 2004). We do so by showcasing underperformance in the centralized governance of IPA bots at the AI frontier (Berente et al. 2021), which require deep, mindful, domain expertise (Butler and Gray 2006, van Giffen and Ludwig 2023) and iterative refinement through learning (Davenport and Kirby 2015, Rai et al. 2019). We thus extend IT governance theory by identifying the limits of centralization for AI governance, which requires high levels of business user interaction (Baird and Maruping 2021, Chen et al. 2022).

Second, we expand the scope of conventional IT governance research that has focused on technology access and consumption (e.g., Gregory et al. 2018, van Giffen and Ludwig 2023). We do so by accounting for decentralized technology production regimes via the democratization of AI. Value in such decentralized technology production emerges through the allocation of decision rights and authorities to non-technical business users in the two new governance activities of implementation and deployment. Therefore, the inclusion of these two new governance activities bends the scope of IT governance research towards the arc of AI governance.

Third, we reveal the boundary conditions of classical IT governance theory, which holds that decentralization is a universally beneficial arrangement (e.g., Tiwana and Konsynski 2010). We do so by uncovering limitations of decentralization of technology production through the democratization of AI deployed in the form of IPA

bots. The effectiveness of AI governance depends on specific combinations of the extent of AI, deployment mode, implementation agency, and hybrid governance mechanisms. These boundary conditions delineate when decentralization of technology production requires additional hybrid governance mechanisms (Brown 1997, Sambamurthy and Zmud 1999) to move democratization of AI beyond the *horseless carriage* phase (Nunamaker et al. 1989) and achieve value at scale from AI.

Collectively, our research departs from the conventional governance literature by reframing the long-standing centralization–decentralization tension in IT governance (Olsen and Chervany 1980, King 1983) for AI governance. Our framing accounts for decentralized technology production, emphasizing not only who initiates technology decisions, but also who produces, implements, and deploys the technology, the extent of its AI components, and how governance activities interact with post-implementation dynamics (Wareham et al. 2014, Svahn et al. 2017, Gregory et al. 2018). We highlight the pathways and limitations of these centralization–decentralization governance mechanisms, thereby closing the loop of knowledge production. Overall, we address the need for reimagining governance mechanisms for AI to appropriately control business user behavior without constraining the success of technology production.

2. THE IT ARTIFACT: IPA BOTS

We study the governance of IPA projects that result in the deployment of IPA bots, which are the IT artifact of this study (Sarker et al. 2019). In line with research that conceptualizes AI as a frontier (Berente et al. 2021), we define IPA bots as a combination of (1) RPA technologies, (2) AI technologies, and (3) process mining based on deep, mindful domain expertise (Butler and Gray 2006, Lacity and Willcocks 2021, Lacity et al. 2021). RPA technologies are software robots (also known as bots) that replace repetitive, manual processes with automated workflows. IPA bots extend rigid, rule-based RPA bots by incorporating an ensemble (Orlikowski and Iacono 2001) of AI technologies, such as machine learning (ML), advanced computer vision, natural language processing (NLP), and large language models (LLMs) within the workflow. Thus, the definitional boundaries of IPA bots evolve with the advancement of the AI frontier. IPA bots leverage the deep domain expertise of business users to diagnose process inefficiencies and streamline sub-processes as they intelligently automate business processes.

Two issues in the context of IPA merit attention. First, IPA bots represent *the decentralization of technology production* as they can be conceived by non-technical business users across the firm, who have accumulated a deep understanding of business processes (Lacity et al. 2021). Furthermore, end-users with little to no coding experience can implement and deploy IPA bots unilaterally using LCNC toolkits, which provide drag-and-drop pre-built components in an integrated visual development environment (Elshan et al. 2023).

Second, as the frontier of AI performance and scope is evolving (Berente et al. 2021), the AI components of IPA bots learn and adapt at a fast pace (Elofson and Konsynski 1993, Baird and Maruping 2021). Once deployed, IPA bots learn through analogy (Liang and Konsynski 1993) by accumulating more data, which sharpens their situational awareness, allowing them to adapt their responses over time (Baird and Maruping 2021). The deep understanding of business processes embedded within IPA bots also enables them to increase their scope. Over time, the performance of IPA bots improves, and they progressively take over decisions where human judgment was previously necessary. They are also increasingly able to handle exceptions effectively by handling various kinds of unstructured data from images, videos, voice recordings, and text (Konsynski and Sprague 1986, Lacity and Willcocks 2021). These improvements in the performance and scope of IPA bots happen without requiring further coding.

We now elaborate on the above through an example. Another example from our fieldwork is presented in Online Appendix A. Consider a system designed for intelligent document handling in a BFSI context. These institutions process large volumes of documents, such as contracts, invoices, and ownership certificates, daily. Traditionally, staff relied on data entry applications to digitize documents. This process was time-consuming, cost-prohibitive, and prone to error. While the use of rule-based engines and optical character recognition technologies provided some benefits, such workflows were limited by their rigidity. Rule-based systems, for example, require extensive reprogramming when document formats change. Now, business users with deep domain expertise can initiate, develop, and deploy intelligent document handling solutions. Using LCNC toolkits, business users can orchestrate IPA bots for solutions tailored to their domain-specific document handling needs. These toolkits incorporate AI technologies through drag-and-drop interfaces and APIs, allowing non-expert users to configure intelligent workflows without extensive

programming. An IPA-based intelligent document handling system would manage the entire corpus of documents. As new documents are added to the corpus, NLP-based AI technologies can automatically extract meaningful information, such as entities and insights. Over time, AI technologies can learn patterns, enabling them to recognize relationships between entities that are specific to this particular business domain. Business users can further train the AI technologies, tuning them to recognize entities pertinent to unique process intricacies within their domain. As the deployment of such a document handling IPA bot matures, it would manage and learn from more instances and a greater variety of documents. Eventually, such an IPA bot, on its own, can handle a broader array of documents without requiring additional programming.

3. BACKGROUND LITERATURE

Our research lies within the broad thematic area of *IT Governance*, which has been summarized by Saunders et al. (2020). This constitutes the boundary of the discourse wherein we situate our study. Our intent is not to duplicate the insights from Saunders et al. (2020), but instead to surface the centralization-decentralization tension in the service of problematizing this literature. Our summative assessment is that *IT Governance* research is inadequate in its engagement with the burgeoning literature on AI systems. Similarly, research on AI systems also inadequately addresses governance issues.

3.1 The Centralization-Decentralization Dichotomy in IT Governance Research

Research has examined the governance of IT projects, which are complex, nonroutine, and entail considerable ambiguity (Kirsch and Cummings 1996, Mähring and Keil 2008, Wiener et al. 2016). IT governance is essential to establish and manage procedures, policies, and decision rights that allow project stakeholders to work effectively (Weill and Ross 2004, Midha and Bhattacharjee 2012).

From its inception, IT governance has been about control (Olsen and Chervany 1980). Control over the planning, delivery, and performance of IT-related activities such as IT projects. This focus on control has historically been framed through dichotomies. Early work on IT governance conceptualized it through the locus of decision-making, distinguishing between centralized and decentralized control (King 1983). Centralized control implied the concentration of decision-making authority within a small group, whereas decentralization meant decision-making occurred across multiple levels of the organization. This dichotomy

shaped how researchers theorized this tension in IT governance. This thinking was extended to differentiate between system development and system operations (Brown 1997), and to identify governance arrangements as distinct patterns of IT-related decision-making (Sambamurthy and Zmud 1999). These arrangements were categorized as centralized, decentralized, or hybrid modes of governance. Weill and Ross (2004), in their seminal work, formalized IT governance as the specification of decision rights and accountability frameworks to encourage desirable behavior in the use of IT and its outcomes. They emphasized the importance of identifying who makes which decisions, who has input, and how decision-makers are held accountable.

This conceptualization led to an extensive stream of research focused on the allocation of decision rights across various IT issues (Tanriverdi 2006, Tiwana 2009). For instance, researchers drew attention to the tension between IT specification (what IT should do) and IT implementation (how IT should be done) (Tiwana and Konsynski 2010) and distinguished between IT application governance (decision rights over business applications) and IT infrastructure governance (decision rights over IT platforms) (Tiwana and Kim 2015). A variety of other dichotomies emerged in the literature: IT staff versus business users (Williams and Karahanna 2013, Constantinides and Barrett 2015), platform owners versus module developers (Tiwana et al. 2010), inter- versus intra-organizational systems (Chatterjee and Ravichandran 2013), and governance of IT versus governance via IT (Drnevich and Croson 2013). These dichotomies have served as productive lenses to structure the IT governance discourse. Yet, they also reflect a dominant focus on formal control structures, largely rooted in an era of static, rules-based IT systems produced by specialized IT departments.

3.2 Problematizing and Rethinking IT Governance Research for AI Systems

Three key assumptions that underpin IT governance research, as showcased in a recent curation (Saunders et al. 2020), are being challenged by advancements in the AI frontier. First, in the past, technical expertise, as well as agency for software development and implementation, lay largely within the IT function (Applegate et al. 1986, Brown 1997, Sambamurthy and Zmud 1999). However, users are no longer just passive consumers or requesters of technology. With the proliferation of LCNC toolkits, business users now possess the wherewithal to produce their own technology solutions, often without direct involvement from IT (Viljoen et al. 2025). This shift blurs the long-standing boundary between users and developers (Elshan et al. 2023),

posing questions about how governance should function when technology production is decentralized.

Second, AI Systems – in particular AI-based IPA bots that we examine in this study – differ significantly from traditional rule-based IT systems. Unlike earlier systems that required explicit logic for all conditions, AI learns and adapts over time by analogy (Liang and Konsynski 1993) and engages with structured and unstructured data (Konsynski and Sprague 1986, Baird and Maruping 2021, Hevner and Storey 2023, Storey et al. 2024). AI systems, such as the AI components of IPA bots, detect patterns and generate algorithmic knowledge (Chen et al. 2022), which evolves through real-world deployment. Hence, AI systems can execute tasks marked by uncertainty and equivocality (Jarrahi 2018), require cognition (Davenport and Kirby 2015, Rai et al. 2019), and entail complex decision-making (Kim et al. 2020, Zhang et al. 2022).

Third, the above dynamics also significantly reduce the need to pre-engineer for all contingencies. This is because AI systems, which underpin IPA bots, no longer require every exception and logic path to be hardcoded in advance (Elofson and Konsynski 1993). Thus, most AI projects, such as those to develop IPA bots, are initially smaller in functional scope than traditional software projects. However, their functional scope improves and increases in scope rapidly over time due to AI's ability to learn and the expanding frontier (Berente et al. 2021). As such, governance must now contend not only with initial design choices but with post-implementation dynamics, including how the AI system is deployed and the extent of business user involvement in the deployed system.

Despite these transformative shifts, the emerging literature on AI systems has paid limited attention to fundamental questions of governance. Prior research has explored user attitudes towards AI, such as algorithmic appreciation versus aversion (Deng et al. 2023); outcomes of AI systems, such human augmentation versus substitution (Brynjolfsson and McAfee 2014, Davenport and Kirby 2015, Ford 2015, Chen et al. 2022); and adoption in domain-specific settings, such as conversational AI agents in customer service (Gnewuch et al. 2023) and AI tools in diagnostic radiology (Lebovitz et al. 2021). Additionally, prior work has focused on either pre- or post-implementation issues related to AI systems (Salge et al. 2015, Queiroz et al. 2024). Research has also recognized the importance of collaborative intelligence (Konsynski et al. 2024), human-AI teaming (Wilson and Daugherty 2018), and the interplay between humans and AI in the

design of organizational processes (Camargo et al. 2020, vom Brocke et al. 2021, Fehrer et al. 2022). Moreover, scholarship in design science research has made progress on the design and deployment of human-AI systems (Storey et al. 2024). However, the overall research on AI systems has been myopic in its treatment of governance and thus inadequate to examine how such systems are governed as these technologies are produced and deployed across the organization. Given that AI deployed in the form of IPA bots differs fundamentally from prior information technologies – it learns, adapts, and can be produced by nontechnical business users – its governance must also differ.

3.3 Resurfacing the Centralization-Decentralization Tension

Research has examined the democratization of technology access in varying contexts – the democratization of IT access and consumerization (Gregory et al. 2018); in-depth case studies of the democratization of AI within a single organization (van Giffen and Ludwig 2023); and the proliferation and democratization of LCNC toolkits (Elshan et al. 2023). However, we now observe the decentralization of technology production through the democratization of AI via IPA bots – a shift that extant literature is inadequate to explain.

This shift from governance of access (Gregory et al. 2018) to governance of production (Lacity et al. 2021, Elshan et al. 2023, van Giffen and Ludwig 2023) marks a significant inflection point. Business users are not merely accessing centrally governed IT assets - they are now creating, deploying, and refining them. This dynamic requires revisiting long-held assumptions in IT governance. In particular, governance must now encompass sets of activities other than those examined in the past, such as approval, monitoring, initiation, and implementation (Tiwana 2009), and adoption and usage (Salge et al. 2015), by accounting for post-implementation deployment activities.

Further, this democratization is also not without challenges (Lacity and Willcocks 2021). User-led development may improve utilization and foster innovation at the edges but can also result in isolated, idiosyncratic implementations (Lacity et al. 2021, Storey et al. 2024). At the same time, centrally mandated IT projects, when implemented without adequate user input, may give space to unregulated and ungoverned shadow IT (Haag et al. 2019, Haag and Eckhardt 2024).

These developments render earlier dichotomies insufficient for guiding governance as AI systems and LCNC toolkits mature. When users are both the ideators and implementers of AI systems, such as IPA bots, the long-standing centralization–decentralization tension must be revisited. The emphasis can no longer be solely on who makes technology decisions but must now also consider how technology is implemented and deployed – by whom, how, and at what level of human involvement (Zhdanov et al. 2022).

In conclusion, the longstanding tension between centralization and decentralization resurfaces in a new form in the era of decentralization of technology production through the democratization of AI deployed in the form of IPA bots. Prior research has not sufficiently addressed how this tension plays out and which governance mechanisms – centralization or decentralization – are most effective. In response, we have problematized the literature (Wareham et al. 2014, Svahn et al. 2017, Gregory et al. 2018) and reframe IT governance by surfacing both the potential and the limits of democratization as a mode of governance in decentralized technology production.

4. RESEARCH DESIGN AND CONTEXT

4.1 Research Design

We integrate induction and abduction in a multi-phase process comprising fieldwork, induction of trees, followed by abduction to formulate plausible explanations based on the trees (Karhade et al. 2015, Lindberg 2020). Doing so allows us to iterate between the zones of theory and empirics to complete the cycle of knowledge creation within the traditions of computationally intensive theory construction (Berente et al. 2019).

In the first phase, we conduct fieldwork and qualitative analysis. We use a hermeneutic approach, representing a “primordial” way of how we come to understand (Gadamer 1975, Boland 1991, Sahaym et al. 2023) “Human understanding is achieved by iterating between considering the interdependent meaning of parts and the whole that they form” (Klein and Myers 1999, p. 72). In our context, we iterate across archived data and descriptions of IPA projects, supplemented by interviews to gain a deeper understanding of the data. We start with a *part* of the documentation describing projects initially yielding a few characteristics. We progressively unearth the *whole* portfolio of IPA projects comprehensively described by a broader set of characteristics. This enabled us to conceptualize the dimensions of (i) Governance, (ii) Process, and (iii) Technology. Our fieldwork allowed us to collect and

transform the archival and interview data into quantitative data. In summary, we adapt the hermeneutic circle of Agar (1986) to discover IPA characteristics along the governance, process, and technology dimensions, which serve as inputs for pattern discovery through induction in the second phase.

The second phase lies in the zone of empirics as it involves the induction of trees, which facilitate the discovery of patterns, yielding a model ground up from the data (Quinlan 1986, 1990). Tree induction is better suited to our context compared to alternative methodologies, such as fuzzy-set QCA, as induction grows the tree by identifying the most informative attributes and linking them to the outcomes. We conducted multiple computational experiments (Karhade et al. 2015, Kathuria et al. 2020, Lindberg 2020) to discover patterns from our data and leveraged suitable heuristics to choose the best representative tree (Quinlan 1990). We expounded context-specific rules (Karhade and Kathuria 2020, Kathuria et al. 2020), which are a series of if-then statements extracted from the tree to elaborate relationships between IPA characteristics and outcomes. This phase supports computationally intensive theory construction to produce insights from patterns discovered in induced trees (Berente et al. 2019).

The third phase involves abductive reasoning, which allows for the sensemaking of patterns discovered via induction (Sætre and Van de Ven 2021). Abduction leverages researchers' expertise and judgment to craft the best plausible explanation for context-specific rules discovered from trees. We interpret empirical evidence by leveraging prior theory and expertise to arrive at a pre-theoretical understanding to elaborate a coherent theoretical explanation that contributes to the current state of the literature (Berente et al. 2019). Specifically, after developing our mental model using trees, we engage in a sensemaking process to generate theory through a *diachronic*, temporal analysis (Holland et al. 1986). By engaging in an attitude of questioning and mindfulness towards the predictions – *reflexivity* (Miranda et al. 2022), we summarize our key theoretical findings to complete the knowledge creation cycle.

4.2 Research Context and Data

We collaborated with a Fortune 200 US multinational IT services and consulting firm to investigate our questions. Data were collected from the company's IPA group, which implements projects exceeding \$200 million annually. The IPA group delivered hundreds of IPA projects between 2019 and 2021, spanning the BFSI, communications, retail, and healthcare domains. Following the norms of engaged scholarship (Van de Ven 2007), the research team

includes an internal researcher who provided access and shared a deep understanding of all the phases involved in the initiation, development, and eventual deployment of IPA projects. With the facilitation of the internal researcher, who was embedded within the IPA group for five years, we were effective and efficient in gathering this data and understanding its meaning (Tremblay et al. 2023).

5. PHASE 1: HERMENEUTIC APPROACH FOR QUALITATIVE ANALYSIS

5.1 Sampling Approach

Our sampling approach is illustrated in Figure 1. We adopted purposeful sampling to identify a targeted sample of *completed* IPA projects. Purposeful sampling involves the deliberate identification of cases based on specific criteria prior to initiating data collection (Crosina and Pratt 2019). We purposefully selected projects implemented in the BFSI sector. Three considerations drove this choice. First, BFSI offers universality in its processes across different geographies, enabling us to maximize generalizability and minimize confounding effects from geographical heterogeneity. Second, by restricting our focus to BFSI, we control interdomain heterogeneity. This enabled us to increase the internal validity of our study. Third, the experience and expertise of our internal researcher guided us in situating the problem in this domain and were vital to conceptualizing governance along the IPA lifecycle. This helped us overcome the ‘outsider’s perspective problem’ when conducting elite informant interviews by identifying the most relevant information (Louis and Bartunek 1992).

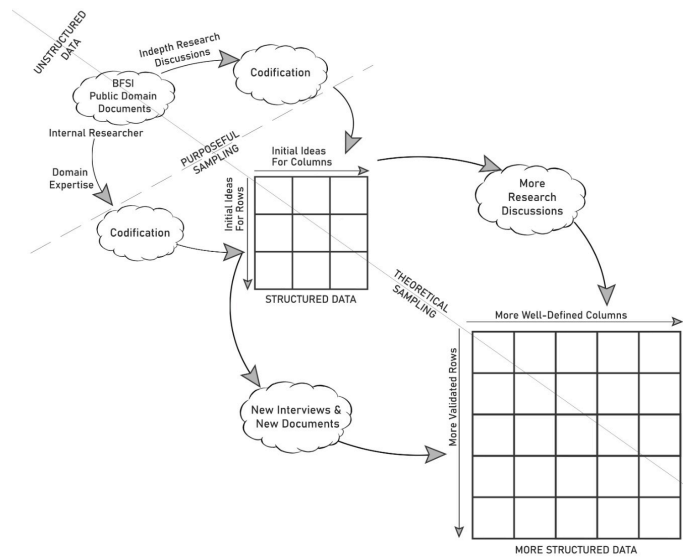


Figure 1: Sampling Approach for Data Collection

We then engaged in theoretical sampling, involving a dynamic process of data collection where the selection

of subsequent cases was guided by emerging insights (Berente et al. 2019). We leveraged multiple sources to gather extensive data for capturing a diverse range of perspectives, thereby gaining a deep understanding of IPA projects. The objectives of theoretical sampling were twofold. First, we identified characteristics of IPA projects, refining and expanding the list through an iterative process of data collection and sampling. Second, we engaged in *synchronic analysis* and *lexical framing* (Berente et al. 2019, Miranda et al. 2022) to cohesively organize these characteristics across the dimensions of Governance, Process, and Technology for subsequent induction in Phase 2.

5.2 Details of Qualitative Methodology

Our methodology for Phase 1, illustrated in Figure 2, uses a hermeneutic approach to collect, make sense of, and transform qualitative data into quantitative data. For initial understanding, we collected thirty *publicly available marketing case studies* of successful IPA projects from the firm's and its clients' websites. These case studies, developed by the sales team, highlighted the benefits of successful IPA projects. To gain deeper insights, we obtained access to fifty additional marketing case studies with restricted public access, used internally by the sales team. This corpus served as an initial source of information on IPA projects. This information, along with our awareness of IPA, knowledge of relevant literature, and personal professional experiences, provided us with a preunderstanding (Sahaym et al. 2023) of the heterogeneity within IPA projects and their outcomes.

In-depth discussions with the sales team revealed that marketing case studies for successful initiatives were derived from *project completion reports*, which summarize IPA projects. *Project completion reports* are generated for every IPA project, although they are not publicly accessible. We sought access to these reports for the projects for which we had collected the *marketing case studies*. Comparisons with *marketing case studies* and discussions with the internal researcher and key members of the sales, delivery, and technology teams validated project completion reports as the primary source of truth for completed IPA projects. These reports provided an updated understanding of characteristics that shape the performance of IPA projects. Following discussions with the internal researcher, our preunderstanding of the Governance, Process, and Technology dimensions crystallized at this stage. Discussions revealed that (i) Utilization and (ii) Repeatability are key outcomes in the eyes of executives responsible for the governance of IPA projects. Thus, discussions helped us formulate a preunderstanding for transforming qualitative information into quantitative data.

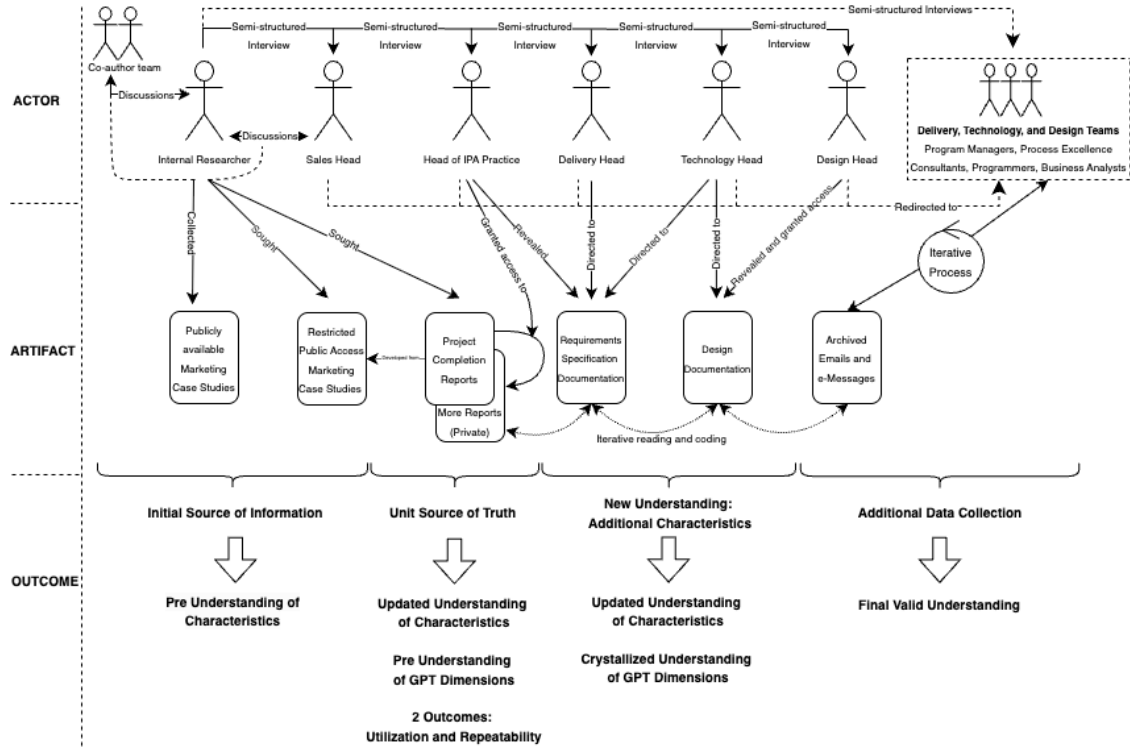


Figure 2: Hermeneutic Process for Phase 1

While *project completion reports* offered a list of characteristics (columns) on multiple completed IPA projects (rows), from our interviews, we discovered that project completion reports are not standardized. Thus, we sought other sources of information to curate our data and to further our understanding. We conducted semi-structured interviews with five elite informants – the Head of the IPA Practice and senior-most members of the sales, delivery, design, and technology teams. These interviews were designed to elicit in-depth information and insights regarding the characteristics and performance outcomes of IPA projects through joint reflective conversations¹ (Gregory et al. 2018). Through these interviews, each lasting a couple of hours, we aimed to invalidate existing identified characteristics to uncover additional traits not initially identified (Agar 1986). Furthermore, these elite informants directed our efforts to sample subsequent groups, interviews, and documents within the firm that could provide us with information to complement the *project completion reports*. Additional documents included *design documentation* and *requirements specification documentation*.

¹ Interviews commenced with preliminary high-level questions. Given the familiarity of the Internal Researcher with the context, they were able to identify subsequent follow-on questions to elicit information and help interviewees reflect and articulate nuanced insights.

Requirements specification documentation, prepared at the start of a project, includes desired outcomes and intended characteristics, while *design documentation* provides details on process design and automation opportunities.

In conjunction with the interviews, we received access to *project completion reports* of completed IPA projects available in the private domain, which increased our sample size (rows) to 198. These documents validated and expanded our understanding of the characteristics of IPA projects. Throughout this process, we iteratively engaged in interviews and data transformation to formulate new understandings, and reach a valid understanding. Hundreds of open-ended reflective interviews and interactions with program managers, process excellence consultants, programmers, and business analysts, collectively totalling approximately 330 hours spanning two years in the field, provided insights and guided subsequent data collection. These interviews served as a source of data, informed us on where to focus our data collection efforts, and provided insights into potential areas for investigation. Doing so supports theoretical sampling as it informs additional data collection and leads to the emergence of a richer sample over time, informed by existing analysis (Berente et al. 2019).

As we combed through the corpus, wherever data about certain characteristics were not available, we turned back to the interview participants. We retrieved information from alternative sources, including emails. Emails represent trace data that preserve event-based provenance of activities (Berente et al. 2019). We maintained notes and memos during data collection to capture emerging insights. This iterative process ensured data collection for each IPA project, using multiple sources, such as project completion reports, requirements specification documentation, design documentation, and interviews. Overall, the corpus of archival documents, semi-structured interviews, informal conversations, and email trace data collectively served as the source we made sense of, theorized to, and coded data from using the hermeneutic circle (Agar 1986, Klein and Myers 1999).

Ultimately, for each IPA project, we triangulated information from various sources to ensure completeness. Twenty-two projects with incomplete or unvalidated data were excluded from the dataset. We ensured the orthogonality of characteristics by removing characteristics that conveyed similar information content across varied sources. Extensive discussions between internal and lead researchers were necessary to achieve consensus on the definitions and meanings of the Governance, Process, and Technology dimensions and their associated characteristics – namely, the final valid understanding. An illustration of the codification

process is available in Online Appendix B. Overall, the identification and theoretical elaboration of these three dimensions is an outcome of *discursive flexibility* wherein, instead of rigidly adhering to a single discourse, we switched among multiple discourses to construe the necessary meanings and representations of our coded and categorized data (Miranda et al. 2022). This process culminated in a dataset of 176 IPA initiatives, defined by characteristics along three dimensions summarized in Table 1.

Table 1: Governance, Process, and Technology Dimensions Informing IPA Success

CHARACTERISTIC (MEASUREMENT SCALE)	PERMISSIBLE VALUES	SOURCES	KEY REFERENCES
GOVERNANCE DIMENSION			
Genesis (Nominal)	Top-down Mandate	Requirements Specification Documentation, Semi-structured interviews	(Doll and Torkzadeh 1989, Kirsch and Cummings 1996, Segars and Grover 1999, Sahay et al. 2009, Constantinides and Barrett 2015, Windeler et al. 2017)
	User-initiated Request		
Sourcing (Nominal)	Buy	Requirements Specification Documentation, Design Documentation, Semi-structured interviews	(Brown 1997, Rai et al. 2009, Susarla et al. 2010, Lacity and Willcocks 2021, Lacity et al. 2021)
	Build		
	Both		
Implementation (Nominal)	User-led	Marketing Case Studies, Requirements Specification Documentation, Design Documentation	(Doll and Torkzadeh 1989, Weill and Ross 2004, LeFave et al. 2008, Tiwana and Konsynski 2010, Haag et al. 2019, Haag and Eckhardt 2024)
	IT-led		
Deployment (Nominal)	Unattended Bot	Marketing Case Studies	(Wilson and Daugherty 2018, Rai et al. 2019, Baird and Maruping 2021, Chen et al. 2022, Konsynski et al. 2024)
	Hybrid Bot		
	Attended Bot		
PROCESS DIMENSION			
Process Intricacy (Ordinal)	High (>100 steps)	Requirements Specification Documentation, Design Documentation, Semi-structured interviews	(Malone and Crowston 1994, Malone et al. 2003) (Lacity and Willcocks 2021, Lacity et al. 2021)
	Medium (50-100 steps)		
	Low (<50 Steps)		
Process Dependency (Ordinal)	Yes (Inter-dependence)	Requirements Specification Documentation	(Malone et al. 2003, Negoita et al. 2018, Lacity and Willcocks 2021, Lacity et al. 2021)
	No (Independence)		
TECHNOLOGY DIMENSION			
Extent of Coupling (Ordinal)	Loose	Design Documentation	(Simon 1962, Weick 1976, Sanchez and Mahoney 1996, Tiwana 2008, Tiwana and Konsynski 2010)
	Tight		
Extent of AI (Ordinal)	High	Project Completion Report	(Lacity and Willcocks 2021, Lacity et al. 2021, Gnewuch et al. 2023, Hevner and Storey 2023, Storey et al. 2024)
	Low		
Extent of Coding (Ordinal)	High (Customization using Bespoke Code)	Project Completion Report, Semi-structured interviews, Requirements Specification Documentation, Design Documentation	(Lacity and Willcocks 2021, Lacity et al. 2021, Elshan et al. 2023)
	Medium (Configuration of Existing Code)		
	Low-code / No-Code		

5.3 Characteristics Informing IPA Projects

5.3.1 The Governance Dimension

At its inception, IT needs were mostly furnished via centralized IT departments in firm headquarters (Applegate et al. 1986). Thereafter, regional offices, due to affordable software and databases, could provide

their IT needs in a decentralized manner. Platforms accelerated decentralization of IT via modular components and interoperable APIs (Tiwana et al. 2010). We now witness decentralization of technology production through the democratization of AI deployed in the form of IPA bots. Non-technical business users can unilaterally initiate, develop, and deploy their own AI in the form of IPA bots to address their specific business needs. Aligned with this notion of decentralized technology production and based on our fieldwork, we conceptualize the governance dimension along four phases spanning *Genesis*, *Sourcing*, *Implementation*, and *Deployment*.

Genesis: When initiating IPA projects, a key governance mechanism is *Genesis*, which we conceptualize in terms of the locus of initiation (Doll and Torkzadeh 1989). *Genesis* is operationalized in two ways: (i) *Top-down Mandate* or (ii) *User-initiated Request*. A top-down mandate indicates that the firm's leadership has directed the *Genesis* of the IPA project. Such mandates exemplify a top management-driven and controlled approach (Kirsch and Cummings 1996) and may stem from strategic initiatives, business needs, or regulatory requirements. Conversely, user-initiated requests arise from the bottom up and are distributed throughout the firm. These requests kickstart IPA projects based on needs identified by business users, process owners, or mid-managers. User-initiated requests embody a ground-up approach involving an empowered user base capable of ideating and initiating IPA projects.

Research has examined change initiation from top-down or bottom-up, depending on the roles of managers across the firm hierarchy. Top-down perspectives see executives as initiators of change, while bottom-up perspectives emphasize the grassroots nature of business users in initiating change (Sambamurthy and Zmud 1999, Segars and Grover 1999). Though top management can be reluctant to change initiated from the grassroots, IPA projects cannot be entirely governed only in a top-down manner (Sahay et al. 2009). Business users can capitalize on their intimate knowledge of business processes. Nonetheless, change initiated by the top management is often broad and aimed at all stakeholders. Thus, both loci of initiation can be critical to governing IPA projects effectively (Constantinides and Barrett 2015, Windeler et al. 2017).

Sourcing: Another key characteristic of the governance dimension that needs to be considered is the *sourcing* of IPA projects. Firms need to decide whether to build their own IPA bots or purchase off-the-shelf products from a software vendor. This choice reflects the “make or buy” decision, which depends on a variety of factors, such as the firm's needs, available resources, and the level of available technical expertise.

The sourcing decision presents a dilemma for firms. When faced with rapid change, firms may consider buying from external vendors as a viable option, as firms can benefit from the specialized capabilities of vendors, thereby reducing the costs of IPA bots (Susarla et al. 2010). This is pertinent for the fast-changing AI components of IPA bots. On the other hand, firms may opt to develop IPA bots internally to achieve greater customization and control (Rai et al. 2009). Overall, despite the touted advantages of outsourcing (Brown 1997), firms must evaluate the trade-offs of both approaches before sourcing IPA projects.

Implementation: Traditionally, only specialized IT teams implemented software projects. Now, as business users can implement IPA projects, there exist two types of IPA *Implementation*: *User-led* or *IT-led implementation*. Doing so delineates authorities and responsibilities for implementing IPA projects. *User-led* IPA projects are implemented by business users, rather than specialized IT teams, whereas specialized IT teams implement *IT-led* IPA projects. Thus, *Implementation* pertains to ‘who’ possesses the agency – decision rights and accountability (Weill and Ross 2004) – for the implementation of the IPA project.

User-led IPA has become viable as more firms decentralize technology production and empower business users to digitize their processes by leveraging LCNC toolkits and their deep, mindful domain expertise (Doll and Torkzadeh 1989). However, increased decentralization may spawn “shadow IT” initiatives (LeFave et al. 2008, Haag et al. 2019, Haag and Eckhardt 2024) across the firm, which could be detrimental if the IT solutions are misaligned with the overall firm strategy. Further, such toolkits are not a replacement for specialized IT teams. Given their deep programming expertise, specialized IT teams can achieve a higher level of customization, security, and scalability when implementing IPA. Thus, centralization of IPA projects through *IT-led* implementation (Tiwana and Konsynski 2010) can be befitting when requiring technical expertise and architectural know-how. However, such centralization could constrain the creativity of business users. Overall, *User-led* and *IT-led* represent contrasting approaches to IPA implementation.

Deployment: A unique governance characteristic is the deployment mode of the IPA bot, which we conceptualize by the extent of ‘how’ involved humans are in the deployed bot. There are three types of deployment modes, namely (i) *Attended Bot*, (ii) *Unattended Bot*, and (iii) *Hybrid Bot* deployment.

Attended Bot deployment involves manual intervention in addition to what bots can unilaterally accomplish.

Human intervention triggers the use of bots to execute business processes. These bots are triggered in response to human actions (Lacity and Willcocks 2021, Lacity et al. 2021), such as clicking on a button. The bot can then take over sub-processes within the process workflow, such as data entry, validation, or processing, and can be programmed to guide the user further as needed. In contrast, *Unattended Bot* deployment comprises bots that operate autonomously to intelligently automate entire business processes. These bots are autonomously triggered in response to pre-specified events. Thus, the *Unattended Bot* proceeds without human involvement and is useful for automating routine, repetitive, rule-based, replicable processes (Lacity and Willcocks 2021, Lacity et al. 2021). Between the two ends of the continuum of collaboration between humans and machines is a *Hybrid Bot*. Deployment of a *Hybrid Bot* involves using bots that can work both with and without human involvement. *Hybrid Bots* offer the flexibility of combining both attended and unattended modes across different sub-processes within the same process. This allows firms to automate workflows that involve both routine and nonroutine sub-processes.

Recent frameworks and empirical studies on human-AI collaboration align with this governance characteristic. In contrast to previous technologies, even simple AI-powered bots are capable of learning through analogy (Liang and Konsynski 1993), and with long enough deployments, can accumulate copious data (Konsynski and Sprague 1986). Deployments are critical to IPA projects as they allow bots to learn from a vast amount of data, eventually allowing them to operate autonomously without needing any more programming or recoding. As a result, AI holds the potential to both *substitute* and *complement* humans' cognitive abilities. By substituting for human actors, AI actors perform specific, rule-based repetitive tasks, obviating the need for constant human intervention (Davenport and Kirby 2015, Berente et al. 2021, Chen et al. 2022). Such AI technologies have evolved into 'autonomous agents' (Baird and Maruping 2021), or *Unattended Bots*, capable of making decisions and acting independently without direct human oversight or knowledge. Contrastingly, machines complement or augment humans to carry out tasks as *Attended Bots*. Intervention by humans enhances the capabilities of bots by providing training as well as explanations for decisions, ensuring ethical standards are upheld in achieving optimal performance (Wilson and Daugherty 2018). Augmentation empowers humans with AI-powered tools to explore solutions together, wherein humans trigger the deployment of bots to participate in execution (Rai et al. 2019). Along this continuum of collaboration lie *Hybrid Bots*, which are a dynamic assembly of human and AI agents that

collaborate as an integrated unit (Konsynski et al. 2024). Ultimately, the appropriate *deployment* approach depends on the specific requirements of each firm’s processes and desired level of human involvement.

5.3.2 *The Process Dimension*

As IPA bots integrate deep, mindful, domain expertise-based process mining with RPA, and AI, the characteristics of the underlying processes significantly shape the trajectories of IPA projects. Early research on the fit of task and technology (e.g., Nunamaker et al. 1989) laid the foundation for an interdisciplinary discourse on process and technology coordination (e.g., Malone and Crowston 1994, Maruping and Agarwal 2004, Negoita et al. 2018). This research culminated in the MIT Process Handbook (Malone et al. 2003), which synthesized key findings on coordinating business processes. Building on this body of work, our revelatory field work, complemented by the expertise of the internal researcher and engagement with key informants, reveals that, in the specific domain of IPA, two process characteristics capture the principal coordination challenges: (i) *Process Intricacy* and (ii) *Process Dependency*.

Process Intricacy: Some business processes constitute multiple sub-processes (Malone and Crowston 1994), with intricate processes requiring more than a hundred steps to be completed for use (Malone et al. 2003). This large magnitude of sub-processes manifests as *process intricacy*. An example of high *process intricacy* from our data is the reconciliation process in banking. This process involves more than a hundred steps, wherein at each step, a different type of transaction is reconciled. There are several categories of transactions, both incoming and outgoing, from simple deposits and withdrawals to payments and trade reconciliations. Each category of transactions can originate from and terminate at multiple sources, both external and internal, such as bank systems, customer accounts, and third-party systems, such as payment processors and exchanges. Each transaction is subject to regulations, increasing the steps in the process and, hence, process intricacy.

Process Dependency: Interdependencies between sub-processes is another dimension which we conceptualize as *process dependency*. This dimension refers to the ability of different digitally enabled processes to either work or not work together seamlessly, given their interdependencies (e.g., Malone et al. 2003, Negoita et al. 2018). Processes that are spawned by or trigger multiple sub-processes to execute tasks are highly interdependent. An illustration of high *process dependency* from our data is the Know Your Customer (KYC) employed by many financial institutions. This process is dependent upon and triggers other sub-processes as required. KYC commences with customers

completing the onboarding sub-process and submitting documentation for verification. Subsequently, a risk assessment sub-process is triggered, which might involve gathering additional data from third-party systems to evaluate creditworthiness. Along the way, the risk profiling sub-process could also get triggered depending upon data discovered from third-party systems. Any delays in the interconnected stages of KYC delay the overall process and, consequently, the acquisition of new customers.

5.3.3 The Technology Dimension

It is essential to consider various technology-related characteristics when implementing IPA bots. As explicated in Section 2, IPA bots represent the decentralization of technology production and improve without requiring further coding. Based on our fieldwork, we identify three technology characteristics that capture and align with our conceptualization, namely (i) *Extent of Coupling*, (ii) *Extent of AI*, and (iii) *Extent of Coding*.

Extent of Coupling: This vital trait refers to the overall architecture of the IPA bot. Coupling between components can be operationalized as loose or tight (Simon 1962, Weick 1976). *Loose Coupling* refers to an IPA bot that is stand-alone and independent of other technological components. Here, the IPA bot operates without being dependent on other systems. In loosely coupled architectures, changes in one component do not affect the behavior of others (Sanchez and Mahoney 1996, Tiwana and Konsynski 2010). *Tight Coupling* refers to an architecture wherein the IPA bot is deployed in an integrated manner with other components in the firm. In this scenario, changes in one part ripple across all interconnected parts (Tiwana 2008). While tightly coupled bots can provide scalability and improved performance, tight coupling also creates challenges, such as data inconsistencies.

Extent of AI: AI is a fast-moving frontier of technologies integral to IPA bots (Berente et al. 2021). An ensemble (Orlikowski and Iacono 2001) of AI technologies, such as ML, NLP, image and object recognition via computer vision, and LLMs, enables IPA bots to tackle unstructured data, handle exceptions, and learn over time (Gnewuch et al. 2023, Hevner and Storey 2023, Storey et al. 2024). While all IPA bots leverage AI technologies (Lacity and Willcocks 2021), our fieldwork surfaced two levels of the *Extent of AI* in the IPA bot. *High Extent of AI* in the IPA bot entails the presence of sophisticated AI technologies. *Low Extent of AI* entails relatively more straightforward and unsophisticated AI technologies. Nonetheless, IPA bots with a Low Extent of AI result in significantly more intelligent business processes compared to simple rule-based RPA systems (Lacity et al. 2021).

Extent of Coding: The third key technology characteristic identified in our fieldwork is the *Extent of Coding* required in the IPA project. *Low-Code / No-Code* toolkits enable users to use visual workflows and an integrated development environment to drag and drop pre-built components for digitizing business processes (Elshan et al. 2023). At the other end of the spectrum, a *High Extent of Coding* is necessary to tackle customized business processes. For example, a high extent of coding may be required for automating non-trivial, bespoke processes that cannot be digitized by merely relying on drag-and-drop tools (Lacity and Willcocks 2021, Lacity et al. 2021).

5.3.4 Success of IPA Projects

We study the success of IPA projects through their *Utilization* and *Repeatability*. *Utilization* (high / medium / low) refers to the extent of use of the IPA bot (Doll and Torkzadeh 1989). It signifies a greater degree and therefore frequency of utilization of the IPA bot (Keil et al. 1995). For instance, a bot that processes a high number of transactions and is thus used frequently would have high utilization, thereby making the IPA project a success. *Repeatability* (Yes / No) refers to the reusability of the IPA bot in other IPA projects (Gamma et al. 1995). It captures whether the IPA bot used to automate a particular process can be reused in other processes within the organization and across its extended enterprise. Collectively, *Utilization* and *Repeatability* capture two dimensions of the success of IPA projects (Lacity and Willcocks 2021, Lacity et al. 2021).

6. PHASE 2: INDUCTION OF TREES

6.1 Details of Tree Induction Methodology

Phase 1 yields the characteristics describing IPA projects and coded data. These serve as inputs to Phase 2, which pertains to the induction of trees through a series of computational experiments – a research design established in prior literature (Karhade et al. 2015, Karhade and Kathuria 2020, Kathuria et al. 2020). In particular, inputs to our computational experiments include 1) IPA projects described by all the governance, process, and technology dimensions and 2) outcomes of IPA projects (i.e., *Utilization* and *Repeatability*). Prior to the induction of trees, we partition the data to create mutually disjoint and non-overlapping training and validation datasets. We employ ten-fold validation, wherein the data are divided into ten partitions. Nine partitions are used for training, and one partition is used for validation. We induce the trees on the training data by applying the C4.5 algorithm (Quinlan 1986, 1990). Trees were induced using Weka by manipulating two

parameters, namely the confidence factor and the minimum number of instances at the leaves (Hall et al. 2009). This process allows us to discover multiple credible approximations of the underlying theoretical rationale (Karhade et al. 2015, Lindberg 2020). C4.5 organizes attributes in a context-dependent manner wherein certain questions are raised depending on answers obtained to questions answered previously (Quinlan 1990). Hence, not all characteristics that were fed to the algorithm as inputs appear in the induced tree.

In this methodology, trees represent theory. The best representative tree was chosen based on three heuristics (Karhade et al. 2015, Kathuria et al. 2020), including high (i) prediction accuracy, (ii) parsimony, and (iii) reliability of knowledge. First, the prediction *accuracy* of trees induced on the training sub-sample is validated on a disjoint testing or validation subsample, which represents a *goodness-of-fit* measure for predictions on unseen data.² Second, *parsimonious* approximations of the underlying rationale are preferred as they serve as an effective decision-making aid. Third, we assess the robustness of the discovered knowledge. All our induced trees yield the same topmost attribute, showing up *reliably* across all trees, representing a robust approximation of the underlying theoretical rationale. Finally, rules are identified from the *Best Representative Tree*. The topmost attribute is the most informative attribute in the tree, and the importance of attributes decreases as we move toward the leaves (end-points), thereby yielding context-specific if-then rules (Quinlan 1986, 1990). For theoretical elaboration, we name the rules appropriately to capture their underlying meaning and articulate them in the results section. The name given to the rule appears below the leaf node (namely, the last node for each pathway in the tree) in the figures depicting the trees.

6.2 Results

6.2.1 Key Findings and Rules Explaining the Utilization of IPA

The theoretical rationale for IPA utilization is illustrated in the tree depicted in Figure 3. We discover three vital findings and extract two rules from the tree. The first key finding pertains to the inclusion of all three dimensions of Governance, Process, and Technology characterizing IPA. In particular, *Governance* characteristics of

² The metrics evaluating the predictive performance, including the prediction accuracy and Area under the Curve scores, confusion matrices, which help conceptualize the false negatives and false positives predicted by the decision tree model, and results of computational experiments to select the best representative trees are presented in Online Appendix C.

Genesis and *Deploy*, the *Process* characteristic of *Process Intricacy*, and *Technology* characteristic of *Extent of Coding* appear in the tree and are thus deemed informative by the tree induction algorithm. Recall that our fieldwork yielded these three dimensions. Thus, Figure 3 validates our theorization of the Governance, Process, and Technology by surfacing their collective role in explaining IPA *Utilization*.

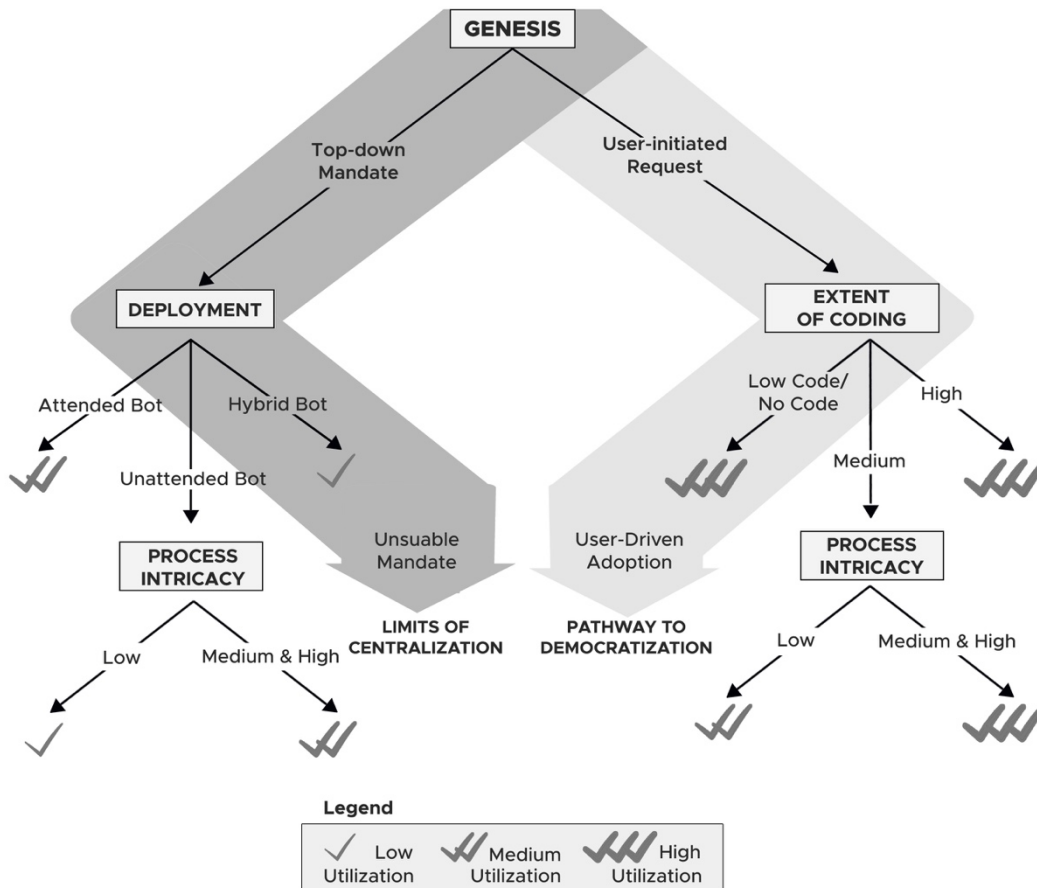


Figure 3: Achieving Utilization

The second key finding is that *Genesis* – a governance characteristic – is the top-most attribute in the tree and therefore, is the most informative characteristic for explaining IPA *Utilization*. In particular, IPA projects initiated by *Business Users* are the only projects that yield high utilization outcomes. In contrast, IPA projects initiated via *Top-down Mandates* never yield any high utilization outcomes. This corroborates that *who* initiates an IPA project is the most important characteristic to explain its successful performance outcomes.

The third key finding is that *Deployment* – a characteristic specific to IPA projects – appears in the

theoretical rationale for high *Utilization* of IPA. Its inclusion in Figure 3 validates that governance as spanning initiation, implementation, and deployment is appropriate for this form of decentralization.

An observation of note is that *Sourcing* is excluded by the classification algorithm from the model explaining *Utilization* of IPA. This non-finding is in stark contrast to traditional software projects, where sourcing via make or buy decisions plays a key role. This is evidenced by extensive prior literature (e.g., Susarla et al. 2010) that is primarily situated in the era prior to the decentralization of technology production. Traditional “make or buy” decisions may thus not be readily applicable in this new era of decentralization. IPA exemplifies the assemblage of solutions by leveraging AI as building blocks via LCNC toolkits and suggests that governance for the decentralization of technology production through the democratization of AI deployed in the form of IPA bots is likely to be driven by different levers.

We extract and showcase two rules that contrast high and low *Utilization*. We do so by traversing the tree starting from the top-most attribute down to the end of every pathway represented by the leaf node (Low/Medium/High *Utilization*). Recall that the name given to the rule appears below the appropriate leaf node in Figure 3.

User-Driven Adoption: We discover that when the *Genesis* of an IPA project is a *User-initiated Request* and the *Extent of Coding* is *low-code/no-code*, the *Utilization* of the IPA is *High*. Formally,

If (Genesis = User-initiated Request) $\wedge$ (Extent of Coding = Low-Code/No-Code), then High Utilization

This is the main classification rule that explains 46 IPA projects. This reveals a *Business User-Driven* narrative. Here, when IPA projects are initiated by business users with deep, mindful domain expertise and when these business users leverage LCNC toolkits to code the IPA bot, the resulting IPA is extensively utilized and therefore adopted (van Giffen and Ludwig 2023).

Unusable Mandate: In contrast, we also discover that when the *Genesis* of an IPA project is a *Top-down Mandate* and *Deployment* is through a *Hybrid Bot*, the *Utilization* of the IPA is *Low*. Formally,

If (Genesis = Top-down Mandate) $\wedge$ (Deployment = Hybrid Bot), then Low Utilization

This is the main classification rule extracted for Low *Utilization*, as it classifies 24 IPA projects. This reveals the misfit of centralized mandates in the era of decentralization of technology production through the democratization of AI deployed in the form of IPA bots. Here, when IPA projects are originated by the firm’s top-down

directive and are coupled with a *Hybrid Deployment* that necessitates manual intervention along with software bots, the resulting IPA is not extensively utilized.

6.2.2 Key Findings and Rules Explaining the Repeatability of IPA

We examine *Repeatability* as a second performance outcome for IPA projects. The theoretical rationale for IPA repeatability is illustrated in the tree depicted in Figure 4. We discover four key findings and extract two rules from the tree. First, we find that *Genesis* emerges as the top-most attribute and therefore, is the most informative characteristic for explaining IPA *Repeatability*. This is similar to our finding from Figure 3 pertaining to *Utilization*. While *Top-down Mandate Genesis* yields poor outcomes for both *Repeatability* and *Utilization*, *User-Initiated Request* leads to mostly successful *Repeatability* and *Utilization* outcomes. This highlights the critical characteristic of involving *business users* as the *who* in initiating IPA projects.

Second, *Deployment* appears in the theoretical rationale for explaining the high *Repeatability* of IPA. This is similar to Figure 3, wherein *Deployment* emerges as a second-level attribute in both figures. However, it is pertinent to note a critical difference between Figure 3 and Figure 4. When explaining *Utilization*, *Deployment* matters for top-down mandates, whereas when explaining *Repeatability*, *Deployment* matters for user-initiated requests. Thus, *Deployment* carries unique explanatory power for both outcomes. Together, these signify and validate our theorizing of deployment as a key characteristic for effective governance in the era of decentralization of technology production.

Third, the *Extent of AI* appears in the theoretical rationale for explaining *Repeatability*. This contrasts with *Utilization*, wherein *Process Intricacy*, instead of *Extent of AI*, is a more informative characteristic. The inclusion of the *Extent of AI* in Figure 4 validates our theorizing of AI as an essential technology characteristic of IPA and helps us identify the limits of democratization.

Again, we observe that *Sourcing* is excluded by the algorithm from the tree explaining *Repeatability*. Hence, “make or buy” decisions are not informative attributes for the performance outcomes of IPA.

We showcase two rules that contrast the presence and absence of *Repeatability*. Recall that rules extracted from the tree represent theoretical explanations, which are labeled below the appropriate leaf node in Figure 4.

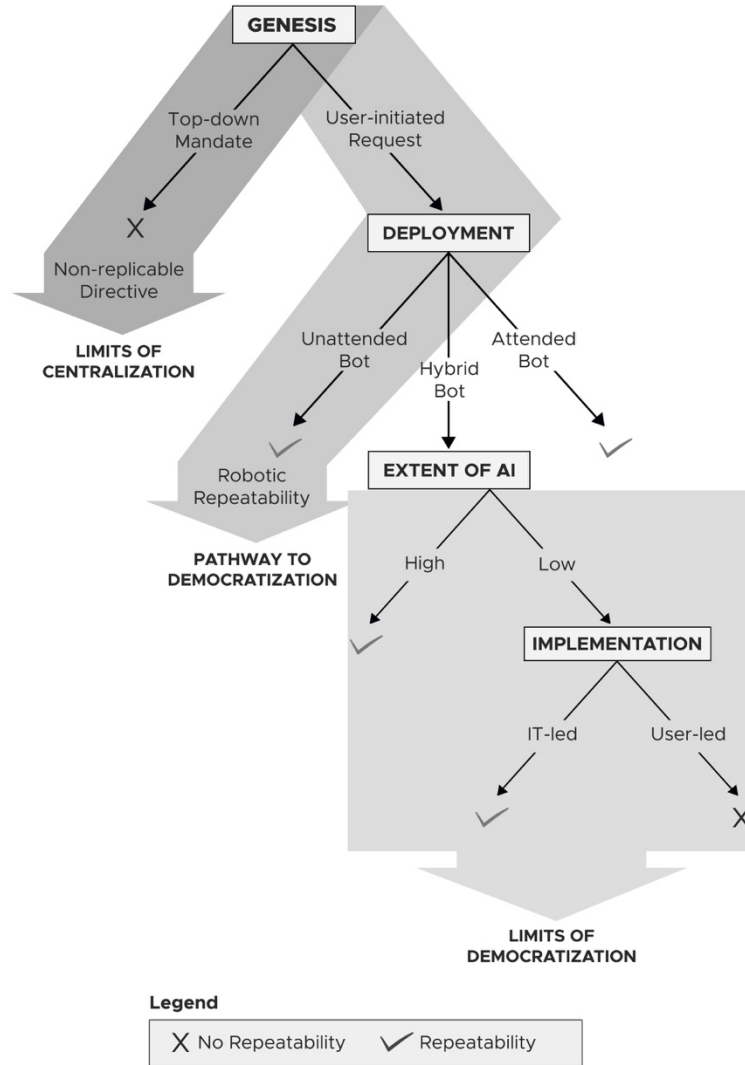


Figure 4: Achieving Repeatability

Non-Replicable Directive: We discover that when the *Genesis* of an IPA project is a *Top-down Mandate*, the IPA is unable to achieve *Repeatability*. Formally,

If (Genesis = Top-down Mandate), then No Repeatability

This is the main classification rule that explains 54 IPA projects that demonstrate a lack of repeatability. This reveals a narrative of an *enforced mandate* that is a misfit in the era of decentralization of technology production through the democratization of AI deployed in the form of IPA bots. Here, IPA projects mandated by the top-level hierarchy of the organization might solve the problem at hand but cannot be repurposed across the firm.

Robotic Repeatability: In contrast, we discover that when the *Genesis* of an IPA project is a *User-initiated Request* and *Deployment* is through an *Unattended Bot*, the IPA is *Repeatable*. Formally,

If (Genesis = User-initiated Request) $\wedge$ (Deployment = Unattended Bot), then Repeatability

This is the main classification rule extracted from the tree for *Repeatability*, as it classifies 35 IPA projects.

This again highlights a *Business User-Driven* narrative. Here, IPA projects initiated by business users, who have domain expertise and context-specific knowledge, and executed without necessitating any human supervision, are highly repeatable in other processes across the organization.

7. PHASE 3: ABDUCTION OF THEORETICAL PROPOSITIONS

We utilized empirical evidence, prior theory, and expertise to inform our pre-theoretical understanding in the form of the Governance, Process, and Technology dimensions for IPA success. Induction enabled us to elaborate a coherent theoretical framework in the form of trees, key findings, and rules that explain the utilization and repeatability of IPA, thereby extending the current state of the literature (Berente et al. 2019, Lindberg 2020). Since theory involves identifying patterns, theory development involves a temporal element, and therefore, theory construction necessarily rests on *diachronic*, temporal analyses (Holland et al. 1986) wherein we identify *relationships between concepts*. Hence, we now undertake the process of abduction, which allows us to articulate a theory that uncovers relationships among concepts of Governance, Process, and Technology dimensions within a boundary set of conditions, elucidating why and how IPA success occurs. This forms the kernel of our theorizing (Leidner and Gregory 2024).

The artifacts that went into the abduction process include all the cases, the two best representative trees for *Utilization* and *Repeatability* (Figures 3 and 4), and the identified rules. Abducting away, we observe all these artifacts and the mosaic they present concurrently, and thereby abstract and reinterpret the deeper meanings they reveal. This allows us to uncover the underlying plausible explanations for conditions that lead to holistic outcomes of IPA projects and thereby governance of decentralization of technology production. We now elaborate upon the outcomes of the process of abduction.

7.1 Limits to Centralization

We reinterpret rules that highlight a narrative of a misfit of centralized mandates in the era of decentralization of technology production. First, we examine the rule *Unusable Mandate*. Recall that this is the main classification rule extracted for Low *Utilization*. We investigate the twenty-four projects classified by this rule to uncover the plausible reasons why these projects are not highly utilized. We discover that business users are responsible for the

Implementation of all these projects. Further, approximately 83% of these projects have high *Process Dependency*, and a large majority have a tight *Extent of Coupling*. This implies that these IPA projects are enforced by the top management onto the business users, who are burdened by the *Deployment* and *Implementation* of these projects. High dependencies and deep automation needs necessitate further ongoing human intervention.

Second, we examine the rule *Non-replicable Directive*, which is the main classification rule for IPA projects that are not repeatable across the firm. We again discover that the *Implementation* of all these fifty-four projects is the responsibility of business users. Furthermore, approximately 89% of these projects have high *Process Dependency*. These attributes illustrate a scenario wherein IPA projects initiated by the top management are imposed upon business users. Users are further encumbered by the implementation and high dependencies of these projects.

Viewed holistically, we abduce away to infer that the top management imposed the requirements and scope of these IPA projects on business users without their input. The business users were then burdened with the cumbersome and complex implementation and ongoing management of these IPA projects. This hurt the overall utilization, (and thus, actual usage (Devaraj and Kohli 2003)), and repeatability of these IPA projects. Together, these two rules highlight severe shortcomings of the top-down mandated Genesis of IPA projects, thereby illuminating the limits of centralization. Formally, this theoretical abduction crystallizes in the proposition:

Proposition 1: Limits of Centralization - The genesis of top-down mandates and necessitating business user involvement in implementation and deployment through hybrid IPA bots (AI-human combination) worsens performance (utilization and repeatability), revealing the limits of centralization for governance in the era of decentralized technology production.

Note that business user-led implementation and the deployment of human-AI hybrid bots are unique characteristics of IPA and are not applicable to traditional software previously. This proposition showcases how these characteristics can have negative consequences for performance when the genesis of IPA is centralized in the era of decentralized technology production through the democratization of AI.

7.2 Pathway to Democratization

We reinterpret the rules that reveal a business user-driven narrative and thus an alignment with decentralization of technology production. First, we examine the rule *User-Driven Adoption*, which is the main classification rule for High *Utilization*. We investigate the forty-six projects classified under this rule to uncover plausible reasons why

these projects are highly utilized. We discovered that business users are responsible for the *Implementation* of approximately 91% of these projects. Further, all these projects have a low *Extent of Coding*. This implies that these IPA projects were initiated by business users, who then applied their mindful domain expertise and situated process knowledge when implementing these projects using LCNC toolkits.

Second, we examine the rule *Robotic Repeatability*, which is the main classification rule for IPA projects that are repeatable across other similar processes. Further investigation into the thirty-five IPA projects classified under this rule reveals that approximately 94% of these bots exhibit a loose *Extent of Coupling*, reflecting their standalone nature. These attributes illustrate a scenario wherein IPA projects are initiated and implemented by business users as independent bots that do not rely on other technological components. In these cases, processes intelligently automated through loosely coupled bots, in turn implemented by context aware business users using LCNC toolkits, beget success, in terms of repeatability.

Viewed holistically, we abduce away to infer that a bottom-up genesis and execution significantly improves both utilization and repeatability. Such an approach is characterized by empowered users initiating and executing the implementation of independent bots through LCNC toolkits or the deployment of unattended bots (AI operating autonomously). These findings reflect a shift in technology production and governance agency toward empowered business users, illustrating a pathway to democratization of AI through IPA. Formally, this theoretical abduction crystallizes in the following proposition:

Proposition 2: Pathway to Democratization - The genesis of user-initiated requests, developed through low-code no-code, or deployed as an unattended bot (AI operating autonomously), improves performance (utilization and repeatability), revealing the pathway of democratization of AI through IPA for effective governance in the era of decentralized technology production.

Note that business user-led implementation and deployment of autonomous intelligent bots are unique features of IPA not applicable to traditional software in prior computing eras. This proposition illustrates how these characteristics can enhance performance when IPA initiatives are aligned with the decentralized nature of technology production, in contrast to the negative consequences observed when such initiatives are centrally imposed.

7.3 Limits to Democratization

We now reinterpret findings that unveil a narrative of the constraints of business user led IPA projects, revealing the boundary conditions of the decentralization of technology production. In the tree for the *Repeatability* of IPA projects (Figure 4), we examine paths and nodes adjoining the rule *Robotic Repeatability*. Our investigation uncovers twenty-one IPA projects that are unable to achieve *Repeatability*. Further abduction reveals an informative pattern. Specifically, the key finding is that when the *Genesis* of the project is a User-Initiated Request, the *Deployment* is in the form of a Hybrid Bot, the Extent of AI is Low, and the Implementation is User-led, the IPA project demonstrates a lack of repeatability. Formally, this pattern can be written as:

$$\begin{aligned} & \text{If } (Genesis = \text{User-initiated Request}) \wedge (Deployment = \text{Hybrid Bot}) \\ & \wedge (Extent\ of\ AI = \text{Low}) \wedge (Implementation = \text{User Led}), \text{ then No Repeatability} \end{aligned}$$

Thus, these projects demonstrate high decentralization as they are initiated by business users, are implemented by business users using LCNC toolkits, and are deployed through hybrid bots – bots that require continuous input or supervision by the business users. We abduce away to infer that while these users effectively identify and solve localized operational issues, the resulting solutions tend to be idiosyncratic and heavily tailored to individual or team-level workflows. This is due to the business users’ myopic understand of the organization’s business processes. By identifying issues in processes close to them, business users myopically solve only their own individual problems. As a result, these IPA bots are not repeatable across other business processes. Viewed holistically, we abduce that although decentralization and business user empowerment can enhance utilization and innovation at the edge, they can also lead to inefficiencies and fragmentation. This occurs when user-led initiation and development are paired with limited extent of AI and hybrid bot deployments. In such cases, the resulting solutions remain siloed, resist reuse, and ultimately hinder broader performance gains. This observation marks a boundary condition in the logic of democratization and crystallizes in the following proposition:

Proposition 3: Limits to Democratization - The genesis of user-initiated requests deployed as a hybrid bot (AI-human combination), even when having low AI with user-led implementation worsens performance (repeatability), revealing the limits of democratization of AI through IPA for governance for in the era of decentralized technology production.

It is important to recognize how such isolated implementations contrast sharply with IPA bots that characterize successful democratization pathways. It is the combination of business-user led implementation and low extent of AI that constrains the generalizability of these solutions to broader organizational contexts. This highlights the importance of involving specialized IT personnel during the implementation of bots that imbibe AI, as such technological complexity may be beyond the capabilities of business users. While decentralization enhances the inclusivity of technology production, this proposition underscores that not all user-led initiatives translate to value, especially when constrained by implementation by business users who lack deep AI understanding.

8. DISCUSSION

8.1 Theoretical Contributions

This study advances the IT governance literature by reframing long-standing assumptions in light of the rise of democratization of AI in the form of IPA bots. Across three distinct governance mechanisms formulated as three propositions, we identify how the interplay of genesis, implementation, deployment mode, and extent of AI shapes performance outcomes, thereby extending IT governance into the era of decentralized technology production.

First, we contribute to the literature on IT governance through our finding that challenges the canonical view whereby centralized governance arrangements reliably produce superior performance through consistency, standardization, and control (Weill and Ross 2004, Tiwana and Konsynski 2010). Prior governance research has primarily examined static, rules-based IT systems produced by specialized IT departments (Applegate et al. 1986, Brown 1997, Sambamurthy and Zmud 1999), where centralization helped manage complexity (Kirsch and Cummings 1996) and ensured alignment with corporate priorities. In contrast, we find that when centrally mandated AI-driven IPA bots lack sufficient user input and engagement, performance can suffer. This suggests that in the context of the AI frontier (Berente et al. 2021), where system value often depends on deep mindful, domain expertise (Butler and Gray 2006, van Giffen and Ludwig 2023), and iterative refinement through learning (Davenport and Kirby 2015, Jarrahi 2018, Rai et al. 2019), the governance mechanism of centralization without embedding user expertise can undermine utilization. We thus extend IT governance theory by identifying the limits of traditional centralization when governing AI-based adaptive systems that require high levels of business user interaction (Baird and Maruping 2021, Chen et al. 2022).

Second, we contribute to the literature by theorizing how decentralized, user-led technology production can be a viable and effective decentralized governance mechanism for AI systems. Much of the conventional democratization literature has focused on access and consumption (e.g., Gregory et al. 2018, van Giffen and Ludwig 2023), with little insight into the production of technology by nontechnical users. In contrast, our research shows that when business users ideate IPA bots, these can achieve both high utilization and repeatability, particularly when the bots entail a high extent of AI. Thus, we expand the scope of IT governance research to account for decentralized production regimes. Herein, decision rights and responsibilities for the new governance activity of *implementation* is embedded in business users rather than the IT function or business unit. Value emerges from combining the domain expertise of business users with enabling LCNC toolkits (Wilson and Daugherty 2018, Lacity and Willcocks 2021, Lacity et al. 2021, Elshan et al. 2023) along with the new post-implementation governance activity of *deployment*, which pertains to the extent of involvement of the business user in operating the AI system. This necessitates the inclusion of these two new governance activities – implementation and deployment – introduced in this study in future IT governance research situated in the AI frontier.

Third, we extend governance theory by identifying the limits and boundary conditions of decentralization of technology production through the democratization of AI deployed in the form of IPA bots. Classical governance research shows that decentralization is advantageous (e.g., Tiwana and Konsynski 2010), with user-led development fostering innovation and responsiveness. In contrast, our research reveals governance configurations where decentralization through democratization impedes performance—specifically, when user-initiated IPA projects are implemented by users, deployed as hybrid (AI–human) bots, and rely on a low extent of AI. Such projects tend to produce idiosyncratic, one-off, non-repeatable solutions that cannot be reused across the organization (Zhang et al. 2022, Storey et al. 2024). This insight introduces an important nuance to IT governance research: decentralization through democratization is not a universally beneficial arrangement. Instead, its effectiveness depends on specific combinations of extent of AI, deployment mode, and implementation agency (Camargo et al. 2020, vom Brocke et al. 2021, Fehrer et al. 2022). In the absence of such combinations, democratized AI will remain in the *horseless carriage* phase (Nunamaker et al. 1989). By uncovering these boundary conditions, we provide a framework for understanding when decentralization of technology production requires additional hybrid governance mechanisms

(Sambamurthy and Zmud 1999), such as coordination or collaboration with specialized IT teams, to achieve performance and value.

Collectively, these contributions reposition IT governance research to account for the realities of decentralized technology production at the AI frontier. We demonstrate that the centralization–decentralization tension – an enduring dichotomy in IT governance research (Olsen and Chervany 1980, King 1983) – requires reframing for AI governance to consider not only who makes technology decisions, but also who produces, implements, and deploys the technology, how extensive its underlying AI components are, and how governance activities interact with post-implementation dynamics. We thereby reimagine governance mechanisms that appropriately control business user behavior without constraining the success of technology production.

8.2 Implications for Practice

Our findings offer actionable guidance for organizations seeking to govern the decentralization of technology production through the democratization of AI deployed in the form of IPA bots.

First, business users across the firm now have the means to initiate, implement, and even unilaterally deploy AI in the form of IPA bots to address their business needs. Neither should such efforts be in the service of dramaturgical framing of “achievements” of AI (Cunha and Carugati 2018), nor should such bottom-up innovation need to manifest in the form of “shadow IT” (LeFave et al. 2008, Haag et al. 2019, Haag and Eckhardt 2024). Instead, centralized IT teams and top management can actively embrace, encourage, and enable such efforts, thereby fostering digital experimentation (Mithas and Kohli 2022) and empowering business users to “step out of the “shadows”. Involvement in the genesis of an IPA project empowers business users to drive change from the grassroots, leveraging their proximity to day-to-day processes and unique insights into operational bottlenecks. This positions them to identify and champion relevant, high-impact applications of IPA bots. Accordingly, senior leaders should remain receptive to user-initiated projects, providing guardrails in the form of collaborations between business users and IT teams whereby proposals can be constructively challenged and refined.

Second, our research highlights the importance of involving business users not only in initiating projects but in contributing throughout the entire lifecycle—from genesis to implementation to deployment. The governance of AI deployed in the form of IPA bots must therefore extend beyond initiation to encompass

implementation and post-implementation oversight. Business users can lead in initiation, co-create value during implementation, and collaborate with IT teams in ongoing monitoring, ensuring that evolving AI behaviors remain aligned with organizational values, ethical norms, and performance goals. While specific activities will require centralized oversight, others can thrive under decentralized governance mechanisms. Hence, it is essential to make deliberate space for governance of the democratization of AI (van Giffen and Ludwig 2023). This balanced approach will enable organizations to harness the benefits of decentralization of technology production while safeguarding operational integrity and performance.

More broadly, our fieldwork enables us to address contemporary conversations on the use of AI and the future of work. *Techno-pessimists* portend the substitution of humans with machines (Davenport and Kirby 2015, Ford 2015), whereas *techno-optimists* herald humans complementing machines (Brynjolfsson and McAfee 2014, Wilson and Daugherty 2018, Rai et al. 2019). Our findings have nuanced implications for both possible futures as we uncover combinations of governance mechanisms that lead to outcomes that are divergent from commonly held expectations. Specifically, though automation underlies the human-machine conflict augured by *techno-pessimists*, automation initiatives can be successful when initiated by business users. In contrast, though augmentation underlies the technological utopia envisaged by *techno-optimists*, such initiatives are less successful when mandated by top management. These insights reveal the importance of aligning governance and participation models with the type of human-machine interaction envisioned and thereby indicate a future reality more complex in practice.

8.3 Strengths and Limitations

Novel theories require diverse lenses to examine phenomena, keen curations of data, disciplined imagination, and thought experiments (Weick 1995). We conduct engaged scholarship to leverage a multi-method, multi-phase investigation that allows us to offer a visual vocabulary. Thus, we espouse the scholarship of Weick to explain governance mechanisms in era of decentralization of technology production. Herein lies the key strength of our study. Nonetheless, there are some limitations to the present study. First, we study a sample of IPA projects in the BFSI industry. Examining other types of AI projects that also use LCNC toolkits from a diverse range of industries could broaden our insights. Second, Phase 1 of our research study allowed us to surface nine characteristics across the dimensions of Governance, Process, and Technology. However, other characteristics, such

as leadership dynamics, decision rights, and organization design, may emerge in the context of other forms of AI bots. Future studies can situate our framework in different contexts to surface additional insights. Third, the cross-sectional nature of our data precludes us from drawing causal conclusions. Gathering longitudinal data is currently not feasible due to the rapidly evolving nature of the phenomena as well as the AI frontier. Future research that can gather such data can advance our understanding.

9. CONCLUSION

We revisit the centralization–decentralization tension in the context of decentralized technology production at the AI frontier, focusing on IPA bots as a salient manifestation of the democratization of AI. Our research reveals that traditional centralized mandates, when paired with the unique learning and adaptive capabilities of AI systems, can actively suppress utilization and stifle organizational reuse of the bots. Conversely, democratization is no panacea. While empowerment of business users through decentralization usually leads to successful outcomes for the deployed bots, when certain boundary conditions are crossed, these same decentralized efforts can produce fragmentation in the form of one-off solutions. Our research challenges core tenets of the IT governance canon, demonstrating that centralization–decentralization logic at the AI frontier must expand to account for the evolution of governance, process, and technological characteristics to realize effective AI governance.

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