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Conceptualizing Process Innovation with Analytics: A Framework and Research Agenda

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Abstract

Organizations are increasingly investing in Process Innovation with Analytics, i.e., the usage of analytics to innovate operational processes. Process innovation with analytics is a challenging and complex endeavor encompassing 1) redesign of processes, 2) development of digital infrastructure, and 3) analytics development. As a result, organizations need guidance on how to approach this complex challenge. While research on IT-enabled process innovation and analytics each offer valuable insights, process innovation with analytics necessitates contextualization of these knowledge bases due to its distinct characteristics. This paper aims to inspire further research into process innovation with analytics by 1) reconceptualizing analytics in the context of process innovation, and 2) proposing a research agenda, consisting of three research directions and five research challenges. The reconceptualization and research agenda are based on the authors' experience from an Action Design Research study at a large global manufacturer and retailer focused on process innovation with analytics. Bridging analytics, process innovation, and infrastructure perspectives, the paper offers a foundation for future scholarly endeavors and calls for further research into 1) digital infrastructures for process innovation with analytics, 2) the relationship between process change and analytics development, and 3) governance of process innovation with analytics.

Keywords: analytics; process innovation; digital infrastructure; machine learning; research agenda; framework

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1. Introduction

Large organizations are investing heavily in analytics. Whereas analytics has historically been used primarily to derive insights in support of tactical and strategic decision-making, advantages in AI and ML have made it possible to use analytics to innovate and improve operational processes [1,12,57]. We refer to this use of analytics to innovate operational processes as Process Innovation with Analytics. We refer to this use of analytics as Process Innovation with Analytics. Specifically, we define Process Innovation with Analytics as the fundamental redesign of operational work processes through the integration of data-driven models that either automate or augment task-level decisions. Unlike traditional IT-enabled process innovation, which often relies on fixed rules, Process Innovation with Analytics is characterized by analytical uncertainty—where the final process design is dictated by the performance of the model as it encounters real-world data. Consequently, Process Innovation with Analytics requires a triadic co-development: the simultaneous and coordinated evolution of the analytical model, the redesigned process, and the digital infrastructure that connects them. Example applications include predictive maintenance and predictive quality in manufacturing, or automated fraud detection and loan application handling in the financial sector.

The IS community has a rich tradition for research into IT-enabled process innovation. The seminal works by [11,15,33] introduced methodologies for bringing IT to the forefront of process innovation and further research has demonstrated the important enabling role of IT infrastructure in

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radically innovating processes [3,8,37]. Similarly, a rich body of literature has emerged on analytics from an organizational perspective (e.g. [19,20,24,58]) and research has developed prescriptive knowledge in the form of methodologies (e.g., [40,47,66]), tools (e.g., [21]) and architectures [28,46] to support analytics development and implementation.

However, Process Innovation with Analytics is different from both traditional IT-enabled process innovation, and traditional analytics research, necessitating a contextualization of these knowledge bases. Unlike classic BPR, which targeted large cross-functional overhauls [11], Process Innovation with Analytics has a narrower focus, targeting the automation or augmentation of specific subprocesses or tasks [54]. Simultaneously, it differs from *analytics for insight*, which typically supports one-time or strategic decision, by requiring deep operational embedding. While traditional analytics systems often exist as standalone dashboards weakly coupled with the organization, Process Innovation with Analytics involves weakly structured technologies [22] that must be tightly integrated into the digital infrastructure to function. This reverses the traditional design logic: rather than a process design dictating requirements as in e.g., [11] or [30], the capabilities discovered during data prototyping often dictate what the process *can* become [18]. Consequently, a 'clean-slate' approach is no longer applicable; the new process must instead be co-developed as a triadic alignment between the data-driven model(s), the work routine, and the existing digital infrastructure.

The phenomenon of process innovation with analytics thus calls for further analytics research that adopts the socio-technical focus present in the research on IT-enabled process innovation and similarly foregrounds the changes required to both processes and digital infrastructure. There is both a need for explanatory research to understand how companies have successfully innovated processes using analytics and prescriptive research to update and contextualize existing methods within analytics development and IT-enabled process innovation.

In this paper, our objective is to inspire further research into process innovation with analytics along these lines by 1) reconceptualizing analytics in the context of process innovation and 2) developing a research agenda consisting of several research challenges along with promising research directions. The reconceptualization and the research agenda presented are based on retrospective sense-making of our experiences from a three-year Action Design Research (ADR) project conducted with a large global manufacturer and retailer based in Denmark. In the ADR project, the goal was to develop prescriptive knowledge for analytics development aimed at process innovation in an enterprise setting through participation in the development of analytics infrastructure and several analytics projects [2]. In making sense of our experiences, it became clear that analytics aimed at process innovation was considerably more complex than analytics aimed at insight and posed additional challenges for the organization's digital infrastructure and governance.

The rest of the paper is structured as follows. First, we introduce the case from our ADR project as a motivating example of the need for and content of process innovation with analytics. We then introduce our conceptualization of process innovation with analytics by drawing on and synthesizing three perspectives: 1) the analytics perspective, 2) the process innovation perspective, and 3) the digital infrastructure perspective. This is followed by a presentation of three research directions connected with this conceptualization along with five research challenges. We then move on to a discussion of our contribution and related work, before concluding with a summary of our work.

2. Research Context & Methodology: An ADR Study

The conceptualization and research agenda presented in the paper resulted from a three-year ADR project [55]. ADR was selected as it allowed for the development and organizational evaluation of IT artefacts in a real-world setting.

Our research was situated within a large global manufacturer and retailer based in Denmark, which was undergoing a large-scale digital transformation of its production operations. The lead author was embedded within the organization and was tasked with exploring several use cases aimed at Process Innovation with Analytics. This exploration took the form of observation and participating in or leading the development and evaluation of analytics systems.

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2.1. The ADR Process

The research was structured into five ADR cycles, each centered on a specific analytics demonstrator. These demonstrators acted as experimental probes used to understand the relationships between the existing digital infrastructure, analytics development, and process redesign.

The conceptualization presented in Section 3 and the research agenda in Section 5 were derived through retrospective sense-making of these five cycles. Table 1 provides an overview of the cycles and how they contributed to the framework and research agenda. The first four cycles sensitized us to 1) the significant impact of the existing digital infrastructure on the innovation process, 2) the impact of analytical uncertainty, and 3) the role of governance. The fifth cycle served to validate our framework and the importance of an approach that adjusts to the state of the digital infrastructure. During the "Formalization of Learning" stages, we synthesized our findings using concepts from digital infrastructure literature (e.g., [34]). This allowed us to move beyond the specific technical successes or failures in the demonstrators to identify the broader socio-technical challenges that define Process Innovation with Analytics.

Table 1. Overview of ADR cycles.

ADR Cycle	Demonstrator	Nature of Intervention	Key Data Sources	Contribution to Framework & Challenges
1: Foundation	Data Quality Monitoring	Embedded first author in the platform team to build a SaaS-based anomaly detection system.	Six months of participative observation notes and documentation.	Highlighted the need for a stable installed base before model building can occur.
2: Exploration	Line Visualization	Developed near real-time dashboards for a production line using a cloud message bus and edge containers.	Field notes and three stakeholder workshops.	Demonstrated that making analytics affordances tangible is a prerequisite for process change.
3: Modeling	Predictive Quality	Attempted ML quality monitoring. Project halted as data access took 3.5 months across siloed teams, and data quality was too poor.	Field notes, model performance logs.	Highlighted analytical uncertainty and socio-technical coordination challenges in legacy infrastructures.
4: Integration	Machine Parameter Optimization	Integrated an ML model into the Manufacturing Execution System via APIs to automate machine adjustments.	Field notes from workshops and participation in a 2-week sprint.	Development can be fast with the right infrastructure, but process approval

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				(*Governance*) is the true bottleneck.
5: Evaluation	Data-driven Maintenance	Final real-world evaluation of a sensor-alert system with process engineers.	15 Semi-structured interviews, system logs, field notes.	Support for our framework and the need for a socio-technical perspective.

2.2. The Empirical Case: Predictive Maintenance & Quality

Our case company was in the process of digitally transforming their operations. In their operations strategy, analytics was one of several technologies under the Industry 4.0 umbrella that was to contribute to improving the productivity of their operational processes. As part of realizing the strategy, an Industry 4.0 unit had been established to drive the effort. The unit's responsibilities included identifying, assessing, and validating potential analytics use cases, with support from IT and external innovation partners. As part of this process, process visions had been developed for key operational processes that leveraged analytics to substantially reimagine the way work was carried out. For their core high-volume automated production process, two key use cases that would feature such analytics-enabled process innovation were 1) predictive maintenance, and 2) predictive quality. We elaborate briefly on these two key use cases, but they were only two of many such initiatives being explored both for this and other operational processes.

Predictive Maintenance: In this use case, the goal was to move from a reactive and interval-based maintenance strategy of the production equipment to a proactive strategy. This proactive strategy would rely on analytics to predict when maintenance is required. While several data sources could be relevant to train such analytical models, sensor and settings data from the production equipment were deemed particularly promising. The benefits of this proactive approach would be a more precise application of maintenance, resulting in both fewer maintenance-related breakdowns and reduced time spent on unnecessary maintenance. Moving to a proactive strategy, would, however, require changes to the existing maintenance processes. Planning of maintenance would have to take outset in model predictions, which would require new procedures for resource allocation and workload leveling. Finally, to truly take advantage of the predictions of the equipment state, the frequency of maintenance planning would have to be updated. At one extreme, models could be making predictions in near-real time, allowing for fast response to changes in the equipment state, but hourly or other planning intervals were also a possibility. Implementing these changes to the maintenance process would require changes to the IT systems supporting the maintenance process, as the processes were IT-enabled.

Predictive Quality: In this use case, the goal was similarly to move from a reactive and interval-based quality inspection strategy to a proactive strategy. Predictive models would be leveraged to predict the quality of the products or parts produced in near real-time, with sensor data from production equipment being the key enabling data source for training the models. The predictive quality approach would result in faster detection of quality problems, thus reducing scrap and increasing production productivity, while removing unnecessary inspections when the production process was operating stably. Similarly, to the predictive maintenance use case, inspection planning and execution would have to become model-driven and the frequency of planning would increase. Furthermore, changes to the production preparation processes would be required to establish a process for training initial models and setting up thresholds for predictions. These process changes would also require changes to the supporting IT systems.

To enable these and other analytics-enabled process innovation use cases, IT was also undergoing a transformation. Common to both the use cases were a need to collect, store, and process large amounts of IoT data and integrate them with data from enterprise systems. This in turn required establishing connectivity to production equipment and building infrastructures for data collection. To meet these needs, the IT department decided to invest in the construction of an IoT data platform that would support all IoT-related analytics use cases by providing a common platform for integrating data from IoT and enterprise systems. Concurrently, a project was established to develop a data collection infrastructure for the core production equipment, requiring connecting thousands of machines and building data pipelines. Related enterprise systems such as warehouse management systems (WMS), enterprise resource planning (ERP), and manufacturing execution systems were also required to develop integrations with the IoT data platform to deliver the data required for use cases. As is evident from this case, delivering on the process innovation potential of analytics was no simple matter and would consist of considerable change to both processes and IT – beyond what is required in traditional analytics.

3. Conceptualizing Process Innovation with Analytics

As exemplified by the two presented use cases, Process innovation with analytics concerns the innovation of operational work processes where embedded analytical systems play a key part in enabling the redesigned work process. While we provided two examples from manufacturing, the phenomenon is not domain specific. Examples from other domains include amongst others AI-assisted screening in radiology, and automated fraud detection in credit card transactions. In all these examples, analytical systems play a key enabling role in the redesign of processes through the use of data to either augment or automate tasks. In that sense, Process innovation with analytics has some similarities to what [13] labeled embedded analytics. A key difference is that embedding analytics into work processes does not necessitate any change in the process. As an example, analytics can be used to augment a single task while leaving the surrounding tasks unchanged.

Process innovation with analytics is essentially a subset of IT-enabled process innovation. It therefore shares similarities with BPR. This was also noted by [14] in their study of AI implementations. As was the case with BPR, they noted that: "The AI system had to be deeply integrated with the organization's existing technology infrastructure and embedded in […] processes". In the motivating case, we similarly saw the need for changes to and integration with the technology infrastructure and process change, in addition to the development of analytics artifacts.

Building on this, our conceptualization of process innovation with analytics consists of a coordinated development of three major areas. First, it involves the development of an analytics system that delivers the analytical capabilities or affordances that enable process redesign. Second, it requires process redesign and development of the new process. Third, it requires the development of the digital infrastructure of the organization, including the integration of the analytics system with this digital infrastructure. The outcome of process innovation with analytics is a newly redesigned process where an embedded analytical system plays a key role. This new process is in turn made possible by changes to the digital infrastructure. Our conceptualization is visualized in Figure 1.

The need to consider and develop both the process and the digital infrastructure means that the scope and complexity of process innovation with analytics is much greater than when analytics is used for insights. When analytics is used for insights, it mainly supports one-time or infrequent decisions, and as a result the analytical systems are at most weakly integrated with the digital infrastructure. This stands in contrast to the ongoing usage and stronger integration needed for process innovation with analytics.

While Process innovation with analytics is in some ways similar to BPR, there are also some important differences, which warrants new research into this subset of IT-enabled process innovation. For one, the scope of process innovation with analytics is most commonly at the

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subprocess or task-level [54], while BPR is cross-functional in scope [11,33]. In process innovation with analytics, the use of analytics will change the tasks themselves as they become automated or augmented but is also commonly accompanied by changes to upstream or downstream tasks [50, p. 197], and the addition of new tasks such as (re-)training models and monitoring data and model quality [29]. Another difference is the uncertainty associated with the capabilities of analytical systems as compared to traditional IT capabilities. With model-based analytics systems experimentation and prototyping using context-specific organizational data is required to estimate their performance [18]. Development thus becomes necessary prior to process redesign. In the following subsections, we expand on each of the three perspectives that form our conceptualization.

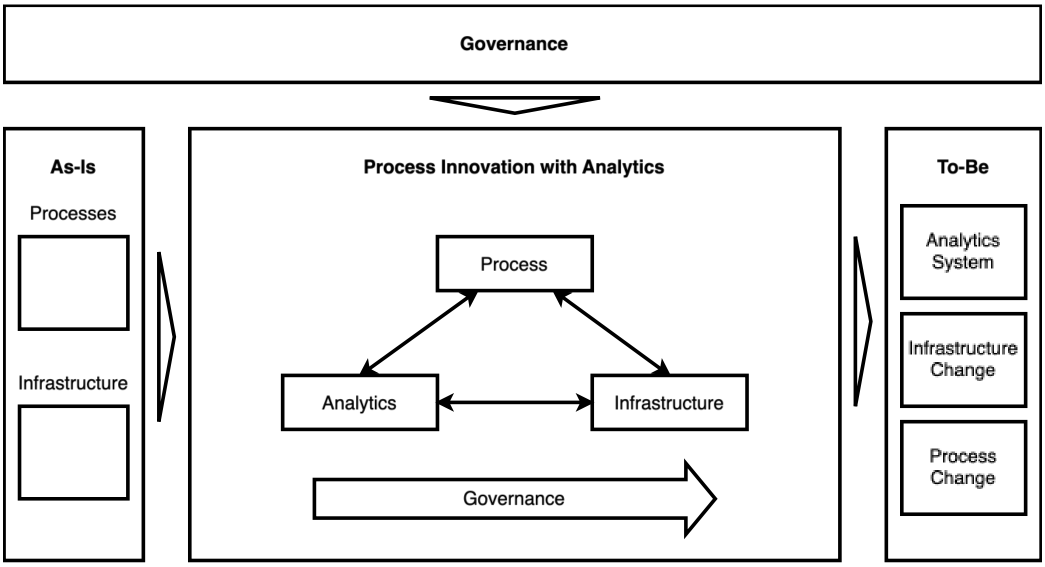

Figure 1. Conceptualization of process innovation with analytics.

3.1. The Analytics Perspective

Analytics is the IT that enables process innovation. Analytics is concerned with the use of data and quantitative methods to enable improved decision-making and action-taking [48]. The process of obtaining value from analytics has been conceptualized as the transformation process of data to information, information to knowledge, knowledge to decisions, and decisions to action. Key activities in this transformation process are understanding the business context and the business problem to be addressed, understanding the data available to address the problem, preparing and processing the data, modelling of the data, evaluation of the analytical outputs, and finally deployment of the analytical outputs, if deemed desirable [66]. Historically, deployment has often taken the shape of standalone applications or dashboards that are only weakly integrated with the technical infrastructure, such as through manual or automated batch extracts of data. This is, however, changing with the operational usage of analytics.

3.2. The Process Innovation Perspective

Adopting a process innovation perspective entails viewing analytics as the technological lever or means for improvement of processes through its informational or automation capabilities. In IT-enabled process innovation, the capabilities of IT become inputs to the design of a new and improved process [15]. The new process design then becomes the blueprint and specification for development of the IT applications necessary to support the redesigned process. In addition to process design and IT development, realizing the redesigned process can require organizational changes such as changes to the organizational structure, new job roles, and compensation schemes [11]. Owing to the complexity of such projects, prototyping the new processes was recommended to confirm whether the new designs worked as planned [11]. All these aspects remain relevant for process innovation with analytics with a few caveats. First, extensive exploration and experimentation with analytics is required before new processes can be properly designed due to the uncertainty surrounding their capabilities. Second, a clean-slate approach as preached in the BPR-era is no longer applicable, as the data from the existing process will often be the key input to analytics development.

One of the key obstacles to realizing IT-enabled process innovation turned out to be IT infrastructure [3]. Rather than being limited to the redesign of processes and supporting IT-applications, organizations discovered that IT-enabled process innovation furthermore could require considerable development of their IT infrastructure. The existing level of IT infrastructure in organizations thus act as an enabler or a constraint in the realization of IT-enabled process innovation. This is also the case for process innovation with analytics, which brings us to the next perspective.

3.3. The Digital Infrastructure Perspective

The digital infrastructure is the landscape of IT applications and infrastructure that enables the organization to carry out work, as well as its users and developers [36]. The emphasis on digital infrastructure in research emerged as a result of the increased ubiquity of IT in organizations. Whereas successful introduction of a new IT application to support work once consisted mainly of developing and implementing an application that met user requirements, the pervasiveness of IT meant that new applications increasingly had to meet additional requirements that ensured a fit between the new system and the existing digital infrastructure. In the context of analytics, new analytical applications thus need to consider both how they enable new process designs, and how they extend and fit with the existing digital infrastructure. Managing the growth and development of the often-complex digital infrastructure to support organizational and process change has proven to be challenging and conflicting philosophies and approaches exist. The two main approaches in research are that of 1) the top-down and modelling-based enterprise architecture approach (e.g., [51]), and 2) the bottom-up and evolutionary information infrastructure approach (e.g., [10]).

All process innovation with analytics requires the development of digital infrastructure, but the nature and extent of development required differs across use-cases. In general, three types of infrastructure changes can be necessary to realize process innovation with analytics. First, analytics infrastructure is required to provide storage and computation resources for analytics development and deployment. Examples include data lakes, data warehouses, and clusters. Second, changes to the existing digital infrastructure can be required to collect data and to provide the necessary access to data and functionality required by the analytics systems. Third, linkages and integrations between the analytics infrastructure and digital infrastructure can be required. This includes both integrations that move data from the digital infrastructure to the analytics infrastructure and integrations that provide analytical outputs such as predictions, recommendations, and prescriptions to the digital infrastructure. In cases where data is already collected, made easily available by the digital infrastructure, and the analytical infrastructure is mature, then the infrastructure development required to realize process innovation with analytics can be relatively modest. In other cases, the infrastructure development required can be considerable.

To summarize, analytics for process innovation requires a broader conceptualization than present in existing analytics research and it differs from traditional IT-enabled process innovation in that it deals with weakly structured technologies resulting in more local process change. Specifically, process innovation with analytics requires coordinated development of analytics systems, development and redesign of processes, and development of the digital infrastructure, such as new analytics infrastructure, changes to the digital infrastructure, and linkages between them. It is thus a complex undertaking involving stakeholders with expertise in process management, IT, and data science. We now turn to the implications of this broader conceptualization for research into analytics and process innovation.

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4. Research Directions & Challenges

In this section, we present three research directions that have the potential to significantly move forward our understanding of process innovation with analytics. For each of the three research directions we present associated research challenges, examples of research questions, as well as suggest promising angles of inquiry, as summarized in Table 2. The three proposed research directions align with our conceptualization of analytics: the first adopts the infrastructure perspective, the second examines the relationship between process and analytics development, and the third adopts a holistic perspective of how to govern the transformation of the three elements of infrastructure, analytics, and process. While analytics on its own is also deserving of much further research, we have, owing to the scope of our paper, focused on the other perspectives and their relationships with analytics. In the following subsections, we introduce and elaborate on each of these three research directions.

Table 2. Research agenda for process innovation with analytics.

Research Direction	**Research Challenge**	**Exemplar Research Questions**	**Promising Angles**
Digital infrastructures for process innovation with analytics	Understanding the influence of the existing digital infrastructure	How does the socio-technical data architecture influence analytics development and deployment? How does the organization structure impact collaboration between data scientists and software developers?	Adoption of an information infrastructure lens in qualitative research (e.g., [10,34])
	Transition strategies: From constraining to enabling infrastructure	What infrastructure building strategies exist and what are their advantages and disadvantages? How can organizations move from silo-oriented legacy systems to enabling modern architectures?	Contextualization of insights from enterprise architecture [51] and classic infrastructure literature [3]. Exploring the potential applicability of *data ecosystems* [27] and *platformization*.
Exploring the relationship between process change and analytics development	Understanding the impact of the existing process	How do characteristics of the existing process impact process innovation with analytics? To what extent must the existing process change to enable analytics supported redesign?	Retrospective and longitudinal case studies of process innovation with analytics focusing on the process of *process change* and the benefits realized.
	Constructing integrated methodologies for developing analytics-enabled processes	How should process redesign and analytics development be sequenced? How can mutual adaptation of process and analytics systems be enabled?	Contextualizing and integrating analytics development and process innovation methodologies.
Advancing our understanding of governance of process	Identifying and understanding successful governance configurations	Which governance configurations are associated with success? How do contextual conditions influence governance?	Contextualizing existing governance models, e.g., Lightweight IT [7] Case studies and configurational analysis to

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innovation with analytics		How do governance mechanisms change throughout the analytics and process lifecycle?	examine interplay of context, governance configurations, and their impacts.

4.1. Digital Infrastructures for Process Innovation with Analytics

Why it is important: Digital infrastructures play a key role in IT-enabled process innovation in general and the same holds true for analytics, where it impacts both development and deployment. It is well established in digital infrastructure research (e.g. [10] and in analytics research (e.g., [27,61]) that the digital infrastructure can act as either an enabler or constraint. Research has also provided insights into the characteristics of infrastructures that are generative of innovation, that being decentralized control and loose coupling [36] and proposed more concrete architectures inspired by the platform architecture [6,28]. A lot is thus known about the "to-be" of enabling digital infrastructures, but the reality is that most companies are far from this state. What is missing is: 1) knowledge about how to navigate within the non-ideal digital infrastructure that organizations possess, and 2) effective strategies for transitioning towards the "to-be" state. The two research challenges below address these in turn.

4.1.1. Challenge 1: Understanding the Influence of the Existing Digital Infrastructure

The existing digital infrastructure, that is the installed base of IT infrastructure, IT systems, developers, and users in an organization, has a large impact on the effort required to conduct process innovation with analytics. IT-enabled Process innovation projects need to interact with the installed base to both access data and functionality present in existing IT systems [8]. For process innovation with analytics, historical data is needed in the development phase to develop and evaluate analytical models, whereas fresh data is needed as input to the analytics system during deployment. The deployment phase will often also need to be able to access functionality in existing IT systems to enable acting on analytical outputs, e.g., by updating information in the system or triggering a workflow. A promising angle for further research is to leverage concepts from the information infrastructure literature (e.g., [8,10]. This stream of research has developed rich concepts for qualitatively analyzing how the installed base of infrastructure influences development. One area where this lens could be fruitfully applied is data accessibility, which has been identified as a key barrier to deploying analytics systems om recent research [61]. Essentially, deployment requires programmatic access to data and functionality, such as via APIs or data pipelines, but this functionality is often missing in many organizations. While the importance of data accessibility is non-controversial, a more nuanced understanding of data availability and its impact on the analytics development process is still needed. Different technical resources supporting data accessibility are likely to have subtle effects on the ease of development. At least as important are the processes through which the technical resources are made accessible. Data accessibility aspects include how resources are discovered, how access is requested and granted, and the ease with which the data is technically accessed, e.g., as facilitated by documentation, software packages, or technical coaching. While research has started suggesting best practices for data accessibility and management under the header of "data democratization" [39], little empirical research has investigated in detail the impacts of these practices on analytics and software development processes. In addition to the processes associated with accessibility, understanding the impact of structural aspects of the installed base remains important. Data scientists and IT developers need to collaborate during development and deployment, but our experience and recent research [43] suggests that this collaboration is challenged by differences in backgrounds, skillsets, and practices. Further research is thus required on how the organization of this relationship influences the development and deployment process.

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4.1.2. Challenge 2: Transition Strategies: From Constraining to Enabling Infrastructures

Transitioning to digital infrastructures that enable process innovation with analytics requires significant development of the digital infrastructure in most organizations. The change encompasses both the need for new analytics infrastructure, development of the operational digital infrastructure, and linking the two infrastructures. Organizations can approach this transition in several ways. Crucial decisions include the degree of reuse and standardization of analytics infrastructure, where the approach can range from local solutions to one global solution for each of the components of the infrastructure. Another decision concerns when and how to realize the infrastructure. Here the main decision is what to build up-front through infrastructure investments and what to build through projects. On the one hand, infrastructure such as data pipelines can be difficult to justify without a specific use-case. For the same reason, seminal works on IT infrastructure [3] and enterprise architecture (EA) [51] suggests implementing infrastructure as part of projects. On the other hand, recent research [5] and our own experience suggests mixing infrastructure and innovation in the same project can be troublesome. Infrastructure and innovation work requires different skillsets and operate at different speed, resulting in tensions and slowing down of innovation. Perhaps because of this, much analytics development does not end up moving the organization towards the to-be architecture and instead develop piecemeal solutions [27]. The question of how to address the transition is thus far from settled and deserves to be revisited in the context of analytics. Empirical research is needed on how successful organizations have approached the transition, along with insights into the challenges faced and benefits and disadvantages of their chosen approach, whether that be ecosystem or platform approaches, or more classic enterprise architecture approaches.

4.2. Exploring the Relationship Between Process Change and Analytics Development

Why it is important: Realizing process innovation with analytics requires both the development of an analytics system offering a set of analytical capabilities and a redesigned process that leverages these capabilities. With traditional IT-enabled process innovation, process design took design precedence and determined requirements for the IT solution [11]. The existing process played only a small role, as the ideal was to start from a blank slate [31]. In process innovation with analytics, the relationship between process redesign and analytics is considerably more complicated and nuanced. On the one hand, the analytical capabilities of analytics systems are often uncertain until a prototype has been built [41] and dependent on data from the existing process [61]. It thus makes it difficult to redesign processes first and increases the significance of the existing process. On the other hand, some idea of the future process is necessary to guide analytics development. As noted by [55] the prioritization of either the process or IT artefact in IT-enabled process innovation is a choice with major implications. However, existing research has yet to 1) address when and whether to pursue incremental or more radical redesigns and 2) sufficiently engage with the issue of how to sequentially organize analytics and process development. One exception is [41] which suggests striking a middle ground. The two research challenges below address these two issues.

4.2.1. Challenge 3: Understanding the Impact of the Existing Process

The fact that the as-is process is responsible for generating the historical data that is used to train and evaluate models in analytics development means that it takes on a central role in establishing the process innovation affordances of analytics. Vial [61] refers to this as the “dual role of data as both output [of processes] and input [to analytics]”. However, as-is processes have mostly been designed for efficient execution and without major consideration of generating data that supports analytical development. The result is that certain process innovation affordances of analytics remain impossible to actualize with the data generated by the existing processes. Managers thus need to decide whether to invest in making intermediary changes to their process to collect the data that would enable future analytics-enabled redesign of their processes. For now, research has not examined the extent of “preparatory” change required to existing processes to enable future redesigns and the role that process characteristics play in this. There is furthermore a need for research into whether and when these preparatory changes and investments pay off. Should managers focus their process innovation efforts on incremental redesigns, i.e., those already possible based on the existing processes, or should they focus on potential and make the necessary investments to transform the existing processes? More radical redesigns potentially present managers with a paradox. Whereas process innovation with analytics is mainly pursued for productivity gains [23,38], the intermediate investments in data collection required to realize more radical redesigns are likely to lower productivity in the short term. Longitudinal case studies are ideal candidates for gaining insights into the process change and investments that are required to realize process innovation with analytics as the innovation process unfolds, whereas retrospective case studies can provide insights into the benefits realized.

4.2.2. Challenge 4: Developing Integrated Methodologies for Analytics-Enabled Processes

The feasibility of an analytics-enabled process redesign often hinges on the predictive or prescriptive performance that can be realized by the analytics system, but this performance is unknown until a model has been evaluated on a context-specific dataset. High levels of analytical performance might afford automation of a task, whereas lower levels are likely to require different levels of human engagement, or even render the redesign undesirable. Existing research suggests two different approaches to IT-enabled process innovation, both of which do not exactly fit the characteristics of analytics: 1) BPR-era methodologies e.g. [11,33], and 2) newer lightweight digital process innovation approaches inspired by agile development (e.g., [5,8,52]. BPR methodologies suggest upfront process design and modelling, which is difficult due to the uncertain capabilities of analytics. On the other hand, the digital process innovation approach recommends using standard and customizable technologies and relying on iterations of mutual adaptation of the technology and process [8,52]. This approach is, however, challenged by the fact that much analytics software remains the result of custom development. While this might change in the future, knowledge is needed regarding how to approach the integrated development of processes and their supporting analytics systems. In practice, we mainly see the bottom-up approach where the analytical artefact takes design precedence and process concerns are introduced later. However, senior leaders at our industrial partner have expressed interest in more strategic and process-oriented approaches to analytics. There is a need for prescriptive guidelines and methodologies that consider how, when, and if traditional process tasks such as process modelling, simulation, and organizational prototyping should enter the innovation process and relate to analytics development. Contextualization and integration of existing methodologies from both analytics and IT-enabled process innovation seems a highly promising direction with considerable potential to improve practice. Due consideration of process aspects in these innovation projects has the potential to reduce both the number of analytical systems that are discarded due to low business value and the extent of adjustments required in the deployment process to make the system usable.

4.3. Advancing Our Understanding of Governance of Process Innovation with Analytics

Why it is important: Governance of process innovation with analytics is complex as it comprises a variety of assets ranging from data, models, and IT systems to processes and involves stakeholders from across the organization. Whereas governance of data, IT systems, and processes are all established research domains individually, research into the governance of analytics models (often termed AI or ML governance) is in its early days, although frameworks have started to emerge (e.g. [53]. Existing research has established that IT-enabled process innovation covers concerns of both IT governance and process governance and has thus suggested the need for relationships between and alignment of process and IT governance [49]. The same holds true for governance of analytics-enabled process innovation with the additional need to establish relationships from IT governance and process governance to analytics governance. There is thus a need to further our understanding of both how to effectively govern analytics and how to align analytics governance with process and IT governance to bring about process innovation with analytics. Governance does, however, not end

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after successful implementation of a new analytics-enabled process but must consider the analytics-enabled process throughout its lifecycle. We turn to the challenge of understanding what makes for successful governance next.

4.3.1. Challenge 5: Identifying and Understanding Successful Governance Configurations

The domain-crossing nature of process innovation with analytics challenges traditional governance frameworks. Early research on IT governance focused on the trade-off between control and innovation, or centralization vs. decentralization [4] and the distribution of decisions rights between IT and business [66]. As a response to the influx of digital innovations and further demands for agility in recent times, many IT organizations have adopted more complex organizational structures and governance arrangements. The most popular has perhaps been bimodal IT [25,32], where innovation and execution-focused IT are governed and organized differently. More recently, further approaches such as platform governance have been suggested as means to strike a balance between innovation and control for the case of new lightweight digital technologies [7,26]. For analytics in particular, platform and ecosystem architectures and governance approaches have likewise been suggested [28] and are widely implemented in practice. Nonetheless, these models do not cover the full scope of activities and assets involved in process innovation with analytics. Governance of process innovation with analytics should cover both the activities involved including use-case specification, development, deployment, organizational implementation, and operations, as well as the assets involved, such as data, models, IT systems, IT infrastructure, and processes. There is thus a need for further understanding of how the existing governance frameworks and arrangements need to be adapted. Research can contribute by identifying successful governance configurations in leading adopters of process innovation with analytics and exploring how and why these configurations support the adoption process. Furthermore, research should explore how contextual factors impact appropriate governance arrangements. We expect that aspects such as characteristics of the process to be innovated and whether the use-case is automation or augmentation is likely to significantly influence the nature of governance. In this pursuit, both case studies and configurational analysis (e.g., as in Mikalef & Krogstie [42]) could be applied to further our understanding. Another interesting challenge concerns governance of the analytical artefact once it is in operation in a new analytics-enabled process. In this situation, the analytical performance (data quality and model performance) becomes a key driver of process performance, especially in the case of automation use-cases. How to effectively govern this setup and distribute roles and responsibilities between IT, data science, and process personnel is an interesting and important challenge and it remains to be seen how much established companies can learn from mature software companies, such as Facebook and Google, that have led the adoption of analytics in business-critical settings.

5. Discussion: Contribution and Related Work

In this paper, we developed a conceptualization and research agenda for process innovation with analytics, intending to bridge analytics and process innovation research. Thus, our study contributes to the ongoing discourse on conceptualizations of business analytics as a field of research [12,17,35,48] by focusing on a specific, complex use case of business analytics, namely process innovation. The use of analytics for process innovation is increasing in the age of AI [12] and thus constitutes an area of research with high practical relevance (see e.g. [14]). Our study is not the first or only study to examine analytics as a means for improving process performance. Particularly active areas of inquiry that address the intersection of analytics and processes include 1) process mining [59], and 2) organizational AI adoption and impact (e.g. [14,29]). While these areas of inquiry have many similarities with process innovation with analytics, there are nevertheless some differences, which we now address.

Process mining is concerned with data-driven improvement of operational processes using event log data generated in process execution systems [60]. Traditionally, process mining focused on offline and descriptive analytics to extract insights into how process work is carried out, and

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identifying opportunities for improvement and redesign [59]. More recently, the focus has moved towards proactive process mining through predictive and prescriptive process analytics [9]. A prominent use-case is that of predictive process monitoring for operational process support [59]. This operational use of analytics is close to our focus, but it differs in that the analytics in predictive process monitoring is used to support ongoing (often ad-hoc) interventions into the existing process, such as reallocating resources or changing process flows [9,45], rather than being used as a means for structured process redesign. Our work highlights an additional and different role of analytics in process innovation from that pursued most strongly in current BPM research. Despite these differences, our emphasis on governance and relations between existing process methodologies and analytics is shared in a recent framework for process mining research [64].

Research on organizational AI adoption and impact is still nascent, given the recency of scaled adoption in the industry. One general difference between our focus and this research stream is the broader scope of AI as a concept as compared to analytics, as the use of AI in IS research often includes robotics and robotic process automation [1,12]. Several practitioner-oriented works have dealt with AI-enabled process innovation and presented initial suggestions based on leading adopters of AI [14,16,57]. Our research focus is closely related to theirs, with the main differences being our focus on the research potentials of the topic rather than managerial prescriptions. A few academically oriented case studies also exist, which have provided initial insights into the AI adoption process and its process impact (e.g. [29,41]). It is this line of work that we see as most closely related to ours, and to which our work makes its contribution by conceptualizing certain aspects of the adoption process. Other related work in this stream of research includes conceptual frameworks of the business value of AI, which emphasizes the role of process change as a mechanism for business value [23]. Finally, this study hinges upon fast evolving topics such as AI/ML and even process mining, and these can be expected to mature considerably, but this will be considered in future work [2].

6. Conclusions

In this paper, we reconceptualized analytics in the process innovation context to highlight how it differs from traditional analytics aimed at insights. Process innovation with analytics requires coordinated development of the digital infrastructure and the new process in addition to an analytics system. This increased scope of the analytics process has major implications for the complexity facing organizations looking to adopt analytics for process innovation and calls for contextualization of the existing knowledge bases related to analytics and process innovation to support them in the process.

We drew on our practical experience with the adoption of analytics for process innovation in an ADR study at a large global manufacturer and retailer based in Denmark to present a research agenda for process innovation with analytics. Specifically, we proposed the need for research along three directions: 1) digital infrastructures for process innovation with analytics, 2) the relationship between process change and analytics development, and 3) governance of process innovation with analytics. The literature is full of technically focused research on analytics from which this work aims to complement. What is needed to support organizations in the adoption and value realization process is research that is socio-technical centered, and this will be the priority going forward. This is the main contribution of this paper. We hope that the conceptualization and research agenda presented here can be a first step in this direction and inspire further research that adopts a process innovation perspective on analytics.

Data Availability: The data generated during and/or analyzed during this study cannot be made publicly available due to confidentiality agreements made with the participating organization to protect its commercial interests. Further information and details regarding the data can be obtained from the corresponding author upon request.

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