5-2-2022

Organizational Intelligence in Digital Innovation: Evidence from Georgia State University

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ORGANIZATIONAL INTELLIGENCE IN DIGITAL INNOVATION: EVIDENCE FROM GEORGIA STATE UNIVERSITY

BY

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

of

Doctor of Philosophy

In the Robinson College of Business

of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2022

ACCEPTANCE

This dissertation was prepared under the direction of the Khaleed Mahmood Fuad's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

ORGANIZATIONAL INTELLIGENCE IN DIGITAL INNOVATION: EVIDENCE FROM GEORGIA STATE UNIVERSITY

BY

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April 21, 2022

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The fourth industrial revolution challenges organizations to cope with dynamic business landscapes as they seek to improve their competitive position through rapid and pervasive digitalization of products, services, processes, and business models. As organizations sense and respond to new opportunities and threats, digital innovations are not only meeting new requirements, unarticulated needs, and market demands, they also lead to disruptive transformation of sociotechnical structures. Despite the practical relevance and theoretical significance of digital innovations, we still have limited knowledge on how digital innovation initiatives are rationalized, realized, and managed to improve organizational performance. Drawing on a longitudinal study of digital innovations to improve student success at Georgia State University, we develop a theory of organizational intelligence to help understand how organizations' digital innovation initiatives are organized and managed to improve their performance over time in the broader context of organizational transformation. We posit that organizational intelligence enables an organization to gather, process, and manipulate information and to communicate, share, and make sense of the knowledge it creates, so it can increase its adaptive potential in the dynamic environment in which it operates. Moreover, we elaborate how organizational intelligence is constituted as human and material agency come together in analytical and relational intelligence to help organizations effectively manage digital innovations, and how organizational intelligence both shapes and is shaped by an organization's digital innovation initiatives. Hence, while current research on organizational intelligence predominantly emphasizes analytic capabilities, this research puts equal emphasis on relational capabilities. Similarly, while current research on organizational intelligence focuses only on human agency, this research focuses equally on material agency. Our proposed theory of organizational intelligence responds to recent calls to position IS theories along the sociotechnical axis of cohesion and has pronounced implications for both theory and practice.

ACKNOWLEDGEMENTS

This study would not be possible without the cooperation of the leaders and key personnel of the Student Success Program (SSP) at Georgia State University (GSU). First and foremost, we thank Dr. Timothy Renick for giving us the opportunity to study such a wonderful story of SSP, and for sharing his vast experience in developing and leading SSP. His visionary leadership is truly unparalleled. He opened the door to his organization for us and we are grateful for the opportunity.

We thank Dr. Allison Calhoun-Brown for sharing her experience in leading SSP initiatives, especially University Advisement Center (UAC). We are thankful to Carol Cohen for giving us the opportunity to interview her. We thank Ben Brandon and Eric Cuevas for sharing their key insights regarding the SSP initiatives, and for coordinating and providing us access to key personnel and resources at GSU. Many thanks to Elisha Jarrett for her valuable insights about managing UAC and for providing us access to other interviewees at UAC. We are thankful to Scott Burke and Candice Lindsey Fifield for sharing their experience in developing and managing the chatbot initiative. We thank Julian Allen and Phil Ventimiglia for sharing their valuable insights. Special thanks to Dr. Ryan Maltese and Dr. Zhewei Gregory for coordinating our study with and providing access to the University Innovation Alliance. We are grateful to all the other key personnel at GSU, who agreed to meet with us and share their valuable experiences.

I am grateful to my dissertation committee for making this study possible. First, I am thankful to Dr. Nicholas Berente and Dr. Richard Baskerville for agreeing to be in my committee despite their myriad responsibilities. Their sage remarks and comments helped me improve the study. Despite their busy schedule, they read my dissertation and provided helpful feedback; for that I express my gratitude. Last but not least, I am ever grateful to Dr. Lars Mathiassen and Dr. Likoebe Maruping for guiding me through this study. I would be lost without their advice.

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CHAPTER 1. INTRODUCTION

1.1. Research Motivation

Today's organizations are situated in the fourth industrial revolution (Industry 4.0) in which digitalization of products, services, processes, and business models is transforming economic, technical, and social systems (Kohli and Melville 2019; Nambisan et al. 2017; Svahn and Henfridsson 2012; Yoo 2010; Yoo et al. 2012; Yoo et al. 2010a). Digitalization is the process of encoding analog information into digital format with subsequent reconfiguration of the sociotechnical arrangements of production and consumption of products and services (Eaton 2012). Examples of digitalization are abundant across industries: going paperless by recording information digitally, automating processes through enterprise systems (e.g., ERP, CRM, SCM), adopting cloud computing (e.g., IaaS, PaaS, SaaS), using digital sensors and implementing internet of things (IoT), commissioning robots and implementing large-scale machine-to-machine communication (M2M), democratizing monetary systems with cryptocurrencies, and integrating advanced analytics and artificial intelligence (AI) to leverage the myriad of data stored digitally. The rapid and pervasive digitalization is changing the nature and structure of products and services (Nambisan et al. 2017) and challenging organizations to cope with dynamic business landscapes as they apply digital technologies to improve their competitive positions (Kohli and Melville 2019).

In response to this formidable challenge, experts predict that 70% of organizations will attempt to go digital, but only 30% of those will succeed (Bort 2015); and, that 40% of organizations will not survive this transformation (Bort 2015). Two infamous examples of business organizations that failed to respond effectively to challenges from new digital technologies are Kodak and Nokia. For Kodak, the challenge came from digital photography technology, while Nokia failed to respond to competition in smartphone technology (Lucas and Goh 2009). Accordingly, a Gartner survey stated in 2018 that 67% of business leaders say their businesses will no longer be competitive if they cannot become significantly more digital by 2020 (Wiles 2018). Similarly, in a survey of corporate board members, 32% indicated that their business revenue is under threat from digitalization, and 60% found that significantly more time should be dedicated to addressing this issue (Weill and Woerner 2015a). Hence, corporate leaders across various industry sectors regard digitalization as a high priority. Such profound concern is both timely and reasonable since digitalization not only transforms businesses operations but also business models (Weill and Woerner 2015b).

The prevalence of digitalization has led to the emergence of a new kind of innovation, namely digital innovation (Kohli and Melville 2019; Nambisan et al. 2017). Innovation, in general, is the introduction and application of novel solutions that meet new requirements, unarticulated needs, or existing market demands (Maranville 1992). Digital innovation, specifically, is innovation enabled by digital technologies that lead to "the transformation of sociotechnical structures that were previously mediated by non-digital artifacts or relationships" (Yoo et al. 2010b, p. 6). Digital innovations use digital technologies to generate or change market offerings, altering entire industries by creating and reshaping business models, structures, and processes to improve performance (Iansiti and Lakhani 2014; Kohli and Melville 2019; Nambisan et al. 2017). As such, digital innovations afford organizations opportunities to solve their traditional business problems by transforming products and services as well as business models, structures, and processes (Haffke et al. 2017).

In order to sustain and improve their performance in digitalized business environments, organizations sense and respond to new opportunities and threats through continuous adaptations and proactive sociotechnical transformations (Tanriverdi et al. 2010). Hence, as a necessary consequence of digital innovation, organizations substantially change their business models, structures, processes, products, and services with digital technologies (Li et al. 2018; Vial 2019; Westerman et al. 2011). These technologies possess the capacity, defined as material agency, to act on their own apart from human intervention, with human agency referring to humans' capacity to form and realize their goals (Lehrer et al. 2018; Leonardi 2011). An empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice is known as a figuration (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). We adopt the definition and conceptualization of figuration by Jonsson et al. (2018).

Further, digital technologies are implicated in organizational practices in two distinct types of figurations—digital representations and digital mediations (Jonsson et al. 2018). A digital representation is a figuration in which technology is used to monitor and produce a particular work space (Jonsson et al. 2018, Ramaprasad and Rai 1996), while a digital mediation is a figuration in which technology is used to share and enact a particular work arrangement (Jonsson et al. 2018, Persson et al. 2009). As such, digital representations focus on the content, i.e., how technology is used to monitor and produce digital content, whereas digital mediations focus on the medium, i.e., how technology is used for digitally mediated cooperative work. Organizations can therefore leverage digital representations as well as digital mediations to organize their practices. Against that backdrop, we introduce and theorize the concept of organizational intelligence to capture the capability of an organization to effectively gather, process, and manipulate information and to communicate, share and make sense of the knowledge it creates. Organizational intelligence is, hence, an organization's capability to process, interpret, encode, manipulate, and access information in a purposeful, goal-directed manner (Glynn 1996), so it can increase its adaptive potential in the environment in which it operates. Organizational intelligence materializes in digital representation and digital mediation figurations that bear elements of both human agency and material agency to generate the adaptive potential that allow organizations to organize and manage their ongoing digital innovation initiatives. However, although digital technologies, such as advanced data analytics and Artificial Intelligence (AI) along with communication and collaboration systems, are revolutionizing how organizations produce and manage knowledge to conduct business and continuously improve performance, we lack theory of how organizations can leverage organizational intelligence to conceptualize, rationalize, and realize digital innovations and how these innovations can recursively improve organizational intelligence as basis for further innovations. Moreover, while current research on organizational intelligence predominantly emphasizes analytic capabilities, this research puts equal emphasis on relational capabilities. Similarly, while current research on organizational intelligence focuses only on human agency, this research focuses equally on material agency.

Digital innovation is increasingly becoming an important area of study because of its pervasiveness. Barrett et al. (2012) examined how the different forms of materiality constituting a novel digital innovation influenced the practices and boundary relations of disparate occupational groups in a pharmacy. Jonsson et al. (2018) studied condition-based maintenance of mining machinery and advanced digital representation and digital mediation as two distinctive figurations in the fusion of digital technology and work. Arvidsson and Mønsted (2018) studied how digital entrepreneurs generate potential for innovation in organizations with four tactics—concealing, sequencing, anchoring, and propagating. Chan et al. (2019) investigated how SMEs achieve agility in response to disruptive digital innovation and proposed a framework on agility based on the dual process of mitigating organizational rigidity and developing innovative capabilities. Oborn et al. (2019) studied innovation trajectories and examined what happens when an innovation becomes implemented and used in locales that are distant and distinct from those where it was initially developed. Beltagui et al. (2020) studied 3D printing and proposed a process model to understand disruptive innovation and digital innovation ecosystems through the lens of exaptation.

In spite of studies such as these, we still have limited knowledge about how organizations' ongoing digital innovation initiatives are organized and managed. Since this process requires breaking existing norms and practices and adopting new ones, it is difficult for organizations to effectively capitalize on digital innovation initiatives. Therefore, there is a critical need to better understand how organizations can capitalize on digital innovation initiatives to transform their business models, structures, and processes by harnessing their digital innovation capabilities. In particular, there is a need to better understand how human and material agency come together in various figurations to produce organizational intelligence as part of organizing and managing digital innovation efforts. Moreover, today's digital technologies are no longer passive tools waiting to be used by humans; they are no longer always subordinate to human agents; and, they can now assume responsibility for tasks with ambiguous requirements and for seeking optimal outcomes under uncertainty (Baird and Maruping 2021). However, extant IS literature gives primacy to human agency in the relationship between humans and technologies for explaining how humans apply digital technologies toward goal attainment, treating digital technologies as passive tools (Baird and Maruping 2021). In this dissertation, we revisit the human agency primacy assumption by (1) theorizing the agentic nature of today's digital technologies as material agency, and (2) presenting the roles of humans and technologies as the entanglement of human and material agencies in forming organizational intelligence.

1.2. Research Design

The objective of this study is to investigate (1) how an incumbent organization applies its organizational intelligence over time to spearhead its digital innovation initiatives, (2) how organizational intelligence is implicated in such ongoing innovation efforts, and (3) how human and material agencies come together to form organizational intelligence. Accordingly, we seek to address the following research question:

How is organizational intelligence implicated in digital innovation initiatives in the context of focused organizational transformation?

Hence, the research context is an incumbent organization's focused transformation undertaken over an extended period of time and the unit of analysis is the various digital innovation initiatives involved in this process. In detail, the dissertation explores (1) the background of each digital innovation initiative in the broader context of the organization's focused transformation, (2) the motivation and rationale behind each initiative, (3) the events and structures that shape each initiative, and (4) the intermediate and ultimate outcomes of the initiatives. In aggregate, the dissertation focuses on (1) the organization's evolving configuration of digital innovation initiatives, (2) how organizational intelligence is implicated in managing and developing these initiatives, and (3) how the initiatives catalyze the ongoing, focused transformation of the organization.

To answer the overarching research question, we apply the theoretical lens of contextualist inquiry, which proposes that complex organizational changes should be studied across three distinct but interrelated perspectives—context, content, and process (Pettigrew 1985; Pettigrew

1987; Pettigrew 1990). Since organizational transformation through digital innovations is essentially a change process, we examine the process and outcomes of digital innovation initiatives through the interactions among context of change, content of change, and process of change. Context of change refers to the environment in which organizations and stakeholders operate and is further delineated as outer and inner context. Outer context describes the environment that the organization operates in, including social, competitive, economic, and political factors. Inner context refers to features of the structural, cultural, and political environment inside the organization through which ideas for change proceed. In our case, the context is the ongoing organizational change through digital innovation initiatives. Content of change is the area subjected to change that could include a new technology or process, the business model or structure of an organization, or a new program, product, or service. In our case, the contents are several ongoing digital innovation initiatives. Process of change refers to the continuous and interdependent sequence of actions and events which explain the origins, continuance, and outcome of the transformation. Processes are studied from two dimensions, the vertical and the horizontal. The vertical dimension refers to the interdependencies between higher and lower levels of analysis, whereas the horizontal dimension provides a temporal view of the transformation.

Digitalization has provided today's organizations access to a plethora of data related to the context, content, and process of change; a phenomenon known as big data. Data about the social, economic, competitive, and political factors in the outer context are readily available from multiple sources. Widespread use of enterprise systems provides access to data about the structural, cultural, and political factors in the inner context as well as about the content of change at different stages of organizational transformation. Digitalization of processes traces the progression and performance of each process at different data points along both vertical and horizontal dimensions. Digital technologies, such as advanced data analytics and AI are used to analyze such big data collected both inside and outside the organization. However, we know little about (1) how the material agency of these digital technologies interacts with the human agency across digital representation and digital mediation figurations, and (2) how an incumbent organization organizes and manages its digital innovation initiatives through such interactions.

Against that backdrop, we introduce (1) analytical intelligence as the capability of an organization to apply digital technologies to analyze critical business data (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017); (2) relational intelligence as the capability of an organization to apply digital technologies to communicate, collaborate, and coordinate (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012); and, (3) organizational intelligence as the entanglement of analytical and relational intelligence in organizational practices (Leonardi 2011; Saldanha et al. 2017). We argue that (1) analytical intelligence manifests as figurations in which human agency comes together with material agency to analyze data in decision making; (2) relational intelligence manifests in figurations in which human agency and material agency come together to enable collaborative practices; and, (3) organizational intelligence comprises both human and material agencies in which analytical and relational intelligence entangle to support organizational practices. As such, we propose a process theory of how organizational intelligence is implicated in organizing and managing an organization’s digital innovation efforts in the context of an ongoing, focused transformation. While current research on organizational intelligence predominantly emphasizes analytic capabilities, this research puts equal emphasis on relational capabilities. Similarly, while current research on organizational intelligence focuses only on human agency, this research focuses equally on material agency. Our conceptualization of analytical and relational intelligence as entanglements of human and material agency and consequent theory of organizational intelligence responds to the recent call by Sarker et al. (2019) to position IS theories closer to the fundamental and unique characteristic of IS research—the sociotechnical perspective.

Empirically, rooted in engaged management scholarship with active collaboration with industry practitioners (Mathiassen 2002; Mathiassen and Nielsen 2008; Van de Ven 2007), we draw on a case study within a large public university in the US, Georgia State University (GSU), which has undertaken many digital innovation initiatives over the last two decades to improve the performance of its undergraduate students, and significantly transformed itself in the process. GSU is a public research university in Atlanta, Georgia, classified as R1, for "very high research activity". Founded in 1913, it is one of the University System of Georgia's four research universities and currently the most comprehensive public institution in Georgia, offering more than 250 degree programs in over 100 fields of study spread across 10 academic colleges and schools. It is also the largest institution of higher education by enrollment based in Georgia and it is in the top 10 in the nation in number of students with a diverse majority-minority student population of around 53,000 students, including approximately 33,000 undergraduate and graduate students at the main campus downtown as of 2020.

The student body at GSU comprises 67% non-white and 58% Pell-eligible students with a majority of first-generation college-bound students. Due to its diverse student body with a majority of first-generation college-bound students, who are challenged socially, economically, and pedagogically, GSU faced a unique challenge of how to improve the undergraduate student performance. To improve the 6-year graduation rate of undergraduate students, GSU implemented many innovations and leveraged digital technologies starting from 1999. Over the last two decades, GSU transformed its programs, structures, and processes through various digital innovation initiatives. In this extended organizational transformation, GSU gradually improved its 6-year graduation rate from 32% in 2003 to 55% in 2018. As a proponent of equity and inclusion, GSU now awards more degrees to African American students than any other non-profit college or university in the US. In 2020, GSU has been recognized as the number one public university for teaching and the number two most innovative university in the US (US News & World Report 2020).

In this dissertation, we conduct a longitudinal qualitative case study of GSU's digital innovation initiatives over the past two decades to improve the success of its students. Based on this empirical inquiry and extant literature, we theorize how organizational intelligence is implicated as an incumbent organization seeks to improve its performance through multiple digital innovation initiatives. With that objective, we collected both primary and secondary data from GSU, including semi-structured interviews of 26 key personnel, press releases, and internal archival documents (e.g., reports, presentations, meeting notes, and personal communications) spanning two decades. Moreover, we read news articles and a book (Gumbel 2020) published on the GSU story. In addition, we attended GSU managers' meetings to understand how critical decisions are made and attended presentations from the leaders of the digital innovation initiatives as they shared their insights and experiences. We analyzed the collected data using provisional coding informed by contextualist enquiry (Miles et al. 2014) and combined that with extant literature to advance theory about organizational intelligence in digital innovation.

Through this in-depth longitudinal qualitative case study of a large organization, this dissertation contributes a theory of how digital innovations are managed over time to improve organizational performance with a focus on the important role of organizational intelligence. To achieve this,

this dissertation takes a comprehensive approach to study many digital innovation initiatives undertaken in the context of ongoing focused organizational transformation and implemented over an extended time period. As a result, we make the following contributions to knowledge on digital innovation: (1) empirically—to provide a detailed narrative of how an organization, as part of a multi-year change program, leveraged organizational intelligence to support digital innovations and how these digital innovations in turn improved its organizational intelligence as basis for further innovations; (2) theoretically—to theorize how organizational intelligence is implicated in improving an organization's processes, structures, and systems through digital innovation initiatives; and (3) practically—to articulate lessons for how managers can build and leverage organizational intelligence as part of digital innovation initiatives aimed at improving the organization's processes, structures, and systems.

1.3. Research Elements

In summary then, we present the key elements of our engaged scholarship research in Table 1 below according to Mathiassen (2017).

Table 1: Research Elements	
P: Problem	We are in the fourth industrial revolution when pervasive digitalization is forcing organizations to increasingly apply digital technologies, such as advanced data analytics and Artificial Intelligence (AI) along with communication and collaboration systems. Although these technologies are revolutionizing how organizations produce and manage knowledge to conduct business and continuously improve performance, we lack theory of how organizations can leverage organizational intelligence to conceptualize, rationalize, and realize digital innovations and how these innovations recursively can improve organizational intelligence as basis for further innovations.
RQ: Research question	How is organizational intelligence implicated in digital innovation initiatives in the context of focused organizational transformation?

A: Area of concern	Organizational intelligence in digital innovation
Fa: Theoretical frame related to A	Organizational intelligence as entanglement of analytical and relational intelligence
Fi: Theoretical frame independent of A	Contextualist Inquiry
M: Research method	Qualitative, longitudinal case study—process study
C: Contribution	• Empirically—to provide a detailed narrative of how an organization as part of a multi-year change program leveraged organizational intelligence to support digital innovations and how these digital innovations in turn improved its organizational intelligence as basis for further innovations. • Theoretically—to theorize how organizational intelligence is implicated in improving an organization's processes, structures, and systems through digital innovation initiatives. • Practically—to articulate lessons for how managers can build and leverage organizational intelligence as part of digital innovation initiatives aimed at improving the organization's processes, structures, and systems.

CHAPTER 2. THEORETICAL BACKGROUND

2.1. Introduction

Digital technologies are deeply embedded in and more central to organizations than ever before (Baptista et al. 2020). We define digital technologies as "combinations of information, communication, computing, and connectivity" (Bharadwaj et al. 2013, p. 471), which make products and services reprogrammable, addressable, sensible, communicable, memorable, traceable, and associable (Yoo 2010; Yoo et al. 2010a). These technologies began as tools to support practices of individuals, but they have since also become the basis for collaboration and coordination among individuals through social interaction and community building, and more recently they have become capable of performing managerial roles with the use of advanced AI capabilities. In today's organizations, digital technologies, with varying degrees of autonomy, come together with humans in the constitution of organizational practices (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). As such, the material agency of digital technologies—the capacity of technologies to act on their own apart from human intervention—entangle with human agency—humans' capacity to form and realize their goals in organizational practices (Lehrer et al. 2018; Leonardi 2011). As rapid and pervasive digital innovation is continually changing the nature of work, we need to understand digitalization based upon contemporary practices, with autonomous artifacts (Lehrer et al. 2018; Leonardi 2011) and spatially and temporally dispersed work arrangements (Yoo 2010), rather than based upon ideas developed in a different era with non-autonomous artifacts (Lehrer et al. 2018; Leonardi 2011) and collocated, locally controlled work arrangements (Forman et al. 2014).

As stated earlier, an empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice is known as a figuration

(Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). In some figurations digital technology is used to monitor and produce a particular work space (Jonsson et al. 2018, Ramaprasad and Rai 1996)—defined as digital representation—in other figurations digital technology is used to enact and share a particular work arrangement (Jonsson et al. 2018, Persson et al. 2009)—defined as digital mediation. Although some, if not all, digital technologies support both digital representation and digital mediation, some digital technologies predominantly support digital representation—defined as representation-dominant technologies—while others predominantly support digital mediation —defined as mediation-dominant technologies.

Representation-dominant technologies, such as data analytics and AI, are increasingly used in organizations to leverage big data. Digital innovations, such as enterprise systems, paved the way to big data through digitally monitoring and recording traces of business processes (Hilbert and López 2011). Big data with a large number of data points offer greater statistical power, and with a myriad of attributes represent higher complexity (Breur 2016). Characterized by volume, variety, and velocity, big data poses new challenges for organizations regarding data analysis, fueling digital innovations in data analytics and more recently AI. Currently descriptive analytics, predictive analytics, prescriptive analytics, and other advanced data analytics methods including AI are being used to extract value from data (Kohavi et al. 2002).

At the same time, as modern organizations digitalize work, people increasingly access and share information with others using mediation-dominant technologies, such as digital communication and collaboration technologies (Jonsson et al. 2018). Digital technologies enable communication, collaboration, and coordination among individuals across spatial, temporal, contextual, and organizational boundaries (Jonsson et al. 2018). Such digitally mediated collaboration and coordination is transforming routines and organizational practices (Leonardi and Bailey 2008), and thus shaping modern organizations (Baptista et al. 2020), through formation of new figurations of material agency and human agency (Lehrer et al. 2018; Leonardi 2011). These figurations influence the emergence of new structures and capabilities in organizations in response to the evolving nature of digital technologies (Baptista et al. 2020).

The evolution in use of digital technologies in organizations has hybridized their use with human activities, transforming organizations into complex sociotechnical systems (Benbya et al. 2020) with meta-human or human-in-the-loop (Rai et al. 2019) figurations never seen before (Lyytinen et al. 2020). As such, the new figurations of organizational practices enabled by representation-dominant and mediation-dominant technologies require engagement beyond the execution and meaning of work; they require questioning the purpose and meaning of organizations. This presents a challenge to capture the profound effects of digital technologies in organizations (Silva and Hirschheim 2007) as emergent sociotechnical figurations (Suchman 2012) to understand their strategic significance to organizations (Dery et al. 2017; Tavakoli et al. 2017). Against that backdrop, we review and discuss three streams of literature—digital innovation, representation-dominant technologies, and mediation-dominant technologies—as foundation for synthesizing them into our theoretical framing in Chapter 3.

2.2. Digital Innovation

Digital innovations afford organizations opportunities to solve traditional business problems by innovating products and services as well as processes, structures, and business models (Haffke et al. 2017). This leads to transformations whereby organizations substantially change their business models, structures, processes, products, and services with digital technologies (Li et al.

2018; Vial 2019; Westerman et al. 2011). In the following, we review different forms of digital innovations followed by key research contributions in each of those forms.

Digital product innovation is the development, creation, and subsequent introduction of digital products with some digital component that are (a) significantly new from the perspective of a community, industry, or market, or (b) substantially enhanced by the addition of digital technology (Fichman et al. 2014). Examples include new enterprise systems (e.g., ERP, CRM), new consumer products (e.g., smartphones, hand-held devices) and new physical products with digital materiality (e.g., devices with AI-enabled virtual assistants, smart cars or self-driving cars). Digitalization reshapes product innovation with digital connectivity and convergence by radically reconfiguring the design and production of most products beyond the traditional concept of product innovation (Lyytinen et al. 2016). As such, today's products encompass complementary services that are necessary to fulfill the value proposition for intended users, that has been called the whole product solution (Fichman et al. 2014; McKenna 1985). Over several decades, the traditional product-oriented model of exchange has been transformed into a service-oriented model of exchange (Vargo and Lusch 2004), through service innovation.

Digital service innovation is the recombination of diverse resources, embodied in or enabled by digital technology, that create novel resources that are beneficial to some in a network of actors (Lusch and Nambisan 2015). Actors play a variety of roles (e.g., service providers, service beneficiaries) in integrating and incorporating resources as well as proactively supporting the value co-creation process to enhance service innovation. As a collaborative process occurring in an actor-to-actor network, service innovation generates new service offerings not previously available to service beneficiaries, including an addition to the current service mix or a change in existing services (Ye and Kankanhalli 2018). Moreover, as organizations continually move away from strictly product-oriented value propositions, with discrete or static transactions, towards services and their service-oriented processes, with dynamic exchange relationships in which value is co-created with various stakeholders, product innovation usually entails additional service innovation (Vargo and Lusch 2004) and process innovation to support value co-creation.

Digital process innovation is the creation of significantly new, from the perspective of the adopter, ways of doing things in an organizational setting enabled by digital technology (Fichman et al. 2014). Business processes can be viewed as sequences of activities that can be understood, modeled, and remodeled as necessary (e.g., Recker et al. 2009; Van der Aalst 2013). Digital process innovation may support various goals in the organization (e.g., improved production flexibility, improved product quality, accelerated time to market; see Pisano 1997) with the ultimate goal of reducing production cost (Davenport 1993; Flynn et al. 1999). However, digital process innovation can also lead to changes in the administrative core, such as new organizational forms or governance structures (Markus 2010; Swanson 1994). As such, we conceptualize digital process innovation broadly to encompass not only new processes in an organizational setting, but also the creation of new structures, capabilities, and strategies that are in some way digitally enabled.

Because of the prevalence of digitalization in recent years, an increasing number of scholars have recognized *digital business model innovation* as a separate class of innovation. A business model defines how an organization creates, captures, and delivers value to its customers, and then converts earnings into profits (Teece 2010). We conceptualize business model more broadly as the means of an organization to create, capture, and deliver value to its stakeholders, either for profit or not for profit; business models include identity, core values, resources, and value proposition of an organization. Following this conceptualization, we define digital business model innovation as a significantly new way of creating, capturing, and delivering business value that is embodied in or enabled by digital technology (Fichman et al. 2014). Digital innovation has become the primary driver of business model innovation in recent years (Teece 2010). Examples include Apple's evolution from offering its customers personal computers and cellular phones to music delivery devices and services, Dell's innovation of a new distribution model by allowing online customization, Walmart's fundamental changes to a networked enterprise structure and value chain, Google's ad-sponsored search business, Netflix's DVD-by-mail subscription service, and Zipcar's auto rental business.

Research on *digital product innovation* focuses on organizations that produce new digital products or physical products with digital components, and on the various supply-side processes, structures, institutions, industry, and market dynamics that support and shape the product's development and diffusion. The boundary around what constitutes a given product innovation can be drawn narrowly around a core technology (e.g., smartphone), or more broadly to also encompass complementary products and services (e.g., streaming services, mobile applications and accessories), referred to as the whole product solution to fulfill the value proposition for intended users (McKenna 1985).

In a study of automotive emission control systems, Lee and Berente (2012) highlight the way the division of innovative labor across firms in the supply chain can be influenced by a particular form of digital innovation known as "digital control systems," which integrate complementary components across a product structure and introduce a level of unpredictability and indeterminacy in the organization of the inter-firm division of innovative labor. They found that although component suppliers engage in relatively more design and invention around the components that they supply, accompanying a shift toward increasingly modular product structures, the evolution of digital controls may reverse this pattern. In the wake of a major shift in the digital control technology, suppliers actually engage in relatively less component innovation compared to their larger manufacturing customers.

In a study of three-dimensional printing, Kyriakou et al. (2017) found that 3D meta-models are reused more often than the 3D models they generate. Based on their findings they proposed a distinct process of knowledge reuse—reuse for customization. Contrary to the two established processes of knowledge reuse—reuse for replication and reuse for innovation—reuse for customization is a process through which designers manipulate the parameters of meta-models to produce models that fulfill their specific needs. Later on, Beltagui et al. (2020) studied 3D printing through the lens of exaptation and proposed a process model to understand disruptive innovation and digital innovation ecosystems. Exaptation is the serendipitous exploitation of latent functionality in existing artifacts for new contexts. Exaptation drives innovations that involve exploiting unintended latent functions of pre-existing technologies.

Barrett et al. (2012) studied a robotic innovation in a pharmacy and examined how the different forms of materiality constituting a novel digital innovation influenced the organizational practices and boundary relations of disparate occupational groups. While the physical materiality of an artifact can be seen and touched, is relatively hard to change, and implicates a specific context of time and place (Yoo 2013), an artifact's digital materiality is what the artifact can do to manipulate digital representations using the incorporated software (Leonardi 2010; Yoo et al. 2012). Barrett et al. (2012) found that engagement with the robot's physical materiality and digital materiality reconfigured boundary relations among occupational groups over time, with significant and contradictory consequences for the pharmacy workers' visibility, skills, status, and jurisdictions.

Digital service innovation has been widely studied. Lusch and Nambisan (2015) offered a broadened view of service innovation, grounded in service-dominant logic, that transcends the previous conception of tangible–intangible and producer–consumer divides. Service-dominant logic draws on the concept of resource liquefaction, which refers to the decoupling of information from its related physical form or device (Lusch and Nambisan 2015; Normann 2001). Throughout human civilization, information was embedded in physical matter (e.g., writings or drawings on stone and paper) and later in other tangible things such as devices. Information must be shared with others to make use of it. However, when information is embedded in physical matter or devices, the ability to share the information becomes limited by the cost and time of physical production and transport. The emergence of digital technologies enabled the digitalization of information and the associated capability to decouple the information from the technologies (or devices) that store, transmit, or process it. Such decoupling enables entanglement of the virtual and material layers of work in different ways (Gaskin et al. 2010; Robey et al. 2003), reshaping the nature of work itself. More importantly, the sociotechnical processes accompanying such digitalization have helped forge new social connections and cognitive models that unleash "generativity" and create innovation opportunities (Tilson et al. 2010).

Lusch and Nambisan's (2015) broadened conceptualization emphasizes the collaborative nature of service innovation occurring in an actor-to-actor network and posits service as the basis of all exchange and as the application of specialized competences for the benefit of any actor in an actor-to-actor network. Moreover, they emphasize value co-creation, which views value as co-created by the service offer(er) and the service beneficiary (e.g., customer) through resource integration. Thus, Lusch and Nambisan (2015) captured all the different concepts and issues that underlie the broadened view of service innovation with their tripartite framework (service ecosystem, platform, and value co-creation). Their framework "reveals the important role that digital innovation can play—as an operand resource and as an operant resource—in enhancing the opportunities for service innovation" (p. 172).

Drawing on service-dominant logic, Lehrer et al. (2018) in their case study developed a theoretical model that explains how the flexible and reprogrammable nature of big data analytics technologies provides features of sourcing, storage, recognition and prediction of event and behavior, rule-based actions, and visualization that afford service automation and human-material service practices. Their model highlights how material agency, in service automation, and the interplay of human and material agencies, in human-material service practices, enable service innovation.

Research on *digital process innovation* uses adopting organizations as the focal point, and investigates when and why organizations adopt new technologies, and how they can successfully assimilate them. Organizations can be adopting technologies supplied by the market or developing and deploying technologies internally. The majority of extant research views digital process innovation as an efficiency-enhancing activity aimed at lowering the cost of producing a product or service (Damanpour and Gopalakrishnan 2001; Davenport 1993; Ettlie and Reza 1992; Gopalakrishnan et al. 1999; Hatch and Mowery 1998; Trantopoulos et al. 2017; Un and Asakawa 2015).

Trantopoulos et al. (2017) proposed a model of process innovation drawing on the knowledge-based view of the organization. Investigating how search in external knowledge sources and information technology for knowledge absorption jointly influence process innovation performance, they established that accessing and integrating knowledge from sources that reside outside the organization, such as customers, competitors, consultants, or universities, is critical to organizations' innovative success. Their findings demonstrate how organizations should coordinate strategies for sourcing external knowledge with specific digital technology investments with a view to improving their innovation performance.

Extending the knowledge-based view, Jonsson et al. (2018) studied how digital technology leads to changes in networked practices. Through a case study on condition-based maintenance of mining machinery, they analyzed how a distributed network of workers made complex knowledge-based decisions on when and how to maintain the mining machinery, using a diverse portfolio of digital technologies. They defined a practice as an emergent way of doing work that is produced through entanglement of specific figurations (Leonardi 2011; Leonardi 2013), where a figuration, as stated earlier, is an empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). Jonsson et al. (2018) proposed two distinct types of figurations—digital representation and digital mediation. As mentioned earlier, a digital representation is a figuration in which digital technology is used to monitor and produce a particular work space (Jonsson et al. 2018; Ramaprasad and Rai 1996), whereas, a digital mediation is a figuration in which digital technology is used to share and enact a particular work arrangement (Jonsson et al. 2018; Persson et al. 2009). Digital representation and digital mediation figurations entangle to produce a particular networked, knowledge-based practice, with the former designating use of digital technology to monitor and produce a work space, and the latter designating use of digital technology to share and enact a distributed work arrangement.

Oborn et al. (2019) examined why and how innovations are reshaped as they become implemented and used in locales that are distinct and distant from those where the innovation was initially developed. Their theorizing re-conceptualizes traditional notions of innovation diffusion by explicating why and how innovations change in unexpected and multiple ways as they move to specific places and engage with local practices and conditions. They put forth an understanding of the dynamics that arise when an innovation trajectory interacts with local trajectories that constitute the local practices and conditions of specific places. They identified four distinct patterns of trajectory dynamics—separation, coordination, diversification, and integration—each of which has its specific and unique implications for the innovation, its implementation, and consequences on the ground. They theorized the processes through which innovations are transformed over time as they interact with multiple local trajectories and the specific innovation outcomes that are generated as a result and developed a model of trajectory dynamics in innovation.

There has not been much research on *digital business model innovation*. Svahn et al. (2017) investigated how incumbent organizations can address competing concerns as they embrace digital business model innovation. With a longitudinal case study of Volvo Cars' connected car initiative, they argue that incumbent organizations face four competing and systemically interrelated concerns— focus (product versus process), capability (existing versus requisite), collaboration (internal versus external), and governance (control versus flexibility). In stark contrast to existing business models and innovation practices, Volvo Cars outlined a vision that would transform its cars into platforms and give them life far beyond the time of production. New digital technology would open up new revenue streams and enhance end-user experience. By disconnecting from traditional automotive cycle plans, the technology could accelerate change and allow the organization to engage with external innovation ecosystems to sync with developments in consumer electronics. Leveraging connectivity by exposing the car to external developers, such as through open APIs, Volvo is expected to inspire a new level of functional diversity in the automotive industry.

2.3. Digital Representation

Representation-dominant technologies create approximate digital rendition of the real world to monitor the behavior of or predict the outcome of real-world processes and systems by analyzing data in digital format. These technologies can monitor and produce work spaces using synthetic abstract models of real-world phenomena, imitating reality as closely as possible (Bailey et al. 2012). Such representational capacity is the fundamental characteristic of these technologies in which “activities, events and objects are translated into and made visible by information” (Zuboff 1988, pp. 10–11). Using representation-dominant technologies people can access, manipulate, and make sense of requisite information (Zammuto et al. 2007). Although representing the real world with data is the primary focus of these technologies, they can also help people communicate to achieve shared understandings through mediation (Carlile 2002). Regardless of its affordances, at the core of a representation-dominant technology is data in digital format.

Digitalization of and digital innovations in products, services, processes, and business models are generating data that is so comprehensive, complex, and rapidly changing that it is difficult, or even impossible, to process using traditional methods, a phenomenon known as big data. The availability of such abundant data is fueling digital innovation of new data analytics technologies. Data analytics is the process of extracting insights from data and transforming data into actions through analysis in the context of organizational decision making and problem-solving. As the availability of data about consumers, suppliers, competitors, and partners proliferates, organizations are expanding the use of large-scale data analytics to make decisions (Brynjolfsson et al. 2011), which involves the exploitation of operational data that is provided as a by-product of the deployment of enterprise systems (Aral et al. 2012; McAfee 2002). Organizations adopt data analytics technologies to examine data sets in order to find trends and draw conclusions about the information they contain. Data analytics technologies and techniques are widely used to enable organizations to make more-informed business decisions, increasingly with the aid of specialized software and systems. More recently, we have seen the introduction of sophisticated algorithmic features and AI capabilities that enable organizations to better leverage data.

Extant literature proposes that AI refers to systems, programs, algorithms, and machines that demonstrate intelligence by perceiving their environment and taking actions that maximize their chance of successfully achieving their goals (Russell and Norvig 2013). AI relies on large data sets to generate classifications, responses, or dynamic predictions that resemble those of a knowledgeable human (Faraj et al. 2018). AI is manifested by digital machines that exhibit characteristics of human intelligence (Huang and Rust 2018), and involves machines mimicking intelligent human behavior (Syam and Sharma 2018). AI relies on several key technologies, such as machine learning, neural networks, deep learning, natural language processing, rule-based expert systems, physical robots, and robotic process automation (Davenport 2018). By employing these technologies, AI provides a means to interpret data, learn from such data, and exhibit flexible adaptation (Haenlein and Kaplan 2019). AI can also be described based not on its underlying technology but rather on its business applications, such as gaining insights from data, automating business processes, or engaging customers and employees (Davenport and Ronanki 2018).

The digital technologies used for data analytics, AI or otherwise, act for a user or other artifact in a relationship of agency with reference to an agreement to act on their behalf (Nwana 1996; Schermer 2007). Such action taken on behalf of the principal implies the authority of the agent to decide which, if any, action is appropriate (Nwana 1996; Schermer 2007). IS literature conceptualizes such authority as material agency, defined as the capacity of an artifact to act on its own apart from human intervention (Lehrer et al. 2018; Leonardi 2011). Agents may be embodied, as when execution of an action is paired with a robot, or as software, such as a chatbot executing on a phone or other computing device. As discussed earlier, tangible artifacts possess physical materiality "that can be seen and touched, that are generally hard to change, and that connote a sense of place and time," (Yoo et al. 2012, p. 1398), while digital artifacts possess digital materiality which refers to "what the software incorporated into an artifact can do by manipulating digital representations" (Yoo et al. 2012, p. 1398). Hence, physical materiality of an artifact can be seen and touched, is relatively hard to change, and implicates a specific context of time and place (Yoo 2013), whereas digital materiality is what the artifact can do to manipulate digital representations using the software incorporated into it (Leonardi 2010; Yoo et al. 2012).

Digital materiality can be broadly conceptualized as the material agency of a computer system, situated in some environment, that is capable of flexible autonomous actions in order to meet its design objectives (Jennings et al. 1998). In that sense, AI is different from other data analytics technologies by possessing a greater degree of autonomy. Early digitalization efforts exploited computers' superior memory systems and processing speed to create machines that would be better at retaining and aggregating data (Schuetz and Venkatesh 2020). Consequently, decision support systems (DSS) were developed to employ "decision rules and models, coupled with an extensive database" (Turban and Watkins 1986, p. 122). DSS allowed human decision makers to query systems to produce factual information in the form of aggregated information, reports, and graphs (Turban and Watkins 1986). However, it was still up to the human decision makers to draw inferences from those data. The next development step was to devise reasoning capabilities (Schuetz and Venkatesh 2020). As a result, expert systems (ES) were developed, "propagating inferences over the knowledge base" (Turban and Watkins 1986, p. 122). The reasoning of expert systems allowed them to mimic human experts (Turban and Watson 1988) by providing explanations for given recommendations.

Early IS research predominantly focused on DSS and ES up until the late1990s (Nevo et al. 2008) at which point several problematic issues with these systems surfaced. Despite their economic success and technological capabilities, many of these systems were quickly abandoned by users (Gill 1995). One of the key challenges was that the systems required structured information to interface with human users (Sviokla 1990). Thus, to formulate information and problems in ways that the systems could understand, humans had to adapt to the specifications of the systems (Paradice and Courtney 1987). As it turned out, this adaptation was problematic because users often did not provide appropriate or adequate data (Kopsco et al. 1988) and hence the systems often arrived at different conclusions than their human users (Paradice and Courtney 1987). Consequently, these systems were gradually abandoned because they relied heavily on user adaptation (Schuetz and Venkatesh 2020).

The next development empowered systems with more autonomy from human users. To that end, intelligent agents were developed as software that can act intelligently and in the place of a human to perform a given task (March et al. 2000). Intelligent agents were no longer reliant on human decision makers, with the power to autonomously react to and stimulate their environments (Russell and Norvig 2013). As such, intelligent agents could autonomously serve human purposes. Some IS research investigated the utility of intelligent agents for autonomously facilitating interorganizational meetings (Glezer 2003), placing bids in auction markets (Adomavicius et al. 2009), and detecting malicious intentions of border-crossing individuals (Nunamaker et al. 2011).

In aggregation, all of these capabilities enabled machines to autonomously know, reason, and act or react. With these capabilities, machines demonstrated significant human-like abilities. However, machines were still inherently reliant on structured data input, making it difficult for users to interact with them. As such, in the pursuit of building human-like machines, it became evident that machines needed cognitive capabilities to make sense of their unstructured environments (Schuetz and Venkatesh 2020). Cognitive capabilities in machines were achieved with recent advances in AI that allow machines to perceive their environments (Schuetz and Venkatesh 2020). Traditionally, humans exclusively possessed the ability to process unstructured data, such as text documents and audio-visual data. However, with the development of more powerful machine learning techniques, machines now have the capability to cluster, classify, and make sense of the unstructured data that represent the world in which we live. Theories of cognitive architecture prescribe that for systems to have cognitive capabilities, they must have components that demonstrate memory, reasoning, action, and perceptive capabilities (Laird et al. 1987). Some of today's AI systems, such as Cognitive Computing Systems (CCS), are considered as the first generation of machines with cognitive capabilities since they possess all of these components (Schuetz and Venkatesh 2020).

Research on AI in the basket-of-eight IS journals and top management journals is sparse and fragmented. Among other publications, taking a strictly technical perspective, Tam and Kiang (1992) introduced an artificial neural network approach to perform discriminant analysis in business research. Vaguely inspired by the biological neural networks that constitute animal brains (Chen et al. 2019), an artificial neural network represents a nonlinear discriminant function as a pattern of connections between its processing units known as artificial neurons. Using bank default data, Tam and Kiang (1992) compared the neural-net approach with logistic regression, linear classifier, KNN, and ID3, and empirically showed that neural-net is a promising method for evaluating bank conditions in terms of adaptability, robustness, and predictive accuracy. Later, Veiga et al. (2000) demonstrated the usefulness of neural-net analysis in uncovering the underlying patterns, or trace effects, of national culture. Utilizing survey data from top executives, they provided an application of the neural-net technique's pattern recognition capability, interpreted the trace effects found, and encouraged the use of neural-net in cross-cultural research in the future.

Taking an organizational perspective, Fowler (2000) evaluated the phenomenon of knowledge management and its relationship to AI technologies of knowledge-based systems, case-based reasoning and neural networks. Fowler (2000) established a knowledge value-chain (KVC) concept and integrated it into a closed loop knowledge activity cycle by linking it to Nonaka's knowledge spiral and related concepts. The potential application of AI was investigated using this framework, applying it within the context of the core business processes underpinning a contemporary knowledge company that is operating at the forefront of computer networking technology. His study thereby illustrates both the potential and the limitations of AI technologies in terms of their capability to support the knowledge management processes.

Taking the perspective of material agency, Nissen and Sengupta (2006) investigated the comparative performance of software agents and humans, across varying levels of ambiguity in the procurement domain, with an experiment that delineates some new boundaries of computer-based decision making quite broadly. They concluded that (1) material agency is shifting from decision support to decision maker, (2) agent support and specification ambiguity create performance inversions, (3) agents create the need for human decision assistants, (4) software and human roles may shift dynamically, and (5) we should address ambiguity at agent run time versus design time. By investigating the capabilities, limitations, and boundaries of agent technology for computer-based decision support in the procurement domain, Nissen and Sengupta (2006) informed digital materiality in computer-based decision making and, more generally, IS research on agent technology design.

Taking a philosophical perspective, Aleksander (2017) addressed the age-old concept of singularity, a hypothetical moment in time when robots equipped with AI would become so advanced that they would surpass humans and make humans redundant through the self-perpetuation of ever smarter robots. The author reviewed the actual level of competence achieved in robotics research laboratories and a plausible impact it would have on singularity. His key thesis is that cognition in machines and even an artificial form of consciousness lead to operations in a set of tasks—the algorithmic category—which is different from that available to truly conscious and cognitive human beings—the life-need category. The central argument of the paper is that the idea of singularity is flawed by a major category error (Ryle 1949): what one calls intelligence in humans satisfies human needs to procreate, to forage for food, and to use locomotion to optimize this foraging. A robot has no such needs. Hence, AI in robots falls into the algorithmic category of development that does not have the life-need characteristics of human intelligence but is directed towards the performance of actions determined by humans and of benefit to humans (Aleksander 2017).

Taking a critical perspective, Ransbotham et al. (2016) identified and explained four mechanisms by which ubiquitous computing makes various entities (people, devices, organizations, societies) more vulnerable: increased interconnectedness, increased visibility, enhanced cloaking, and decreased costs. They argued that while ubiquitous computing benefits society in numerous ways, it unfortunately also has potential to create new vulnerabilities. Ransbotham et al. (2016) intended to stimulate thought and research into understanding and mitigating these vulnerabilities by outlining a research agenda for future research on digital vulnerabilities spanning four areas that are, or could become, significant societal problems with implications at multiple levels of analysis: online harassment and incivility, technology-driven economic inequality, industrial Internet of Things, and algorithmic ethics and bias (Ransbotham et al. 2016).

Taking an ethical perspective, Martin (2019) argued whether developers have a responsibility for their algorithms later in use, what they are responsible for, and the normative grounding for that responsibility. Algorithms silently influence our lives. Today, algorithms determine whether someone is hired, promoted, offered a loan, or provided housing as well as which political ads and news articles consumers see. Yet, the scope of responsibility for algorithms in these important decisions and the accountability of people developing the algorithms are not clear. Martin (2019) conceptualized algorithms as value-laden, rather than value-neutral, in that algorithms reinforce or undercut ethical principles, create moral consequences, and enable or diminish stakeholder rights and dignity. In addition, algorithms are important actors in ethical decisions and can influence the delegation of roles and responsibilities within these decisions. As such, organizations developing algorithms are accountable for determining how significant a role individuals would be permitted to partake in the subsequent algorithmic decision. Contrary to current arguments, Martin (2019) proposed that if an algorithm is designed to preclude individuals from taking responsibility within a decision, then the designer of the algorithm should be held accountable for the ethical implications of the specific algorithm in use.

Although AI has been studied from different perspectives in IS and management literature for three decades, theory development related to AI has been stagnant. Hence, scholars repeatedly advocate conducting new studies on AI and motivate developing theories related to AI. Kumar et al. (2018) studied the characteristics of problems at the interface between Operations Management (OM) and IS and reviewed past research that has been instrumental in setting the direction and tone of research at this interface. They extended their discussion to provide directions for future research in the domains of deep learning and AI, and Internet of Things and Industry 4.0.

Davenport et al. (2020) outlined a bright future for AI in marketing, in that AI is likely to substantially change both customer behaviors and marketing strategies. Building on not only extant research but also engaged interactions with practice, the authors proposed a multidimensional framework to understand the impact of AI, noting the importance of dimensions pertinent to task types, intelligence levels, and whether the AI is embedded in a physical robot. Whereas prior research had typically addressed a subset of these dimensions, Davenport et al. (2020) attempted to integrate all three dimensions in a single framework. Moreover, the authors proposed a research agenda that not only addresses how customer behaviors and marketing strategies will change in the future, but also highlights important policy questions relating to privacy, bias, and ethics. Furthermore, the authors suggested that AI will be more effective if it augments, rather than replaces, human actors.

Finally, Schuetz and Venkatesh (2020) suggested that AI artifacts, that demonstrate more human-like cognitive abilities, are not a typical technological advancement but an unprecedented advance toward human-like systems. Such systems can perceive their environments, adapt to situations, and interact with humans and other technologies. The increasingly human-like capabilities of such AI artifacts challenge five fundamental assumptions that IS researchers have held about how users interact with digital artifacts: (1) the direction of the user-artifact relationship, (2) the artifact's awareness of its environment, (3) functional transparency, (4) reliability, and (5) the user's awareness of artifact use. Schuetz and Venkatesh (2020) argued that the disruption of these five assumptions present a unique opportunity for novel theory development in and associated contributions to our extant body of knowledge on AI.

Building on that argument, Baird and Maruping (2021) posited that today's digital technologies are no longer passive tools waiting to be used by humans; they are no longer always subordinate to the human agent; and, they can now assume responsibility for tasks with ambiguous requirements and for seeking optimal outcomes under uncertainty. Although "information systems use" has been the dominant theoretical paradigm for explaining how humans apply digital technologies toward goal attainment, such a view gives primacy to human agency in the relationship between humans and technologies (Baird and Maruping 2021). As such, models and theories in the "information systems use" research stream tends to treat the technological artifact as a passive tool that lacks the ability to initiate action and accept rights and responsibilities for achieving optimal outcomes under uncertainty. Baird and Maruping (2021) argued that a new generation of "agentic" information systems and digital technologies requires revisiting the human agency primacy assumption. They introduced delegation, based on agent interaction theories, as a foundational and powerful lens through which to understand and explain the relationship between humans and digital technologies, and developed a theoretical framework around delegation that provides a scaffolding to guide future theorizing and focuses on the human–technology dyad as the elemental unit of analysis. Building on Baird and Maruping (2021), this dissertation (1) theorizes the agentic nature of today's digital technologies as material agency, and (2) presents the human-technology dyad as the entanglement of human and material agencies in conceptualizing, rationalizing, and realizing digital innovations.

2.4. Digital Mediation

The digital technologies of today are still limited in their capability to solve problems. Even the most sophisticated AI technologies of today are classified as narrow AI, implying that a particular AI artifact accomplishes tasks or solves problems in a narrow domain (Pennachin and Goertzel 2007). Examples of narrow AI include email spam filters (Sakkis et al. 2001), virtual assistants (Hoy 2018), algorithmic trading (Lins and Lemke 2014), medical diagnosis (Kermany et al. 2018), and self-driving cars (Thrun 2010). Although AI has surpassed humans in their ability to perform in some narrowly specified tasks—examples include IBM's Deep Blue defeating a world champion in chess (Warwick 2017), Google's AlphaGo defeating a Go master (Borowiec 2016), and IBM's Watson supercomputer out-performing human contestants to become the champion on the popular game show Jeopardy (Markoff 2011)—we are a long way from developing AI artifacts that would possess human-like capabilities of general intelligence. Many researchers predict that today's narrow AI research in different domains will eventually be incorporated into a machine with artificial *general* intelligence (AGI), combining all the narrow skills (Kurzweil 2005; Roberts 2016). Importantly, although AI artifacts far exceed humans in computational capabilities, they lack the contextual knowledge related to problems due to their narrow scope.

Hence, organizational practices require participation and interventions from humans who communicate, collaborate, and coordinate through mediation-dominant technologies. As modern organizations innovate new forms of work arrangements (Aguinis and Lawal 2013), such as virtual teams (Chudoba et al. 2005) and global outsourcing (Levina and Vaast 2008), they face challenges of discontinuities—stemming from physical locations, time zones, organizational affiliations, and national or professional culture—threatening cohesion of work (Chudoba et al. 2005). Mediation-dominant technologies bridge geographical, temporal, and cultural boundaries in highly distributed work arrangements that allow the involved actors to share information from the work space for joint decision making and problem solving (Jonsson et al. 2018). While mediation-dominant technologies can provide digital representations of the real-world, their main purpose is to help organizations interact with the environment (Kallinikos 2009). As such, mediation-dominant technologies transform organizations into complex sociotechnical systems (Benbya et al. 2020) with meta-human or human-in-the-loop (Rai et al. 2019) work arrangements that are co-created by the features of these technologies and the knowledge and experience of the people involved.

Since the early 1980s, organizations have been witnessing a considerable increase in the use of mediation-dominant technologies, such as digital communication and collaboration technologies. The networked personal computer, e-mail, the Internet, off- and online databases, the World Wide Web, electronic conferences, digital libraries, and chatbots are but a few of the mediation-dominant technologies that increasingly influence organizational practices. Semiotics—the study of the production, transmission and interpretation of meaning represented symbolically in signs and messages (Andersen 1990)—proposes six elements in any communication (Jakobson 1960; Mingers and Willcocks 2014; Mingers and Willcocks 2017); (1) producer: the person(s) or system(s) sending or initiating a message; (2) consumer: the person(s) or system(s) receiving and interpreting a message; (3) content: the meaning or information carried in a message within a particular context; (4) message: the particular sequence of signs or the form within which the content is expressed or represented; (5) code: the cultural system of meanings that underlies a message and allows the signs to convey meaning; and (6) medium: the physical mode of transmission of the message. Once the content of a message has been created and encoded, the producer makes it available for the consumer through a medium. The medium must have some form of physical embodiment that makes it accessible to the senses. Today's mediation-dominant technologies are primarily visual (e.g. screen, text, video), auditory (e.g. sound), or tactile (e.g. touchscreen), but they can also be virtual (e.g. virtual or augmented reality) (Schultze 2010; Schultze and Orlikowski 2010). A mediation-dominant technology used as the medium of communication is not merely some transparent or neutral means of message transmission that has no effects on the content or the appearance of the message, in most cases the medium is a rather essential part of the message (Mcluhan 1964; Mingers and Willcocks 2014; Mingers and Willcocks 2017). As such, a medium can be characterized in terms of its affordances— the things that the medium enables to happen or occur—and its liabilities— the things that the medium suppresses or disallows (Volkoff and Strong 2013).

As modern organizations digitalize work, people increasingly access and share information and work remotely with others mediated by technology (Jonsson et al. 2018). Mediation-dominant technologies provide not only an ability to capture and organize knowledge, but also a medium to enable different users to co-create and understand knowledge and quickly share it with other relevant stakeholders (Fowler 2000). IS literature recognizes such interrelationships between the technical and the social through the lens of practice theory (Feldman and Orlikoski 2011), based on a duality assumption in which the social and the technological are mutually constituting (Feldman and Orlikoski 2011). Such entanglement of digital technologies and social practices can manifest at individual, group, and organizational levels.

At the individual level, material agency and human agency are entangled in the sense that features of technology that provide opportunities for or constraints on action (Leonardi and Barley 2008, p. 162) do not exist independently in ready-made forms, but rather emerge from the entanglement in practice with the purpose, goals, and plans of human agency (Pickering 1993; Yoo 2010). Therefore, as individuals' activities are entangled with various digital artifacts, the contour and possibilities of our everyday experience is constantly shaped and reshaped by material agency (Orlikowski 2007). Moreover, Dourish (2001) notes that “the source of meaning (and meaningfulness) is not a collection of abstract, idealized entities; instead it is to be found in the world in which we act, and which acts upon us” (p. 116). Therefore, as the material environment with which we interact is augmented with digital technologies that mediate our experiences, the constancy of the meaning of familiar everyday activities is dissolved (Yoo 2010). Thus, with the emergence of digitally mediated practices, the meaning of everyday activities is transformed.

At the group level, as we use mediation-dominant technologies with others, we orient ourselves toward an artifact to interact with others who may or may not be co-present (Yoo 2010). Digitalization of organizational practices fuels transformations in a way where distributed agency exists not only in relation with technology artifacts, but also with space, time, and other individuals (Yoo 2010). Hence, digital technology influences our experience of time and space as we engage in group interactions in virtual spaces (Yoo 2010), in that the evolution of modern communication technology has lifted out social life from the here and now, causing a separation between time and space (Giddens 1990). As many of our group interactions are mediated and shared through digital technologies, our knowledge and experiences are shaped through subtle, but constant negotiations with others as we orient ourselves toward these artifacts. Development of digital mapping technologies, sensor networks, digital tagging of physical locations and artifacts, and smart mobile devices that can interact with these digitalized artifacts create a complex hybrid network of people, places, artifacts, tools, and contents resulting from on-going interactions among them (Yoo 2010).

At the organizational level, as organizations try to embed various forms of mediation-dominant technologies into their products, services, and processes (Yoo 2010), work is moving out from the office into a multiplicity of new locations (Felstead and Jewson, 2000; Felstead et al., 2005), changing the nature of work both within and beyond managerial and organizational boundaries. Digital innovation is directly influencing the way organizations innovate and thus create strategic disequilibrium in the market (Fichman 2004; Lyytinen and Rose 2003; Swanson 1994; Swanson and Ramiller 1997, Swanson and Ramiller 2004). Digital innovations in products and services will likely affect the organizational capability and structure (Tripsas 2009) and institutional relationships (Benner 2008), changing the nature of reciprocal relationship between the identity of actors and the artifacts they produce (Sennett 2008). The social heterogeneity and technological malleability of digital technology will make digitalized products generative, the capacity to produce unprompted changes driven by heterogeneous uncoordinated actors (Tuomi 2002; Zammuto et al. 2007; Zittrain 2006). As digitalized products become more generative, and their innovations thus become more unbounded, the organizational challenges to manage the innovation process will become increasingly nonlinear and complex (Boland et al. 2007; Van de Ven et al. 1999).

At the group and organizational levels, individuals need to collaborate and coordinate their work to achieve organizational goals. Mediation-dominant technologies have been shown to support both temporal and contextual coordination of activities (Bardram 2000; Chua and Yeow 2010). The coordination of emergent and provisional collaborative work involves activities and interactions among humans and digital technologies not explicitly prescribed by management in advance (Venters et al. 2014). This approach emphasizes the role of spatiality, contextuality, and temporality in collaboration and coordination processes, which require synchronization and appropriate resource sharing (Bardram 2000; Kellogg et al. 2006; Reddy et al. 2006) and that the emergent dynamics of collaboration and coordination can be accounted for by highlighting the temporally unfolding and contextually situated nature of work (Faraj and Xiao 2006; Kling et al. 2001; Monteiro and Hanseth 1995). Hence, studies have examined the collaboration and coordination mechanisms through digital tools, technologies, and interactions, thereby encapsulating how emergent practices assist individuals in realizing a collective performance (Kellogg et al. 2006; Kling 1991). Further, they have noted the impact of variable time horizons and temporal rhythms in complex work (Reddy et al. 2006).

The computer supported cooperative work (CSCW) literature reveals that organizational practices depend heavily on tools, technologies, and environments as integrating mechanisms for the social production of action (Barley and Kunda 2001; Schmidt and Bannon 2013). The challenge of mediation-dominant technologies that support the coordination of cooperative work activities, is that they not only have to support the execution of the underlying theory built into a model, but also the practice of what needs to be done under current conditions by transforming some normative construct (e.g. plan, procedure, contingency) into appropriate executable action (Negoita et al. 2018; Schmidt and Bannon 2013). In other words, the model underlying such technologies (e.g. ERP, CRM, SCM) breaks down in view of the situated nature of work (Negoita et al. 2018; Schmidt and Bannon 2013). Consequently, collaboration and coordination technologies need to support practitioners in making the technologies an integral part of their practices (Negoita et al. 2018; Schmidt and Bannon 2013). The limitation is fundamental, in that the discourse model underlying such technologies is predicated on a strict abstraction from the materiality of work practices and from the organizational arrangement in which the practices are embedded (Negoita et al. 2018; Schmidt and Bannon 2013).

In Jonsson et al.'s (2018) study of a mining company they investigated digital sensor technologies to monitor its machinery including mills, transportation belts, gearboxes, elevators and shaking tables based on data about temperature, vibrations, pressure, speed and more of relevant components (Jardine et al., 2006). They found that recording, monitoring, and analyzing such data afforded assessment of a machine's condition and predict breakdowns. At the same time, this condition-based approach developed a new maintenance organization where a remote center with specialized analytic capabilities monitored and diagnosed machinery from across multiple organizations. This new, distributed organization integrated remote and onsite work and applied diagnostic software to continuously produce a digital version of each machine based on sensor data. In this arrangement, remotely located analysts with skills in interpreting sensor data analyzed and compared information about machines operating in different organizations and industries and they utilized mediating digital technologies to collaborate closely with onsite workers. As such, Jonsson et al. (2018) showed how digital technologies enable collaboration and coordination among individuals across spatial, temporal, contextual, and organizational boundaries by mediating work practices.

Leonardi (2011) suggested that employees in today's organizations increasingly collaborate and coordinate by working with flexible technologies and flexible routines, that are intimately tied to the technologies and enable social interactions through the imbricated nature of human and material agencies. Thus, the imbrication metaphor, similar to the notion of entanglement, helps us understand how the social and the material become interwoven in practice and continue interlocking in ways that produce the infrastructures that people use to get their work done. Scholars have suggested that organizational routines are often designed to be flexible (Essen 2008; Howard-Grenville 2005), arguing that people can alter the performance of a routine—their patterns of social interaction—while still maintaining its ostensive qualities—the broad understanding of what the routine should do (Feldman and Pentland 2003). Digital technologies are also increasingly flexible in the sense that people have resources to redesign, reinvent, and reconfigure their material features so that the technology does new things. Thus, when people work with both flexible routines and flexible technologies and wish to change their work practices, they have a choice between changing the routine or changing the technology. Leonardi (2011) showed that the increasing flexibility of routines and technologies in organizations affords an opportunity to look more closely at the way in which human and material agencies change in response to one another. Influenced by past patterns of imbrication, the concordant changes constitute and bring reconfigurations to the routines and technologies through which practices are accomplished (Leonardi 2011). When both routines and technologies are flexible, human and material agencies are in a process of continual imbrication such that the organizational arrangements they constitute are always in flux.

Leonardi and Bailey (2008) showed how routines and organizational practices change to accommodate digitally mediated collaboration and coordination across spatial, temporal, contextual, and organizational boundaries. Addressing the knowledge transfer problems that arise when communication and storage technologies are employed to accomplish work across time and space, Leonardi and Bailey (2008) studied an organization that sent engineering tasks from home sites in Mexico and the United States to an offshore site in India through computer-aided engineering applications. These applications transform input, such as, physical dimensions, location coordinates, and material properties, into computational models that can be shared electronically among engineers around the world as they work together. Digital artifacts created via such technologies often embody implicit knowledge that must be precisely communicated and interpreted to successfully act upon the artifacts. Leonardi and Bailey (2008) explored what problems might arise in interpreting this implicit knowledge across time and space, and how individuals might remedy these problems by changing organizational practices. To resolve and prevent such knowledge-related problems, individuals from the home sites innovated five new work practices to transfer occupational knowledge to the offshore site—defining requirements, monitoring progress, fixing returns, routing tasks strategically, and filtering quality—that revolved around transferring primarily occupational knowledge, and to a lesser extent product and organizational knowledge, to the offshore site. All five practices arose solely because digital technologies were employed to mediate the collaboration and coordination of engineering tasks that would otherwise have been completed by sending engineers form the offshore site to the home sites.

2.5. Summary

In organizational practices, the material agency of digital artifacts is entangled with human agency in a variety of figurations (Lehrer et al. 2018; Leonardi 2011). Jonsson et al. (2018) proposed to distinguish between digital representation and digital mediation figurations as two complementary ways in which digital technologies are implicated in organizational practices. While digital representation focuses on the content, i.e., how digital technologies are used to monitor and produce digital content, digital mediation focuses on the medium, i.e., how digital technologies can be used for digitally mediated cooperative work. In the same way as Zuboff (1988) focused on automate and informate as fundamental characteristics of information systems, Jonsson et al. (2018) zoomed in on representation and mediation as key characteristics of how digital innovations shape contemporary work arrangements. Although digital representation and digital mediation figurations may exist independently of each other, many contemporary organizational practices are produced through their coexistence (Jonsson et al. 2018). Table 2 summarizes the key concepts in the background literature that informs our empirical analyses and subsequent theorizing.

Table 2: Key Concepts in Background Literature	
Concept	**Definition**
Digital Technology	Combinations of information, communication, computing, and connectivity that makes products and services reprogrammable, addressable, sensible, communicable, memorable, traceable, and associable (Bharadwaj et al. 2013; Yoo 2010; Yoo et al. 2010a).
Digital Innovation	Introduction and application of novel solutions, enabled by digital technologies, that lead to the transformation of sociotechnical structures that were previously mediated by nondigital artifacts or relationships (Yoo et al. 2010a).
Human Agency	Humans' capacity to form and realize their goals (Lehrer et al. 2018; Leonardi 2011).

Material Agency	The capacity possessed by digital technologies to act on their own apart from human intervention (Lehrer et al. 2018; Leonardi 2011).
Figuration	An empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013).
Digital Representation	A figuration in which digital technology is used to monitor and produce a particular work space (Jonsson et al. 2018; Ramaprasad and Rai 1996).
Digital Mediation	A figuration in which digital technology is used to share and enact a particular work arrangement (Jonsson et al. 2018; Persson et al. 2009).
Representation-dominant Technology	A digital technology that predominantly supports digital representation.
Mediation-dominant Technology	A digital technology that predominantly supports digital mediation.

Digital innovations afford organizations opportunities to solve their business problems by innovating products and services as well as processes, structures, and business models (Haffke et al. 2017). Although there is substantial research on digital product innovation (Barrett et al. 2012; Beltagui et al. 2020; Kyriakou et al. 2017; Lee and Berente 2012; Leonardi 2010; Yoo 2013; Yoo et al. 2012), service innovation (Gaskin et al. 2010; Lehrer et al. 2018; Lusch and Nambisan 2015; Normann 2001; Robey et al. 2003; Tilson et al. 2010), and process innovation (Damanpour and Gopalakrishnan 2001; Jonsson et al. 2018; Oborn et al. 2019; Trantopoulos et al. 2017; Un and Asakawa 2015) and some research on business model innovation (Svahn et al. 2017), research is limited on how organizations conceptualize and realize digital innovations in the context of focused organizational transformation. Moreover, although representation-dominant technologies, such as AI and underlying data analytics, have been studied from an organizational perspective (Fowler 2000), a material agency perspective (Nissen and Sengupta

2006), a philosophical perspective (Aleksander 2017), a critical perspective (Ransbotham et al. 2016), and an ethical perspective (Martin 2019), and mediation-dominant technologies, such as digital communication and collaboration technologies, have been studied at the individual level (Leonardi and Barley 2008), collective level (Yoo 2010), and organizational level (Fichman 2004; Lyytinen and Rose 2003), there is a lack of theorizing on how these two types of technologies come together and complement each other in enabling organizations to realize their ongoing digital innovations in the context of focused organizational transformation. Furthermore, unless and until we develop representation-dominant technologies with complete autonomy, i.e., AI with human-like capabilities of general intelligence, there will always be humans in the loop in organizational practices, necessitating mediation-dominant technologies to facilitate communication, collaboration and coordination. Although digital innovation efforts are driven by such entanglement of human and material agencies that create digital representation and digital mediation figurations in organizational practices, there is a lack of theorizing on how organizations can realize digital innovations by exploiting such entanglement.

Against that backdrop, this dissertation empirically investigates how an organization successfully organized and managed its digital innovation initiatives as part of a large-scale organizational change program over an extended period based on multiple representation-dominant and mediation-dominant technologies. We find that the organization's success in digital innovation can be explained by its ability to combine and configure multiple representation-dominant and mediation-dominant technologies into new and productive organizational practices. Based on these empirical findings and extant literature, we propose a novel theory of organizational intelligence in digital innovation that explains how organizations can improve performance and support innovation over time by continuously entangling analytical and relational intelligence capability through multiple figurations of human and material agency.

Our conceptualization of figuration as an empirically observable entanglement of human and material agency in the constitution of organizational practices (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013) brings us closer to the root of IS discipline—the sociotechnical perspective (Sarker et al. 2019), which has, for long, been the axis of cohesion for the IS discipline, generating new IS research agenda and capturing the very essence of IS research (Avgerou et al. 2004; Bostrom et al. 2009; Chiasson and Davidson 2005; Lee 2004; Sarker et al. 2019; Sawyer and Jarrahi 2014). The sociotechnical perspective considers not only the technical artifacts but also the individuals and collectives that develop and use the artifacts in social (e.g., organizational, psychological, cultural, and economic) contexts (Briggs et al. 2010). As such, the sociotechnical perspective privileges neither the technical nor the social, rather views outcomes as emerging from the interactions between the two (Sarker et al. 2019). With our theory development based on figurations, we respond to the recent call by Sarker et al. (2019) to position our theory based on the fundamental and unique characteristic of IS research—the sociotechnical axis of cohesion.

CHAPTER 3. THEORETICAL FRAMING

3.1. Introduction

To survive and thrive, organizations need to collect, process, analyze, and interpret information and apply critical thinking and creativity to innovate products, services, processes, and business models. As such, organizations need intelligence—the capacity for understanding, analyzing, interpreting, learning, reasoning, planning, innovating, critical thinking, and problem-solving—to create and retain knowledge that can be applied towards changing and adapting the organization. Although, intelligence has been studied extensively in humans (Neisser et al. 1996), animals (Shettleworth 2009), and plants (Michmizos and Hilioti 2019), and in machines as AI (Russell and Norvig 2013), we have limited knowledge about it in organizational contexts. We argue that organizational intelligence can be a central concept in understanding and explaining how organizations manage digital innovations over time as part of focused organizational transformation. Moreover, we posit that, as new digital technologies demonstrate some form of intelligence, it is important to understand how they bring human and technological intelligences together in new organizational practices. Hence, in the following, as basis for our empirical analyses and subsequent theorizing, we elaborate and explain organizational intelligence in digital innovation as entanglement of analytical and relational intelligence in which human and material agencies come together in organizational practices.

3.2. Intelligence

Even though ideas about the nature of intelligence have existed for thousands of years (Cianciolo and Sternberg 2008), the definition of intelligence is still controversial (Legg and Hutter 2007). In an attempt to reach consensus on a definition, a group of 52 academic researchers (out of 131 invited) in fields associated with intelligence issued a public statement in the Wall Street Journal in 1994 titled “Mainstream Science on Intelligence” (Gottfredson 1997). In that statement the researchers defined intelligence as “a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—'catching on,’ ‘making sense’ of things, or ‘figuring out’ what to do” (Gottfredson 1997, p. 13).

Although much of what we know about intelligence has been discovered since the late nineteenth century, the first people to contemplate on the nature of intelligence were not psychologists or educators, but philosophers. The Greek philosopher Plato compared people’s intelligence to blocks of wax, differing in size, hardness, moistness, and purity, suggesting that a person whose block of wax was overly hard or soft and muddy or impure would suffer intellectual deficits (Cianciolo and Sternberg 2008). Much later, in the eighteenth century, philosopher Immanuel Kant proposed that there are different kinds or facets of intelligence, and that there is heterogeneity in the degree to which people possess them (Cianciolo and Sternberg 2008).

There has been a plethora of research on intelligence in modern psychology, yet “when two dozen prominent theorists were asked to define intelligence, they gave two dozen, somewhat different, definitions” (Neisser et al. 1996, p. 77; Sternberg and Kaufman 2011). In an effort to reconcile the dissimilar conceptualizations of intelligence, the Board of Scientific Affairs of the American Psychological Association published a report in 1995 titled “Intelligence: Knowns and Unknowns” (Neisser et al. 1996), in which the board found that although considerable clarity had been achieved in some areas of research on intelligence, no single conceptualization had yet answered all the important questions, and none commanded universal assent (Neisser et al. 1996). The board acknowledged the concepts of “intelligence” as attempts to clarify and organize the differences in the capability of individuals to understand complex ideas, to learn from experience in the internal environment, to adapt effectively to the external environment, to engage in various forms of reasoning, and to overcome obstacles by thinking (Neisser et al. 1996). Moreover, although such individual differences can be substantial, they are never entirely consistent: a certain person's intellectual performance will vary on different occasions, in different domains, as judged by different criteria (Neisser et al. 1996).

Although humans have been the primary focus of intelligence research, scientists have also investigated intelligence in animals and found some form of intelligence or cognitive ability in different species, such as dogs (Coren 2006), great apes (Premack and Premack 1983; Reader et al. 2011), elephants (Hart et al. 2001; Herculano-Houzel et al. 2014), rodents (Matzel and Sauce 2017), birds (Iwaniuk and Nelson 2003), dolphins (Gregg 2013; Marten and Psarakos 1994), fish (Ari and D’Agostino 2016), reptiles (Cooper et al. 2019; Gutnick et al. 2020), and cephalopods (Tricarico et al. 2014). These animals have demonstrated some form of cognitive ability of problem solving, numerical and verbal reasoning, innovation, habit reversal, social learning, and responses to novelty. Some researchers argue that even plants exhibit intelligence by sensing and modelling external and internal environments and adjusting their morphology, physiology, and phenotype accordingly to ensure self-preservation and reproduction (Trewavas 2003; Trewavas 2005).

Unlike the natural intelligence displayed by humans and animals, many of today’s digital or physical artifacts exhibit capability to perceive their environment and take actions that maximize their chance of successfully achieving pre-defined goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013). The term “artificial intelligence (AI)” is often colloquially used to describe machines that mimic cognitive functions associated with the human mind, such as learning and problem solving (Russell and Norvig 2013). Experts on AI divide AI into two types: artificial general intelligence (AGI), also called strong AI, and specialized AI, also called weak AI. Weak AI focuses on specific tasks and is already at work in our homes, cars, and workplaces, from digital virtual assistants to self-driving cars and all the way to unmanned land rovers that explore and photograph the surface of Mars (McPherson 2017). AGI, a long-time goal of AI researchers, would be a true thinking machine, with human-like capability to learn on its own and modify its own programming without human input. In theory, AGI would be able to solve any problem that a human could. AGI would not be narrowly tailored to perform a specific task in particular contexts, instead it would be able to deal with a broad range of problems and contexts (McPherson 2017).

The advent of AI has inspired the rational agent perspective of intelligence (Russell 2019; Russell and Norvig 2013). An agent can be any entity, natural or artificial, that acts in an environment (Poole and Mackworth 2010; Russell 2019; Russell and Norvig 2013). An agent typically cannot observe the state of the entire world directly; it has neither infinite memory nor unlimited time to act. Given its perceptual and computational limitations, an agent demonstrates intelligence by doing what is appropriate for its circumstances and goals, being flexible to changing environments and changing goals, learning from experience, and making appropriate choices (Poole and Mackworth 2010). Today's representation-dominant technologies act as rational agents by creating synthetic abstract models of the real world, monitoring and learning from the environment, and analyzing and predicting outcomes of real-world processes and systems. Today's mediation-dominant technologies also act as rational agents by facilitating human communication, collaboration, coordination, and intervention in new forms of work arrangements across geographical, temporal, and cultural boundaries. In this dissertation, drawing from the rational agent perspective of intelligence, we conceptualize individuals and digital technologies as rational agents in an organizational context. Moreover, we differentiate intelligence from knowledge in that, with the same amount and configuration of knowledge about the environment, rational agents with varying levels of intelligence would demonstrate difference in perceiving the environment and, hence, would reach different decisions. Knowledge is both the input to and the output from a rational agent's application of intelligence. As rational agents perceive an environment, they use existing knowledge as input to make sense of the environment, and from applying existing knowledge in decision making they produce new knowledge as output. Furthermore, we distinguish between two types of figurations in which intelligence of human agents comes together with intelligence of technological agents to form analytical intelligence and relational intelligence, respectively.

3.3. Analytical Intelligence

As defined earlier, analytical intelligence is the capability of an organization to apply digital technologies to analyze critical business data (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017). Analytical intelligence refers to the ability of an organization to process and apply logical reasoning by identifying patterns and making accurate predictions about the outcome of complex events (Koke and Vernon 2003; Sternberg 1985; Sternberg 1993). Moreover, analytical intelligence enables an organization to comprehend, reason, predict, plan, solve problems, think abstractly, innovate, and learn in ways that inform decision processes, enable effective actions, increase organizational knowledge, and help to establish and achieve business goals (Popovič et al. 2012; Wells 2008).

Organizations today encounter greater competition and faster dynamism in the marketplace due to globalization and rapid ongoing technological developments (Božič and Dimovski 2019). To gain, maintain, and improve its competitive advantage, an organization needs to constantly monitor and learn from its environment both inside and outside the organization. As such, the capability to quickly sense and respond to environmental changes in order to seize ephemeral market opportunities is essential for surviving and thriving in today's high-velocity environments (D'Aveni et al. 2010; Overby et al. 2006; Park et al. 2017; Sambamurthy et al. 2003). Digital technologies play an indispensable role in developing such organizational capability (Chakravarty et al. 2013; Lee et al. 2015; Lu and Ramamurthy 2011; Overby et al. 2006; Sambamurthy et al. 2003; Tallon and Pinsonneault 2011).

In today's increasingly digitalized business environments, organizations strive to achieve the capability to quickly sense and respond to rapidly changing environments by investing in digital technologies that can collect, store, and analyze data (Park et al. 2017). As a prominent example, enterprise systems have rapidly evolved to become fused with business processes (Park et al. 2017). Organizations can, both internally and externally, use such technologies in their interactions with employees, customers, and partners (El Sawy 2003; Yoo 2010; Zammuto et al. 2007), and collect data at every interface and interaction in business processes, supply chains, and transactions (Chen et al. 2012; Wixom et al. 2014). Such data produced through the use of enterprise systems (Aral et al. 2012; McAfee 2002) are complemented by other data, such as individuals' activities, locations, relationships, clickstreams, and keyword searches, all of which can offer comprehensive information about the internal and external environment of the organization (Wu and Brynjolfsson 2014; Wu et al. 2020).

Consequently, today's organizations have access to a plethora of data, a phenomenon known as big data. The most accepted conceptualization of big data proposes a definition encompassing the three Vs: volume, variety, and velocity (Douglas 2001), as supported by many studies (Lycett

2013; McAfee and Brynjolfsson 2017; Raghupathi and Raghupathi 2014; Russom 2011). Volume refers to the amount of data, which is increasing rapidly due to the widespread use of smart devices and digitalization of content (Newell and Marabelli 2015; Rusitschka et al. 2014). Variety refers to the sources and types of data: organizations are now dealing with structured data (e.g., numbers, dates), semi-structured data (e.g., XML documents), and unstructured data (e.g., social media data, videos) from within and outside the organization (Abbasi et al. 2016; Li et al. 2008). Velocity refers to the speed at which the data is generated, which is almost in real-time (Ertemel 2015).

Big data is so comprehensive and rapidly generated that human agency alone is inadequate for analyzing it. The formidable challenge of effectively manipulating big data to derive business value necessitates the use of data analytics technologies (Lycett 2013; Yulinsky 2012) to process, transform, and analyze data, find patterns, extract useful insights, and support or automate decision making in a timely manner (Wu et al. 2020). Data analytics refer to a combination of representation-dominant technologies, systems, methods, processes, and tools based on programming, statistics, predictive analytics, data mining, and natural language processing (Russom 2011; Wu et al. 2020) to acquire, store, analyze and transform business and market data into relevant knowledge for use in making better business decisions (Chen et al. 2012; Davenport et al. 2012; Wixom and Watson 2012). These analyses and decision-making processes can be automated using AI. Such use of representation-dominant technologies emphasizes the notion of "data as a resource" (Arthur and Owen 2019; Kambatla et al. 2014) and that incorporating data, and knowledge extracted from data, in decision making can confer competitive advantage to organizations (Brown et al. 2012; Brynjolfsson et al. 2011; Bughin et al. 2010; LaValle et al. 2011).

Representation-dominant technologies, such as data analytics and AI, can provide knowledge workers timely access, effective analysis, and intuitive presentation of the right information, enabling them to make the right decisions or take the right actions (Popovič et al. 2012). Acting as rational agents, such technologies demonstrate intelligence by providing information about past or current events, finding patterns in past events, helping organizations understand why something happened in the past, providing accurate projections of future happenings, and recommending one or more courses of action and showing the likely outcome of each (Ghasemaghaei et al. 2018). Thus, representation-dominant technologies can ostensibly help organizations to quickly sense and respond to important business events (Park et al. 2017) by generating business insights and improving organizational decision making (Cao and Duan 2015; Gillon et al. 2012; Petrini and Pozzebon, 2009). Consequently, organizational researchers have referred to data analytics artifacts as “rationality carriers” (Cabantous and Gond 2011), that have the potential to bring an organization to a higher state of analytical decision-making orientation with embedded analytical models (Kulkarni et al. 2017).

Representation-dominant technologies, as rational agents, not only demonstrate intelligence they also support unprecedented agility by massively reducing the time to access, analyze, and apply information in decision making (Seddon et al. 2017); a level of agility that humans as rational agents can never achieve on their own. For instance, IBM’s Watson computer required only one month to access and analyze 23 million medical papers from many different disciplines to identify 6 new proteins that are linked to many types of cancer suppressors, whereas it took 30 years for many human researchers to identify only 28 such proteins (Chen et al. 2016; Wu et al. 2020). Moreover, data analytics systems allow organizations to establish knowledge-creation routines as essential dynamic capabilities (Božič and Dimovski 2019) and to process considerable amounts of information, thereby facilitating the creation of new knowledge (Chen et al. 2015; Olszak 2014; Shollo and Galliers 2016). In some cases, such systems can replace human agency in routinized decisions (Wu et al. 2020), and in most cases, they enable more tasks to be performed by a single person, broadening decision authority through aggregation of data (Hammer 1990; Wu et al. 2020).

Although representation-dominant technologies can act as rationality carriers (Cabantous and Gond 2011), they are necessary but insufficient, by themselves, for developing organizational capabilities (Kulkarni et al. 2017; Ulrich and Lake 1991), such as analytical intelligence. "It is people who make analytics work and who are the scarce ingredient in analytic competition" (Davenport and Harris 2007, p.131), not the organization's access to sophisticated analytics technologies (Kulkarni et al. 2017). Colas et al. (2014) found that only a fraction of the organizations that invested in data analytics reported their initiatives as successful. Arguably, most organizations could not take full advantage of using these technologies due to the lack of available analytical skills of people (Colas et al. 2014; Ghasemaghaei et al. 2018). Hence, having the right talent and skills to analyze and interpret data are important factors in generating business insights from the use of data analytics that would lead to better organizational decision-making (Ghasemaghaei et al. 2018; Wong 2012). Consequently, Bharadwaj (2000) and Santhanam and Hartono (2003) include human resources—with their analytical, technical, and management skills and other intangibles such as knowledge assets, both explicit and tacit—in their conceptualization of organizational capabilities.

Consistent with Bharadwaj's (2000) and Santhanam and Hartono's (2003) frameworks, we emphasize the role of human analytical skills and domain knowledge in the conceptualization of analytical intelligence. Humans, as rational agents, bring into the organizational context the ability to process and apply logical reasoning by identifying patterns and making accurate predictions about the outcome of complex events (Sternberg 1985; Sternberg 1993). First, the domain knowledge and expertise of humans inform the analytics technologies what data to collect and include in analysis, how to analyze them, and for what objectives (Draganidis and Mentzas 2006). As such, the analytical skills of humans are transferred to and entangle with these technologies in organizational practices. Second, after analysis by technologies, it is humans who need to make sense of the results, frame the results in a particular context, combine knowledge from several contexts to understand the results, and finally decide on actions (Seddon et al. 2017), using human analytical intelligence. In other words, it is humans who have the complementing agency to look at the data, assign meaning to it, search for patterns, derive insights, and sense opportunities, not technologies (Seddon et al. 2017). Finally, it is human analytical intelligence that is used to develop and enhance such technologies. The requirements of these technologies are initially not completely clear (Wixom and Watson 2001) and evolve during use (Kulkarni et al. 2017). As a result, in most organizations, they undergo systematic, iterative enhancements based on human suggestions and reviews (Kulkarni et al. 2017). Using their analytical intelligence, humans control and steer the initial development and continuous enhancement process of such technologies by providing valuable input, such as changing data dimensions, evolving business rules, and resolving conflicts (Yeoh and Koronios, 2010).

As such, we posit that analytical intelligence manifests as figurations in which human intelligence comes together with technological intelligence to analyze data in decision making. Viewing organizations as information processing systems (Daft and Lengel 1986; Daft and Weick 1984; Galbraith 1973; Morgan 1986; Park et al. 2017; Thomas et al. 1993), we conceptualize how humans and technologies, as rational agents, complement each other's analytical intelligence in data-driven decision making. While technologies with their immense computing power scan, collect, filter, find patterns in, and learn from enormous amounts of data very quickly (Park et al. 2017; Seddon et al. 2017), humans with their cross-domain explicit and tacit knowledge interpret, make sense of, derive insights from, give meaning to, and learn from such analysis (Kulkarni et al. 2017; Seddon et al. 2017). Although technological intelligence can entirely replace the need for human intelligence in many routinized decisions (Wu et al. 2020), there are areas involving creativity and insight where human intelligence is still incontestable (March and Simon 1958; McAfee and Brynjolfsson 2017).

3.4. Relational Intelligence

We define relational intelligence as the capability of an organization to apply digital technologies to communicate, collaborate, and coordinate (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012).. As modern organizations digitalize work, people increasingly access and share information and work remotely with others mediated by technology, constituting new sociotechnical configurations and emerging practices (Jonsson et al. 2018). Today's distributed organizations continuously produce digital representations of reality. Relational intelligence alludes to the fact that organizational realities are constructed, co-created, and perceived through a relational process of sensemaking among many stakeholders (Dachler 1992; Maak and Pless 2006) with varied domain knowledge and intelligence. This relational process requires communication, collaboration, and coordination among stakeholders and is mediated by digital technologies. As such, relational intelligence manifests as figurations in which human communication enabled by technology facilitates collaborative practices.

An important aspect of intelligence is making sense of the internal and external environment (Gottfredson 1997). While humans (Neisser et al. 1996), animals (Shettleworth 2009), and plants

(Michmizos and Hilioti 2019) can make sense of their environment and construct reality individually, in the organizational context, perceiving the environment and co-creating reality involves knowledge of and intelligence in different domains (Dachler 1992; Maak and Pless 2006). Organizational sensemaking is based on the premise that reality is an ongoing accomplishment that emerges from efforts to create order and make retrospective sense of what occurs (Weick 1993). Such sensemaking involves active information seeking and sharing that provides insight into the meaning individuals and organizations ascribe to events through different forms of engagement and discourse (Hur et al. 2019). Thus, organizational sensemaking is a relational process of social construction (Berger and Luckmann 1966) in which meanings materialize through individuals' attempt to interpret and explain sets of cues from their environment (Maitlis 2005) with their corresponding domain knowledge and expertise. As such, organizations demonstrate collective intelligence that emerges from the collaboration, collective efforts, and competition of many individuals (Nguyen et al. 2019), mediated by digital technologies.

The computer supported cooperative work (CSCW) literature articulates organizational sensemaking with the concept of "awareness" (Schmidt 2002) to explain how digital technologies facilitate sensemaking among cooperating actors as they produce, gather, and redistribute information from everyday activities. Awareness refers to cooperating actors taking heed of the context of their joint effort, and it is achieved by practices through which cooperative activities are tacitly and unobtrusively aligned and integrated (Schmidt 2002). A stream of literature takes a communicational approach and studies the situated and distributed character of cooperative work, in which digital technologies facilitate communication among cooperating actors (Schmidt 2002). Another stream takes a computational approach and attempts to explain organizational sensemaking through a process in which digital technologies collect, disseminate, and integrate information concerning cooperative activities (Syri 1997; Prinz 1999). Regardless of the perspective taken, it is accepted in CSCW literature that awareness is achieved, and hence organizational sensemaking is realized, through collective use of digital technologies.

Although representation-dominant technologies, such as data analytics and AI, can analyze the environment, find patterns, make predictions, and prescribe actions (Russell and Norvig 2013), these technologies have insufficient knowledge of the problem domain (Russell et al. 2015). Humans, as rational agents, possess such domain knowledge to interpret, give meaning to, and extract insights from the findings of data analytics and AI analyses. Such interpretations may require knowledge about several domains possessed by different individuals. Moreover, although advanced data analytics and AI can predict outcomes and prescribe actions (Russell and Norvig 2013), they rarely provide explanation of or justification for the predictions and prescriptions (Russell et al. 2015). This necessitates human intelligence to unravel the reason and underlying mechanism of a probable outcome and to rationalize a course of action through a social process of considering alternatives, spanning multiple domains. Hence, a relational process of communication, collaboration, and coordination among humans, with cross-domain knowledge and expertise, becomes essential to interpret and act on the findings of digital technologies.

Mediation-dominant technologies, such as email, smartphones, and hand-held devices facilitate communication among individuals; information systems, such as enterprise collaboration systems, facilitate collaboration and coordination among individuals possessing cross-domain knowledge; and enterprise systems, such as knowledge management system (Zhang and Venkatesh 2017), enterprise resource planning (ERP) (Jacobs 2007), customer relationship management (CRM) (Mithas et al. 2005), facilitate knowledge sharing and transferring through a common repository of knowledge. Using such digital technologies, individuals share and combine knowledge across domains to solve a problem and in the process co-create new knowledge. As such, digital technologies mediate the essential social process of sensemaking among humans across spatial and temporal boundaries (Jonsson et al. 2018).

Another important aspect of intelligence is learning from experience (Gottfredson 1997). While humans (Neisser et al. 1996), animals (Shettleworth 2009), and plants (Michmizos and Hilioti 2019) have control over a single undivided memory system to store knowledge gained from experience and retrieve that knowledge in novel situations as necessary, in the organizational context, knowledge gained from experience is distributed among several memory systems of individuals and technologies (Weick and Roberts 1993). Organizational learning is defined in terms of acquiring, retaining, and transferring knowledge at the individual and group levels (Huber 1991, Robey et al. 2000), as the dynamic process of creating new knowledge and transferring it to when and where it is needed and used, resulting in the creation of new knowledge that needs to be retained for later transfer and use (Kane and Alavi 2007). Hence, organizational learning is related to the concept of knowledge management, which is also primarily concerned with the organization's ability to create and transfer knowledge (Kane and Alavi 2007). While knowledge management tends to emphasize the static stocks of knowledge held by an organization and the characteristics of that knowledge, organizational learning emphasizes the dynamic processes through which knowledge is developed by organizations (Vera and Crossan 2002). This knowledge creation is also a social process in which individuals combine and recombine their corresponding domain knowledge (Gruber et al. 2013). As such, knowledge creation, transfer, and retention can be regarded as social processes involving communication, interaction, collaboration, and discourse among organizational members (Kane and Alavi 2007).

Enterprise systems, such as ERP (Jacobs 2007), CRM (Mithas et al. 2005), can work as memory systems for an entire organization by acquiring, retaining, and transferring information across the organization, facilitating communication and collaboration among individuals. These systems can store information and knowledge of past experience that can be used to generate new knowledge by facilitating the sociotechnical process of organizational learning. Other information systems, such as knowledge management systems (Zhang and Venkatesh 2017) and learning management systems (Davis et al. 2009), can function as a repository of information and knowledge that is essential for organizational learning. Mediation-dominant technologies, such as communication and collaboration systems, enable the social process of learning from experience in which individuals combine and recombine their corresponding domain knowledge and experience. As such, organizational learning through knowledge creation, transfer, and retention manifests as social processes involving communication, interaction, collaboration, and discourse among organizational members mediated by digital technologies.

Finally, the most important aspect of intelligence is rationality—the ability to reason. The rational agent perspective (Russell 2019; Russell and Norvig 2013) assumes that an agent on its own typically cannot observe the state of all relevant parts of the real world directly; it has neither infinite memory nor unlimited time to act. Given its perceptual and computational limitations, an agent demonstrates intelligence by doing what is appropriate for its circumstances and its goals, being flexible to changing environments and changing goals, learning from experience, and making appropriate choices (Poole and Mackworth 2010). As such, the rational agent perspective reiterates the concept of bounded rationality—the idea that rationality is limited by the tractability of the decision problem, the cognitive limitations of the agent, and the time available to make the decision (Gigerenzer and Selten 2002; Simon 1955). Due to bounded rationality, decision-makers act as satisficers, seeking a satisfactory solution rather than an optimal one. When rational agents, both human and artificial, combine their intelligence and knowledge, they are able to gain more control over the decision problem, tackle problems that are more complex, overcome the cognitive limitations of a single agent, and work in parallel to reduce the time required to make the decision. Such collective reasoning requires a relational process, among rational agents, of knowing who knows what, communicating the unique knowledge and perspective of each agent, and devising a solution more satisfactory, if not optimal, than those developed by any single agent.

While individuals, with their diverse knowledge and expertise, offer different perspectives to the relational processes of rationality, digital technologies play an instrumental role in such relational processes. Enterprise systems, such as human resource management systems (Boon et al. 2019), keep track of the unique knowledge, skills, and perspectives of individuals in the organization. Such technologies facilitate the relational processes by identifying potential contributors to decision-making processes and sharing information about the contributors to others. Organizations can search and retrieve information about potential contributors and include them in the relational processes of decision making. While humans bring values, preferences, and beliefs as well as explicit and tacit knowledge to the relational process of devising solutions, digital technologies facilitate the process by providing a solution-space to search, evaluate, and identify possible solutions and a knowledge-space to communicate and debate on such solutions. As such, digital technologies are increasingly being used to share, mediate, and enact decision-making relational processes (Persson et al. 2009). As such, we posit that relational intelligence manifests as figurations in which human intelligence comes together with technological intelligence in decision making through communication, collaboration, and knowledge sharing.

3.5. Organizational Intelligence

We define organizational intelligence as an organization's capability to process, interpret, encode, manipulate, and access information in a purposeful, goal-directed manner (Glynn 1996).. Although Wilensky (1967) first coined the term “organizational intelligence” to refer to the input to the organization's decision making process (Huber 1990) and to the output or product of an organization's efforts to acquire, analyze, and interpret information external to the organization (Porter 1980; Sammon et al. 1984), we view organizational intelligence as the capability to undertake such processes, rather than to their input or output. Hence, an organization applies organizational intelligence to gather, process, and manipulate information and to communicate, share and make sense of the knowledge it creates. Today’s business environments are constantly changing through new digital innovations. To survive and thrive in such dynamic environments, an organization as a whole needs the capability to gather information about the environment, to make sense of the information gathered, to innovate, to generate knowledge, and to act effectively based on the knowledge it generates (Akgun et al. 2007). Organizational intelligence refers to such capability of an organization to reactively adapt to its environment based on its objectives and to proactively shape and change itself or the environment (Weber et al. 1996). An organization demonstrates its intelligence when it responds to the changing conditions, problems, and other issues in its environment in an adaptive manner by transforming itself (Doise and Mugny, 1984) or the environment (Weick et al. 2005). In this sense, intelligence is the disposition of an organization to reactively adapt to environmental changes (Akgun et al. 2007) or proactively enact new environmental changes (Weick et al. 2005).

Although intelligence has been studied extensively at an individual level referring to the basic cognitive processes, including perception, learning, encoding, memory, and reasoning of individuals (Glynn 1996), organizational intelligence emerges from the patterned interactions among individuals that constitute the organization (Brown and Duguid 1991; Lave and Wenger 1991). An organization is a system of "intersubjectively shared meanings" sustained through social interactions (Walsh and Ungson 1991, p. 60), in which organizational symbols, systems, structures, culture, patterns of interaction, and relational processes distribute and encapsulate organizational intelligence (Glynn 1996). Organizational intelligence arises from embedded interactions concerning the creation of meaning, the social construction of reality, and the development of organizational culture and symbolism (Glynn 1996). As such, in organizations intelligence exists beyond individuals, distributed within the structural and symbolic systems of the collective (Glynn 1996). Organizational intelligence is not simply the aggregate of the intelligence of its individual members since interactions can affect the relationship between the intelligence of individuals and the intelligence of the organization. In other words, an organization can be smarter than the sum of its individual members. While individuals are limited in their capacity to process information, this limitation is overcome by the collective. Conversely, however, individual members can collectively be smarter than the organization when organizational systems fail to institutionalize intelligent ideas or recognize the intelligent contributions of individuals (Glynn 1996).

The idea that an organization can exceed the sum of the capabilities of its individuals by processing information and thinking collectively is not new. Weick and Roberts (1993) developed the concept of "collective mind" to explain organizational performance in situations that require impeccable operational reliability in real-time. Studying the operations of a busy aircraft carrier, they assert that there are "a million accidents waiting to happen" (Wilson 1986, p. 21) in theory, yet almost none of them do, in reality. They explain such consistently reliable operation in a turbulent environment with the concept of collective mind. They conceptualize collective mind as a pattern of attentive interrelations of actions in a social system, consisting of many individuals. Actors in such social systems construct and conduct their actions, understanding that the system consists of connected actions by themselves and others, and interrelating their actions within the system. Ongoing variation in the aggregate mental processes of a collective mind influences comprehension of unfolding events and incidence of errors. As attentive interrelating and mindful comprehension increase, organizational errors decrease. Hence, organizations preoccupied with reliability spend more time and effort organizing for controlled information processing (Schneider and Shiffrin 1977), mindful attention (Langer 1989), and attentive action (Ryle 1949). These intensified efforts of collective minding enable people to understand more of the complexity in their environment and to respond with fewer errors.

While collective minding focuses on processing information by many individuals, due to the advent of digital technologies as rational agents, such technologies also become actors in the collective thinking and decision making. To capture this socio-technical phenomenon, we adopt the concept of figuration, which is an empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013. Our conceptualization of figuration emphasizes that rational agents, both humans and digital technologies, come together to form organizational practices, and that although human and material agencies are independently observable it is their entanglement that produces, sustains, or brings change to organizational practices. Similar to this concept of entanglement, Leonardi (2011) also relied on the notion of figurations to propose the concept of "imbrication," which means to arrange distinct elements in overlapping patterns so that they function interdependently. Building on Leonardi's (2011) argument, if we were to examine organizational intelligence applied in organizational practices under a microscope, we would discover two distinct types of figurations: analytical and relational intelligence, noticing that each figuration is made up of entangled building blocks of human and material agencies and how the two types of figurations entangled to produce organizational intelligence.

Organizational intelligence comprises both analytical intelligence and relational intelligence figurations. On one hand, organizations apply analytical intelligence to process critical business data to better understand its business and market and make timely business decisions (Jonsson et al. 2018). Analytical intelligence enables organizations to process and apply logical reasoning by identifying patterns and making accurate predictions about the outcome of complex events (Koke and Vernon 2003). Digital technologies as rational agents, through their capability to process, transform, and analyze huge amount of data, can acquire, store, analyze and transform business and market data and information into relevant knowledge for use in making better business decisions (Chen et al. 2012; Davenport et al. 2012; Wixom and Watson 2012). Such technologies contribute to organizational intelligence by providing information about past or current events, finding patterns in past events, helping firms understand why something happened in the past, providing accurate projections of future happenings, and recommending one or more courses of action and showing the likely outcome of each (Ghasemaghaei et al. 2018). Humans, as rational agents with their cross-domain explicit and tacit knowledge, contribute to analytical intelligence by applying logical reasoning, making sense of analyses and their results, deriving insights, identifying patterns, and making accurate predictions about the outcome of complex events (Seddon et al. 2017). As such, analytical intelligence enables organizations to comprehend, reason, predict, plan, solve problems, think abstractly, innovate, and learn in ways that inform decision processes, enable effective actions, increase organizational knowledge, and help to establish and achieve business goals (Popovič et al. 2012; Wells 2008) in dynamic environments.

On the other hand, organizations apply relational intelligence to accommodate socio-technical processes of sensemaking, learning from experience, and reasoning through communication, networking, collaboration, and coordination (Jonsson et al. 2018). Since organizational realities are constructed, co-created, and perceived through a relational process of sensemaking among many stakeholders (Dachler 1992; Maak and Pless 2006), relational intelligence facilitates active information seeking and sharing that provide insight into the meaning individuals and organizations ascribe to events through the different orders of engagement discourse (Hur et al. 2019). Such relational processes materialize meanings through individuals' attempts to interpret and explain sets of cues from their environments (Maitlis 2005), mediated by digital technologies. Moreover, relational intelligence facilitates the social processes of acquiring, retaining, and transferring knowledge at the individual and group levels (Robey et al. 2000), and creating new knowledge and learning from experience through combination and recombination of existing knowledge. Humans and digital technologies together, as rational agents, act as the memory systems for the entire organization, facilitating learning from experience. Furthermore, while individuals, with their diverse knowledge and expertise, offer different perspectives to the relational processes of rationality, digital technologies play an instrumental role in such relational processes. Humans bring values, preferences, and beliefs as well as explicit and tacit knowledge to the relational processes, whereas digital technologies mediate communication, collaboration, and coordination among humans that help them to rationally devise solutions, affording more control over complex problems and fueling data-driven decision making. Together, humans and digital technologies, with their relational intelligence, push the boundaries of bounded rationality.

As such, organizational intelligence comprises both human and material agencies in analytical and relational intelligence that entangle to support organizational practices. Organizations need analytical intelligence to create knowledge through analysis that would be interpreted through social processes using relational intelligence; conversely, organizations need relational intelligence to interpret and make sense of any knowledge co-created through analytical intelligence. Although, analytical and relational intelligence complement each other in organizational decision-making processes, in some cases one might dominate the other. Even though, in a certain decision-making process and at a certain point in time, organizations might require either intelligence more than the other or either intelligence only, organizational intelligence manifests as an ongoing entanglement of both analytical and relational intelligence.

3.6. Summary

Table 3 summarizes the key concepts in our theoretical framing that inform our empirical analyses and subsequent theorizing.

Table 3: Key Concepts in Theoretical Framing	
Concept	**Definition**
Intelligence	A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience (Gottfredson 1997).

Rational Agent	Any entity, natural or artificial, that demonstrates intelligence by acting in an environment in a way that is appropriate for its circumstances and goals, being flexible to changing environments and changing goals, learning from experience, and making appropriate choices (Poole and Mackworth 2010; Russell 2019; Russell and Norvig 2013).
Analytical Intelligence	The capability of an organization to apply digital technologies to analyze critical business data (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017).
Relational Intelligence	The capability of an organization to apply digital technologies to communicate, collaborate, and coordinate (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012).
Organizational Intelligence	An organization's capability to process, interpret, encode, manipulate, and access information in a purposeful, goal-directed manner (Glynn 1996).

In addition, Table 4 summarizes the perspectives involved in our conceptualization of organizational intelligence as entanglement of analytical and relational intelligence in which both human and material agency come together to form organizational practices. On one hand, digital technologies, as rational agents, can collect and analyze huge amounts of data, encapsulating complexity and reducing the analysis time. Through such analyses, these technologies can create digitalized abstract descriptions of the environment and predict future trends based on past data. Humans, as rational agents, can interpret the results of such analyses and make sense of the environment using situated cross-domain knowledge. Their interpretation and sensemaking can generate explanation of the environment and prescription for a course of action through theses and antitheses. Thus, in practice, digital technologies and humans together produce analytical intelligence figurations of organizational intelligence.

On the other hand, humans can network among themselves to combine and recombine knowledge in sensemaking and interpretation of the environment, leading to collaboration and co-creation of knowledge. Digital technologies can play an instrumental role in such collaborations by providing access to and sharing data, information, and knowledge about the environment. Such digital mediation enables communication, collaboration, and coordination and facilitates learning from experience through connected actors and shared knowledge across the organization. Thus, in practice, humans and digital technologies together produce relational intelligence figurations of organizational intelligence.

Table 4: Perspectives in Organizational Intelligence		
	Analytical Intelligence	**Relational Intelligence**
Human Agency	**Process:** interpreting data and making sense of the environment **Outcome:** explanation of the environment and prescription of action	**Process:** networking to connect actors and combine knowledge about the environment **Outcome:** collaboration and co-creation of knowledge
Material Agency	**Process:** collecting and analyzing data about the environment **Outcome:** description of the environment and prediction of trends	**Process:** providing access and sharing knowledge about the environment **Outcome:** connected actors and shared knowledge

Together then, organizational intelligence comprises both human and material agencies in which analytical and relational intelligence entangle to support organizational practices. As such we identify four different but connected components (see Table 4) of organizational intelligence: (1) analytical human agency, (2) analytical material agency, (3) relational human agency, and (4) relational material agency. Although in some organizational practices and decision-making processes, one of these components may dominate, organizational intelligence manifests as an ongoing entanglement among these components.

Our conceptualization of analytical and relational intelligence as entanglement of human and material agency positions our theory of organizational intelligence closer to the root of IS discipline—the sociotechnical perspective (Sarker et al. 2019). Specifically, our research falls into type IV of IS research along the sociotechnical axis of cohesion in which the social and the technical together produce outcomes through their interplay (Sarker et al. 2019). More specifically, our theorization builds upon the critical realism tradition of the socio-material perspective (Leonardi 2011, 2012, 2013), in which socio-material entanglements of human and material agencies, which are ontologically separate, result in new affordances, constraints, and routines related to organizational practices (Leonardi 2011). As such, we respond to the recent call by Sarker et al. (2019) to position our theory based on the fundamental and unique characteristic of IS research—the sociotechnical axis of cohesion.

CHAPTER 4. CONTEXTUALIST INQUIRY

4.1. Introduction

Rapid and pervasive digitalization is changing the nature and structure of products, services, processes, and business models (Nambisan et al. 2017), leading to the emergence of digital innovations (Kohli and Melville 2019; Nambisan et al. 2017) and consequent transformation of economic, technical, and social systems (Kohli and Melville 2019; Nambisan et al. 2017; Svahn and Henfridsson 2012; Yoo 2010; Yoo et al. 2010a; Yoo et al. 2012). Such disruptive transformation is rendering previous systems, processes, and roles inadequate (Nambisan et al. 2017) and challenging organizations to cope with dynamic business landscapes as they apply digital technologies to improve their competitive positions (Kohli and Melville 2019). In order to sustain and improve their performance in digitalized business environments, organizations sense and respond to new opportunities and threats through continuous adaptations and proactive transformations (Tanriverdi et al. 2010), that require breaking existing norms and practices and adopting new ones. As such, the consequence of digital innovation is complex organizational transformation. Hence, we adopt contextualist inquiry as a frame for investigating digital innovations and advancing new theory.

Pettigrew (1985, 1987, 1990) proposed contextualist inquiry as a theory of method to study organizational change. Contextualist inquiry posits that the phenomena and outcomes of organizational change can be examined through the interactions among context, content, and process of change (Pettigrew 1985, 1987, 1990). Context of change refers to the environment in which organizations and stakeholders operate and is further delineated as outer and inner context. Outer context describes the environment that the organization operates in, including social, competitive, economic, and political factors. Inner context refers to features of the structural, cultural, and political environment inside the organization through which ideas for change proceed. Content of change is the area subjected to transformation including business models, value propositions, technologies, systems, organizational structures, routines, and processes, and the people involved. Process of change refers to the continuous and interdependent sequence of actions and events in the origins, continuance, and outcome of the transformation. Processes are studied from two dimensions, the vertical and the horizontal. The vertical dimension refers to the interdependencies between higher and lower levels of analysis, while the horizontal dimension provides a temporal view of the transformation.

Contextualist inquiry is particularly well suited to study organizational change processes and can provide a comprehensive view of the challenges and opportunities involved in complex organizational transformations. As such, contextualist inquiry has been adopted in some organization and IS research. Weaver et al. (2015) combined the perspectives offered by contextualist inquiry and actor–network theory (Latour 2005) to propose an integrative framework on how organizational citizenship behavior develops in a large, heterogeneous organization, through a detailed case study of recycling at a large university. Due to lack of a formal organizational structure to address sustainability concerns in a university, the recycling initiatives are mainly voluntary and emerging in nature, and outcomes are, as a consequence, highly uncertain, and fragile. They argued that contextualist inquiry and actor–network theory combined provided novel and crucial insights into the emergence, development, and establishment of organizational citizenship behaviors, and that outcomes are contingent upon interactions between the content, context, and process of such initiatives and the related networks of human and non-human actors.

Mindel and Mathiassen (2015) advanced research into administrative health information technologies, drawing on contextualist inquiry framework of organizational transformation. Stating that while IS research increasingly focused on clinical health information technologies, potential of digital technologies as an enabler of hospitals' administrative activities remained by and large unexplored, they reviewed the diverse body of academic literature related to revenue cycle management of US non-profit hospitals and juxtaposed the findings with the prevalent discourse in practitioner publications. Their analyses revealed major gaps between extant theory and the problems faced in practice. Drawing on these insights they proposed research themes and theoretical lenses that can help bridge the gap between theory and practice of revenue cycle management.

Napier et al. (2011) applied contextualist inquiry to develop a framework that integrates a generic process for improving software organizations with existing theory on contextual ambidexterity, through an action research study of a small software firm. They applied their framework to analyze how the software firm improved its coordination of products, projects, and innovation efforts. Like all software organizations, the focal firm increasingly faced contradictory strategic choices as they developed customized and packaged solutions for the market: it needed to explore new technology and market opportunities while simultaneously exploiting software products in relation to existing customers; adapt to emerging customer needs while at the same time improving efficiency of software development processes; and, consider both incremental and radical innovations. Claiming that the integration of such opposing strategies requires software organizations to become ambidextrous, the authors offered principles on how software managers can build ambidextrous capability to improve firm-level coordination.

While contextualist inquiry can be applied as a method for empirical investigations, the three aspects of contextualist inquiry can also inform theory development related to organizational transformation (Pettigrew 1985, 1987, 1990; Van de Ven and Poole 2005). Since we are developing a process theory of how organizational intelligence is implicated in an incumbent organization's digital innovations in the context of focused organizational transformation, we adopt contextualist inquiry to provide a comprehensive view of three aspects of digital innovations in which analytical intelligence and relational intelligence of humans and technologies interact to support organizational practices to realize organizational transformation.

4.2 Context of Change

The outer and inner contexts of an organization both influence and are influenced by its digital innovations. Although factors in the outer context originate from cultural, societal, technological, political, or geographical conditions (King 1990; Wejnert 2002) in the market, industry, sector, or economy outside the organization, they influence organizational activities and decision making (Jemison 1981). Organizations conduct activities related to the influential factors of the outer context as they obtain inputs from, respond to demands in, and offer services or products to the outer context. The outer context provides organizations both opportunities—information, resources, technology—and constraints—regulation, restriction, competition (Damanpour and Schneider 2006). Digital innovations can change the organization in response to and impact the constraints in the outer context by exploiting new opportunities. Moreover, innovation scholars have often posited that the primary stimulus for innovation and change come from the outer context. Hence, characteristics of an organization's outer context are critical to its ability to innovate (Camison-Zornoza et al. 2007).

While the outer context of an organization establishes the opportunities and constraints for potential change through digital innovation, the inner context informs decision makers on what changes are necessary and feasible (Armenakis and Bedeian 1999). As such, an organization needs to appreciate its inner context of structural, cultural, and political arrangements to ascertain and realize possible digital innovations (Camison-Zornoza et al. 2007). The current structures in an organization display inertia to (Cameron and Green 2019) and influence the outcome of (Sirkin et al. 2005) any change initiative. While organizational structures are static and rigid influencers of change, culture affects change in a dynamic way from initiation through realization (Cameron and Green 2019). Finally, authority and power dynamics inside an organization both influences and is influenced by change initiatives (Cameron and Green 2019). Moreover, it is the inner context of an organization that affords development and application of resources and capabilities to realize change.

The inner and outer contexts of an organization emphasize digital innovation as a dynamic problem–solution design challenge (von Hippel and von Krogh 2016) in which digital innovation management becomes a sporadic, parallel, and heterogeneous generation, forking, merging, termination, and refinement of problem–solution design pairs (Nambisan et al. 2017). Innovation problems are primarily associated with unidentified and latent needs of stakeholders, while solutions refer to the functionalities, features, and affordances of digital technologies and the surrounding sociotechnical configurations. As such, digital innovation involves the continuous matching of the capabilities of new or newly recombined digital technologies with unidentified or unmet needs. Thus, with an understanding of the context of change, digital innovations can be viewed as ongoing couplings between stakeholder needs, digital technology features, and related sociotechnical configurations.

4.3. Content of Change

The content of change refers to the specific areas of transformation, including business models, technologies, organizational structures and processes, and the people involved. Digital innovations have the potential to transform an organization’s existing business model, including its value proposition (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). A business model defines how an organization creates, captures, and delivers value to its customers, and then converts earnings into profits or a sustained competitive position (Teece 2010). As such, the business model includes identity, core values, resources, and value proposition of an organization. The features and functionalities of digital technologies afford an organization substantially new opportunities to create, capture, and deliver value to its stakeholders that is embodied in or enabled by digital technology (Fichman et al. 2014). Due to pervasive digitalization, digital innovation has in this way become the primary driver of business model change in recent years (Teece 2010).

An organization’s technologies, and how organizations use them to create value, is another specific content that changes with digital innovation. With the digital revolution of cyber-physical systems that has been unfolding since the middle of the last century, the digital technologies that underlie computers, robots, and smart equipment are changing rapidly, becoming more powerful, and transforming organizations much faster than in the past (Demirkan et al. 2016). Enabled by the layered modular architecture of digital technologies, digital innovations generate potential opportunities to advance and realize further innovation and to upgrade the current technology portfolio of organizations (Yoo et al. 2010).

To reap the benefits of digital innovations, organizations need to change their existing structures and processes. Digital technologies alter how value is generated and offered to stakeholders. One of the critical barriers to novel ways of value generation is the inertia and unsuitability of current organizational structures and processes to execute new strategies (Porter and Heppelmann 2015). At the core of the problem lies the uncertainty organizations face about where and how to allocate and align digital capabilities within their organizational structures and processes (Bilgeri et al. 2017). Realization of digital innovations necessitates novel structural and processual configurations and development of capabilities that transcend traditional functional boundaries (Agarwal and Sambamurthy 2002). Furthermore, while it seems evident that organizations are in need of new digital skills and competencies to successfully transform themselves, it often remains unclear where to position new capabilities within the existing organizational structures and how to design newly introduced processes and entities (Porter and Heppelmann 2015). As such, digital innovations force organizations to transform their existing structures and processes to accommodate new forms of organization.

Finally, digital innovations are only as effective as the level of knowledge, skills, capabilities, and expertise of the people who apply them in organizational practices. Permeation of novel and divergent digital technologies in the global workplace has changed the nature of work and the roles that people play in applying these technologies to ensure the effective performance of organizations (Fenech et al. 2019). The possibility of billions of people connected by digital communication and collaboration technologies, in conjunction with unprecedented processing power, storage capacity, and access to knowledge via data analytics and AI technologies, creates enormous opportunities as well as formidable challenges for organizations (Zehir et al. 2020). As such, human resource development is a specific content of change that is key for reaping the benefits of digital innovations.

4.4. Process of Change

The process of change refers to the continuous and interdependent sequence of events that shapes the origins, continuance, and outcome of change, including the vertical dimension of interdependencies between higher and lower levels of change, and the horizontal dimension of how change unfolds over time (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). Through the process of change, an organization continually renews its structures, capabilities, and direction to serve the evolving needs of internal and external stakeholders (Moran and Brightman 2001). In the presence of pervasive digital innovations, the process of change is omnipresent and perpetual, both at an operational and a strategic level (Burnes 2004), occurring continually over time at every level of the organization.

The horizontal dimension of the process of change denotes the temporal development of events and emphasizes a social construction in which time is conceived as not just a long sequence of simple and uncomplicated events (Ladurie 1979; Pettigrew 1990), but rather with events as stepping stones that together form “the persistent patterns of the long term” (Ladurie 1979, p. 111). Hence, as the process of change is carried out in organizations, the horizontal dimension represents how the discrete events, that make up the experience of change, are generated and executed (Morgan 1986). What is critical is not just the events but the underlying logics of the unfolding process of change that give events meaning and significance (Pettigrew 1990). As such, the horizontal dimension of the process of change not only narrates a sequence of events chronologically, but also reveals the underlying logics in those events, interprets patterns in those events, locates when they occur in socially meaningful time cycles, and explains how and why these patterns occur in particular chronological sequences (Pettigrew 1990).

The vertical dimension of the process of change focuses on how change progresses at different levels—individual, group, organizational—within an organization, along with interdependencies among higher and lower levels. While large-scale change at the organizational level does not occur without widespread changes at the individual level, changes at the individual level in turn are catalyzed by changes at the organizational level (Whelan-Berry and Gordon 2000). As such, change can be conceptualized as 'top-down' or 'bottom-up' based on the roles played by people across the hierarchy (Raes et al. 2011). Top-down change is initiated higher up in the hierarchy (Carpenter et al. 2004) and executed by individuals at lower levels (Balogun and Johnson 2005), whereas bottom-up change is conceptualized or suggested by individuals (Glaser et al. 2016) and gets authorized and institutionalized at the organizational level (Friesl and Kwon 2016). In a specific process of change there can be interactions between top-down and bottom-up flow of change. As such, the vertical dimension of the process of change captures the nonlinear cross-level progress and attainment of organizational change.

Finally, the process of change requires a motor or theory to effectuate change (Pettigrew 1985; Pettigrew 1987). Throughout the cross-level, perpetual, and nonlinear process of change organizations, groups, and individuals rely on theories to make decisions and on motors to execute decisions (Cameron and Green 2019). We develop and put forth organizational intelligence as a theory that explicates and as a motor that drives the process of change in digital innovations, and as a capability that is recursively influenced by that process.

4.5. A Model of Digital Innovation

As basis for our empirical investigation and theorizing, we propose a process model of digital innovation, which is an adaptation of the interactions among context, content, and process, as suggested in contextualist inquiry (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). The process model was developed based on the initial theoretical framing and the preliminary analysis of the data. Figure 1 illustrates the three activities that together constitute the process of digital innovation: (1) understanding the context, (2) innovating the content, and (3) evaluating the outcome. Moreover, as Figure 1 suggests, the process of digital innovation is highly iterative in which there are (1) forward progressions from understanding the context to innovating the content further to evaluating the outcome, and (2) feedback loops from innovating the content to understanding the context, and from evaluating the outcome to both innovating the content and understanding the context.

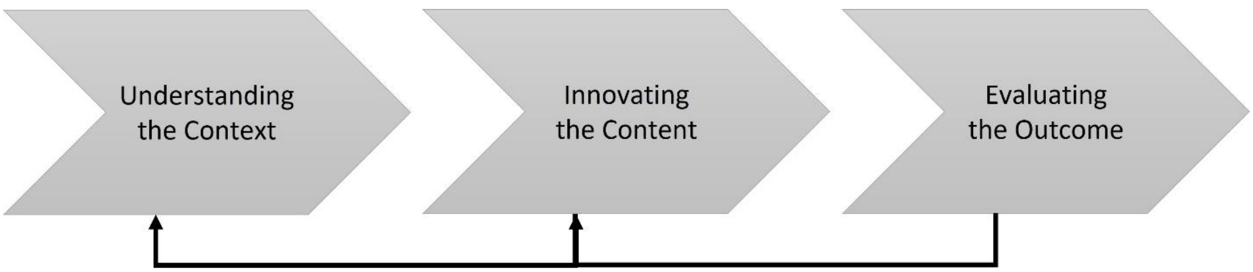

Figure 1: A Model of Digital Innovation

Understanding the context. In the first step of the process of digital innovation, organizational actors purposefully and proactively explore the inner and outer contexts of the organization in order to identify ways to achieve the organizational objectives of the focused transformation, challenges and obstacles in achieving such objectives, and how to overcome these challenges and obstacles by innovating and applying digital technologies. Since the outer and inner contexts of an organization change dynamically, organizational actors need to periodically explore the context.

Innovating the content. In the second step of the process of digital innovation, organizational actors innovate the content of change. With an understanding of the inner and outer contexts, organizational actors evaluate options and select appropriate content to innovate in order to achieve the organizational objectives of the focused transformation. In our case the innovated contents include the specific digital technologies, the processes and services developed around those digital technologies, and the managerial, structural, and cultural aspects of the organization transformed through such digital technologies. While innovating the content of change, organizational actors may need to better understand specific aspects of the context, which also changes dynamically. As such, the process of digital innovation is recursive in which organizational actors iteratively move back and forth between understanding the context and innovating the content.

Evaluating the outcome. In the third step of the process of digital innovation, organizational actors evaluate the outcome of the innovation. By first selecting a metric to assess the impact of the innovated content, organizational actors periodically evaluate whether the innovated content helped the organization achieve its objectives as part of the focused transformation. The result of such evaluation informs organizational actors about the efficacy and efficiency of the innovated content in achieving organizational objectives. Based on the evaluation, organizational actors may revisit the second step of innovating the content and iteratively develop the innovated content. Similarly, evaluation of the impact of the innovated content may lead organizational actors to periodically re-explore the organizational context.

4.6. Summary

Digital innovations are part of complex organizational transformations. A contextualist inquiry allows us to examine such organizational change, by simultaneously analyzing the environment within which the change occurs, the specific organizational elements that goes through change and the successive interconnection of events that lead the change to occur (Pettigrew 1985). While change is rationalized by sensing and interpreting the contexts, initiated by selecting and evaluating the contents, and effectuated by experimenting and administering the process, organizational intelligence is required and created in decision making and activities in every step. Digitalization has provided today's organizations access to a plethora of data regarding the context, the content, and the process of change. Organizations have access to data about the social, economic, competitive, and political factors in the outer context. With widespread use of enterprise systems, organizations have access to data about the structural, cultural, and political factors in the inner context as well as about the content of change at different stages of the organizational transformation. Digitalization of processes helps organizations trace the progression and performance of each process at different points along both vertical and horizontal dimensions. On one hand, in terms of analytical intelligence, organizations employ analytical material agency to collect and analyze, and analytical human agency to interpret and make sense of this data. On the other hand, in terms of relational intelligence, organizations apply relational material agency to access and share, and relational human agency to connect and combine knowledge extracted from this data. As such, digital innovations are conceptualized, initiated, managed, and realized through perennial interactions among analytical and relational intelligence in organizational practices. Hence, studying the role of organizational intelligence in digital innovation using contextualist inquiry affords us the opportunity to inform extant literature on how digital innovations are realized within a particular context, through transforming specific contents, and effectuated by processes.

CHAPTER 5. RESEARCH DESIGN

5.1. Longitudinal Process Study

Our study is motivated by the overarching research question of how organizational intelligence is implicated in digital innovation initiatives in the context of focused organizational transformation to improve performance over time. Hence, we are interested in understanding the process of change and development in an organization through its digital innovation initiatives, and how organizational intelligence influences and is influenced by this process. Since process studies are undertaken to examine research questions dealing with how or why things change and develop over time (Poole et al. 2000; Van de Ven 2007), we opted for a process study. Process studies are centrally concerned with how change unfolds (Van de Ven 2007); in our case, we are focusing on an organization's digital innovation initiatives in the context of focused organizational transformation, which is defined as a difference in state, form, or quality over time in an organizational entity (Van de Ven and Poole 1995). Process studies explain how things change over time with process models, taking a historical perspective on the sequences of incidents, activities, or stages that unfold over the duration of change (Pentland 1999; Van de Ven 2007). As such, process models focus on progression (i.e., the nature, sequence, and order) of activities or events that an organizational entity undergoes as it changes over time (Langley 1999; Van de Ven 2007), with temporality as an inseparable characteristic. Since process studies of how entities change and develop over time necessarily involve analysis of longitudinal data (Van de Ven 2007), we apply a longitudinal study design.

A longitudinal study design involves repeated observations of the same entities and variables over shorter or longer periods of time, using data collected at different points in time (Shadish et al. 2002). Since longitudinal studies track the same entities over time, they are more powerful than cross-sectional observational studies, because of their ability to exclude time-invariant unobserved differences and include temporal order of events (van der Krieke et al. 2017). Longitudinal studies can be either retrospective, where data is obtained from historical documents and interviews about past events, or prospective, where data is collected in real-time through field study of a change process (Van de Ven 2007). We apply a combination of retrospective and prospective data collection, in which we collected all data about events before the beginning of the study in 2019 from archival documents and retrospective interviews and tracked ongoing changes after the study began in real time through interviews, participant observations, and emerging reports and publications. Change can be empirically determined by longitudinal observations of the entity over two or more points in time on a set of dimensions, and then noticing a difference over time in these dimensions; if there is a noticeable difference, we can conclude that the entity has changed and can attempt to explain how it changed (Poole et al. 2000; Van de Ven 2007).

Intimate familiarity with the phenomenon from qualitative, rich data can provide the information needed to engage in longitudinal studies (Van de Ven 2007). Such qualitative case studies investigate a contemporary phenomenon in its real-world context, especially when the boundaries between phenomenon and context are not intelligibly evident and the relevant behaviors cannot be manipulated (Yin 2009). The essence of a qualitative case study is that it tries to illuminate a decision or set of decisions: why they were taken, how they were implemented, and with what result (Schramm 1971). As such, adoption of a qualitative case study design becomes increasingly appropriate as the research questions seek to explain some present circumstance—how or why some social phenomenon happens—and as the research questions require an extensive and in-depth description of some social phenomenon (Yin 2009).

Since we are interested in understanding how organizational intelligence is implicated in digital innovation initiatives in the context of focused organizational transformation, through a comprehensive narrative of the GSU case, we apply qualitative case study method in this research.

In our in-depth case study of GSU, we adopt an engaged scholarship perspective (Van de Ven 2007), which proposes that a deeper form of research, engaging both academics and practitioners, is needed to generate knowledge that meets the dual criteria of rigor and relevance for theory and practice (Hodgkinson et al. 2001; Simon 1976; Van de Ven 2007). Engaged scholarship involves negotiation and collaboration between researchers and practitioners in a learning community based on mutual respect; such a community jointly produces knowledge that can both advance the scientific enterprise and enlighten a community of practitioners (Pettigrew 2003; Van de Ven 2007). Inspired by this perspective, instead of viewing our focal organization, GSU, as a data collection site, we view it as a learning workplace, an idea factory, where we co-create knowledge with practitioners on important questions and issues by testing different views of and alternative ideas on a common phenomenon (Van de Ven 2007).

We are using GSU as our only case, since a single-case qualitative study allows researchers to focus intensively and retain a holistic and real-world perspective on organizational and managerial processes (Yin 2009). The findings of a single-case study are generalizable to theoretical propositions and not to populations or universes (Yin 2009). In this sense, a case study does not represent a "sample," and in doing case study research, our goal is to expand and generalize theories—analytic generalizations—and not to extrapolate probabilities—statistical generalizations (Lee and Baskerville 2003; Lipset et al. 1956; Yin 2009). Accordingly, since a qualitative case study can be used to ground the development of a theory (Van de Ven 2007), and since we are developing a theory of organizational intelligence in digital innovation, we deem a qualitative single-case study as an appropriate method. Moreover, within the single overarching case of GSU, we analyze its digital innovation initiatives as embedded cases (Yin 2009). As such, our unit of analysis is individual digital innovation initiatives as they progressed over time within the context of a focused organizational transformation at GSU. Such an embedded case study design enables us not only to focus on each digital innovation initiative intensively, but also to analyze and explain the broader temporal and organizational context in which these initiatives progressed (Yin 2009). In this intensive embedded case study, we started with coding of the collected data based on provisional codes (Miles et al. 2014; Saldaña 2015; Yin 2009). Coded utterances were used in within-case and cross-case analyses (Miles et al. 2014; Saldaña 2015; Yin 2009). The context of the four embedded cases were also analyzed based on the coded utterances. Finally, we theorized about organizational intelligence by connecting our findings with extant literature. Definition of key concepts of this study is provided in Appendix C.

5.2. Research Setting

Our longitudinal, qualitative case study is of GSU's digital innovation initiatives over the past two decades (1999-2020) to improve the success of its students. Founded in 1913, GSU is the most comprehensive public higher education institutions in Georgia and one of the University System of Georgia's four research universities. GSU currently offers more than 250 degree programs in over 100 fields of study spread across 10 academic schools and colleges. As of 2020, GSU is among the top 10 universities in the nation that has a diverse majority-minority student body. GSU has around 53,000 students, approximately 33,000 of whom are undergraduate and graduate students at the main campus in downtown Atlanta, making it the largest institution of higher education by enrollment based in Georgia.

The student body at GSU comprises 67% non-white and 58% Pell-eligible students with a majority of first-generation college-bound students. Due to its diverse student body with a majority of first-generation college-bound students, who are challenged socially, economically, and pedagogically, GSU faced a unique challenge of how to improve the undergraduate student performance. To improve the 6-year graduation rate of undergraduate students, GSU implemented many innovation initiatives and leveraged digital technologies starting from 1999. Over the last two decades, GSU thus transformed its programs, structures, and processes through various digital innovation initiatives. Through this long-term organizational transformation, GSU gradually improved its 6-year graduation rate from 32% in 2003 to 55% in 2018. As a proponent of equity and inclusion, GSU now awards more degrees to African American students than any other non-profit university or college in the US. In 2020, GSU has been recognized as the number one public university for teaching in the US and the number two most innovative university in the US (US News & World Report 2020).

To improve student success, GSU faced unique challenges from its socio-economic context of Georgia, the highly competitive higher education context in the US, and the evolving technological context around the world. Georgia's diverse demography implies that the majority of students at GSU are African-American, Hispanic, and immigrants from around the world. Moreover, a majority of students is first-generation college students from low-income families. Nationally, these demographics are historically far behind other demographics in associate and baccalaureate degree attainment (Stewart 2020). Moreover, they lack in pedagogical background, understanding of academic progression and pitfalls, and knowledge of the bureaucratic governance of college education. At the same time, increasingly competitive higher education institutions around the world have to negotiate rapidly changing landscapes of digital technologies. GSU sensed these unique problems in its outer context and interpreted them as an opportunity to innovate its structures, processes, systems, and value propositions. Moreover, GSU had to consider its existing managerial, structural, and cultural arrangements in its inner context to ascertain and realize possible solutions. In response to the formidable challenges, since 1999, GSU initiated digital innovations in four key areas to support a student's educational journey—teaching, monitoring, engaging, and financing—as depicted in Figure 2.

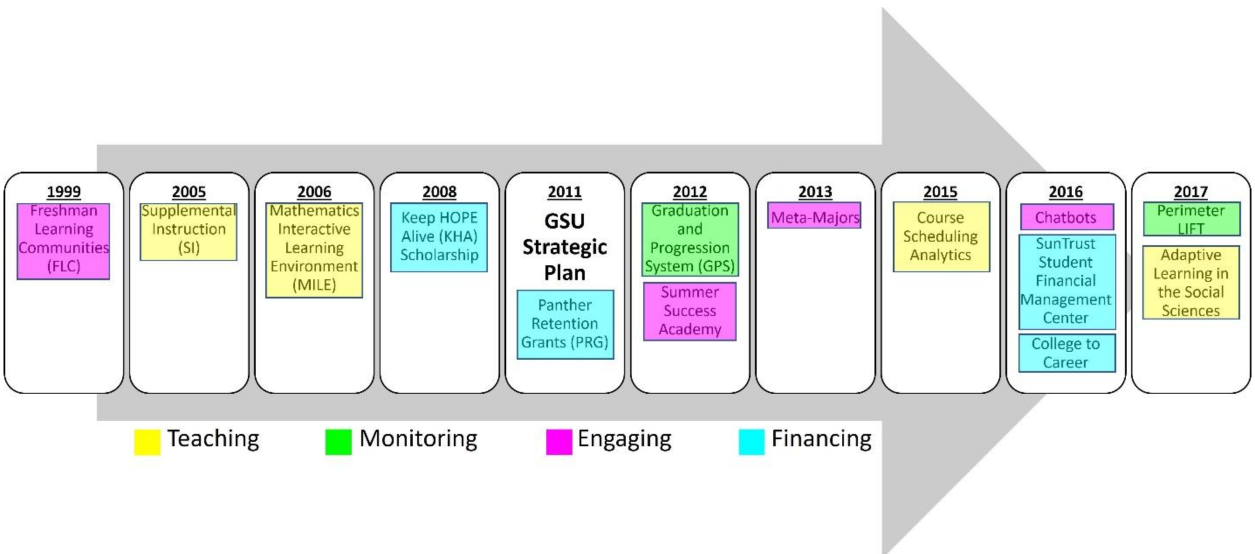

Figure 2: GSU's Digital Innovation Initiatives (1999-2020)

At the heart of GSU's transformation is the visionary leadership of the President of GSU and Senior Vice President for student success. Under their leadership, in 2011 GSU accelerated its existing activities, created the organizational structure of the Student Success Program, and launched new initiatives to improve student success through a five-year strategic plan with five goals: become a national model for undergraduate education through demonstrating that students from all backgrounds can achieve academic and career success at high rates; significantly grow and strengthen the base of distinctive graduate and professional programs by developing the next generation of researchers and societal leaders; become a leading public research university by addressing the most challenging issues of the 21st century; become a leader in understanding the complex challenges of cities and developing effective solutions; and, achieve distinction in globalizing the university. Through this timely, bold, and visionary strategic plan, GSU made a conscious decision to build on over ten years of various student success initiatives to transform itself enabled by digital innovations. The Office of Student Success Program led the way from the top by initiating and implementing the digital innovation initiatives over the years, which lead to transformation at every level of the organization. As such, a vertical structure of organic leadership fueled the ongoing horizontal transformation process and the realization of change through digital innovations, from inception to fruition.

5.2.1. Innovation in Teaching

To help the underprivileged students in their academic journey, GSU launched *Supplemental Instruction (SI)* in 2005 (Figure 2). SI is a series of regularly scheduled review and study sessions for students taking historically difficult courses led by SI Leaders, who are other students who have already taken the course, earned an A- or better in the course, and have a GPA above 3.0. In SI sessions, students discuss material covered in lectures, ask questions, solve practice problems, compare notes, organize study material to maximize study time, learn study techniques, and identify relevant campus resources. Students attend SI sessions to develop effective study strategies and habits that lead to higher grades, learn how to manage academic stress and anxiety, establish enjoyable and beneficial relationships with peers, engage in an interactive learning environment, and maintain motivation to complete courses successfully and progress towards graduation. Before SI, average GPA in courses identified was 2.6 with non-pass (DFW) rates of more than 20%. During spring 2018, students who attended SI sessions earned an average GPA of 3.22 in these courses, compared to 2.59 for students who did not attend, and non-pass rates were 30% lower.

To improve the performance of its student body, GSU also experimented with adaptive learning technologies (ALT) that use computer algorithms to support learning. ALT select and adapt the presentation of materials and activities based on each student's experiences and responses to previous questions and tasks. GSU initiated its digital innovations based on ALT in 2006 through its *Mathematics Interactive Learning Environment (MILE)* (Figure 2). Mathematics has been historically challenging for underprivileged students, who consistently underperformed or failed in introductory gateway mathematics courses. To break this pedagogical barrier, GSU redesigned its introductory mathematics courses—pre-calculus, college algebra, and elementary statistics—using MILE. Before the redesign, drop, fail and withdrawal (DFW) rates were regularly above 40% in these courses. After failing or underperforming once, students had to retake the course, often picking up another D or F. As a result, each semester hundreds of students lost their scholarships and dropped out because of this one requirement.

GSU no longer offers conventional lecture-focused sections of any of these mathematics courses. Instead, students attend MILE lab sessions in large groups with dedicated lab instructors and teaching assistants. In each lab session, students work on the same material, sitting at individual terminals and using adaptive learning systems, all the while receiving support from teaching assistants orchestrated by lab instructors. All students are hence working in parallel, and the teaching assistants are walking around engaging with students one-on-one. With MILE, GSU was able to drop DFW rates across the three mandatory mathematics courses to an average of 23% in 2014 from 31% in 2007, helping hundreds of additional students pass the required mathematics courses in their first attempt each semester. Encouraged by this success, in 2017 GSU deployed *Adaptive Learning in Social Sciences* (Figure 2) with courseware in five gateway courses in political science, economics, and psychology. The involved professors praised the

ALT, emphasizing that they help students manage enormous amounts of information in a structured way that is tailored to their evolving knowledge and capabilities.

Due to the socio-economic context in Georgia, most students at GSU have to work while in college, making it difficult for them to manage time conflicts while scheduling courses. GSU has made it easier for students to select their courses by offering block schedules powered by predictive analytics. Since 2015, GSU uses *Course Scheduling Analytics* (Figure 2) to offer and schedule courses for upcoming semesters, based on course registration data in the most recent semesters. Instead of selecting from a catalog of 3,000 courses, students choose between five or six different schedule blocks—morning only, afternoon only, Monday and Wednesday classes, Tuesday and Thursday classes—choices that enable students to have reliable blocks of time to devote to education, employment or other responsibilities. Another advantage of predictive course scheduling is that GSU can ensure that all the courses the students take will facilitate their academic progression, and there is good course availability for students who register early for classes as well as those who register later.

GSU maintains "Common Meeting Patterns and Start and End Times for Course Scheduling" using a unified clock schedule. The system maintains clock schedules for 1-6 credits. Use of space on each campus reflects the clock schedule for the campus. A production schedule and process coordination system is applied to ensure timely scheduling in each semester. Access to update actual course data within the student record system is limited to assigned college schedulers, who meet on a regular basis to ensure university-wide coordination. The schedule for each upcoming term is created using predictive analytics on data from the previous similar terms as a base.

5.2.2. Innovation in Monitoring

Since the majority of students is underprivileged, due to the socio-economic context in Georgia, GSU closely monitors and frequently advises each student. Starting in 2011, GSU has collaborated with the company Education Advisory Board (EAB) to continuously develop a *Graduation Progression System (GPS)* (Figure 2) that monitors and detects problems students face and complementary advising technologies that help students avoid or overcome these problems. GPS uses predictive analytics and a system of more than 800 alerts to track all undergraduate students daily, identify at-risk behaviors, and have advisers respond to alerts by intervening in a timely manner to get students back on track. The high impact of such data-driven monitoring systems on improving student success is echoed in previous research (Devlin and Bushey 2019).

GSU has created a centralized structure of trained academic advisers, the University Advisement Center (UAC), to monitor the alerts and respond with timely, proactive advice to students at scale with 70 advisers. The previous advising organization was fragmented and fraught with problems such as no common record keeping, high student to adviser ratio, little systematic tracking, and little coordination. The UAC has implemented a vertical governance structure for common advising systems and technologies that offers systematic record keeping and tracking, coordination among advisers, significantly reduced student-adviser ratio, and career paths and systematic training for academic advisers. As such, the goal of UAC is to give students the information that they need when they need it to make decisions that lead to increased retention, progression, and graduation. UAC is continually working towards this goal through individualized education planning, proactive risk targeting, and personalized interventions.

In August 2012, the GPS system went live. Based on 144,000 student records and 2.5 million grades in the previous 10 years, the system uses analytical models to predict potential problems for any student and refer them to an academic adviser at UAC for advisement. In the 2019-2020 academic year, the GPS system generated more than 55,000 individual advisement sessions between students and advisers to address specific alerts generated by GPS and to get students back on a path toward graduation. Before GPS went live, many students had confusion about which courses to register for and which major to choose. Since GSU initiated GPS advising, progression rates increased by 16 percentage points, the number of students in majors fitting their academic abilities increased by 13 percentage points, and the number of students changing their majors in the sophomore, junior and senior years decreased by 32%. Moreover, freshman fall-to-spring retention rates increased by 5 percentage points and graduating seniors are taking fewer excess courses in completing their degrees. Accordingly, the SVP of student success praised the GPS advising system by commenting that “we are engaging with students and really changing their trajectory.”

GSU consolidated with Georgia Perimeter College (GPC) in 2016. GPC is a two-year institution with multiple campuses around the metro Atlanta area. GSU has deployed its GPS system, with grant funding, and extended its advising services to increase graduation rates for these additional 20,000 students seeking associate degrees with 42,000 meetings between students and advisers in 2017-2018. In the 2016-2017 academic year, the GPS platform was launched at GPC and GSU hired an additional 30 academic advisers for GPC. GPS has proven to be equally effective in improving outcomes for associate and baccalaureate degree students. In both cases, 90% of the upfront costs were directed toward personnel, not technology. In addition to supporting students seeking associate degrees, this latest extension of the GPS system and advising services provide

GSU with the opportunity to better understand and support transfer pathways between two- and four-year institutions.

In 2017, GSU implemented the *Learning, Income and Family Transformation (LIFT)* program (Figure 2), with the support of State Farm, to continue improving these outcomes by combining data-driven academic advisement with scholarships, leadership training, employment opportunities, and more to help students from every background stay on track for graduation. LIFT forms an integrated suite of student success programs that tracks student progress to provide the help needed to overcome a variety of obstacles and to take students from high school to college graduation. Through monitoring progress across hundreds of indicators, LIFT identifies potential issues and implements proactive solutions to facilitate progression and graduation. After participating students earn a two-year degree, they are guided towards transition to either a four-year degree program or a career. With data-driven predictive analytics and student-centric proactive advising, GSU continues to improve the performance of its students.

5.2.3. Innovation in Engaging

At a large public university such as GSU, incoming freshmen can feel overwhelmed by the size and scope of the campus and the choices they face. To help freshmen get accustomed to college environment and life, GSU initiated *Freshmen Learning Communities (FLC)* (Figure 2) in 1999 and continually developed other programs around it. In 2013, FLCs were integrated with common academic interests otherwise known as *"Meta-Majors"* (Figure 2) or "career pathways." Since 2013, upon registration, all students are required to enroll in one of seven meta-majors or career pathways: Arts, Education, Health, Humanities, Policy and Social Science, STEM, and Exploratory. After students have selected their meta-major, they are given options of several block schedules, which are pre-populated course schedules including courses relevant to their first year of study. Block schedules accommodate students' work schedules and help to improve class attendance. On the basis of block schedules, students are assigned to FLCs which organize the freshmen class into cohorts of 25 students arranged by meta-majors. Students in the same cohort travel through their classes together, building study partners, friendships, and support along the way. Freshmen who enroll in FLCs have a one-year retention rate that is 5 percentage points higher than freshmen who do not enroll in FLCs. In fall 2018, 70% of freshmen class were in FLCs. 92% of incoming freshmen were enrolled in the thematic block schedules in the first year of rolling out career pathways at Perimeter College. In fall 2018, GSU offered 96 majors and more than 3,400 courses. Requiring all students to choose a meta-major or career pathway puts students on a clear path to degree, allowing them flexibility in selecting future specialization in a particular program of study, while also ensuring that their early course credits will be counted towards their final majors. Implemented in conjunction with a suite of faculty-led programming and major maps that inform students about the differences among specific academic majors during their first semester, FLCs and meta-majors provide direction and clarity in what previously had been an unstructured and confusing registration process.

Summer Success Academy (SSA) (Figure 2) was initiated for bachelor's students in 2012 as an alternative to deferring weaker freshman admits to the following spring semester. SSA uses predictive analytics to identify at-risk admitted students in the fall freshman class and registers these students in a seven-week summer session before fall classes. In these summer sessions the students pursue 7 credit hours of college credit while immersed in FLCs, near-peer mentoring, and a suite of mindset-building activities. In SSA, students have the support of all of GSU's tutoring, advising, financial literacy, and academic skill programs at their disposal. All students are in FLCs, work with near-peer tutors, and participate in community and campus projects, all designed to heighten the students' sense of belonging and confidence. In 2018, the retention rate for the SSA cohort was 94%, compared to an 83% retention rate for the remainder of the freshmen class who were, on paper, better prepared academically for college. It is important to note that when GSU was deferring enrollment until the spring semester, as is the common practice nationally, these same students were being retained at only a 50% rate. This results in more than 100 additional freshmen being retained via the SSA annually than was the case under the old model. In the summer of 2017, GSU launched the first application of the SSA program to Perimeter College, the Perimeter Academy. Among the first cohort of 60 students, 92% were retained in the spring semester, compared to 70% for students overall.

The journey of college education is overwhelming for all students even before it begins, especially for first-generation, low-income students. Many students fail to navigate the path towards college education after high school graduation, becoming victims of "summer melt." They accept offers of admission during summer but never show up for fall classes. 19% of GSU's incoming freshman class were victims of summer melt in 2015. Although they had been accepted and had confirmed their plans to attend, these students never showed up for classes. GSU tracked these students using National Student Clearinghouse data and found that, one year later, 274 of them (74% of whom were low-income) never attended a single day of class at any institution.

To successfully begin and continue their college education, accepted students need answers to questions about registration, admissions, financial aid, FAFSA, housing, immunization, academic advising, and dining. While student advisers may have answers to these questions, not all students can reach them. Moreover, students also feel hesitant and vulnerable to share personal information with a stranger. As such, GSU spotted an opportunity to be far more proactive and personal in communicating with students transitioning from high-school graduation to the first day of college and was one of the first institutions nationally to deploy an artificial intelligence (AI) chatbot to reduce summer melt. Today, the chatbot is a platform for communicating with all students, incoming or continuing alike, on myriad of issues.

In summer 2016, GSU collaborated with the company Admit Hub to deploy its first *chatbot* (Figure 2)—a texting system named after the school mascot 'Pounce.' Students communicated with Pounce by texting any question 24/7 from their smart phones to get answers. GSU initially built a knowledge base of 2,000 commonly asked questions and their answers. Pounce replied to 201,000 student questions, in the three months leading up to the fall 2016 classes. Pounce replied to student questions within seconds, with an average response time of 7 seconds. Similar usage and performance were tracked in 2017 and 2018. With the help of Pounce, GSU has lowered summer melt by 22% in 2016, which translates into 324 more students, mostly first-generation and low income, showing up for freshman fall classes. In the previous year, these students were sitting out the college experience altogether. Applying Pounce, GSU decreased summer melt by an additional 4 percentage points, in 2017 and 2018.

Students regularly asked Pounce questions on a broad range of topics. "How do I complete the FAFSA?" "What is the difference between a grant and a loan?" "What do I do if I can't find or don't have immunization records?" After receiving a question from a student, the AI capability integrated in Pounce determines if there is an appropriate answer in the knowledge base and provides the answer to the student. Otherwise, the student's question is directed to a staff member to write an answer and add that to the knowledge base. As such, the knowledge base of

Pounce continues to grow, and the AI capability learns to derive the meaning of more questions over time.

Students communicated with Pounce in surprising ways. They used the system more heavily at 1:00 am than at 9:00 am—a clear indictment of GSU's traditional business hour practices. They also confided problems to the chatbot they would never have shared with a human being, knowing that the chatbot would not judge them. With Pounce, the playing field of access to information has been leveled. In most cases, students do not need access to someone with personal knowledge of college bureaucracies to get help, they just need access to the chatbot. As the project director of the chatbot stated, "this technology lets us touch students faster and more effectively."

After Pounce's success in admission, GSU expanded its knowledge base to help students in retention. Today the chatbot sends reminders, conducts guided tutorials, takes surveys, and provides targeted human support on topics including academics, financing education, student life, student organizations, housing, meal plans, sports, and more. Critical to Pounce's success was building an adequate knowledge base of answers that students can rely on. Currently, the knowledge base includes 3,000 answers and the chatbot continues to learn daily. During the difficult times of COVID-19, Pounce has been heavily used to disseminate information regarding the virus, its prevention, and changes in policies, rules, and courses.

5.2.4. Innovation in Financing

After the financial crisis in 2008, GSU had to rethink how it could help its students financially. The Hope scholarship supports 59% of GSU students who come from Pell-eligible households, where the annual income in the previous year was less than $30,000. The Hope scholarship, with more than $6,000 per student, provides access to college for thousands of GSU students. But for the students who cannot maintain a GPA of 3.0, the loss of Hope forces them to drop out for financial reasons. That is why in 2008 GSU launched the *Keep Hope Alive (KHA)* (Figure 2) scholarship program to help students regain their Hope scholarship after they had lost it. Students sign a contract to receive $500 for each of the first two semesters after losing Hope. According to the contract, the students must participate in a series of interventions and programs designed and developed to get them back on track academically and to educate them to make better financial choices to regain the Hope scholarship. The rigorous academic restoration plan, designed to help students improve their GPAs and regain the Hope scholarship, includes attending workshops, meeting with advisers, and participating in financial literacy training. Before KHA, regaining the Hope Scholarship after losing it was statistically improbable; only about 9% of GSU students were able to do so. From 2011 to 2017, more than 55% of students in KHA regained the Hope scholarship at the next marker, in the process GSU leveraged $1,000 KHA scholarship investment by gaining between $6,000 and $12,000 of tuition based on Hope scholarship back again. Institutional Hope retention rates have increased from 49% in 2008 to 75% in 2015. The six-year graduation rate has increased from 20% in 2008 to 38% in 2017, for students who lost their Hope scholarship at some point.

Panther Retention Grants (PRG) (Figure 2), launched in 2011, is another program to help students financially. PRG provides micro-grants each semester to students to help them cover modest financial shortfalls, enabling them to pay tuition and fees and thus preventing students from dropping out. In fall 2018, more than 18,000 of GSU's more than 25,000 bachelor-seeking students (72%) had some level of unmet need. Even after grants, loans, scholarships, family contributions, and the income generated from the student working 20 hours a week, the students lacked sufficient funds to attend college. Each semester, hundreds of qualified students drop out from their classes for lack of payment, at times for as little as $300. PRG provides the emergency funding to students and the opportunity to stay enrolled. PRG staff examine the drop lists for students with unmet need using academic analytics to identify students near graduation who have modest balance deficits for tuition and fees. These students are offered micro-grants on the condition that they agree to certain activities, including participating in financial literacy modules and meeting with a financial counselor to map out plans to finance the rest of their education. The timeliness of the intervention and access to good data analytics are the keys to success. In 2018, more than 2,000 GSU students were brought back to the classroom and kept on the path to graduation through the PRG program. Since the PRG program's inception in 2011 and until spring semester 2018, 11,027 grants have been awarded to Atlanta campus and Perimeter College students; of these, 86.5% students have gone on to graduate. The program has prevented literally thousands of students from dropping out of college education.

In fall 2016, supported by a gift from the SunTrust Foundation, GSU opened the *SunTrust Student Financial Management Center (SFMC)* (Figure 2). Believing that more students will persist if their financial problems are identified early and addressed proactively, the center applies predictive analytics parallel to those critical to GSU's ground-breaking GPS academic advising system. In the case of SFMC, financial data spanning ten previous years were analyzed to identify early warning signs of student financial problems. The analysis revealed that some financial decisions made even before the students first set foot on campus may influence whether a student ever graduates, such as a student choosing a single dorm rather than living at home or with roommates in the summer before the freshman year. A core objective of the SFMC is to provide students the support and guidance they need to avoid or overcome financial problems that can cause them to drop out. Building on a similar system that GSU has already deployed for academic advising, the initiative extends predictive analytics to financial advisement. A financial alert system, created in part through engagement with the EAB, is accessible by college academic assistance staff, campus advisers, and student retention staff. Certified financial counselors at the SFMC now track students daily and reach out to offer advice and support when problems are identified. In spring and summer of 2017, the SFMC conducted 72,121 in-person, online and phone interactions, 62% of which focused on FAFSA verification, student loans, status of aid, and Hope Scholarship questions. They found that FAFSA problems, missing or incomplete documents, and parent loans were among the most common issues faced by students. An additional 6% of interactions were about Satisfactory Academic Progress appeals. Combining information currently in Banner, the student information and records system, with experiences observed during the past year, the SFMC has identified 16 risk triggers that are aligned with the data. With 93% of GSU undergraduates receiving federal aid, a major challenge for GSU is getting students to resolve their balances and take the necessary steps to address outstanding financial-aid obligations. Students who visited the SFMC in fall 2017 semester were 6 percentage points more likely to complete all financial-aid requirements and bring their balances down to zero than the rest of the student body. With a campus of 53,000 students, this translates into more than 3,000 financially able students ready to start the semester who would have dropped out without the assistance of the SFMC.

Finally, to cater to the financial motivation of education, in 2016 GSU launched the *College to Career* program (Figure 2), which is a campus-wide effort to inform students about the career competencies they are acquiring through the curricular and co-curricular activities at GSU; to document these competencies in a robust fashion in faculty- and peer-reviewed e-portfolios through archiving textual, audio, and video evidence; and to help students articulate the competencies through oral discourses, resumes, and cover letters. All students are now provided with e-portfolios upon matriculation at GSU. The program awards faculty and departmental grants to encourage instructors to integrate course-works highlighting career competencies into both lower-level and capstone courses. Digital technologies have been implemented to share real-time job data of metro Atlanta with students, starting even before they arrive on campus. All freshmen are now on-board career-pathway-based learning communities in their first semester. In 2018, GSU became the first university in US to partner with Road Trip Nation to create a searchable video archive on the careers of GSU alumni. The College to Career program received remarkable response from the students. In 2017 alone, GSU students posted more than 700,000 artifacts—evidence of their career competencies—to their e-portfolios. As part of their first-semester orientation courses, all students complete a first resume. Visits by first- and second-year students to University Career Services have increased by more than 100% since 2015. The Brookings Institution 2017 Rankings of Social Mobility ranked GSU first in Georgia and 25th in US for "social mobility," which measures the movement of students from the bottom quintile of Americans by annual household income at matriculation to the top half of Americans by annual household income fifteen years later.

5.3. Data Collection

For our longitudinal qualitative case study of GSU's digital innovation initiatives, we collected both primary and secondary data from GSU. We conducted semi-structured interviews of 26 key personnel connected to the innovation initiatives. A schedule of these interviews is provided in Table 5. The interviewees were chosen from administration, academia, advising, and operation based on their important role and contribution to each of the innovation initiatives. Before each interview, we researched the background and current designation of the interviewees and prepared appropriate questions to ask accordingly. Since the interviewees played divergent roles in GSU's innovation initiatives, semi-structured interviews with questions specific to each interviewee was deemed appropriate. The interviews lasted at least an hour. During the interview, we asked questions about how and when the interviewee joined GSU, what was their background, how they progressed their career at GSU, what are their current and past responsibilities, how they contributed to GSU's innovation initiatives, and what insights or opinions they would like to share with us regarding GSU's innovation initiatives. We digitally recorded each interview and took notes for future data analysis. Appendix A provides the interview protocol that we followed. After each interview, we debriefed to discuss what new knowledge we had gained, how it related to previous knowledge gained and the implication of this new knowledge for the entire study. We digitally recorded these debriefings as well.

Table 5: Schedule of Interviews

#	Designation of the Interviewee	Date of Interview	Duration (Hours)
1	Senior Vice President for Student Success	7/29/2019	1.5
2	Senior Director of Student Success Analytics	8/27/2019	1.5
3	Vice President for Student Engagement and Programs	9/3/2019	1.5
4	Assistant Vice President for University Advisement	9/3/2019	1.5
5	Associate Vice President for Undergraduate Admissions and Housing	9/3/2019	1.5
6	Director of Undergraduate Studies, College of Arts & Sciences	10/22/2019	1
7	Project Director and University Innovation Alliance Fellow	10/22/2019	1
8	Director, Learning Technology, CETL	10/22/2019	1
9	Precalculus Course Coordinator; Mathematics Assistance Complex (MAC) Coordinator	10/22/2019	1
10	Assistant Director, University Advisement Center	10/23/2019	1
11	Director, University Advisement Center, Perimeter Campus	10/23/2019	1
12	Assistant Director, University Advisement Center	10/23/2019	1
13	Senior Director, Student Success Program	12/4/2019	1.5
14	Director, University Advisement Center, Atlanta Campus	3/12/2020	1.5
15	Assistant Director, University Advisement Center, Atlanta Campus	3/12/2020	1.5
16	Graduation Counselor	3/12/2020	1
17	Academic Adviser	3/12/2020	1
18	Academic Adviser	3/12/2020	1

19	Director of Institutional Research	4/2/2020	1.5
20	Project Director of Retention Chatbot	4/3/2020	1.5
21	Associate Director of Student Success	5/5/2020	1.5
22	Deputy CIO, Application Solutions	5/22/2020	1.5
23	Chief Learning Innovations Officer, Assistant Vice President, CETL	8/11/2020	1.5
24	Chief Innovation Officer	8/18/2020	1
25	Liaison with EAB	9/15/2020	1
26	Clinical Associate Professor, Director of Undergraduate Studies, Department of Economics, Andrew Young School of Policy Studies	9/17/2020	1.5

Besides in-depth interviews, we also collected GSU internal archival documents. Since 2013, GSU maintained internal annual reports on its innovation initiatives known as Complete College Georgia (CCG). We collected all CCG reports from 2013 to 2018. These reports discuss in detail the initiation, progression, and future direction of all innovation initiatives at GSU. The academic advisers at the UAC go through periodic training and receive two documents—adviser manual and adviser toolkit—that describe in detail the advising process and the technologies used in advisement. We collected the January 2020 versions of the adviser manual and toolkit. Every fall and spring GSU conducts a day-long seminar known as Campus Visit, where leaders of the innovation initiatives give informative presentations on the innovation initiatives.

Representatives of higher education institutions from around the world convene in these campus visits to learn about GSU's Student Success Program. We attended one day-long campus visit on January 31, 2020 and collected the presentations from the leaders. Apart from the campus visits, leaders of the innovation initiatives periodically give presentations and submit documents to nonprofit foundations with a hope to acquire funding to further progress GSU's initiatives. We collected some key examples of these presentations and documents as well. The Student Success Program holds weekly manager meeting to discuss past performance, current activities, and future trends in the innovation initiatives. We attended one such meeting to observe the proceedings and took detailed notes. A printed handout with updated information about the Student Success Program is given to every participant in these meetings, which we also collected. The story of GSU's success has been studied in detail by a world-renowned author in a book (Gumbel 2020), which we have collected and analyzed as a secondary source of data. Many press releases, newspaper articles, and online articles have been published on GSU's innovation initiatives over the years. We collected key examples of these publications as well. We also observed how students learn mathematical concepts using adaptive learning technology and interact with teaching assistants and instructors at the MILE lab. Appendix B provides a list of the documents we collected, coded, and analyzed.

5.4. Coding and Analysis

We analyzed the collected data according to guidelines from Miles et al. (2014), Saldaña (2015), and Yin (2009). We coded all collected data using a set of provisional codes deductively developed (Miles et al. 2014) from the three aspects of contextualist inquiry—context, content, and process of change—and the four components of organizational intelligence in our theoretical framing—analytical human agency, analytical material agency, relational human agency, and relational material agency (Table 6). Codes were developed based on extant literature, and revised inductively based on empirical evidence during the coding process (Miles et al. 2014; Saldaña 2015). Before actual coding began, the author went through coding training under the supervision of the adviser. Three documents were randomly selected, and the author and the adviser coded these documents individually, one by one, according to the provisional codes. After coding each document, intercoder reliability was calculated as the ratio of the number of instances where both coders agreed about the coded utterances to the number of total instances of coded utterances. The intercoder reliability gradually improved from 75% for the first document, to 86% for the second document, and finally to 91% for the third document. Disagreements about the coding was discussed and the definition of the provisional codes were revised and updated. Table 6 provides the final version of the provisional codes and their definitions.

The provisional codes are in a hierarchical structure: the three top level codes, under each digital innovation, are context of change (Figure 3), content of change (Figure 4), and process of change (Figure 5). All other codes fall under these three aspects of contextualist inquiry at different levels. This hierarchical structure of provisional codes was used to code utterances about each individual digital innovation initiative. For coding, we used NVivo, a software that allows automated simultaneous coding for hierarchical codes; meaning that any utterance coded at a lower level of the hierarchy will automatically be coded at higher levels. Through the coding process we generated summaries of segments of data with descriptive codes and memos that capture insights from these data segments. We further analyzed these coded segments across all of GSU's digital innovation initiatives to find patterns and develop a comprehensive empirical account of the implication of organizational intelligence in these initiatives.

Table 6: Provisional Codes

Code	Operational Definition
Context of Change	The environment in which organizations and stakeholders operate (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Outer Context	The framework of social, technological, competitive, economic, and political factors in which organizations and stakeholders operate (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Inner Context	The features of the structural, cultural, and political environment inside the organization through which ideas for innovation proceed (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Content of Change	The specific areas of transformation, including business models, technologies, organizational structures and processes, and the people involved (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).

Process of Change	The continuous and interdependent sequence of events that shapes the origins, continuance, and outcome of a transformation (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Vertical Dimension	The interdependencies between higher and lower levels of change (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Horizontal Dimension	The sequence of events through which change unfolds over time (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990).
Organizational Intelligence	The capability of an organization to process, interpret, encode, manipulate, and access information in a purposeful, goal-directed manner, so it can increase its adaptive potential in the environment in which it operates (Glynn 1996).
Analytical Intelligence	The capability of an organization to apply digital technologies to analyze critical business data (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017).
Analytical Human Agency	The human component of analytical intelligence
Analytical Material Agency	The technological component of analytical intelligence
Relational Intelligence	The capability of an organization to apply digital technologies to communicate, collaborate, and coordinate (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012).
Relational Human Agency	The human component of relational intelligence
Relational Material Agency	The technological component of relational intelligence
Other	Any interesting or unexpected utterance that is not covered by the codes defined above

Figure 3 illustrates the hierarchy of codes related to the context of change, which captured utterances about the environment in which organizations and stakeholders operate, with outer context capturing the framework of social, technological, competitive, economic, and political factors in which organizations and stakeholders operate, and inner context capturing the features of the structural, cultural, and political environment inside the organization through which ideas for innovation proceed (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). One aspect of intelligence is to observe and understand the contexts and react or adapt accordingly (Neisser et al. 1996). As such, instances of applying analytical human agency, analytical material agency, relational human agency, or relational material agency to monitor and interpret the outer or the inner context were coded accordingly. Related to the outer and inner contexts, utterances that do not specifically state application of human or material agency were coded as analytical or relational intelligence; and, instances that do not clarify whether analytical or relational intelligence was applied were coded as organizational intelligence. Overall descriptions of the outer and inner contexts, and generic renditions of the contexts were coded respectively. Any interesting or unexpected utterance that does not fall into these categories were coded as other.

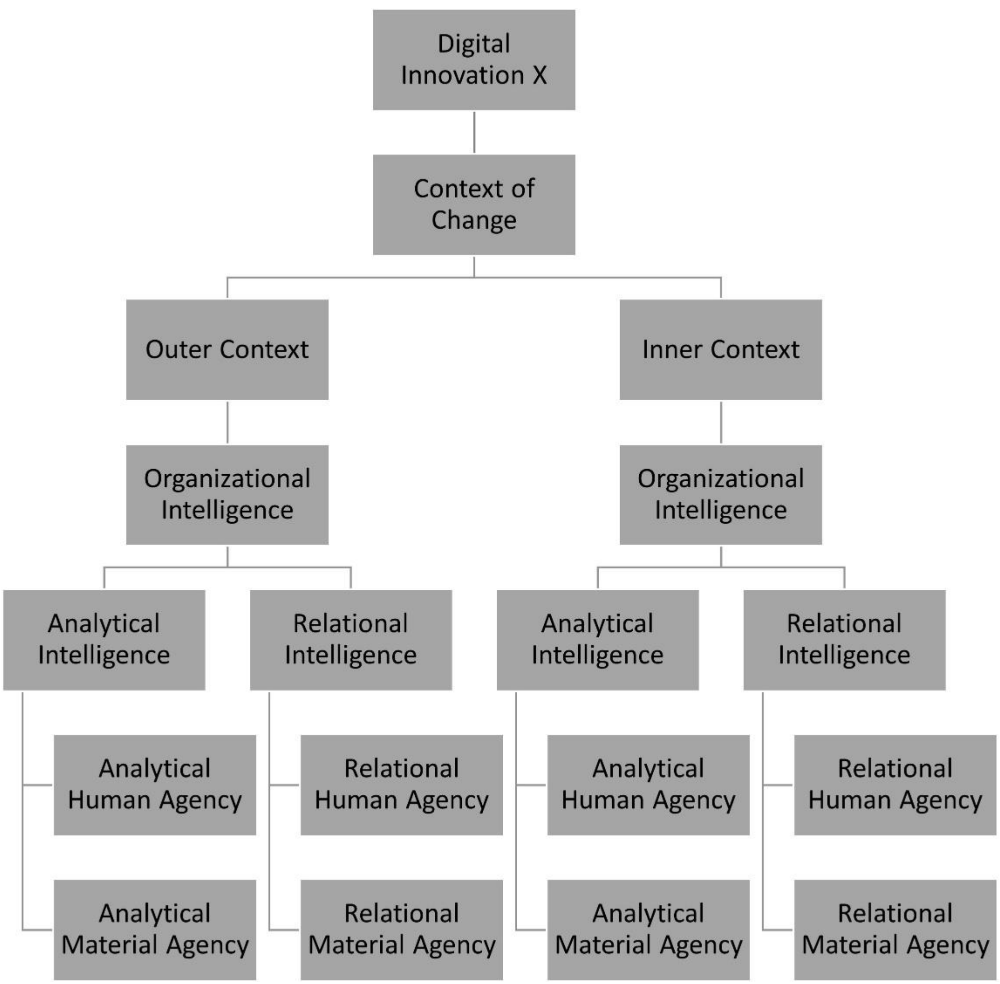

Figure 3: Codes for the Context of Change

Figure 4 illustrates the hierarchy of codes on the content of change, which captured utterances about the specific areas of change, including business models, technologies, organizational structures and processes, and the people involved (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). Instances where analytical human agency, analytical material agency, relational human agency, or relational material agency was applied to a particular area of change were coded accordingly. Utterances that do not specifically state application of human or material agency in an area of change were coded as analytical or relational intelligence; and, instances that do not clarify whether analytical or relational intelligence was applied were coded as organizational intelligence. Generic descriptions about the content of change were coded accordingly. Any interesting utterance that does not fall into these categories were coded as other.

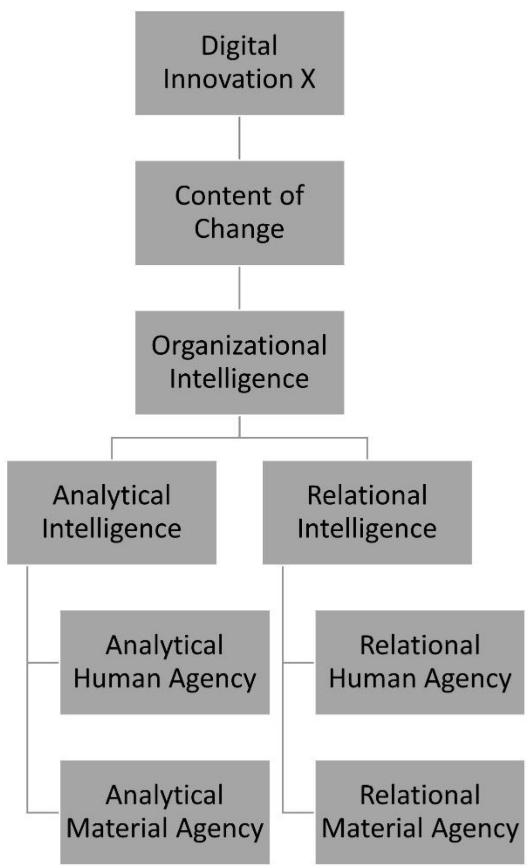

Figure 4: Codes for the Content of Change

Figure 5 illustrates the hierarchy of codes related to the process of change, which captured utterances about the continuous and interdependent sequence of events that shapes the origins, continuance, and outcome of change, with the vertical dimension capturing the interdependencies between higher and lower levels of change and the horizontal dimension capturing the sequence of events through which change unfolds over time (Pettigrew 1985; Pettigrew 1987; Pettigrew 1990). Instances of applying analytical human agency, analytical material agency, relational human agency, or relational material agency to execute the process of change vertically or horizontally were coded accordingly. Related to the vertical and horizontal dimensions of the process of change, utterances that do not specifically state application of human or material agency were coded as analytical or relational intelligence; and, instances that do not clarify whether analytical or relational intelligence was applied were coded as organizational intelligence. Overall descriptions of vertical and horizontal dimensions, and generic renditions of the process of change were coded respectively. Any interesting or unexpected utterance that does not fall into these categories were coded as other.

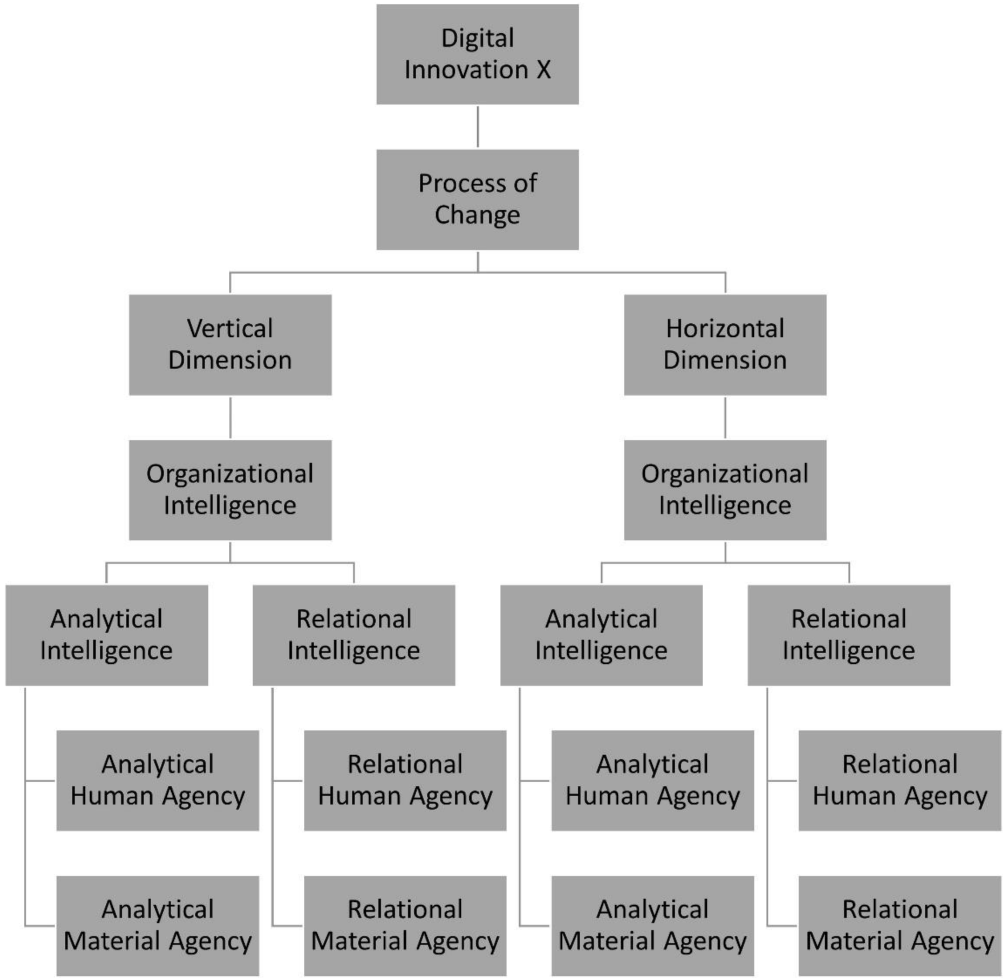

Figure 5: Codes for the Process of Change

5.5. Process Model and Theory Development

The development of the process model and the theory involved both deductive and inductive reasoning (Van de Ven 2007). We used basic principles of logical deductive reasoning to define our concepts—context, content, and process—and to specify relationships and conditions among these concepts (Van de Ven 2007) in light of extant literature on contextualist inquiry (Pettigrew 1985, 1987, 1990). Similar deductive reasoning was applied to define concepts related to organizational intelligence (e.g., analytical intelligence, relational intelligence) and figurations (e.g., human agency, material agency). We also specified relationships and conditions among these concepts (Van de Ven 2007) in light of extant literature on intelligence (Glynn 1996;

Russell and Norvig 2013; Wilensky 1967) and figurations (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). Appendix C provides definitions of the key concepts. We went into coding and analysis of each digital innovation initiative with these predefined concepts and their preconceived relationships (Van de Ven 2007). However, although we conjectured that organizational intelligence would be present in the three aspects of contextualist inquiry, we did not hold any preconceived notion of the process involved in rationalizing, realizing, and managing the digital innovations. While we conjectured entanglement of human and material agency in analytical and relational intelligence, the specific steps and their sequence involved in the process of rationalizing, realizing, and managing the digital innovations through such entanglement was developed inductively (Van de Ven 2007). After coding the collected data based on the provisional codes, we inductively developed the process model on the implication of organizational intelligence in digital innovation (Miles et al. 2014; Saldaña 2015; Yin 2009) as consisting of three steps: understanding the context, innovating the content, and evaluating the outcome (Figure 1). Moreover, coded utterances were used in cross-case analysis and in the analysis of the organizational transformation context of the four embedded cases (Miles et al. 2014; Saldaña 2015; Yin 2009). Finally, we theorized about organizational intelligence by connecting our findings with extant literature. As such, our theorizing partly took place at the beginning of the research, and partly was based on the analysis of data.

CHAPTER 6. RESULTS

The digital innovation initiatives at GSU fall under four broad categories—in teaching, in monitoring, in engaging, and in financing (Figure 2). Our analysis of the collected data revealed that although there were several innovation initiatives, in some of them the role of digital technologies was less dominant and for some we have less comprehensive data. Hence, in the following (sections 6.1, 6.2, 6.3, and 6.4) we present detailed analyses of four select digital innovation initiatives, one in each category, that played dominant roles in GSU's Student Success Program and for which we had rich empirical material. We reveal how organizational intelligence was implicated in each case, by first introducing the case and then accounting for the three steps in our analytical model in Figure 1—understanding the context, innovating the content, and evaluating the outcome. For each step, we present empirical evidence of the entanglement of human and material agencies in the observed figurations of analytical intelligence and relational intelligence, followed by evidence of how analytical and relational intelligences entangled to form organizational intelligence, and finally a summary and overview of the findings. After the presentation of the four cases, we present a cross-case analysis (section 6.5) and conclude the chapter with an analysis of the context of organizational transformation in which the four cases where embedded (section 6.6).

6.1. Case 1: Organizational Intelligence during Digital Innovation in Teaching

6.1.1. Introduction

To improve student learning, GSU faced unique challenges from its socio-economic context. Georgia's diverse demography implies that the majority of students is African-American, Hispanic, and immigrants from around the world, and most students are first-generation college students from low-income families[1]. Nationally, first-generation, low-income students are historically far behind other student groups in baccalaureate degree attainment[2]. To improve the performance of this student body, GSU experimented with adaptive learning technologies (ALT) that use computer algorithms to support learning by selecting and adapting the presentation of materials and activities based on each student's responses to previous questions, tasks, and experiences.

GSU initiated its digital innovations based on ALT in math courses in 2006[3], it reinforced these innovation efforts through its strategic plan in 2011[4], and beginning in 2017, extended ALT to the Social Sciences[5]. The rationale for adopting ALT initially was that mathematics historically had been challenging for underprivileged students, who consistently failed or underperformed in introductory gateway mathematics courses. To break this pedagogical barrier, GSU redesigned its introductory mathematics courses applying ALT. As one of the decision-makers commented about ALT:

> *It is a very effective mechanism to train our students in math … it is not only that this is interactive learning, more importantly it is math. That could be a huge lever for improving student success.*

Like all other innovation initiatives, digital innovation in teaching was a highly collaborative effort rationalized by data-driven decision making[6]. As such, through the digital innovation in teaching, GSU demonstrated organizational intelligence in understanding its pedagogical context, realizing digital innovation in teaching, and evaluating its innovation efforts throughout.

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[1] 2013 Complete College Georgia Status Report: Georgia State University
[2] According to Stewart (2020)
[3] Timeline of Student Success Initiatives at Georgia State University
[4] GSU Strategic Plan 2011-2016/21
[5] 2018 Complete College Georgia Status Report: Georgia State University
[6] According to Renick (2020)

This organizational intelligence was evidenced as entanglement of analytical and relational intelligence.

6.1.2. Understanding the Context

To achieve the objective of improving the graduation rate, GSU had to explore and understand its context to figure out the pedagogical challenges students faced on their path to graduation. In understanding the context, GSU demonstrated both analytical intelligence (AI#1) and relational intelligence (RI#1), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#1). Resource scarcity and time constraints compelled GSU to identify and focus on the pedagogical challenges with the greatest negative effect on retention, progression, and ultimately graduation. Hence, GSU decided to identify high-enrollment courses with high DFW rates—a metric defined as the percentage of students who got a D or F or Withdrew from a course[7]. The higher the DFW rate, the worse effect a course has on retention, progression, and graduation. This decision to narrow the search to high-enrollment courses with high DFW rates ensured that GSU focused its efforts on those courses in which a large percentage of students were struggling or failing. Such a decision demonstrates analytical human agency in understanding the context, as decision makers explored the pedagogical context and identified problematic courses. However, GSU also had to analyze enrollment data and grade records of courses digitally stored in their basic information system called Banner[8]. As one of the decision makers commented:

> *One of the metrics that we look at in Banner, across all our sections is the DFW rate ... It's the number of students who got a D or F or withdrew from the course*

[7] Georgia State University College Completion Plan 2012

[8] 2013 Complete College Georgia Status Report: Georgia State University

divided by the total number of students of the course; the higher the percentage, the worse the outcomes.

Analyzing Banner data to identify high-enrollment courses with high DFW rates demonstrates analytical material agency, as technology was applied to explore the pedagogical context and identify problematic courses. While analytical human agency was necessary to decide where to focus on in the context, it was analytical material agency that informed the decisions. Similarly, while analytical material agency facilitated data analyses, analytical human agency was essential for making sense of analyses results. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in understanding the teaching context. Together, the decision to focus on high-enrollment courses with high DFW rates (analytical human agency) and the analysis of Banner data to identify such courses (analytical material agency) constituted a figuration of analytical intelligence (AI#1) through which GSU was able to understand its context and identify pedagogical challenges.

Relational Intelligence Figuration (RI#1). As far as relational intelligence is concerned in understanding the context, there was knowledge sharing and discussions among GSU administrators, staff, and faculty members in exploring and explaining the high DFW rates in introductory math courses. To assess the depth of the problems, faculty members conducted pedagogical research. Based on the reported success of ALT in introductory math courses, in 2016, faculty members in social sciences experimented with ALT[9]. Funded by the Bill & Melinda Gates Foundation they expanded ALT to first-year courses in the social sciences (e.g., Psychology, Economics, and Political Science). GSU also launched a study with Stanford University in 2018 to test the efficacy of ALT, in which researchers conducted experimental

[9] 2017 Complete College Georgia Status Report: Georgia State University

studies and perceptive surveys to document the context and experiences at GSU[10]. The experiments investigated the effect of ALT and the perceptive surveys revealed student perception about ALT. One of the pedagogical researchers commented:

> *In our perceptive survey, we were asking the students about how much time they spend. Again, all of this is subjective, right? But the more time they spend, the better they thought they were going to do. And, they generally did better at the end of the semester. We also asked, will you use similar techniques of working outside of class in other classes? ... we had a sizable number who said "yes, this helped me learn. I will apply this kind of approach to other classes."*

In conducting such experiments and surveys, knowledge sharing took place among the pedagogical researchers, research sponsors, and stakeholders at GSU, each contributing their own expertise. Collaborations among them facilitated design, development, and conduct of the experiments and surveys. As such, collective human intelligence of the collaborators was instrumental for understanding the teaching context, demonstrating relational human agency.

These relational endeavors were facilitated by general communication and collaboration technologies and by analysis of data stored in Banner. In communications and discussions among stakeholders at GSU and in every step of the research projects and the perceptive surveys, Banner provided data about the context and facilitated communication and collaboration among the people involved. Moreover, the implemented ALT itself played a role in representing specific pedagogical contexts and in facilitating transfer of knowledge from ALT instructors to students. Students attended ALT courseware sessions in large groups with dedicated instructors. In each session, students sat at individual terminals working on the same chapter of material using ALT. ALT kept track of each student's past performance and presented content accordingly. If a student faced any problem or had any question, one of the involved ALT instructors explained

[10] 2018 Complete College Georgia Status Report: Georgia State University

the content represented by the ALT to the specific student[11]. In this way, ALT mediated communication and exchange of knowledge between students and course instructors. The relational role of these technologies in facilitating communication, collaboration, and knowledge sharing exemplifies relational material agency in understanding the context. While relational human agency was necessary to combine knowledge and expertise of many people in understanding the context, it was relational material agency that facilitated such combinations. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to understand the teaching context. Together, the collaborative efforts of people in understanding the pedagogical context (relational human agency) and the role of technologies in representing the context with data (relational material agency) constituted a figuration of relational intelligence (RI#1) in understanding the teaching context.

Organizational Intelligence (OI#1). AI#1 ensured analyses of many different representations of the context based on data, focusing on different aspects. The results of these analyses were informative, but as such they were also fragmented and at times incomplete. RI#1 ensured that the analyses were collated, through collaboration, communication, and discussion, to arrive at a more comprehensive picture of the teaching context. While AI#1 was necessary to produce informative yet fragmented snippets of the context, RI#1 was essential to collate and corroborate such fragments to portray a more comprehensive picture of the context. As such, in understanding the context, the analytical intelligence figuration AI#1 and the relational intelligence figuration RI#1 entangled to constitute OI#1.

[11] 2018 Complete College Georgia Status Report: Georgia State University

Applying OI#1, in 2008, GSU identified three mandatory introductory math courses—College Algebra, Pre-Calculus, and Introduction to Statistics—that had the worst effect on retention, progression, and graduation. Every year at GSU, more than 8,000 freshmen enroll in these courses combined. Unfortunately, the average DFW rates of these courses were 43% in 2008. To get their math requirements out of the way, hundreds of freshmen were enrolling in one of these courses during their first fall, earning an F, then reenrolling in spring with no concrete prospects for doing any better and earning another F. Earning a D or withdrawing was not helpful either, since satisfactory grades in these courses were required for many majors and for maintaining scholarships. By the end of the freshmen year, many students had lost their Hope scholarships, were on academic probation, or had simply become discouraged. As a result, these three courses alone were responsible for thousands of students dropping out of GSU every year[12].

6.1.3. Innovating the Content

Efforts to understand the pedagogical context, compelled GSU to initiate digital innovation in teaching. Throughout the iterative process of digital innovation in teaching, GSU demonstrated both analytical intelligence (AI#2) and relational intelligence (RI#2), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#2). Appreciating the depth of the pedagogical challenges, GSU understood that minor tweaks in the problematic courses (e.g., College Algebra, Pre-Calculus, and Introduction to Statistics) would not be sufficient to improve retention, progression, and graduation. Hence, starting in 2006 GSU experimented with ALT in these introductory math courses, at a time when such an approach was relatively uncommon

[12] 2014 Complete College Georgia Status Report: Georgia State University

nationally[13]. GSU piloted sections of these courses using ALT modules, becoming an early adopter of ALT in higher education. In these experiments, GSU compared the performances of two groups of students: one group of students worked on their own on ALT exercises at computer stations at home and across campus; the other group of students spent one hour a week in a math lecture and three hours a week in an ALT lab working on personalized ALT exercises. Analysis of data from these experiments showed that the gains in student performance were minimal for the first group, whereas the gains in student performance were significantly greater for the second group[14]. As one faculty member and pedagogical researcher commented about the focus of their experiments:

> *Can adaptive learning help students do better in class? You know, and that could be for a number of reasons. I think I had that question at the beginning of the study. But of course, we're now at the end of our study. And, I have found that students have indeed learned better. But that's largely because of what our courseware makes them do, that is it makes them actually read. And, unsurprisingly, if students read, they will do better.*

GSU realized that the key was keeping students together as a group in a lab and having instructors present in the lab to answer any questions and lead larger discussions when needed. Based on this insight, GSU established Mathematics Interactive Learning Environment (MILE) labs. Students attended MILE lab sessions in large groups with dedicated instructors. In each lab session, students sat at individual terminals working on the same chapter of material using ALT and receiving support from instructors. All students were hence working in parallel, and the ALT instructors were walking around engaging with students one-on-one[15]. Moreover, in a lab

[13] 2013 Complete College Georgia Status Report: Georgia State University
[14] 2014 Complete College Georgia Status Report: Georgia State University
[15] 2018 Complete College Georgia Status Report: Georgia State University

session, the ALT analyzed past performance of students and presented learning material accordingly.

In innovating the content, GSU demonstrated human intelligence to design, develop, and conduct experiments with ALT. Technologies, such as Banner and ALT itself, were used to facilitate the experiments and to analyze the results. Through such experimentation and analyses, GSU was able to innovate MILE. As such, the innovation of MILE labs was possible because of analytical human agency in designing, conducting, and analyzing the experiments and analytical material agency in generating the results from those experiments by analyzing Banner data and in analyzing past performance of students from the ALT[16]. Together, the experimentation with ALT models (analytical human agency) and the analysis of those experiments and past performance of students (analytical material agency) constituted AI#2—a figuration of analytical intelligence—through which GSU was able to realize digital innovation in teaching.

Relational Intelligence Figuration (RI#2). As far as the figuration of relational intelligence (RI#2) is concerned in innovating the content, knowledgeable faculty members were selected to spearhead the digital innovation in teaching. In experimenting with ALT and in designing and developing appropriate ALT courseware, these faculty members shared knowledge with other GSU faculty members, GSU administrators, course content publishers, and courseware developers[17]. In a way, the knowledge possessed by these faculty members about a subject matter was transferred to students through the ALT courseware. Moreover, each semester faculty members provided training for ALT instructors on how to help students learn course material using ALT. In these training sessions, knowledge was transferred from faculty members to ALT

[16] 2018 Complete College Georgia Status Report: Georgia State University
[17] Based on the interview with a pedagogical researcher

instructors. In actual ALT lab sessions, pedagogical knowledge about a certain subject matter was transferred from faculty members and course instructors to ALT students. ALT students also provided feedback to the ALT instructors and faculty members about the ALT courseware. Encouraged by initial success of MILE labs, in 2016, faculty members in social sciences started experimenting on expanding ALT to undergraduate courses in Psychology, Economics, and Political Science[18]. Their experiments investigated the efficacy of ALT in social sciences. Again, knowledge sharing took place among the pedagogical researchers, research sponsors, and stakeholders at GSU in designing and conducting such experiments[19]. These collaborative efforts demonstrate relational human agency in realizing digital innovation in teaching, as innovating MILE and ALT in social sciences depended on the collective efforts of multiple involved actors.

Application of relational human agency was a necessary condition in innovating teaching, but not a sufficient one. Relational material agency was also demonstrated in every step of rationalizing, designing, and developing ALT. GSU administrators and pedagogical researchers had to use analytics on Banner data in the pilot study, in later experiments in social sciences, and in perceptual surveys[20]. Results of such analyses was used to facilitate debates and discussions among the stakeholders to assess the efficacy of and to determine the appropriate mode for ALT. Analytics of Banner data enabled knowledge sharing among faculty members, GSU administrators, research sponsors, content publishers, and courseware developers facilitated by general communication and collaboration technologies. Knowledge of the faculty members was transferred to the students through the courseware developed using ALT. ALT itself analyzed

[18] 2017 Complete College Georgia Status Report: Georgia State University
[19] Based on the interview with the Director of Learning Technologies
[20] According to Renick (2020)

past performance of students and presented personalized course contents to students accordingly[21]. An ALT coordinator commented about the MILE labs:

> *The key to the success of the program [MILE] is not only that it's digital. No, it is that it's relational. Of course, there are all these young people here [instructors] that are smart mathematicians, and the technology becomes basically a trigger or some focus that helps them interact with the students. So, the students learn when they are ready to learn, when they have a problem, rather than when someone is just talking to them.*

As such, analytics done by ALT facilitated transfer of knowledge from course instructors to students, interaction and communication between them, and flow of feedback from students to instructors. While relational human agency was necessary to conduct the experiments, relational material agency was essential to share and discuss the results of the experiments. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to innovate the content. Together, the collaborative efforts of people for rationalizing, designing, and developing ALT courseware (relational human agency) and the mediating role of technologies in facilitating interaction, communication, collaboration, and knowledge sharing (relational material agency) constituted RI#2—a figuration of relational intelligence.

Organizational Intelligence (OI#2). In innovating the content, AI#2 ensured experimentation with different modes of ALT and selection of appropriate modes of teaching; and RI#2 ensured communication, collaboration, and knowledge sharing among decision makers, instructors, and students. While AI#2 was necessary to design, develop, and conduct experiments and evaluate different modes of ALT, RI#2 was essential to discuss and rationalize the results of the experiments, to select the appropriate mode of ALT, to develop ALT courseware, to train ALT

[21] 2018 Complete College Georgia Status Report: Georgia State University

instructors, and to disseminate knowledge to students using ALT. As such, the analytical intelligence figuration AI#2 and the relational intelligence figuration RI#2 entangled to constitute OI#2 in innovating the content.

6.1.4. Evaluating the Outcome

In understanding the pedagogical context and iteratively innovating the content, GSU continually evaluated the outcome of its efforts. Such evaluation was used to justify their decisions or to revise their course of actions. In evaluating the outcome, GSU demonstrated both analytical intelligence (AI#3) and relational intelligence (RI#3), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#3). First and foremost, GSU decided to use DFW rate as the metric to identify problematic courses and to evaluate the efficacy of ALT in improving student performance in those courses as time progressed[22]. While in understanding the context GSU analyzed DFW rates across courses to identify courses in which students were failing or struggling in large numbers, in evaluating the outcome GSU monitored the DFW rates of ALT courses across time to assess the efficacy of ALT courseware. Initially, by analyzing DFW rates, GSU identified three problematic courses (e.g., College Algebra, Pre-Calculus, and Introduction to Statistics) and experimented with ALT in these courses. The experiments involved piloting sections with ALT modules and comparing the performances of two groups of students: one group of students worked on their own on ALT exercises at computer stations at home and across campus and the other group of students spent one hour a week in a math lecture and three hours a week in an ALT lab. To evaluate the outcome of each mode of ALT, GSU compared the DFW rates of the two groups and found that the gains in student performance were minimal for

[22] Georgia State University College Completion Plan 2012

the first group, whereas the gains in student performance were significantly greater for the second group[23]. As such, by comparing the outcomes of two modes of ALT courses, using the DFW rates, GSU was able to evaluate the efficacy of different modes of ALT. Beside DFW rate, GSU also monitored GPA and pass rates of students who took ALT courses in related courses taken later, to evaluate the overall effect of ALT in improving retention, progression, and graduation[24].

Selection of DFW rate as the metric to observe and consequent evaluation of ALT courseware using that metric demonstrates the important role of analytical human agency in evaluating outcomes. Analytical human agency was also applied in evaluating the outcome of the later experiments with ALT in social sciences and perceptive surveys. However, these evaluations were facilitated by Banner as the repository for all data related to all courses across time. Over time, Banner provided the necessary data, including DFW rates, GPA, and pass rates, to evaluate the efficacy of ALT. As one decision maker commented:

> *Banner basically does all of the heavy lifting for everything that kind of is a transaction that the university or one of the university students go through, and that's a very broad statement because it does a ton of things.*

As such, analytics done on Banner data to evaluate the efficacy of ALT over time demonstrates analytical material agency in evaluating outcomes. While analytical human agency was necessary to select the appropriate metrics and to evaluate any outcome based on those metrics, it was analytical material agency that facilitated storage, computation, retrieval, analysis, and comparison of the metrics. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in the endeavors to evaluate the outcome. Together,

[23] 2014 Complete College Georgia Status Report: Georgia State University
[24] 2018 Complete College Georgia Status Report: Georgia State University

the selection and monitoring of DFW rates, GPA, and pass rates (analytical human agency) and the analyses of Banner data in assessing the efficacy of ALT (analytical material agency) constituted AI#3—a figuration of analytical intelligence—through which GSU was able to continuously evaluate the outcome of its digital innovation efforts in teaching.

Relational Intelligence Figuration (RI#3). As far as the figuration of relational intelligence (RI#3) is concerned in evaluating the outcome, there were interactions and discussions among GSU administrators, faculty members, course content publishers, courseware developers, and ALT lab instructors in deciding the appropriate metric to monitor, and in evaluating and explaining the outcome of the pilot study, facilitated by general communication and collaboration technologies [25]. These stakeholders shared knowledge and proposed theses and antitheses in explaining how and why different modes of ALT had generated different results. Such collaborative evaluation of ALT in the pilot study led to the innovation in teaching. A decision maker commented about this collaboration:

> *When the course coordinators made their selections … vendors began working with the courseware developers to set up the course the way they would want. They also were requested to work with instructional designers to redesign the way they teach the course to incorporate adaptive learning … Our recommendation, and this was based on some work from Arizona State, was that part of the ALT course grading needed to be a percentage of the course grade … So, that happened throughout the latter half of spring and summer semester until they were ready for pilot in fall 2017.*

Through such discourse on the results of the initial pilot study, appropriate modes of pedagogy were selected, and ALT was extended to social sciences[26]. Apart from evaluation of ALT based on DFW rate, GPA, and pass rates, student perception about ALT was also collected through

[25] Based on the interview with a pedagogical researcher
[26] 2018 Complete College Georgia Status Report: Georgia State University

perceptive surveys. Moreover, the pedagogical researchers shared their own evaluation of the ALT courses[27]. Such insights helped further improve the efficacy of ALT. These collaborative efforts exemplify relational human agency in evaluating outcomes.

However, communication and discussion among stakeholders in evaluating outcomes of ALT was also supported by Banner facilitating access and analysis of DFW rates, GPA, and pass rates. In initial pilot study and in later pedagogical experiments and perceptive surveys, Banner facilitated storage of and access to data, the analysis of which enabled collaborative discourse among the stakeholders. As such, analytics conducted on Banner data exemplify relational material agency in evaluating the outcome of ALT courseware. Even today, GSU monitors the DFW rates in Banner to assess the efficacy of ALT in math and social sciences and explains such effect through discussions. While relational human agency was necessary to collectively evaluate the efficacy of an innovated content from different points of view, it was relational material agency that facilitated such collective discourse. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to evaluate the outcome. Together, the collaborative discourse of people in assessing and explaining the effect of ALT (relational human agency) and the analyses of Banner data in facilitating such collaboration (relational material agency) constituted RI#3—a figuration of relational intelligence—through which GSU was able to evaluate the outcomes of the digital innovation efforts in teaching.

Organizational Intelligence (OI#3). In evaluating the outcomes of the innovation efforts, AI#3 ensured analyses of Banner data to assess the efficacy of ALT, and to select the appropriate

[27] Based on the interview with a pedagogical researcher

mode of ALT and innovate MILE; and RI#3 ensured collaborative discourse that supported and complemented such analytic efforts in evaluating the efficacy of ALT. While AI#3 was necessary to select a metric and to assess the efficacy of ALT based on that metric, RI#3 was essential to collectively interpret and explain such assessment. As such, the analytical intelligence figuration AI#3 and the relational intelligence figuration RI#3 entangled to constitute OI#3 in evaluating outcomes.

In 2017-18 academic year, there was solid evidence of the positive effects of MILE[28]. All 8,500 seats of Introduction to Statistics, College Algebra, and Pre-Calculus offered at the GSU were taught using MILE. Before the launch of MILE, 43% of all GSU undergraduate students attempting introductory math courses were receiving non-passing grades; since the launch of MILE, non-pass rates for these courses have been reduced by 35%. As a result, 1,300 more undergraduate students annually are passing math courses in their first attempt than was the case before the launch of MILE. STEM completion rates at GSU have more than doubled over the last six years, with the greatest gains being seen by underserved populations. Students taking MILE lab sessions not only pass math courses at significantly higher rates, but also perform at higher levels in next-level courses reliant on math skills.

6.1.5. Summary and Overview

In digital innovation in teaching, GSU demonstrated organizational intelligence to understand the pedagogical context (AI#1 and RI#1), to iteratively innovate the media and modes of pedagogy (AI#2 and RI#2), and to continually evaluate the outcomes (AI#3 and RI#3). First, the initial understanding of the pedagogical context revealed courses in which a large number of students were failing or struggling (analytical human agency) and these problematic courses were

[28] 2018 Complete College Georgia Status Report: Georgia State University

identified by analyzing Banner data (analytical material agency). These efforts involved both human and material agencies that together constituted an analytical intelligence figuration AI#1 in understanding the context. The identified problematic courses had the worst effect on retention, progression, and ultimately graduation. There were discussions among the decision makers regarding the underlying causes of the problem (relational human agency), facilitated by analytics done on Banner data and by general communication and collaboration technologies (relational material agency). These collaborative efforts involved both human and material agencies that together constituted a relational intelligence figuration RI#1in understanding the context. While AI#1 was necessary to produce informative yet fragmented snippets of the context, RI#1 was essential to collate and corroborate the fragments to portray a more comprehensive picture of the context. As such, AI#1 and RI#1 together constituted OI#1, through which GSU was able to identify and explain the cause of the problem in its pedagogical context that hindered the graduation rate.

Second, with an understanding of its context, GSU decided to change the media and modes of the problematic courses by adopting ALT. GSU experimented with different modes of ALT (analytical human agency) and selected the most effective mode by analyzing Banner data (analytical material agency). As such, realizing digital innovation in teaching students involved both human and material agencies that together constituted an analytical intelligence figuration AI#2 in innovating the content. At the same time, the pedagogical researchers shared knowledge with stakeholders inside and outside GSU (relational human agency), mediated by analytics on Banner data and facilitated by general communication and collaboration technologies (relational material agency). Hence, collaborative innovation of ALT involved both human and material agencies that together constituted a relational intelligence figuration RI#2. While AI#2 was necessary to design, develop, and conduct experiments and evaluate different modes of ALT, RI#2 was essential to discuss and rationalize the results of the experiments, to select the appropriate mode of ALT, to develop ALT courseware, to train ALT instructors, and to disseminate knowledge to students using ALT. As such, AI#2 and RI#2 together constituted OI#2, through which GSU was able to innovate MILE labs and later ALT courseware in social sciences.

Third, to evaluate outcomes continually, GSU selected DFW rate as the metric and monitored that metric in understanding the pedagogical context and in assessing the efficacy of ALT (analytical human agency), applying analytics on Banner data (analytical material agency). Hence, evaluating outcomes involved both human and material agency that together constituted a figuration of analytical intelligence (AI#3). Moreover, decision makers continuously engaged in collaborative discourse to assess and explain the efficacy of ALT (relational human agency), facilitated by analysis of Banner data and by general communication and collaboration technologies (relational material agency). These collective evaluations involved both human and material agency that together constituted a figuration of relational intelligence (RI#3). While AI#3 was necessary to select a metric and to assess the efficacy of ALT based on that metric, RI#3 was essential to collectively interpret and explain such assessment. As such, AI#3 and RI#3 together constituted OI#3, through which GSU was able to evaluate the outcomes of its innovation efforts. These evaluations helped GSU readjust their focus of understanding the context and revise their efforts in innovating the content.

Apart from the forward progression of digital innovation in teaching, from context to content and further to outcomes, GSU iteratively explored its academic context and innovated ALT based on insights from the evaluation of the outcome of past innovations. Since 2006, when one MILE lab was launched, GSU has been collecting and analyzing data on student performance in mathematics to evaluate the outcome of ALT[29]. Based on these ongoing evaluations, GSU has experimented with different modes of ALT and gradually improved the efficacy of and the number of MILE labs[30]. These iterative innovations of MILE labs demonstrate the feedback from evaluating the outcome to innovating the content. Moreover, after initial success of MILE labs, GSU explored the applicability of ALT in a different context, namely in social sciences[31]. These efforts demonstrate the feedback from evaluating the outcome to understanding the context. As such, the digital innovation in teaching students was an ongoing process in which organizational intelligence in each iteration was a means for understanding the pedagogical context and innovating the content, and at the same time organizational intelligence continued to develop as a result of these efforts.

6.2. Case 2: Organizational Intelligence during Digital Innovation in Monitoring

6.2.1. Introduction

Since the majority of its students is underprivileged, due to the socio-economic context in Georgia, GSU had a high dropout rate in the past[32]. To reduce the dropout rate, GSU decided in 2011 to closely monitor and frequently advise students by adopting predictive analytics and redesigning academic advising[33]. GSU collaborated with Education Advisory Board (EAB) to continuously develop a graduation progression system (GPS) that monitors and detects problems students face and complementary advising technologies that help students avoid or overcome these problems. GPS uses predictive analytics and a system of more than 800 alerts to track all

[29] 2013 Complete College Georgia Status Report: Georgia State University
[30] Based on the interview with a pedagogical researcher
[31] Based on the interview with a pedagogical researcher
[32] According to Renick (2020)
[33] GSU Strategic Plan 2011-2016/21

undergraduate students daily, identify at-risk behaviors, and have advisers respond to alerts by intervening in a timely manner to get students back on track[34].

GSU created a centralized structure of trained academic advisers, the University Advisement Center (UAC), to monitor the alerts and respond with timely, proactive advice to students at scale[35]. UAC consolidated, centralized, and replaced the previous fragmented advising organization that was fraught with problems. UAC has implemented a vertical governance structure for common advising systems and technologies that offer systematic tracking and record keeping, and coordination among advisers. Through UAC, GSU significantly reduced student-to-adviser ratio by hiring new academic advisers and providing systematic training for them. As such, the goal of UAC is to give students the information that they need when they need it to make decisions that lead to increased retention, progression, and graduation. UAC is continually working towards this goal through individualized education planning, proactive risk targeting, and personalized interventions. As the SVP of student success commented:

> *With GPS advising, we are engaging with students and really changing their trajectory towards graduation.*

GPS enables GSU to monitor every undergraduate student and predict any potential problems they might face using analytics; and UAC facilitates avoiding or overcoming such problems through personalized intervention and academic advising. GPS advising is a digital innovation that is highly collaborative and rationalized by data-driven decision making. As such, through the digital innovation in monitoring students, GSU demonstrated organizational intelligence in understanding its academic context, realizing digital innovation in monitoring and advising its

[34] 2018 Complete College Georgia Status Report: Georgia State University
[35] Building University Infrastructure: Student Advisement

students, and evaluating its monitoring innovation efforts throughout. This organizational intelligence was evidenced as entanglement of analytical and relational intelligence.

6.2.2. Understanding the Context

To achieve the objective of reducing dropout rate, GSU had to explore and understand its academic context to figure out how students could be better monitored and advised throughout their path to graduation. In understanding the context, GSU demonstrated both analytical intelligence (AI#4) and relational intelligence (RI#4), both constituted as entanglements of human agency and material agency.

Analytical Intelligence Figuration (AI#4). As recently as 2010, 5,700 students dropped out of GSU every year[36]. In preparation for the new GSU strategic plan, the GSU President requested an assessment of the impact of academic advising on combating dropout rates[37]. Such an assessment helped GSU understand the academic context and identify problems. At that time, GSU had a collection of fragmented academic advising systems that had developed piecemeal over time. Within this complex advising structure, the university and its colleges maintained six different advising offices with a very high student-to-adviser ratio, little coordination, no common record-keeping, little systematic tracking, and no common training for the advisers[38]. One of the leaders of the Student Success Program expressed his frustration:

> *Advising was decentralized. So, there was one office of advising that was run by the university, which was for the freshmen as they first came in. And, then very soon thereafter, they'd be funneled out to the colleges, and most of the advising would occur at these decentralized offices…it was very problematic…the first real challenge was to turn that advising unit around.*

[36] According to Renick (2020)
[37] GSU Strategic Plan 2011-2016/21
[38] 2013 Complete College Georgia Status Report: Georgia State University

Moreover, while advisers were working hard and most students left advising sessions pleased with their advisers, the assessment drew a sobering picture of the impact of advising on graduation rates overall. With a campus-wide ratio of 800 students per adviser, advisers mostly put out fires by responding to the students who came for advising each day. These students fell into two basic categories: first, there were honors students who were conscientious on all issues related to their program, and hence most of these students would graduate with or without the help they received from advisers[39]. Second, there were failing students who, by academic policy, were forced to see advisers because their GPA had dropped below 2.0. These students were foundering and, while the advice from their advisers was appreciated, data showed that GSU was getting to them too late to turn most of their trajectories around. As such, despite the advice they received, most of these students still failed to graduate. Ironically, the students who advisers were not seeing at scale were B and C students, who tend to fly under the radar at many universities and rarely raise their hands for attention. GSU realized that these were precisely the students who might be turned from college dropouts into college graduates with the right advice at the right time[40]. GSU also realized that it would have to find indications that a student was going off track, not after the student's GPA had plummeted and the student was on probation with one foot already out the door, but at the first sign of a misstep. Consequently, GSU became one of the first higher education institutions to adopt predictive analytics in monitoring students[41].

Such efforts to understand the academic context demonstrate analytical human agency, as decision makers explored and analyzed the context, identified problematic aspects in advising,

[39] According to Renick (2020)
[40] According to Renick (2020)
[41] According to Gumbel (2020)

selected a group of students as the main target group for advising, and decided to redesign advising around predictive analytics. However, GSU also had to analyze retention progression and graduation (RPG) data digitally stored across fragmented advising systems in these efforts. Analyzing RPG data to explore academic advising demonstrates analytical material agency in understanding the context, as technology was applied to comprehend the academic context and identify problematic issues. While analytical human agency was necessary to identify and explain problematic issues in advising, it was analytical material agency that informed the efforts. Similarly, while analytical material agency facilitated RPG data analyses, analytical human agency was essential for making sense of analyses results. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in understanding the academic context. Together, the decision to redesign academic advising with predictive analytics (analytical human agency) and the analysis of RPG data to reach that decision and to identify problems in advising (analytical material agency) constituted a figuration of analytical intelligence (AI#4) through which GSU was able to understand its context.

Relational Intelligence Figuration (RI#4). At a large, decentralized institution such as GSU, multiple data systems managed by different stakeholders across the organization can undermine data consistency and reliability in monitoring students. To understand the academic context correctly and comprehensively, all concerned people at GSU, and its technology partners had to have access to clean, reliable data. Since the advising systems were decentralized before 2012, people at different organizational units worked together to consolidate the fragmented systems to render a complete picture of the academic context[42]. As an example, in 2008, GSU was unable to reliably report which bachelor students were enrolled in which majors. The major field in Banner

[42] According to Gumbel (2020)

was infinitely flexible. This meant that staff members could enter any term into the field, and Banner would accept this entry as the student's major. In 2008, substantive discussions about the use of data with department chairs and faculty members quickly devolved into discussions about the quality of the data[43].

A first step in GSU's transition to monitor students and predict their behavior was cleaning up the data. In the case of the major field in Banner, GSU introduced a gold standard for the terms that could appropriately be entered by staff and began to run nightly reports to revise and correct any terms entered into the major field during the previous 24 hours that did not adhere to the gold standard, enabling any discrepancies to be corrected immediately. Gold standard of data, including acceptable terms for majors, were established through discussions among stakeholders across the organization. Eventually the data became more reliable and the substantive discussions with chairs and faculty members began to focus on the crucial topics of improving student success rather than issues of data quality[44].

Second, multiple sources of data had to be united into a single platform. In the past, various offices across GSU collected their own data on individual servers. Campus discussions often hinged on whose data was being cited, and this meant decisions were often difficult to come by or, worse, ill informed. In 2009, the GSU President declared the university's central data system as the official source of data for university meetings and decision making. While different offices could informally run their own data systems, data from such systems would not be used in formal decision making[45]. Not surprisingly, deans, vice presidents and other leaders quickly began to collaborate with the institutional research office to ensure that their data were properly

[43] According to Renick (2020)
[44] According to Renick (2020)
[45] 2013 Complete College Georgia Status Report: Georgia State University

vetted and then centrally housed, and that any new systems adopted would be compatible with the university platform. Today, GSU's data warehouse, IPORT, offers 200 publicly accessible screens that pull data from multiple data sources from across the organization and that are updated nightly. IPORT has become the accepted data source of record[46]. The Chief Innovation Officer commented:

> *These systems are the key sources of data, and you want to pull data out of that and leverage it with these other tools…to drive student success.*

In understanding the academic context through data, knowledge sharing took place among the stakeholders at GSU. Collaborations among them facilitated setting the gold standard for data, cleaning data, consolidating data across fragmented systems, and ensuring reliability of data. As such, these collaborations were instrumental for understanding the academic context correctly and comprehensively, demonstrating relational human agency. At the same time, the relational role of technologies, such as, RPG, IPORT, Banner, and general communication and collaboration technologies, in facilitating communication, collaboration, and knowledge sharing exemplifies relational material agency in understanding the academic context. While relational human agency was necessary to collate data from fragmented sources and corroborate the reliability and consistency of data in understanding the context, it was relational material agency that facilitated such collation and corroboration. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to understand the academic context. Together, the collaborative efforts of people in understanding the academic context (relational human agency) and the role of technologies in representing the context with

[46] According to Gumbel (2020)

data and in facilitating communication and collaboration (relational material agency) constituted a figuration of relational intelligence (RI#4) in understanding the academic context.

Organizational Intelligence (OI#4). AI#4 ensured an understanding of the problems and shortcomings in monitoring and advising students and an appreciation of reliable data in predicting student behavior. RI#4 facilitated collaboration, communication, and discussion among stakeholders about consistency and reliability of data that correctly and comprehensively represented the academic context. While AI#4 was essential in deciding the means and focus of student monitoring and advising, RI#4 was necessary in corroborating such decisions. As such, in understanding the academic context, the analytical intelligence figuration AI#4 and the relational intelligence figuration RI#4 entangled to constitute OI#4.

6.2.3. Innovating the Content

Understanding the academic context compelled GSU to initiate digital innovation in monitoring and advising students through predictive analytics. Throughout an iterative process of digital innovation in monitoring, GSU demonstrated both analytical intelligence (AI#5) and relational intelligence (RI#5), both constituted as entanglements of human agency and material agency.

Analytical Intelligence Figuration (AI#5). GSU's move to predictive analytics started with identifying indicators that a student was going off track. Such indicators would be useful in predicting potential problems for students early at the first sign of a misstep and before it was too late[47]. In 2011, with the help of EAB, GSU used ten years of its own data, 144,00 student records, and 2.5 million grades in a big data project[48]. The goal was simple: Can GSU find identifiable academic behaviors by students (i.e., indicators) that correlate in a statistically

[47] According to Renick (2020)
[48] 2014 Complete College Georgia Status Report: Georgia State University

significant way to their dropping out of the university? While the initial projection was that GSU might be able to identify only a few dozen such indicators, gradually, it found more than 800 indicators that correlated statistically significantly to students dropping out or academically failing. The developed predictive analytics model in GPS tracks each student on these indicators daily[49].

Some indicators were identified by analyzing registration records. Since college requirements differ by major, students can easily get off path by attempting a course for which they were unprepared or a course that does not fit their program. If these mistakes are not caught up front, students too often end up with failing grades or being forced to withdraw from a course in the middle of the term. Analyses of the registration records also revealed “toxic combinations” of courses. For example, students may pass calculus and physics at good rates if they take the two courses in different semesters, but when they take the courses at the same time, success rates plummet. The predictive analytics model tracks such indicators from students’ registration records[50].

Analyzing class attendance data, GSU found that there is a strong correlation between class attendance and success. Since it is nearly impossible to get thousands of faculty members to take class attendance daily, GSU monitors the electronic footprint students leave behind as a proxy for attendance. These proxies include students signing on to the campus Wi-Fi system or to the course’s learning management platform[51].

[49] Based on the interview with a decision maker at Student Success Program
[50] According to Renick (2020)
[51] Based on the interview with a decision maker at Student Success Program

Analysis of early grades in students' majors revealed that the grades that students earn in the first course they take in their majors are highly predictive of their chances for success. For example, at GSU, political science students who earn an A or a B in their first political science course graduate at a 75% rate; those who receive a C in that first course graduate at a 25% rate. GSU historically had done nothing with the C students but to pass them on to upper-level and more demanding coursework, where for 75% of these students, the C grades would turn to Ds and Fs. By using early grades in a major as an indicator, the goal is to address the problem while it still can be corrected—not after the student has collected a string of failing grades, has lost a scholarship, or is on academic probation[52].

Analyzing grades in prerequisite courses, GSU found that two students can sit in the same course and earn the same grade, and yet one is at risk for dropping out while the other is not. For example, if a student earns a C in College Algebra and is an English major, he or she may have a 90% chance of graduating; conversely, if the student earning the C grade in the same course is a neuroscience major, the chances of graduating may drop to 20%. The reason is simple: C-level math skills may be enough to get a student through the rest of the required courses for the English major, but they may be wholly inadequate to equip the student to tackle senior-level coursework in neuroscience[53]. The Deputy Chief Innovation Officer commented:

> *So, we dedicated a team of people, who were very familiar with the data in our underlying systems, on basically a full-time basis to identify those [indicators]. I think now we are up to some eight hundred different indicators integrated in the predictive analytics framework.*

In innovating the predictive analytics model, GSU demonstrated analytical human agency, since knowledge and experience of people was used in exploring, targeting, analyzing, rationalizing,

[52] According to Renick (2020)
[53] Based on the interview with a decision maker at Student Success Program

and explaining the indicators. Analytical human agency ensured that GSU was focusing on and selecting the appropriate indicators to monitor. Technologies, such as RPG, IPORT, and Banner facilitated such analyses in identifying the statistically significant indictors by providing the necessary data and computational capability. The GPS itself conducted statistical computations on all data to select an appropriate set of indicators as it was being developed. Together, the exploration of potential indicators to monitor students (analytical human agency) with the data and computational capability provided by technologies (analytical material agency) constituted AI#5—a figuration of analytical intelligence—through which GSU was able to realize digital innovation in monitoring students.

Relational Intelligence Figuration (RI#5). Stakeholders from different units at GSU communicated, discussed, and collaborated in selecting the indicators to develop the predictive analytics model of GPS[54]. Knowledge sharing took place across the organization in rationalizing, selecting, and explaining the indicators. Moreover, such efforts transcended the organizational boundaries of GSU and included the technology partner EAB and a task force named Enhanced Advising Processes (EAP). As its technology partner, EAB gradually developed the GPS system through collaboration and knowledge sharing with GSU. The applicability and significance of potential indicators selected by GSU were evaluated by EAB as it developed the predictive model[55].

The EAP task force had the objective of seeking innovative approaches to enhance advising at all 35 University System of Georgia (USG) institutions. The 26-member team examined current academic advising processes and formulated appropriate recommendations to improve the

[54] Based on the interview with a decision maker at University Advisement Center
[55] Based on the interview with a decision maker at Student Success Program

quality and effectiveness of advising at all USG institutions. EAP assessed planning, information, and evaluation of academic advising and made recommendations designed to improve student engagement and academic success through the advising process at all USG institutions, which shared knowledge with each other. EAP's assessment of institutional efforts included both quantitative and qualitative metrics so that each institution would have an opportunity to describe how their academic advising system met student needs[56].

Predicting potential problems for students using GPS is only part of the solution for the dropout problem. When GPS identifies at-risk behaviors, using predictive analytics with a system of more than 800 indicators, it sets up one-on-one meetings with academic advisers. Academic advisers respond to alerts generated by GPS by intervening in a timely manner to get students back on track[57]. The prediction of problems and the interventions of advisers together is known as GPS advising. To facilitate GPS advising, GSU has created UAC as a centralized structure of trained academic advisers to monitor the GPS alerts and respond with timely, proactive advice for students at scale. EAB and GSU collaboratively innovated complementary advising systems and technologies (e.g., Navigate, DegreeWorks) to guide students to avoid or overcome such problems. GPS and these complementary advising systems and technologies together act as a navigation system that guides students through their educational journey[58]. As a leader of the UAC commented:

> *The different platforms that we do utilize include Navigate, which is through EAB. And we have DegreeWorks, and Banner. And, those are our primary technology touch points that we use; we also do a heavy amount of work in Excel. So, we utilize all those in every single advising session that we meet with a student. We're*

[56] Task Force on Enhanced Advising Processes: Assessment of Institutional Efforts
[57] According to Renick (2020)
[58] Based on the interview with a decision maker at University Advisement Center

using them to connect the dots to make sure we are holistically advising the student, and proactively engaging the student population as best as possible.

Collaborative efforts within and across organizations in identifying and selecting predictive indicators demonstrate relational human agency in innovating the predictive model, by involving human intelligence in rationalizing and explaining the indicators. Relational human agency is also demonstrated by the actual interventions of advisers as they provide personalized advice to help students avoid or overcome predicted problems. However, the exploration of potential indicators through collaboration would not be possible without digital technologies that facilitated access to data, statistical computation conducted on that data, and communication and collaboration among the stakeholders. In collaboratively innovating advising, analyses done on student registration records, class attendance data, early grades in students' majors, and grades in prerequisite courses were all facilitated by systems such as RPG, IPORT, and Banner. Similarly, GPS and complementary advising systems (e.g., Navigate, DegreeWorks) facilitated personalized communication between an adviser and a student in each intervention. Use of such information systems demonstrates relational material agency. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to innovate the content of monitoring students. Together, the collaborative efforts of people in exploring and selecting advising solutions (relational human agency) and the mediating role of technologies in facilitating computation, communication, collaboration, and knowledge sharing (relational material agency); and, the interventions of advisers to help students with personalized advice (relational human agency) and the mediating role of technologies in facilitating communication, conversation, and knowledge sharing (relational material agency) constituted RI#5—a figuration of relational intelligence.

Organizational Intelligence (OI#5). AI#5 ensured exploration of potential indicators in monitoring students and selection of predictive indicators through statistical computation, whereas RI#5 facilitated collaboration, communication, and discussion among stakeholders about academic advising based on predictive analytics. While AI#5 was essential in identifying potential problems for students, RI#5 was necessary in timely interventions to help students avoid or overcome such problems. Without monitoring students through predictive analytics (AI#5), personalized advising (RI#5) is not possible. Similarly, without personalized advising in interventions (RI#5), monitoring students through predictive analytics (AI#5) cannot solve the dropout problem. As such, in innovating the content of monitoring students, the analytical intelligence figuration AI#5 and the relational intelligence figuration RI#5 entangled to constitute OI#5.

6.2.4. Evaluating the Outcome

In understanding the academic context of and in iteratively innovating the content of monitoring students, GSU continually evaluated the outcome of its efforts. Such evaluation was used to justify decisions or to revise courses of action. In evaluating the outcome, GSU demonstrated both analytical intelligence (AI#6) and relational intelligence (RI#6), both constituted as entanglements of human agency and material agency.

Analytical Intelligence Figuration (AI#6). GSU monitored different metrics to continuously evaluate the outcome of the innovated GPS advising system. Six-year graduation rate in 2011, before launching GPS advising, was 48% at the bachelor level. In its first year of operation in 2012-13 academic year, the GPS system was used in 15,800 advisement sessions. 2,452 students were converted from off path to on path for graduation, and 900 had their schedules corrected during registration when markers were triggered indicating that they had signed up for wrong or unnecessary courses. According to GPS analytics, the net impact of the first year of the GPS advising initiative was a 1.1 percentage point increase in the institutional graduation rate[59].

In the 2019-20 academic year (the most recent collected data), the GPS system generated more than 55,000 individual meetings between students and advisers to discuss specific alerts and get students back on a path toward graduation. Before GPS went live, many students were confused on which major to choose and which courses to register for. Since GSU initiated GPS advising, the number of students in majors that fit their academic abilities increased by 13 percentage points, progression rates increased by 16 percentage points, and changes of major in the sophomore, junior and senior years decreased by 32%. Also, freshman fall-to-spring retention rates increased by 5 percentage points and graduating seniors are taking fewer excess courses in completing their degrees. Six-year graduation rate was up 7 percentage points at the bachelor level compared to the graduation rate in 2011[60].

The objective of innovating GPS advising was to reduce dropout rate and thus improve retention, progression, and graduation rates by monitoring students with predictive analytics and advising students with personalized interventions. Much like the GPS systems in cars that keep drivers on course and navigate them to the desired destination, GPS advising keeps students on track to graduation without going far off path, wasting time, money, or worse, dropping out. The metrics to evaluate the impact of GPS advising were selected accordingly. With GPS advising, students are notified the moment that they make a wrong turn and advisers can help them with the steps to get back on path again[61]. As the leader of the Student Success Program commented:

> *GPS advising is helping students navigate their whole academic program.*

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[59] 2014 Complete College Georgia Status Report: Georgia State University

[60] 2018 Complete College Georgia Status Report: Georgia State University

[61] According to Renick (2020)

In selecting, monitoring, and explaining the metrics, GSU demonstrated analytical human agency, since the rationale for each metrics was established through human intelligence. At the same time, computation, analysis, and monitoring of such metrics was facilitated by many information systems. GPS itself keeps track of the predicted problems and the consequent interventions. Complementary advising systems, such as, Navigate and DegreeWorks keep track of the interactions between advisers and students. Finally, basic information systems, such as, RPG, IPORT, and Banner facilitate computation and analysis of evaluation metrics[62]. While analytical human agency was necessary to rationalize and explain the effects of different metrics, it was analytical material agency that facilitated the computation and comparison of such metrics. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in the endeavors to evaluate the outcome of the GPS advising innovation. Together, the selection and explanation of the evaluation metrics (analytical human agency) and the computation and analysis of those evaluation metrics (analytical material agency) constituted a figuration of analytical intelligence (AI#6) through which GSU was able to evaluate the outcome of its innovations in monitoring and advising students.

Relational Intelligence Figuration (RI#6). All the metrics used to evaluate the outcome of GPS advising were selected after collaborative discussions among GSU administrators, Student Success Program leaders, and UAC decision makers. The rationale for selecting a metric to assess the outcome were presented and debated, from different points of view and levels of expertise. Collaborative discussions also took place in explaining the registered values of metrics. Theses and antitheses were put forth in explaining what the metrics mean and why the

[62] Based on the interview with an adviser at University Advisement Center

metrics registered a certain value[63]. In 2012, GSU started the UAC with 43 academic advisers. After initial positive performance according to the metrics, UAC gradually increased the number of advisers to 70 in 2020, bringing the student-to-adviser ratio closer to the industry-accepted 300:1 level. In evaluating the outcome of GPS advising, GSU also monitored the performance of each adviser, apart from monitoring the metrics related to retention, progression, and graduation[64]. As one decision maker at the UAC commented:

> *Of course, we measure the performance of each adviser. There is randomness there. But if an adviser is advising for five years, then you can remove the randomness and then you can talk about the success rate of her students.*

Each adviser is also required to record a summary text of each advising session. These text records of advising sessions are analyzed by administrators to evaluate the performance of the advisers and for training purposes. Advisers also have weekly meetings with administrators to discuss specific issues they faced during the week related to the advising process and the technologies used in advising. Based on the discussions of these meetings, UAC improves the advising process, revises training materials, and requests changes in the technologies. Requests about updating GPS and Navigate are communicated to EAB through the liaison person at GSU. Based on these suggestions, EAB updates GPS and Navigate accordingly.

In collaboratively selecting, monitoring, and explaining the metrics, GSU demonstrated relational human agency, since the rationale for each metric was established through joint discourse. At the same time, the collaborative computation, analysis, and monitoring of such metrics was facilitated by GPS, complementary advising systems, such as, Navigate and DegreeWorks, and basic information systems, such as, RPG, IPORT, and Banner. Collaboration

[63] Based on the interview with a decision maker at University Advisement Center
[64] According to Renick (2020)

among the stakeholders was further facilitated by general communication and collaboration technologies. The use of these information systems and technologies demonstrates relational material agency in evaluating the outcome. While relational human agency was necessary to rationalize and explain the effects of different metrics through discussing theses and antitheses from different points of view, relational material agency was necessary to facilitate the computation and comparison of such metrics. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to evaluate the outcome of the GPS advising innovation. Together, the selection and explanation of the evaluation metrics (relational human agency) and the computation and analysis of those evaluation metrics and discussions about the metrics facilitated by general communication and collaboration technologies (relational material agency) constituted a figuration of relational intelligence (RI#6) through which GSU was able to evaluate the outcome of its innovations in monitoring and advising students.

Organizational Intelligence (OI#6). In evaluating the outcomes of the innovation efforts in monitoring and advising students, AI#6 ensured computation and analyses of data to assess the efficacy of GPS advising, using different metrics, and selection of the appropriate metrics; and, RI#6 ensured collaborative discourse that supported and complemented such analytic efforts in evaluating the efficacy of GPS advising. While AI#6 was necessary to select appropriate metrics and to assess the efficacy of GPS advising based on those metrics, RI#6 was essential to collectively form, interpret and explain such assessment. As such, the analytical intelligence figuration AI#6 and the relational intelligence figuration RI#6 entangled to constitute OI#6 in evaluating the outcomes of the innovation efforts in monitoring and advising students.

6.2.5. Summary and Overview

In digital innovation in monitoring, GSU demonstrated organizational intelligence to understand the academic context (AI#4 and RI#4), to iteratively innovate GPS advising (AI#5 and RI#5), and to continually evaluate the outcomes (AI#6 and RI#6). First, in its digital innovations to monitor and advise students, GSU developed an understanding of the academic context by exploring problematic aspects in current practices (analytical human agency) through analysis of RPG data (analytical material agency). These efforts involved both human and material agencies that together constituted an analytical intelligence figuration AI#4. At the same time, collaboration among stakeholders was essential for understanding the academic context comprehensively (relational human agency), mediated by digital technologies, such as, RPG, IPORT, and Banner to support communication, collaboration, and knowledge sharing (relational material agency). These collaborative efforts involved both human and material agencies that together constituted a relational intelligence figuration RI#4. While AI#4 was essential in deciding the means and the foci of student monitoring and advising, RI#4 was necessary to corroborate findings and decisions. As such, in understanding the academic context, the analytical intelligence figuration AI#4 and the relational intelligence figuration RI#4 entangled to constitute OI#4.

Second, with an understanding of its academic context, GSU decided to innovate proactive advising based on predictive analytics. In these efforts, knowledge and experience of people was used to explore, target, analyze, rationalize, and explain indicators (analytical human agency), facilitated by technologies, such as RPG, IPORT, and Banner to identify statistically significant indictors (analytical material agency). As such, realizing digital innovation in monitoring and advising students involved both human and material agencies that together constituted an analytical intelligence figuration AI#5. At the same time, these efforts required collaboration within and across organizations to identify and select predictive indicators and interventions of advisers (relational human agency) enabled by digital technologies that facilitated access to and computation of data, communication and collaboration, and actual interventions (relational material agency). Hence, collaborative innovation of GPS advising involved both human and material agencies that together constituted a relational intelligence figuration RI#5. While AI#5 was essential in identifying potential problems for students, RI#5 was necessary to create timely interventions to help students avoid or overcome such problems. As such, in innovating the content, the analytical intelligence figuration AI#5 and the relational intelligence figuration RI#5 entangled to constitute OI#5.

Third, in digital innovations to monitor and advise students, GSU periodically evaluated the performance of the GPS advising by selecting, monitoring, and explaining different metrics (analytical human agency). Computation, analysis, and monitoring of the metrics were facilitated by GPS, complementary advising systems, such as, Navigate and DegreeWorks, and basic information systems, such as, RPG, IPORT, and Banner (analytical material agency). Hence, evaluating outcomes involved both human and material agency that together constituted a figuration of analytical intelligence (AI#6). At the same time, collaborative discourse was necessary for selecting, monitoring, and explaining the metrics (relational human agency), facilitated by GPS, Navigate, DegreeWorks, RPG, IPORT, Banner, and general communication and collaboration technologies (relational material agency). These collective evaluations involved both human and material agency that together constituted a figuration of relational intelligence (RI#6). While AI#6 was necessary to select appropriate metrics and to assess the efficacy of GPS advising based on those metrics, RI#6 was essential to collectively interpret and explain the assessments. As such, the analytical intelligence figuration AI#6 and the relational intelligence figuration RI#6 entangled to constitute OI#6 in evaluating outcomes of the innovation efforts in monitoring and advising students.

Apart from the forward progression of digital innovation in monitoring and advising students, from context to content and further to outcomes, GSU iteratively explored its academic context and innovated GPS advising based on insights from evaluation of the outcome of past innovations. Since 2012, when GPS advising went live, the retention, progression, and graduation rates gradually improved[65]. Hence, GSU periodically explored problematic aspects in the evolving academic context[66]. These continued explorations helped understand changes in the academic context and readjust the means and the foci of the innovation efforts[67]. Similarly, innovation of GPS advising was an iterative process, in which GSU gradually developed the predictive analytics model, included more predictive indicators, and improved the predictive power of the model[68]. After every such development of the predictive model of GPS advising, GSU evaluated its performance[69]. As such, the digital innovation in monitoring and advising students was an ongoing process in which organizational intelligence in each iteration was a means for understanding the academic context and innovating the content, and at the same time organizational intelligence continued to develop as a result of these efforts.

[65] 2013 Complete College Georgia Status Report: Georgia State University; 2014 Complete College Georgia Status Report: Georgia State University; 2015 Complete College Georgia Status Report: Georgia State University; 2016 Complete College Georgia Status Report: Georgia State University; 2017 Complete College Georgia Status Report: Georgia State University; 2018 Complete College Georgia Status Report: Georgia State University

[66] Based on the interview with a decision maker at Student Success Program

[67] Based on the interview with a decision maker at Student Success Program

[68] According to Renick (2020)

[69] Based on the interview with a decision maker at University Advisement Center

6.3. Case 3: Organizational Intelligence during Digital Innovation in Engaging

6.3.1. Introduction

Success in college education requires students to engage with their institution both academically and administratively[70]. Transitioning to college can be very difficult for students, as they face substantial administrative requirements once enrolled. As such, the journey of college education is overwhelming even before it begins, especially for first-generation, low-income students, many of whom fail to navigate the path towards college education after high school graduation[71]. To successfully begin their college education, accepted students need answers to questions about financial aid, FAFSA, registration, immunization, housing, admissions, and academic advising[72]. Although student advisers may have answers to these questions, they cannot reach all students. Moreover, students also feel vulnerable and hesitant to share personal information with a stranger[73]. Missteps with required processes can threaten students' ability to start college education and persist.

Hence, GSU realized that it needed to be far more proactive and personal in interacting with students between high-school graduation and the first day of college classes. In 2016, GSU collaborated with Admit Hub to deploy an artificial intelligence (AI) chatbot—a texting system named after the school mascot 'Pounce'—and became one of the first institutions nationally to adopt AI chatbots. In 2019, Pounce became a platform for communicating with all students, incoming or continuing alike, on myriad of issues[74]. As the project director of the chatbot commented:

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[70] According to Page et al. (2020)
[71] Based on the interview with a decision maker at Student Success Program
[72] Association Governing Boards 2019
[73] Based on the interview with the Project Director of the retention chatbot
[74] Based on the interview with the Project Director of the admission chatbot

This technology [Pounce] lets us touch students faster and more effectively.

Like all other innovation initiatives in GSU's Student Success Program, digital innovation in engaging students was a highly collaborative effort rationalized by data-driven decision making. As such, through the digital innovation in engaging and informing, GSU demonstrated organizational intelligence in understanding its context, realizing digital innovation in engaging, and evaluating its innovation efforts throughout. This organizational intelligence was evidenced as entanglement of analytical and relational intelligence.

6.3.2. Understanding the Context

To achieve the objective of engaging and informing students, GSU had to explore and understand its context to figure out the administrative challenges students faced after acceptance and on their path to graduation. In understanding the context, GSU demonstrated both analytical intelligence (AI#7) and relational intelligence (RI#7), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#7). GSU's innovation in engaging and informing students was initially motivated by reducing the adverse effects of a problem in its context known as summer melt[75]. Summer melt is a phenomenon where students fail to navigate the path towards college education after high school graduation, by accepting offers of admission during summer, but not showing up for fall classes[76]. In 2008, 10% of GSU's incoming freshman class were victims of summer melt which grew to 19% in 2015[77]. Although they were accepted and had confirmed their plans to attend, these students never showed up for classes in fall. GSU tracked these students using National Student Clearinghouse data and found that, one year later,

[75] Based on the interview with the Project Director of the admission chatbot
[76] According to Castleman and Page (2014)
[77] 2016 Complete College Georgia Status Report: Georgia State University

hundreds of them (74% of whom were low-income students) never attended a single day of college at any institution[78].

To understand the challenges students faced to start their college education, GSU analyzed admission data stored in Banner along with National Student Clearinghouse data and demographic data about the incoming students[79]. These analyses revealed that students found the FAFSA application process the most difficult to complete. Since majority of GSU students come from low-income families, they are dependent on FAFSA for supporting their college education. Most of the students who were victims of summer melt did not complete their FAFSA applications. By analyzing data, GSU realized that there was a lack of informational support for students to complete FAFSA applications, and since the process is very complicated students get frustrated and eventually give up. Many incoming students are not able to attend college because of lack of timely information about the FAFSA application. Other challenges students faced were completing all admission requirements, registering for courses, securing GSU housing, obtaining and submitting immunization records, and enrolling for academic advising[80].

With an understanding of the challenges students faced to enroll in college, GSU decided that it needed to create a tool that would help students through these complex processes, guiding them step by step. As the director of the admissions chatbot commented:

> *We asked ourselves "what was it that ultimately caused them not to enroll in any institution?" And we then took that data, analyzed it, and decided, okay, we need to do a better job, we need to add a tool that will allow us to be that 24 hours-a-day, seven-days-a-week, voice for them.*

[78] 2018 Complete College Georgia Status Report: Georgia State University
[79] Based on the interview with a decision maker at Student Success Program
[80] Based on the interview with the Project Director of the admission chatbot

GSU's decision to identify the underlying causes of summer melt by exploring the challenges students faced from high school graduation to college enrollment demonstrates analytical human agency, as decision makers explored the administrative context and identified challenges. In addition, analyzing Banner data, National Student Clearinghouse data, and demographic data to identify the challenges students face in college enrollment demonstrates analytical material agency, as technology was applied to explore the administrative context and identify challenges. While analytical human agency was necessary to focus on the underlying causes of summer melt, it was analytical material agency that informed the decision and revealed the causes. Similarly, while analytical material agency facilitated data analyses, analytical human agency was essential for making sense of analyses results. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in understanding the administrative context. Together, the decision to focus on underlying causes of summer melt (analytical human agency) and the analysis of data from various sources to identify such causes (analytical material agency) constituted a figuration of analytical intelligence (AI#7) through which GSU was able to understand its context and identify administrative challenges for students.

Relational Intelligence Figuration (RI#7). The summer melt phenomenon was hardly unique to GSU[81]. Two nationally renowned researchers, Benjamin Castleman and Lindsay Page, had been researching it for a long time and given it the name, "summer melt." Castleman and Page's research found that as many as one in five high school students who enrolled in college backed out before the start of freshman year because of unforeseen administrative challenges. Often, these students received inadequate guidance from high school counselors, then lost access to that

[81] According to Gumbel (2020)

guidance altogether once the school year was over. They couldn't easily seek alternative help from their prospective colleges because they weren't physically there yet, and any office they might try to reach were either overwhelmed or short-staffed over the summer, or both. In some cases, students would not realize they had paperwork to fill out at all. In other cases, they would find the paperwork overwhelming, particularly the financial aid forms. Sometimes, the processes themselves would act as deterrents to kids already harboring doubts that they belonged in college at all[82]. In their 2014 book, Castleman and Page discussed the findings of their research and described such administrative challenges as

> *…daunting for college-educated parents, let alone students who are the first in their family to go to college.* (p. 44)

Castleman and Page's book (2014) became a must read for decision makers at GSU[83]. Moreover, when GSU approached Admit Hub with the summer melt problem, the co-founders of Admit Hub not only devoured the summer melt book, they also reached out to Lindsay Page at the University of Pittsburgh and proposed collaborating on a solution together. From there on, it was a three-party collaboration among (1) GSU with their strategic goals and administrative support, (2) Page with her years of research experience on summer melt, and (3) Admit Hub with their technological expertise[84]. Together, they initially identified fourteen different steps that students needed to take between February, when GSU sent out its admission letters, and the start of the next fall semester. Through discussions, they realized that phone calls and emails were not nearly as effective in reaching, engaging, and informing students as texting or social media platforms. Texting was the best of all since it did not require a student to have access to a computer or even a smart phone. Texting also did not require the student counselor to befriend a student or jump

[82] According to Castleman and Page (2014)
[83] Based on the interview with a decision maker at Student Success Program
[84] Based on the interview with the Director of admission chatbot

through other social media hoops before initiating contact. Collaboratively, the three parties realized that unlike phone calls and emails, which required human beings to manage the communications, an AI chatbot would be able to engage the entire applicant pool of around sixteen thousand with minimum human intervention[85]. Overall, these collaborative efforts to understand the context demonstrate relational human agency.

At the same time, analytics conducted on Banner data, National Student Clearinghouse data, and demographic data enabled the collaboration in understanding the context at GSU. Moreover, the three parties worked in contemporary digitalized work environments with email, document sharing and teleconferencing to facilitate and support effective communication and collaboration, despite distances between team members. Use of these data-specific and general communication technologies demonstrates relational material agency to share knowledge and facilitate collaboration in exploring the administrative context and identifying challenges. While relational human agency was necessary to collate data from fragmented sources and corroborate the reliability and consistency of data in understanding the context, it was relational material agency that facilitated such communication, collaboration, collation, and corroboration. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to understand the administrative context. Together, the collaborative efforts of people in understanding the administrative context (relational human agency) and the role of technologies in facilitating collaboration and knowledge sharing (relational material agency) constituted a figuration of relational intelligence (RI#7) in understanding the context.

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[85] According to Gumbel (2020)

Organizational Intelligence (OI#7). AI#7 ensured analyses of many different representations of the context based on data, focusing on different aspects. The results of these analyses were informative, but as such they were also fragmented and at times incomplete. RI#7 ensured that the analyses were collated, through collaboration, communication, and discussion, to arrive at a more comprehensive picture of the administrative context. While AI#7 was necessary to produce informative yet fragmented snippets of the context, RI#7 was essential to collate and corroborate such fragments to portray a more comprehensive picture of the context. As such, in understanding the context, the analytical intelligence figuration AI#7 and the relational intelligence figuration RI#7 entangled to constitute OI#7.

6.3.3. Innovating the Content

An understanding of the administrative context compelled GSU to initiate digital innovation in engaging and informing students with an AI chatbot. Throughout the iterative process of digital innovation in engaging, GSU demonstrated both analytical intelligence (AI#8) and relational intelligence (RI#8), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#8). In innovating the AI chatbot, GSU developed a knowledge base of text-based answers to more than 3,000 commonly asked questions by incoming students about financial aid, registration, immunizations, housing, and so forth[86]. Administrative staff, who were knowledgeable about the processes required to successfully enroll in GSU, prepared the answers[87]. In a way, the knowledge of humans was transferred to the AI chatbot through the knowledge base. Admit Hub placed this knowledge base on the texting

[86] 2018 Complete College Georgia Status Report: Georgia State University
[87] Based on the interview with a decision maker at Student Success Program

platform so that students could text questions 24 hours a day, 7 days a week and get informed about the administrative processes. When a student asks a question to the chatbot, the AI integrated in the chatbot determines if there is an appropriate answer to the question in the knowledge base or, alternately, whether the student's question needs to be directed to a staff member to write an answer and add it to the knowledge base. As such, the knowledge base continues to grow. In addition, the AI keeps learning the semantic meaning of questions in their appropriate contexts over time[88].

Because GSU was losing a lot of students in the FAFSA process, it set up guided tutorials through the AI chatbot (Pounce), to help students complete this complex process. Pounce walks a student through each page of the FAFSA, while answering individualized questions about the FAFSA process[89]. As the director of the admission chatbot provided an example of the personalized reply by Pounce:

> *If a student asked Pounce "Hey Pounce, which parent do I mention on my FAFSA?" And then pounce came back and said, "What's your parents' marital status?" And the student wrote back "Divorced." And Pounce said, "Well, whoever your divorced parent is, you should be using their information on your FAFSA."*

In the FAFSA tutorial, GSU set up 90 different communication flows centered around the next steps that students need to complete for successful enrollment. With the help of Admit Hub, GSU set up a communication flow for each of the things that students needed to do[90]. Moreover, Pounce is also programmed to "nudge" a student about completing next steps. Since there are a lot of next steps for students to complete, sometimes they get frustrated and just completely stop

[88] According to Gumbel (2020)
[89] Based on the interview with the Project Director of the admission chatbot
[90] According to Page et al. (2020)

at one point in the process. Pounce would identify those students and proactively reach out to them, motivating them to complete the processes[91].

Gradual development of the knowledge base for the AI chatbot demonstrates analytical human agency since knowledge and expertise of the administrative people are transferred to the technology. At the same time, the chatbot accumulates such knowledge over time and learns the meaning of the questions posed by students in specific contexts. Such learning by the AI chatbot demonstrates analytical material agency. While analytical human agency was necessary to enrich the knowledge base, analytical material agency was essential in iteratively learning from the knowledge base through interactions with students. As such, the innovation of the AI chatbot was possible because of analytical human agency in designing, developing, and updating the knowledge base and analytical material agency in learning to find correct answers from the knowledge base. Together, the gradual development of the knowledge base (analytical human agency) and the iterative learning by the AI chatbot (analytical material agency) constituted AI#8—a figuration of analytical intelligence—through which GSU was able to realize digital innovation in engaging and informing students.

Relational Intelligence Figuration (RI#8). From the very beginning, innovation of the AI chatbot was a three-party collaboration among (1) GSU with their strategic goals and administrative support, (2) Page with her years of research experience on summer melt, and (3) Admit Hub with their technological expertise[92]. As such, innovating the AI chatbot was a collaborative effort. The administrative staff at GSU who contributed their process knowledge to the knowledge base worked together to gradually enrich the knowledge base. Discussions and

[91] Based on the interview with the Project Director of the admission chatbot
[92] According to Gumbel (2020)

knowledge sharing took place among them to corroborate the acceptable flow of every process to ensure that the correct information about the administrative processes is communicated to the students[93]. Moreover, as administrative processes changed over time, the knowledge base was updated after discussions among the administrative staff about the appropriate revision in the corresponding processes. Admit Hub provided technological support and designed, developed, and updated the knowledge base[94]. A decision maker at Student Success Program commented about the collaboration inside GSU:

> *We have a dedicated team. And in fact, the admission bot still sits kind of administratively with the admissions office. They have a dedicated chat bot team. And now for our retention bot for enrolled students, we have a dedicated chatbot team and that team actually reports to me. It's led by a project director. They're monitoring the bot's responses to questions that come in from students.*

Initially, the three parties pulled together a list of 250 potential questions and answers, specific to the GSU context, which they fine-tuned with Page and with Hunter Gehlbach, an educational psychologist and linguistic consultant from the University of California, Santa Barbara. Such collaborative efforts ensured that the answers were understandable and amiable for the students. Together they constructed a flowchart of potential exchanges with the chatbot that correctly and comprehensively reflected the administrative context at GSU[95]. In 2016, through a random control trial, the three parties collaboratively enriched the knowledge base, modified the language of the answers, and improved the learning of the AI integrated in the chatbot[96]. The AI chatbot started with 250 answers in the knowledge base, and through collaboration the number of answers in the knowledge base gradually grew to more than 3,000 today[97]. As such,

[93] Based on the interview with a decision maker at Student Success Program
[94] Based on the interview with the Project Director of the admission chatbot
[95] According to Gumbel (2020)
[96] Based on the interview with the Project Director of the retention chatbot
[97] 2018 Complete College Georgia Status Report: Georgia State University

collaboration between these three parties to iteratively create the chatbot demonstrates relational human agency.

At the same time, the collaboration was facilitated by various analytical technologies, such as Banner, that recorded traces of administrative processes and were used to corroborate the correct answers for the knowledge base. The AI chatbot itself also facilitated collaboration among the three parties by mediating discussions and knowledge sharing as it was being developed and tested. Although the three parties did not use any specific, advanced communication and collaboration technologies, they all worked on contemporary digitalized work environments with email, document sharing and teleconferencing to facilitate and support effective communication and collaboration, despite distances between team members. Together, the use of these technologies to enable collaboration demonstrates relational material agency in innovating the chatbot. While relational human agency was necessary to collaboratively design, develop, and enrich the knowledge base, relational material agency was essential to share knowledge and corroborate appropriate answers for the knowledge base. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to innovate the content. Together, the collaborative efforts of people for rationalizing, designing, developing, and enriching the knowledge base (relational human agency) and the mediating role of technologies in facilitating interaction, communication, collaboration, and knowledge sharing (relational material agency) constituted RI#8—a figuration of relational intelligence in innovating the AI chatbot.

Organizational Intelligence (OI#8). In innovating the content, AI#8 ensured development of the knowledge base and learning of the AI based on that knowledge base; and RI#8 ensured communication, collaboration, and knowledge sharing among people both inside and outside

GSU. While AI#8 was necessary to design, develop, enrich, and update the knowledge base and train the AI, RI#8 was essential to discuss and corroborate the correct and comprehensive answers to include in the knowledge base. As such, the analytical intelligence figuration AI#8 and the relational intelligence figuration RI#8 entangled to constitute OI#8 in innovating the content.

6.3.4. Evaluating the Outcome

In understanding the administrative context and iteratively innovating the content, GSU continually evaluated the outcome of its efforts. Such evaluation was used to gradually improve the performance of the AI chatbot innovation. In evaluating the outcome, GSU demonstrated both analytical intelligence (AI#9) and relational intelligence (RI#9), both constituted through entanglement of human agency and material agency.

Analytical Intelligence Figuration (AI#9). GSU periodically evaluated the performance of the AI chatbot based on different metrics[98]. Initially, since the objective of the admission chatbot was to reduce summer melt, GSU monitored this metric to assess the efficacy of the AI chatbot. In 2016-17 academic year, in the first year of using the chatbot, summer melt at GSU declined by 19%[99]. In the three months leading up to the fall 2016 classes, Pounce replied to 200,000 student questions, with an average response time of 7 seconds[100]. Similar usage was tracked in 2017-18 academic year, in which summer melt declined by an additional four percentage points[101]. Moreover, a random control trial of the implementation of the AI chatbot at GSU not only confirmed the effectiveness of the chatbot in reducing summer melt, but also showed that

[98] Based on the interview with the Project Director of the admission chatbot
[99] 2017 Complete College Georgia Status Report: Georgia State University
[100] 2017 Complete College Georgia Status Report: Georgia State University
[101] 2018 Complete College Georgia Status Report: Georgia State University

the positive benefits were disproportionately enjoyed by students from underserved backgrounds[102].

To evaluate whether the AI was indeed providing students the correct answers, the chatbot team monitored the questions students asked and corresponding replies of the AI. Students asked Pounce questions on a broad range of topics. “How do I complete the FAFSA?” “What is the difference between a grant and a loan?” “What do I do if I can’t find or don’t have immunization records?” After receiving a question from a student, the AI capability integrated in Pounce determines if there is an appropriate answer in the knowledge base or, alternately, whether the applicant’s question needs to be directed to a staff member to write an answer and add that to the knowledge base. As such, the chatbot team included new answers in the knowledge base based on new questions from students and updated old answers in the knowledge base according to the changes in the administrative processes. Over the years, technical bugs and glitches were fixed by Admit Hub to improve Pounce’s performance[103].

Motivated by the positive impact of the chatbot on summer melt, in the 2018-19 academic year, GSU extended the chatbot to provide proactive outreach and support to help undergraduates navigate administrative processes and take advantage of campus resources. As the project director of admission chatbot commented:

> *We had seen such good results from our year one and year two with the chatbot. It only made sense to keep it going. And we had also surveyed students around that time. I'm seeing how many of you would like to see this go beyond the admissions process. And something like 80 to 90% of the students said they want to see this continue.*

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[102] According to Page and Gehlbach (2017)
[103] Association Governing Boards 2019

A team of centralized university administrators orchestrated outreach "campaigns" to support students across three broad domains: (1) academic supports; (2) social and career supports; and (3) administrative processes. Of the three message domains, outreach was most effective when focused on administrative processes, many of which were time-sensitive and for which outreach could be targeted specifically to students for whom it was relevant based on administrative data. By the end of the academic year, rates of FAFSA filing and registration for the subsequent fall semester were approximately three percentage points higher, suggesting positive effects on year-to-year college persistence. The positive effects on fall enrollment persisted into summer 2019, at which time the GSU administration judged that the study results were compelling enough to conclude the experiment and roll the chatbot system out to all students[104]. Over the years, GSU gradually increased the number of answers in the knowledge base from 250 in 2016 to 3,000 today[105].

Selection of the metrics and assessment of the performance of the chatbot according to those metrics demonstrate the important role of analytical human agency in evaluating outcomes. Analytical human agency was also applied in the initial random control trial and later experiments with the chatbot in improving retention. However, these evaluations were facilitated by Banner and other administrative information systems[106]. Moreover, the chatbot itself monitored and recorded its usage, which was analyzed to evaluate its performance[107].

Analysis of data in Banner, administrative information systems, and the chatbot demonstrate analytical material agency in evaluating outcomes. While analytical human agency was

[104] According to Page et al. (2020)
[105] 2018 Complete College Georgia Status Report: Georgia State University
[106] Based on the interview with a decision maker at Student Success Program
[107] Based on the interview with the Project Director of the admission chatbot

necessary to select the appropriate metrics and to evaluate any outcome based on those metrics, it was analytical material agency that facilitated storage, computation, retrieval, analysis, and comparison of the metrics. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in the endeavors to evaluate the outcome. Together, the selection and monitoring of the metrics (analytical human agency) and the analyses of data in assessing the efficacy of the chatbot (analytical material agency) constituted AI#9—a figuration of analytical intelligence—through which GSU was able to continuously evaluate the outcome of its digital innovation efforts in engaging and informing students.

Relational Intelligence Figuration (RI#9). Evaluating the outcome of the AI chatbot innovation was highly collaborative among the three parties stated earlier. Each party brought their own perspective and expertise to the evaluation[108]. In 2016, through a random control trial, they tested the efficacy of the first version of the chatbot[109]. Later, in 2018 they also collaborated in experimenting with the extension of the chatbot to retention[110]. In the initial trial and the later experiments, GSU ensured that the answers in the knowledge base were correct and comprehensive[111]; Page tested whether the answers were understandable and amiable, and whether the chatbot had a real impact on reducing summer melt and improving retention[112]; and, Admit Hub provided technological support to ensure that the AI was providing the correct answers from the knowledge base to the students based on their questions and that the AI was correctly learning the semantic meaning of the questions[113]. Based on analysis of these trials and experiments, new answers were added to the knowledge base, old answers were revised

[108] According to Gumbel (2020)
[109] Based on the interview with a decision maker at Student Success Program
[110] According to Page et al. (2020)
[111] Based on the interview with the Project Director of the admission chatbot
[112] According to Page et al. (2020)
[113] Based on the interview with a decision maker at Student Success Program

according to changes in administrative processes, and corrections and modifications were made to the AI[114]. The project director of the admission chatbot commented about this collaboration:

> *We use the admissions knowledge base as the foundation for the retention bot. But Admit Hub helped restructure the questions and the communications, and select the types of students for the random control trial and those kinds of things was all part of this process and really worked out very, very well. Also Lindsay Page is doing the result analysis on that project as well.*

The collaborative efforts in evaluating the outcome of the AI chatbot innovation demonstrate relational human agency, since they involved knowledge and expertise of the three parties: GSU's administrative knowledge, Page's extensive knowledge of summer melt, and Admit Hub's technological knowledge and expertise. However, technologies, such as, Banner, administrative information systems, general communication and collaboration technologies, and the chatbot itself, facilitated the collaboration by mediating communication and knowledge sharing among the parties. The role of these technologies in evaluating the performance of the AI chatbot demonstrates relational material agency. While relational human agency was necessary to collectively evaluate the efficacy of the innovated content from different points of view, it was relational material agency that facilitated such collective discourse. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to evaluate the outcome. Together, the collaborative discourse of people in assessing the performance of the chatbot (relational human agency) and the analyses of data stored in different information systems in facilitating such collaboration (relational material agency) constituted RI#9—a figuration of relational intelligence—through which GSU was able to evaluate the outcomes of the digital innovation efforts in engaging and informing students.

[114] Based on the interview with a decision maker at Student Success Program

Organizational Intelligence (OI#9). In evaluating the outcomes of the innovation efforts, AI#9 ensured selection of the appropriate metrics, and analyses of data to assess the efficacy of the AI chatbot according to those metrics; and RI#9 ensured collaborative discourse that supported and complemented such analytic efforts in evaluating the efficacy of the AI chatbot. While AI#9 was necessary to select the metrics and to assess the efficacy of the chatbot based on those metrics, RI#9 was essential to collectively interpret and explain such assessment. As such, the analytical intelligence figuration AI#9 and the relational intelligence figuration RI#9 entangled to constitute OI#9 in evaluating outcomes.

6.3.5. Summary and Overview

In digital innovation in engaging, GSU demonstrated organizational intelligence to understand the administrative context (AI#7 and RI#7), to iteratively innovate the AI chatbot (AI#8 and RI#8), and to continually evaluate the outcomes (AI#9 and RI#9). First, the initial understanding of the administrative context revealed the underlying causes of summer melt (analytical human agency) and these problematic issues were identified by analyzing data using different information systems (analytical material agency). These efforts involved both human and material agencies that together constituted an analytical intelligence figuration AI#7 in understanding the context. There were discussions among three different parties regarding the underlying causes of summer melt (relational human agency), facilitated by analytics conducted on digitally stored data (relational material agency). These collaborative efforts involved both human and material agencies that together constituted a relational intelligence figuration RI#7 in understanding the context. While AI#7 was necessary to produce informative yet fragmented snippets of the context, RI#7 was essential to collate and corroborate the fragments to portray a more comprehensive picture of the context. As such, AI#7 and RI#7 together constituted OI#7, through which GSU was able to identify and explain the underlying causes of the problems in its administrative context that hindered admission and retention.

Second, with an understanding of its context, GSU decided to engage and inform students about the required administrative processes by creating an AI chatbot. GSU gradually enriched the knowledge base of the chatbot (analytical human agency) and the AI integrated in the chatbot kept learning the semantic meaning of questions and their appropriate answers (analytical material agency). As such, realizing digital innovation in engaging and informing students involved both human and material agencies that together constituted an analytical intelligence figuration AI#8 in innovating the content. At the same time, the three parties involved shared their own expertise and knowledge (relational human agency), mediated by analytics conducted on digitally stored data and by general communication and collaboration technologies (relational material agency). Hence, collaborative innovation of the AI chatbot involved both human and material agencies that together constituted a relational intelligence figuration RI#8. While AI#8 was necessary to design and develop the chatbot, and enrich its knowledge base, RI#8 was essential to discuss and rationalize every step of the innovation. As such, AI#8 and RI#8 together constituted OI#8, through which GSU was able to innovate the AI chatbot for engaging and informing students.

Third, to evaluate outcomes continually, GSU selected the appropriate metrics, and monitored those metrics in assessing the efficacy of the AI chatbot (analytical human agency), applying analytics on data using different information systems (analytical material agency). Hence, evaluating outcomes involved both human and material agency that together constituted a figuration of analytical intelligence (AI#9). Moreover, the three parties involved continuously engaged in collaborative discourse to assess and explain the efficacy of the chatbot (relational human agency), facilitated by analysis of digitally stored data and by using general communication and collaboration technologies (relational material agency). These collective evaluations involved both human and material agency that together constituted a figuration of relational intelligence (RI#9). While AI#9 was necessary to select the metrics and to assess the efficacy of the chatbot based on those metrics, RI#9 was essential to collectively interpret and explain such assessment. As such, AI#9 and RI#9 together constituted OI#9, through which GSU was able to evaluate the outcomes of its innovation efforts. These evaluations helped GSU readjust their focus of understanding the context and revise their efforts in innovating the content.

Apart from the forward progression of digital innovation in engaging, from context to content and further to outcomes, GSU iteratively explored its administrative context and innovated the AI chatbot based on insights from the evaluation of the outcome of past innovations. Since 2016, when the admission chatbot was introduced, GSU has been collecting and analyzing data on enrollment and retention to evaluate the outcome of the chatbot[115]. Based on these ongoing evaluations, GSU updated and modified the chatbot and gradually enriched the knowledge base[116]. These iterative innovations of the AI chatbot demonstrate the feedback from evaluating the outcome to innovating the content. Moreover, after initial success of the AI chatbot in reducing summer melt, GSU explored the applicability of the chatbot in a different context, namely in improving retention[117]. These efforts demonstrate the feedback from evaluating outcomes to understanding the context. As such, the digital innovation in engaging and informing students was an ongoing process in which organizational intelligence in each iteration

[115] Based on the interview with a decision maker at Student Success Program
[116] Based on the interview with the Project Director of the admission chatbot
[117] Based on the interview with the Project Director of the retention chatbot

was a means for understanding the administrative context and innovating the content, and at the same time organizational intelligence continued to develop as a result of these efforts.

6.4. Case 4: Organizational Intelligence during Digital Innovation in Financing

6.4.1. Introduction

For a majority of GSU students, college education is a financial challenge[118]. In 2016, 55% of undergraduate students at GSU were Pell-eligible[119]—individuals who are categorized as low-income by federal standards and who qualify for federal Pell grants. Apart from the pedagogical, academic, and administrative challenges of college education, these students constantly struggle with financial challenges. Consequently, according to the United States Department of Education, Pell-eligible students nationally have a six-year graduation-rate of 39%, a rate that is 20 points lower than the national average[120]. The adverse effect of financial challenges is so great that it is eight times more likely that an individual in the top quartile of Americans by annual household income will hold a college degree than an individual in the lowest quartile[121]. As one of the decision makers at GSU's Student Success Program commented:

> *Finances are a huge issue for our students. With proper financial planning and education, we think, our students could do a lot better and that is why we utilized some resources to help them do well financially.*

With an objective to help students stay in college and graduate in time, GSU introduced predictive analytics in providing financial interventions and financial literacy training for low-income, at-risk students[122]. In 2016, with funding from SunTrust Foundation, GSU established the Student Financial Management Center (SFMC)[123]. Similar to the GPS advising system for

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[118] Based on the interview with a decision maker at Student Success Program
[119] 2017 Complete College Georgia Status Report: Georgia State University
[120] According to Horwich (2015)
[121] Indicators of Higher Education Equity 2015
[122] Based on the interview with a decision maker at Student Success Program
[123] SunTrust Student Financial Management Center Year Two Report

monitoring and advising students on academic issues, SFMC created a financial predictive analytics system, in collaboration with Education Advisory Board (EAB), for monitoring financial issues of and providing financial counselling to students[124]. A central objective of the SFMC is to deliver students the help they need before financial problems become severe enough to cause them to drop out of college education[125].

Through SFMC and its predictive analytics system, GSU monitors every undergraduate student and predicts any potential financial issues they might face; and, SFMC facilitates avoiding or overcoming such problems through personalized intervention and financial counselling. Such a digital innovation was highly collaborative and rationalized by data-driven decision making. As such, through the digital innovation in financing students, GSU demonstrated organizational intelligence in understanding the financial context for student success, realizing digital innovation in monitoring student finances, counselling them on potential problems, and evaluating the innovation efforts throughout. This organizational intelligence was evidenced as entanglement of analytical and relational intelligence.

6.4.2. Understanding the Context

To achieve the objective of reducing dropouts due to financial issues, GSU had to explore and understand its context to identify the financial challenges students faced, how such challenges could be monitored, and how students could be counselled to avoid or overcome such challenges so they could progress toward graduation. In understanding the context, GSU demonstrated both analytical intelligence (AI#10) and relational intelligence (RI#10), both constituted as entanglements of human agency and material agency.

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[124] According to Renick (2020)

[125] 2018 Complete College Georgia Status Report: Georgia State University

Analytical Intelligence Figuration (AI#10). Establishment of SFMC was rationalized by exploring the financial context to understand the challenges students faced financially. GSU analyzed data from different sources including financial data from office of student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources[126]. Through such analyses, GSU realized that with 93% of undergraduate students receiving federal aid, a major challenge for GSU was getting students to take the steps to address outstanding financial aid obligations and to resolve their balances[127].

GSU realized that for most undergraduate students, admission, retention, progression, and graduation depended on financial aid readiness, which is similar to financial readiness but involves scenarios where funding for college is completely covered by federal, state, or institutional funds[128]. Analyses of student financial data revealed an important correlation between retention and the completion of FAFSA. Results of these analyses suggested that students who completed a FAFSA were twice as likely to enroll in the following year which compelled GSU to focus on increasing the number of new students completing the FAFSA[129].

Analyses also suggested that students with high unmet needs have a higher risk of dropping out. Through these observations GSU decided to reduce the number of students with high unmet need by focusing on the financial aid packaging process[130]. GSU realized that a financial predictive analytics system was needed to help students with financial counselling. As such, GSU collaborated with EAB to develop a new predictive analytics financial tracking tool, enabled by robotic process automation (RPA), to follow student progression through the financial aid

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[126] Based on the interview with a decision maker at Student Success Program
[127] 2018 Complete College Georgia Status Report: Georgia State University
[128] Based on the interview with a decision maker at Student Success Program
[129] SunTrust Student Financial Management Center Year Two Report
[130] Based on the interview with a decision maker at Student Success Program

process. Every day, the predictive analytics system analyzes changes in student financial data to alert SFMC and financial aid staff about students at risk[131].

Exploring the financial challenges students faced, GSU realized that it needed to be more proactive in informing students about financial aid options, in helping students become financial aid ready, in predicting potential financial problems of students, and in providing timely financial counselling to avoid or overcome such problems[132]. As one decision maker at Student Success Program commented:

> *We are financial aid promoters. We just want to make sure students are aware of the options. We map out this plan about preparing for next year. We say to students "submit your FAFSA on time, make sure you complete verification; if selected, make certain that you follow up; make use of the resources. May be there's a scholarship that you're unaware about, that can help support you and your progression to completion."*

GSU's efforts to understand the financial context for student success demonstrate analytical human agency, as decision makers explored and analyzed the context, identified financial challenges students faced, and decided to establish SFMC and apply predictive analytics. However, in exploring the financial context, GSU also had to analyze financial data from student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources. Analyzing data using these information systems demonstrates analytical material agency in understanding the context, as technology was applied to comprehend the financial context and identify problematic issues. While analytical human agency was necessary to identify and explain problematic issues in financing, it was analytical material agency that informed such efforts. Similarly, while analytical material agency facilitated data analyses, analytical human agency was essential for making sense of analyses

[131] SunTrust Student Financial Management Center Year Two Report
[132] According to Renick (2020)

results. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in understanding the financial context. Together, the identification of the need to establish SFMC and develop financial predictive analytics (analytical human agency) and the analysis of data from different information systems to reach that decision and to identify financial challenges (analytical material agency) constituted a figuration of analytical intelligence (AI#10) through which GSU was able to understand the financial context for student success.

Relational Intelligence Figuration (RI#10). Exploration of the financial context involved collaboration both within and beyond GSU. A dedicated team consisting of people form Student Success Program, office of admissions, office of student accounts, and office of institutional innovations gradually explored the financial context to identify challenges students faced[133]. Such collaborative exploration was facilitated by analysis of financial data from student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources[134]. At the same time, EAB collaborated with GSU in exploring the financial context to identify early indicators of financial problems that were used to develop the financial predictive analytics system[135]. While people at GSU contributed their knowledge and expertise about the internal processes at GSU, EAB contributed its technological knowledge and expertise to the collaboration in understanding the financial context. As one decision maker at Student Success Program commented:

> *After initial success of GPS advising, we wanted to apply predictive analytics in financial advising, as it was much needed. We extended our collaboration with*

[133] Based on the interview with a decision maker at Student Success Program
[134] Based on the interview with a decision maker at Student Success Program
[135] Based on the interview with a decision maker at Student Success Program

EAB in developing a predictive analytics system that generates alerts about potential financial problems for students.

In collaboratively understanding the financial context through analysis of data, discussions and knowledge sharing took place among the stakeholders at GSU and EAB. Their collaboration facilitated exploration of the financial challenges, explanation of the root causes, and identification of solutions using predictive analytics. Each stakeholder brought their own knowledge and expertise and provided their own perspective in analyzing, explaining, and rationalizing the financial context. As such, these collaborations were instrumental for understanding the financial context correctly and comprehensively, demonstrating relational human agency. At the same time, analysis of financial data from student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources facilitated discussion and knowledge sharing among the stakeholders, mediated by general communication and collaboration technologies. The relational role of these information systems and technologies in facilitating collaboration and knowledge sharing exemplifies relational material agency in understanding the financial context for student success.

While relational human agency was necessary to collate data from fragmented sources and corroborate the insights from the data in understanding the context, it was relational material agency that facilitated such collation and corroboration. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to understand the financial context. Together, the collaborative efforts of people in understanding the financial context (relational human agency) and the role of technologies in representing the context with data and in facilitating communication and collaboration (relational material agency) constituted a figuration of relational intelligence (RI#10) in understanding the financial context for student success.

Organizational Intelligence (OI#10). AI#10 ensured an understanding of the financial challenges students faced and a potential solution using predictive analytics. RI#10 facilitated collaboration, communication, discussion, and knowledge sharing among stakeholders through analysis of data from different sources that together comprehensively represented the financial context. While AI#10 was essential in deciding the means and focus of monitoring and counselling students' financial situation, RI#10 was necessary in collating and corroborating such decisions. As such, in understanding the financial context of student success, the analytical intelligence figuration AI#10 and the relational intelligence figuration RI#10 entangled to constitute OI#10.

6.4.3. Innovating the Content

Understanding the financial context compelled GSU to initiate digital innovation in monitoring and counselling students on financial issues through predictive analytics. Throughout an iterative process of digital innovation in financing, GSU demonstrated both analytical intelligence (AI#11) and relational intelligence (RI#11), both constituted as entanglements of human agency and material agency.

Analytical Intelligence Figuration (AI#11). With an understanding of the financial context, GSU realized the need for predicting financial problems early and counselling students to avoid or overcome such problems[136]. Consequently, in an effort to mitigate the financial risks to student retention that are created by collegiate expenditures, GSU has been iteratively innovating its content in financing students since 2016[137]. Predicated on the premise that more students will persist if their financial problems are identified early and addressed proactively, GSU deployed a

[136] Based on the interview with a decision maker at Student Success Program
[137] Based on the interview with a decision maker at Student Success Program

financial predictive analytics system parallel to the earlier groundbreaking GPS academic advising system. Through a collaboration with EAB, GSU used ten years of student financial data and more than 140,000 undergraduate student records to develop the predictive analytics system. Sixteen early indicators of financial problems for students were selected by analyzing this financial data[138]. The financial predictive analytics system identifies early warning signs of students' financial decisions that put them at risk of attrition. GSU discovered that some financial decisions made before the students even first set foot on campus may determine whether a student ever graduates, such as a student choosing a single dorm room rather than living at home or with roommate in the summer before the freshman year. As such, the enhanced predictive analytics system includes information about student housing choices as well as past due histories to target students for financial counseling[139]. As one decision maker at Student Success Program commented:

> *It [the financial predictive analytics system] tracks students daily and SFMC reaches out to offer support and advice when problems are identified.*

In innovating the financial predictive analytics model, GSU demonstrated analytical human agency, since knowledge and experience of people was used in exploring, targeting, analyzing, rationalizing, and explaining the indicators. Analytical human agency ensured that GSU was focusing on and selecting the appropriate indicators to monitor. Information systems and technologies, such as financial records of student accounts, Banner, RPG, and internal and external sources of demographic data facilitated such analyses in identifying the statistically significant indictors by providing the necessary data and computational capability. The financial predictive analytics system itself conducted statistical computations on all data to select an

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[138] 2018 Complete College Georgia Status Report: Georgia State University
[139] SunTrust Student Financial Management Center Year Two Report

appropriate set of indicators as it was being developed. Together, the exploration of potential indicators to monitor student finances (analytical human agency) with the data and computational capability provided by technologies (analytical material agency) constituted AI#11—a figuration of analytical intelligence—through which GSU was able to realize digital innovation in financing students.

Relational Intelligence Figuration (RI#11). Stakeholders from different units at GSU communicated, discussed, and collaborated in selecting the early indicators to develop the financial predictive analytics model. Knowledge sharing took place across the organization in rationalizing, selecting, and explaining the indicators[140]. Moreover, these efforts transcended the organizational boundaries of GSU and included the technology partner EAB, which collaborated with GSU in exploring and identifying early indicators of financial problems for students that were used to develop the financial predictive analytics system[141]. EAB identified early indicators of potential financial problems by analyzing data form information systems such as financial records of student accounts, Banner, RPG, and internal and external sources of demographic data[142]. The applicability and significance of potential indicators selected by GSU were evaluated by EAB as it developed the predictive model. Indicators included in the financial predictive analytics model were selected based on discussions among the stakeholders[143]. As such, EAB gradually developed the financial predictive analytics system through collaboration and knowledge sharing with GSU.

[140] Based on the interview with a decision maker at Student Success Program
[141] SunTrust Student Financial Management Center Year Two Report
[142] Based on the interview with a decision maker at Student Success Program
[143] Based on the interview with a decision maker at Student Success Program

Predicting potential financial problems for students is only part of the solution. When the financial predictive analytics system identifies at-risk behaviors, it sets up one-on-one meetings with financial counselors. Financial counselors respond to alerts by intervening in a timely manner to get students back on track through counselling[144]. To facilitate financial counseling, GSU has employed certified financial counselors at SFMC to monitor the alerts generated by the financial predictive analytics system and respond with timely, proactive financial counselling for students at scale[145]. As a decision maker at Student Success Program commented:

> *It's [SFMC] kind of a counseling type financial advice center. When financial problems are predicted, financial counselors reach out to students. So, they can help students process their financial aid or get loans or do whatever students need. They can also help students talk through long term planning.*

Collaborative efforts within and across organizations in identifying and selecting predictive indicators demonstrate relational human agency in innovating the predictive model, by involving human intelligence in rationalizing and explaining the indicators. Relational human agency is also demonstrated by the actual interventions of financial counsellors as they provide personalized counselling to help students avoid or overcome predicted problems. However, the exploration of potential indicators through collaboration would not be possible without digital technologies that facilitate access to data, statistical computation conducted on that data, and communication and collaboration among the stakeholders. The collaborative innovation of the financial predictive analytics was facilitated by analyses done on financial data from office of student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources[146]. Use of these information systems demonstrates relational material agency. As such, relational human agency and relational

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[144] SunTrust Student Financial Management Center Year Two Report
[145] 2018 Complete College Georgia Status Report: Georgia State University
[146] Based on the interview with a decision maker at Student Success Program

material agency entangled to produce relational intelligence in the endeavors to innovate the content of financing students. Together, the collaborative efforts of people in exploring and selecting predictive indicators (relational human agency) and the mediating role of technologies in facilitating computation, communication, collaboration, and knowledge sharing (relational material agency) constituted RI#11—a figuration of relational intelligence.

Organizational Intelligence (OI#11). AI#11 ensured exploration of potential indicators in monitoring student finances and selection of predictive indicators through statistical computation, whereas RI#11 facilitated collaboration, communication, and discussion among stakeholders about developing the predictive analytics system and supporting students. While AI#11 was essential in identifying potential problems for students, RI#11 was necessary in timely interventions to help students avoid or overcome such problems. Without monitoring students through predictive analytics (AI#11), personalized financial counseling (RI#11) is not possible. Similarly, without personalized financial counseling through interventions (RI#11), monitoring students through predictive analytics (AI#11) cannot solve the dropout problem. As such, in innovating the content of financing students, the analytical intelligence figuration AI#11 and the relational intelligence figuration RI#11 entangled to constitute OI#11.

6.4.4. Evaluating the Outcome

In understanding the financial context of and in iteratively innovating the content of monitoring and counselling students on financial issues, GSU continually evaluated the outcome of its efforts. Such evaluation was used to justify decisions or to revise courses of action. In evaluating the outcome, GSU demonstrated both analytical intelligence (AI#12) and relational intelligence (RI#12), both constituted as entanglements of human agency and material agency.

Analytical Intelligence Figuration (AI#12). GSU selected and monitored different metrics to evaluate the efficacy of SFMC and its financial predictive analytics system in decreasing attrition and in improving retention and prospects of timely graduation[147]. In the first six months of its operations in 2016-17 academic year, SFMC conducted 72,121 in-person, online, and phone interactions with students. 62% of the interactions focused on loans, FAFSA verification, status of aid, and Hope Scholarship questions. Analyzing these interactions, GSU found that missing or incomplete documents, FAFSA problems, and parent loans were among the leading issues faced by students. An additional 6% of interactions focused on satisfactory academic progress appeals[148]. Based on these evaluations, SFMC offered periodic student and community outreach programs to improve student financial literacy and to provide information on how to complete FAFSA[149].

For the fall 2017 semester, students who visited the SFMC were 6 percentage points more likely to complete all financial-aid requirements and bring their balances down to zero. Students who visited the SFMC in preparation for the fall 2018 semester were 20.6% more likely to complete all financial-aid requirements and become financial aid ready[150]. GSU monitored the financial aid readiness metric closely, which is similar to financial readiness but includes scenarios where funding for college is completely covered by federal, state or institutional funds[151]. As one decision maker at Student Success Program commented:

> *We decided to use financial aid readiness rather than financial readiness as the metric to follow, because most of our students entirely depend on some form of funding or financial aid for their college education.*

[147] Based on the interview with a decision maker at Student Success Program
[148] 2018 Complete College Georgia Status Report: Georgia State University
[149] Based on the interview with a decision maker at Student Success Program
[150] SunTrust Student Financial Management Center Year Two Report
[151] 2018 Complete College Georgia Status Report: Georgia State University

70.0% of the students, who completely relied on financial aid or funding, were financial aid ready with only one interaction from SFMC, a 27.6% percentage point improvement over those students with no interaction[152]. Overall, data analysis showed a substantial aggregate impact from the work of SFMC and its financial predictive analytics system. Motivated by this initial success in helping enrolled students financially, SFMC extended its operations by offering campaigns to improve financial literacy of the incoming students in 2018[153].

In selecting, monitoring, and explaining the metrics, GSU demonstrated analytical human agency, since the rationale for each metric was established through human intelligence. At the same time, computation, analysis, and monitoring of such metrics was facilitated by many information systems. The financial predictive analytics system itself keeps track of the predicted financial problems and the consequent interventions. Other information systems, such as financial records of student accounts, Banner, RPG, and demographic data from internal and external sources, facilitate computation and analysis of these evaluation metrics. While analytical human agency was necessary to rationalize and explain the effects of different metrics, it was analytical material agency that facilitated the computation and comparison of such metrics. As such, analytical human agency and analytical material agency entangled to produce analytical intelligence in the endeavors to evaluate the outcome of the digital innovation in financing towards student success. Together, the selection and explanation of the evaluation metrics (analytical human agency) and the computation and analysis of those evaluation metrics (analytical material agency) constituted a figuration of analytical intelligence (AI#12) through

[152] SunTrust Student Financial Management Center Year Two Report
[153] Based on the interview with a decision maker at Student Success Program

which GSU was able to evaluate the outcome of its innovations in financing students towards success.

Relational Intelligence Figuration (RI#12). Evaluation of the efficacy of SFMC and its financial predictive analytics system in reducing attrition was conducted collaboratively. Such collaboration included stakeholders from both within and outside the organization. People from Student Success Program, office of admissions, office of student accounts, and office of institutional innovations brought their own knowledge and expertise to evaluate different aspects of the innovation in student financing. Discussions and knowledge sharing took place in selecting, rationalizing, and monitoring the appropriate metrics, and in explaining the metrics from different perspectives[154]. Such collaborative assessment was facilitated by analysis of financial data from office of student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources[155]. EAB also contributed their technological expertise in these analyses. The results of these analyses and consequent discussions informed EAB on gradually developing the financial predictive analytics system and improving its predictive accuracy[156]. The financial predictive analytics system itself analyzed its own performance and efficacy of the interactions with financial counsellors. These analyses were used to further develop the predictive system[157]. As one decision maker commented:

> *We are still learning from data about how to better help the students become financial aid ready, and we have a close collaboration with them [EAB] which we think will last a long time.*

[154] Based on the interview with a decision maker at Student Success Program
[155] Based on the interview with a decision maker at Student Success Program
[156] Based on the interview with a decision maker at Student Success Program
[157] Based on the interview with a decision maker at Student Success Program

In collaboratively selecting, monitoring, and explaining the metrics, GSU demonstrated relational human agency, since the rationale for each metric was established through joint discourse. At the same time, the collaborative computation, analysis, and monitoring of such metrics was facilitated by analysis of financial data from office of student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources. Collaboration among the stakeholders was further facilitated by general communication and collaboration technologies. The use of these information systems and technologies demonstrates relational material agency in evaluating the outcome. While relational human agency was necessary to rationalize and explain the effects of different metrics through discussing theses and antitheses from different points of view, relational material agency was necessary to facilitate the computation and comparison of such metrics. As such, relational human agency and relational material agency entangled to produce relational intelligence in the endeavors to evaluate the outcome of the innovation in financing students. Together, the selection and explanation of the evaluation metrics (relational human agency) and the computation and analysis of those evaluation metrics and discussions about the metrics facilitated by general communication and collaboration technologies (relational material agency) constituted a figuration of relational intelligence (RI#12) through which GSU was able to evaluate the outcome of its innovation in financing students towards success.

Organizational Intelligence (OI#12). In evaluating the outcomes of the innovation efforts in financing students, AI#12 ensured computation and analyses of data to assess the efficacy of the financial predictive analytics system using different metrics, and selection of the appropriate metrics; and RI#12 ensured collaborative discourse that supported and complemented such analytic efforts in evaluating the efficacy of the predictive system. While AI#12 was necessary to select appropriate metrics and to assess the efficacy of the predictive system based on those metrics, RI#12 was essential to collectively form, interpret, and explain such assessment. As such, the analytical intelligence figuration AI#12 and the relational intelligence figuration RI#12 entangled to constitute OI#12 in evaluating the outcomes of the innovation efforts in financing students towards success.

6.4.5. Summary and Overview

In digital innovation in financing, GSU demonstrated organizational intelligence to understand the financial context (AI#10 and RI#10), to iteratively innovate the financial predictive analytics system (AI#11 and RI#11), and to continually evaluate the outcomes (AI#12 and RI#12). First, in its digital innovations to monitor student finances and to proactively counsel them, GSU developed an understanding of the context by exploring financial challenges students faced (analytical human agency) through analyses of financial data from office of student accounts, enrollment data from Banner, admissions and retention data from RPG, and demographic data from internal and external sources (analytical material agency). These efforts involved both human and material agencies that together constituted an analytical intelligence figuration AI#10. At the same time, collaboration among stakeholders was essential for understanding the financial context comprehensively (relational human agency), mediated by digital technologies to support communication, collaboration, and knowledge sharing (relational material agency). These collaborative efforts involved both human and material agencies that together constituted a relational intelligence figuration RI#10. While AI#10 was essential in identifying financial challenges students faced, RI#10 was necessary to corroborate findings and decisions. As such, in understanding the financial context for student success, the analytical intelligence figuration AI#10 and the relational intelligence figuration RI#10 entangled to constitute OI#10.

Second, with an understanding of the context, GSU decided to create proactive financial counselling based on predictive analytics. In these efforts, knowledge and experience of people were used to explore, target, analyze, rationalize, and explain indicators (analytical human agency), facilitated by technologies, such as financial records of student accounts, Banner, RPG, and demographic data from internal and external sources, to identify statistically significant indictors (analytical material agency). As such, realizing digital innovation in student financing involved both human and material agencies that together constituted an analytical intelligence figuration AI#11. At the same time, these efforts required collaboration within and across organizations to identify and select predictive indicators and interventions of financial counsellors (relational human agency) enabled by digital technologies that facilitated access to and computation of data, communication and collaboration, and actual interventions (relational material agency). Hence, collaborative innovation of SFMC involved both human and material agencies that together constituted a relational intelligence figuration RI#11. While AI#11 was essential in identifying potential financial problems for students, RI#11 was necessary to create timely interventions to help students avoid or overcome such problems. As such, in innovating the content, the analytical intelligence figuration AI#11 and the relational intelligence figuration RI#11 entangled to constitute OI#11.

Third, in digital innovations to monitor student finances and counsel them, GSU periodically evaluated the performance of the financial predictive analytics system by selecting, monitoring, and explaining different metrics (analytical human agency). Computation, analysis, and monitoring of the metrics were facilitated by financial records of student accounts, Banner, RPG, and demographic data from internal and external sources (analytical material agency). Hence, evaluating outcomes involved both human and material agency that together constituted a figuration of analytical intelligence (AI#12). At the same time, collaborative discourse was necessary for selecting, monitoring, and explaining the metrics (relational human agency), facilitated by financial records of student accounts, Banner, RPG, and demographic data from internal and external sources, and mediated by general communication and collaboration technologies (relational material agency). These collective evaluations involved both human and material agency that together constituted a figuration of relational intelligence (RI#12). While AI#12 was necessary to select appropriate metrics and to assess the efficacy of the innovation in financing based on those metrics, RI#12 was essential to collectively interpret and explain the assessments. As such, the analytical intelligence figuration AI#12 and the relational intelligence figuration RI#12 entangled to constitute OI#12 in evaluating outcomes of the innovation efforts in financing students.

Apart from the forward progression of digital innovation in financing students, from context to content and further to outcomes, GSU iteratively explored the financial context for student success and innovated the financial predictive analytics system based on insights from evaluation of the outcome of past innovations. Since 2016, when the financial predictive analytics system went live, the attrition rate gradually decreased[158]. Hence, GSU periodically explored problematic aspects in the evolving financial context[159]. These continued explorations helped understand changes in the financial context and readjust the means and the foci of the innovation efforts. Similarly, innovation of the financial predictive analytics system was an iterative process, in which GSU gradually developed the financial predictive analytics model, included more indicators, and improved the predictive power of the model. After every such development

[158] 2016 Complete College Georgia Status Report: Georgia State University; 2017 Complete College Georgia Status Report: Georgia State University; 2018 Complete College Georgia Status Report: Georgia State University
[159] Based on the interview with a decision maker at Student Success Program

of the predictive model, GSU evaluated its performance[160]. As such, the digital innovation in financing students towards success was an ongoing process in which organizational intelligence in each iteration was a means for understanding the financial context and innovating the content, and at the same time organizational intelligence continued to develop as a result of these efforts.

6.5. Cross-Case Analysis

Comparing and contrasting our analyses of the four embedded cases of digital innovation at GSU, we focused on three key characteristics of organizational intelligence as evidenced in relation to the innovation process and outcome: the roles played by technology, collaboration, and learning. The analyses of these characteristics across the four cases are detailed below and summarized in Table 7, 8, and 9.

6.5.1. Role of Technology

Technology played an instrumental role as enabler of organizational intelligence in the four digital innovation initiatives. The role of technology in both the innovation process and outcome across the four cases are detailed below and summarized in Table 7.

Table 7: Role of Technology

Focus	Case 1: Digital Innovation in Teaching	Case 2: Digital Innovation in Monitoring	Case 3: Digital Innovation in Engaging	Case 4: Digital Innovation in Financing
Innovation Process	• Computing DFW rates of high enrollment courses to identify problematic courses • Facilitating communication and collaboration among stakeholders • Computing DFW rates of ALT courses	• Computing and identifying statistically significant indicators for predictive model • Identifying the main target group of students for advising through analysis of past data • Facilitating communication, collaboration, and	• Computing summer melt rate based on data in different information systems • Enabling analyses of data about administrative challenges students face through research and experiments	• Analyzing financial data to identify problems and challenges students face • Computing and identifying statistically significant indicators for financial predictive model • Facilitating communication, collaboration, and

[160] Based on the interview with a decision maker at Student Success Program

	periodically to evaluate their impact on improving student learning	discussions among stakeholders about indicators	• Facilitating communication, collaboration, and discussions among stakeholders about administrative challenges	discussions among stakeholders about financial challenges students face
Innovation Outcome	• Analyzing student performance in previous tasks and activities • Presenting appropriate learning material based on student performance in previous tasks and activities • Mediating communication between students and course instructors through the ALT courseware	• Predicting potential problems for all undergraduate students daily based on 800 indicators • Identifying students who might face problems and setting up timely advising sessions • Enabling discussions about problems in advising sessions between students and advisers	• Enabling storage, retrieval, and gradual expansion of knowledge base • Enabling record keeping and analyses of student interactions with chatbot • Facilitating identification of shortcomings and problems in the knowledge base	• Predicting potential financial problems daily for undergraduate students • Identifying students who might face financial problems and setting up timely counselling sessions for them • Facilitating discussions between students and financial counsellors at a counselling session

Innovation Process. In the process of digital innovation in teaching students, digital technologies were used to compute the DFW rates of high enrollment courses to identify problematic courses. It was critical to identify such problematic courses in order to create new media and modes that could improve student success in the courses. Throughout the process of digital innovation in teaching, general communication and collaboration technologies facilitated interaction, communication, discussion, collaboration, and knowledge sharing among stakeholders. Finally, after ALT was introduced in the problematic courses, digital technologies computed the DFW rates of ALT courses periodically to evaluate the impact on improving student learning. Through such periodic evaluations, different media and modes of ALT were tested to find the best ones, and to support introduction of ALT in new courses.

In the process of digital innovation in monitoring students, digital technologies were used to compute and identify statistically significant indicators for the predictive model in GPS. General communication and collaboration technologies and GPS facilitated debates and discussions among stakeholders about the indicators. Through such computation and collaboration, the indicators were selected and rationalized, and the predictive power and accuracy of GPS were improved gradually. Digital technologies were also used to analyze data to identify the main target group of students for advising.

In the process of digital innovation in engaging students, digital technologies were used to compute the summer melt rate based on data in different information systems. Researchers also investigated the root causes of summer melt through experiments. Digital technologies enabled analyses of data in those experiments about administrative challenges students faced and facilitated communication, collaboration, and discussions among stakeholders to identify administrative challenges.

In the process of digital innovation in financing students, technologies were used to analyze financial data to identify problems and challenges students faced. It was a crucial first step in helping students financially. In this process, general communication and collaboration technologies facilitated communication, collaboration, discussions, and knowledge sharing among stakeholders. Digital technologies also computed and identified statistically significant early indicators for the financial predictive model.

Innovation Outcome. The outcome of digital innovation in teaching students was ALT courseware for problematic courses in mathematics, psychology, economics, and political science. Students attended ALT lab sessions at individual terminals to learn course material by interacting with ALT. ALT analyzed student performance in previous tasks and activities and presented appropriate learning material accordingly. When students had questions or faced problems, they raised their hand, and the ALT course instructors answered their questions and helped them solve the problems through individual interactions. As such, ALT mediated discussions and conversations between students and course instructors about learning material presented by the ALT courseware.

The outcome of digital innovation in monitoring students was GPS advising, which applied predictive analytics using 800 indicators to monitor all undergraduate students daily. GPS predicted potential problems for all undergraduate students and identified students who might face problems. To help students avoid or overcome potential problems, GPS scheduled one-on-one advising sessions between the identified students and academic advisers. GPS and complementary advising systems also facilitated discussions about potential problems between students and advisers in advising sessions.

The outcome of digital innovation in engaging students was the AI chatbot. The chatbot itself enabled storage, retrieval, and gradual expansion of the knowledge base for responding to student inquiries. It also enabled record keeping and analyses of student interactions with the chatbot, which facilitated identification of shortcomings and problems in the knowledge base. Based on identified shortcomings and problems new questions and answers were added to the knowledge base and existing questions and answers were revised and updated.

The outcome of digital innovation in financing students was SFMC and its financial predictive analytics system, which predicted potential financial problems for undergraduate students daily. Through such predictions, the financial predictive analytics system identified students who might face financial problems and scheduled individual counselling sessions for them with financial counsellors at SFMC. During the counselling sessions, the financial predictive analytics system facilitated conversations and discussions between students and financial counsellors about potential financial problems and how to avoid or overcome them.

6.5.2. Role of Collaboration

The digital innovations at GSU were conceptualized and realized through collaboration as an important characteristic of organizational intelligence. The role of collaboration in both the innovation process and outcome across the four cases are detailed below and summarized in Table 8.

Table 8: Role of Collaboration

Focus	Case 1: Digital Innovation in Teaching	Case 2: Digital Innovation in Monitoring	Case 3: Digital Innovation in Engaging	Case 4: Digital Innovation in Financing
Innovation Process	• Explaining pedagogical challenges through discussions of theses and antitheses • Selecting and rationalizing ALT as a solution to pedagogical challenges • Experimenting with different media and modes of ALT to select appropriate option	• Ensuring consistency, reliability, and quality of data across fragmented information systems • Exploring the academic context to identify potential early indicators of problems • Consolidating the many fragmented advising systems into one centralized advising system	• Exploring administrative context to identify causes of summer melt • Exploring, identifying, and explaining administrative challenges students face • Collaborating with researchers and Admit Hub to find a solution to administrative challenges students face	• Collaboratively discussing financial problems and challenges students face • Identifying and explaining root causes of financial problems and challenges students face • Rationalizing potential indicators of and solutions to financial problems and challenges students face through discussions
Innovation Outcome	• Developing ALT courseware through collaboration between faculty members and courseware developers • Training course instructors about	• Developing predictive model iteratively through collaboration with EAB • Sharing knowledge among advisers at different levels	• Collaborating with Admit Hub to iteratively develop AI chatbot • Collaborating amongst administrative staff to gradually develop and	• Collaborating with EAB to iteratively develop financial predictive analytics model • Collaborating with SunTrust Foundation to establish SFMC

	ALT courseware through faculty members sharing knowledge • Transferring knowledge from course instructors to students through discussions on ALT course materials	through periodic training and weekly meetings • Providing academic advising to students to help them avoid or overcome potential problems through UAC	populate chatbot knowledge base • Collaborating with academic researchers to make language of answers understandable and amiable for students	• Providing financial interventions, counselling, and financial literacy training for low-income, at-risk students through SFMC

Innovation Process. In the process of digital innovation in teaching students, the stakeholders collaboratively identified and explained pedagogical challenges through discussions of theses and antitheses. Through such collaboration, the stakeholders discussed and debated different solutions, which lead to the selection and rationalization of ALT to address the identified pedagogical challenges. After choosing ALT as the solution, pedagogical researchers collaborated with other stakeholders in experimenting with different media and modes of ALT to select the appropriate option.

In the process of digital innovation in monitoring students, GSU staff from different organizational units collaborated to ensure consistency, reliability, and quality of data across many fragmented information systems. Decision makers collaboratively explored the academic context to identify early indicators of problems that could be included in the GPS predictive analytics model. To improve academic advising, the stakeholders worked together to consolidate the many fragmented advising systems into one centralized advising system under UAC.

In the process of digital innovation in engaging students, stakeholders collaboratively explored the administrative context at GSU to identify root causes of summer melt. After exploring the administrative context, the stakeholders identified and rationalized the specific administrative challenges students faced that lead to summer melt. Finally, GSU collaborated with academic researchers and Admit Hub to find a solution to the administrative challenges students faced.

In the process of digital innovation in financing students, GSU collaboratively discussed and debated potential financial problems and challenges students faced. Through such discourse, the stakeholders identified and rationalized the root causes of financial problems and challenges students faced. Through the collaboration with EAB, GSU tested and selected potential indicators of and solutions to financial problems and challenges students faced and decided to apply financial predictive analytics.

Innovation Outcome. The outcome of digital innovation in teaching students was a sociotechnical system for learning with ALT courseware. GSU faculty members developed ALT courseware through collaboration with ALT courseware developers. ALT course instructors were trained by these faculty members who shared knowledge about the content of the courseware and how to teach that content using ALT. As revisions and modifications were made to the ALT courseware, the ALT course instructors were retrained. Finally, during the ALT course sessions knowledge was transferred from course instructors to individual students through face-to-face discussions on ALT course materials.

The outcome of digital innovation in monitoring students was GPS advising for monitoring and advising students using predictive analytics. The predictive analytics model of GPS, as an outcome of digital innovation, was developed and continually improved through a long-term collaboration between GSU and EAB. In this collaboration, GSU shared knowledge about its academic context and EAB contributed technological knowledge. Knowledge sharing also took place among the academic advisers at different levels through periodic training and weekly meetings about how to best use the GPS and complementary advising systems. In such discourse, new requirements emerged, and new features of GPS and complementary advising systems were developed through collaboration with EAB. Finally, when GPS predicted potential problems for students, academic advisers at UAC intervened through face-to-face sessions with timely advice to help individual students avoid or overcome potential problems.

The outcome of digital innovation in engaging students was the AI chatbot. Students faced significant administrative challenges in getting admitted to and in continuing education at GSU. The AI chatbot provided necessary information and guidance to students to help them complete the required administrative processes. The AI chatbot, as an outcome of digital innovation, was the result of a long-term collaboration between GSU and Admit Hub. In this collaboration, GSU shared crucial knowledge about its administrative context and Admit Hub contributed its technological knowledge. Administrative staff at GSU also collaborated to gradually develop and populate the knowledge base for the chatbot, and GSU collaborated with academic researchers to ensure that the language and tone of the answers in the knowledge base were understandable and amiable for students.

The outcome of digital innovation in financing students was a sociotechnical solution with SFMC and its financial predictive analytics system. As an outcome of digital innovation, the financial predictive analytics system was a result of a long-term collaboration between GSU and EAB. In this collaboration, GSU shared crucial knowledge about its financial context and EAB contributed its technological knowledge. The resultant financial predictive analytics system monitors student finances and predicts potential financial problems everyday using sixteen early indicators. Based on the predictions of the financial predictive analytics system, financial counsellors at SFMC provided financial interventions, counselling, and financial literacy training for low-income, at-risk students. The SFMC itself was established through a collaboration with SunTrust Foundation.

6.5.3. Role of Learning

Finally, as an essential characteristic of intelligence, learning played a crucial role across the four digital innovation initiatives. The role of learning in both the innovation process and outcome across the four cases are detailed below and summarized in Table 9.

Table 9: Role of Learning

Focus	Case 1: Digital Innovation in Teaching	Case 2: Digital Innovation in Monitoring	Case 3: Digital Innovation in Engaging	Case 4: Digital Innovation in Financing
Innovation Process	• Innovating new features and functionalities of ALT through evaluation and experimentation • Improving efficacy of ALT courseware through evaluation and experimentation • Extending ALT courseware to new contexts, from mathematics to psychology, economics, and political science	• Gradually increasing the number of early predictors from a few dozens to more than 800 • Gradually improving the power and accuracy of predictive model • Exploring the changing academic context periodically after introduction of GPS advising	• Identifying and correcting technical problems in the chatbot and its AI and knowledge base • Adding new features, functionalities, and outreach services to the chatbot to better serve students • Expanding the use of the chatbot from admission to retention	• Gradually increasing number of predictors in financial predictive analytics model • Gradually improving power and accuracy of financial predictive analytics model • Exploring changing financial context periodically after introduction of financial counselling
Innovation Outcome	• Redesigning ALT courseware through evaluation and experimentation • Revising ALT course materials based on their efficacy in improving student learning • Training course instructors periodically on redesigned ALT courseware and	• Redesigning GPS and complementary advising systems according to changing academic context • Redesigning GPS advising based on predictive analytics according to changing academic context • Training advisers periodically on	• Gradually increasing the number of answers in knowledge base from 250 to more than 3,000 • Chatbot gradually learning the meaning of more questions posed by students through AI • Reducing errors in understanding meaning of	• Updating financial analytics system according to changing financial context • Revising financial counselling based on predictive analytics according to changing financial context • Training financial counsellors

	revised course materials	redesigned GPS and complementary advising systems and processes	questions posed by students and in providing correct answers	periodically on updated financial predictive analytics system and counselling process

Innovation Process. In the process of digital innovation in teaching students, GSU collaborated with courseware developers to develop new features and functionalities of the ALT courseware through evaluation and experimentation. Pedagogical researchers at GSU experimented with ALT by piloting sections with ALT courseware in mathematics courses. In these experiments, the researchers compared the performances of two groups of students: one group of students worked on their own on ALT exercises at computer stations at home and across campus; the other group of students spent one hour a week in a math lecture and three hours a week in an ALT lab working on personalized ALT exercises. Analysis of data from these experiments showed that the gains in student performance were minimal for the first group, whereas the gains in student performance were significantly greater for the second group. The pedagogical researchers also conducted perceptual surveys to understand student perception about ALT courseware. By learning from these evaluations and experiments, GSU gradually improved the efficacy of the ALT courseware. Importantly, GSU faculty members learned from creating ALT courseware in introductory mathematics courses and based on this initial success, GSU transferred lessons learned to other faculty members to create ALT courseware in new contexts, from mathematics to psychology, economics, and political science.

In the process of digital innovation in monitoring students, GSU gradually increased the number of early predictors in the predictive model of GPS from a few dozens to more than 800. By incrementally including more indicators to the predictive model of GPS, GSU gradually improved the predictive power and accuracy of the model. At the same time, GSU kept exploring the changing academic context periodically after introducing GPS advising to identify and select new indicators and to evaluate the impact of GPS advising on student success.

In the process of digital innovation in engaging students, GSU collaborated with Admit Hub to identify and correct technical problems in the chatbot and its AI and to expand its knowledge base. As a result, the AI integrated in the chatbot kept learning the meaning of questions posed by students and the chatbot staff kept including new answers and updating old answers in the knowledge base. In collaboration with Admit Hub, GSU introduced new features, functionalities, and outreach services through the chatbot to better serve students. Finally, after initial success of the chatbot in admission, GSU leveraged lessons learned to expand the use of the chatbot to retention.

In the process of digital innovation in financing students, GSU collaborated with EAB to periodically update the financial predictive analytics system according to changing financial context and revise financial counselling based on the updated financial predictive analytics. Such ongoing revision of the financial counselling was realized through periodic training of financial counsellors on the updated financial predictive analytics system and financial counselling process.

Innovation Outcome

The sociotechnical system built around ALT courseware, as the outcome of digital innovation in teaching students, was periodically improved and redesigned through learning based on evaluation and experimentation. Students learned through ALT courseware and face-to-face individual interactions with ALT course instructors. Pedagogical researchers conducted experiments and perceptual surveys to evaluate the efficacy of ALT courseware and to select best media and modes of ALT. ALT course materials were revised based on their efficacy in improving student learning. Learning also took place when GSU trained the ALT course instructors periodically on redesigned ALT courseware and revised course materials. This broader learning by instructors and faculty members fed back to iteratively develop the ALT courseware, and subsequently transfer the learning to new contexts in other courses.

As the outcome of digital innovation in monitoring students, GPS advising helped students learn how to maneuver their academic journey at GSU through its large-scale monitoring and dedicated and timely advising. GSU periodically explored and learned from its changing academic context and modified GPS and complementary advising systems accordingly. With each modification of GPS and complementary advising systems, GSU redesigned the advising and intervention process according to the changing academic context. Learning also took place when GSU periodically trained the academic advisers on the changing academic context and advising systems and processes.

The sociotechnical system built around the AI chatbot, as the outcome of digital innovation in engaging students, was conceptualized, implemented, and improved through continual learning by GSU. Through such learning from its evolving administrative context, GSU gradually increased the number of answers in the knowledge base of the chatbot from 250 to more than 3,000. By using the AI chatbot students learned about required administrative processes and how to complete them to get admission or continue their study at GSU. The AI integrated in the chatbot also became smarter as time progressed, through learning the meanings of more questions posed by students. In collaboration with Admit Hub, GSU gradually reduced the errors of the chatbot in understanding the meanings of questions posed by students and in providing correct answers to students.

As the outcome of digital innovation in financing students, SFMC and its financial predictive analytics system helped students learn about potential financial problems and how to avoid or overcome them. GSU periodically learned from its changing financial context and updated or modified the financial predictive analytics system accordingly. To help students financially with timely counselling, GSU periodically revised the financial counselling based on changes in predictive analytics and the financial context. To keep the financial counsellors up to date about changes in the financial context, the financial predictive analytics system, and the financial counselling process, GSU periodically trained the financial counsellors. As such, financial counsellors also learned about updated financial predictive analytics system and counselling process.

6.5.4. Summary

Across the four embedded cases, and as summarized in Table 7, 8, and 9 above, we observe the important roles of technology, collaboration, and learning in shaping organizational intelligence across the observed digital innovation processes and outcomes. While each of these characteristics had significant influence in realizing the respective digital innovations, the strength of their influence varies from case to case. For example, the role of technology had the greatest influence in GPS advising (Case #2) followed by the financial predictive analytics system (Case #4), the ALT (Case #1), and the AI chatbot (Case#3), in descending order. Without the use of predictive analytics technology in GPS advising it would not be possible to monitor more than 20,000 undergraduate students daily using 800 different indicators. Technology plays a similar key role in the financial predictive analytics system, but with only sixteen indicators. Although technology also plays significantly influential roles in both the AI chatbot and ALT, the role is different in these digital innovations compared to advising and financing. In the ALT teaching, the system keeps track of individual student performance based on preprogrammed logic to present new course material customized for each individual student. In the AI chatbot, the AI continually learns the semantics of the questions posed by students to provide appropriate answers. Moreover, while technology, collaboration and learning played different roles in realizing digital innovation, they all played a significant role across all cases as summarized in Table 7, 8, and 9. Hence, it was only through the combined influence of the organizational intelligence characteristics that the digital innovations were realized. Finally, in realizing the different digital innovations, the specific combination of technology, collaboration, and learning was also different. For example, in GPS advising the combination involved the role of technology in monitoring students and predicting problems, the role of collaboration with EAB in gradually developing the predictive analytics model, and the role of learning by academic advisers about how to best utilize GPS and complementary advising systems. In contrast, in ALT the combination involved the role of technology in representing course material and mediating discussions, the role of collaboration among faculty members, course instructors, and courseware developers in developing and updating the courseware, and the role of learning by pedagogical researchers about the best media and modes of ALT through experimentation. As such, there was heterogeneity in how technology, collaboration, and learning characteristics in organizational intelligence combined to realize the four digital innovations at GSU in terms of innovation processes and outcomes.

6.6. Analyses of the Context of Organizational Transformation

The digital innovation initiatives at GSU were embedded into a context of organizational transformation that reflected and recursively influenced the organizational intelligence implicated in the initiatives and their outcomes. As detailed in the following and consistent with our contextualist inquiry[161] framing, we observed strategic, structural, managerial, and cultural contextual characteristics in how GSU realized its digital innovation initiatives. Such characteristics provide further evidence of application of organizational intelligence in not only driving digital innovation but also transforming the organization.

6.6.1. Restructuring to Support Innovation

At the heart of GSU's Student Success Program was the visionary leadership of President Mark Becker and Senior Vice President for Student Success, Timothy Renick. Dr. Renick started at GSU in 1986 as one of two faculty members of the then newly formed Religious Studies Department. In 1987 he became the chair of the department and spearheaded the creation of BA in religious studies program. He was simultaneously the director of the honors program. From the very beginning of his career at GSU, Dr. Renick held many important administrative positions related to education. Because of his rich experience in higher education administration, in July of 2008, he was appointed as the Associate Provost for Academic Programs, and he started overseeing enrollment and registration of students. The current Student Success Program gradually and incrementally evolved from this organizational structure[162]. As Dr. Renick commented:

> *So, the President offered me the position and I took it, in July of 2008 … So, I just hit the 11-year mark. And that is then the place from where this Student Success Program eventually spanned out. Yeah, it is not only the place where it began, but even from that first moment in the first month, it was already expanding.*

At that time, there was a small advising office serving freshmen named the Student Advisement Center (SAC), which was the only centralized organizational structure under Dr. Renick. SAC advised freshmen as they first came in to GSU and then, very soon thereafter, they would be

[161] Pettigrew 1985; Pettigrew 1987; Pettigrew 1990
[162] Based on the interview with Dr. Timothy Renick

funneled out to the colleges. In 2009, due to many problems with SAC, there were discussions about closing SAC altogether. During the same time, Dr. Becker started his tenure as the president of GSU. Dr. Renick convinced Dr. Becker and other decision makers to expand and experiment with SAC. Because of SAC's impact on improving student success in the following years, under the leadership of Dr. Renick, the SAC was not closed and gradually evolved into the university-wide centralized advising structure named the University Advisement Center[163].

Under the leadership of Dr. Becker and Dr. Renick, in 2011 GSU accelerated its activities to improve student success through a five-year strategic plan with five goals: become a national model for undergraduate education by demonstrating that students from all backgrounds can achieve academic and career success at high rates; significantly strengthen and grow the base of distinctive graduate and professional programs by developing the next generation of researchers and societal leaders; become a leading public research university by addressing the most challenging issues of the 21st century; be a leader in understanding the complex challenges of cities and developing effective solutions; and, achieve distinction in globalizing the university[164]. To achieve these goals, the Student Success Program was established under the leadership of Dr. Renick as the centralized organizational structure to spearhead digital innovation initiatives for improving student success[165]. Today, the Student Success Program is one of three main vertical organizational structures at GSU with more than 1000 employees under Dr. Renick, who in turn directly reports to the president [166].

[163] Based on the interview with Dr. Timothy Renick
[164] GSU Strategic Plan 2011-2016/21
[165] Based on the interview with Dr. Timothy Renick
[166] 2018 Complete College Georgia Status Report: Georgia State University

Through its bold and timely strategic plan and the establishment of the Student Success Program, GSU made a conscious decision to build on ten years of various student success initiatives to transform itself enabled by digital innovations. Because of the initial success with SAC, the Student Success Program gradually took control of the initiatives that were introduced before 2011, namely Freshmen Learning Communities, Supplemental Instructions, Mathematics Interactive Learning Environment Labs, and Keep Hope Alive. The Student Success Program experimented with these initiatives, expanded their scope, and improved their efficacy[167]. The Student Success Program also introduced new digital innovation initiatives starting 2011, namely Panther Retention Grants, Graduation Progression System, Summer Success Academy, Meta-Majors, Course Scheduling Analytics, Chatbots, Student Financial Management Center, College to Career, and Adaptive Learning Technologies in Social Sciences[168]. Although the organizational structure of the Student Success Program led the way from the top by initiating and implementing each digital innovation, their success depended on leaders at every level of the organizational structure. As such, a vertical structure of organic leadership fueled the ongoing horizontal transformation process and the realization of change through digital innovations, from inception to fruition[169].

6.6.2. Data-Driven Innovation

What contributed most to the success of the digital innovations at GSU was its data-driven decision making[170]. GSU is far from alone among higher education institutions in turning to big data in recent years. According to a 2017 survey, 91% of colleges and universities are currently expanding their use of data and 89% are deploying predictive analytics at least in some

[167] 2013 Complete College Georgia Status Report: Georgia State University
[168] 2018 Complete College Georgia Status Report: Georgia State University
[169] Based on the interview with Dr. Timothy Renick
[170] Based on the interview with Dr. Timothy Renick

capacity[171]. What distinguishes GSU is the timing and extent of its use of data to improve student success. GSU has consistently been at the leading edge nationally of the adoption of new data-based and technology-enabled student support initiatives, and it has implemented these initiatives at scale[172]. As a decision maker at the Student Success Program commented:

> *I think in many ways, success came organically from the approach we've taken from the beginning, which is absolutely day to day data oriented. There's not a day when I'm not looking at data in front of me.*

GSU was among the very first institutions in the US to deploy predictive analytics in academic advising[173]. Over the years, GSU has developed the capability to track every undergraduate student across more than 800 data-based risk factors every day using GPS advising. Monitoring and advising with GPS has resulted in more than 300,000 proactive interventions with students[174]. GSU also pioneered the use of predictive analytics in awarding financial aid with the launch of its micro-grant program, Panther Retention Grants, in 2011. The program, which is aimed at keeping students with high probabilities of graduating from dropping out, has awarded more than 13,000 grants since its inception, with 85% of grant recipients going on to graduate[175]. In 2016, GSU became one of the first universities in the nation to deploy artificial intelligence (AI) for student-success purposes by developing the AI chatbot—"Pounce”. Pounce is an automatic texting platform that answers students’ questions about required administrative processes and other issues 24 hours a day, seven days a week. The chatbot answered more than 200,000 student questions in its first three months of operation[176].

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[171] Data and Analytics for Student Success 2017
[172] Based on the interview with Dr. Timothy Renick
[173] 2013 Complete College Georgia Status Report: Georgia State University
[174] 2018 Complete College Georgia Status Report: Georgia State University
[175] 2013 Complete College Georgia Status Report: Georgia State University
[176] According to Renick (2020)

Collectively, these data-driven initiatives have allowed GSU to accomplish a goal that was previously believed to be attainable only by small, elite institutions with low student to faculty ratios: delivering personalized and timely support to students at scale. Rather than waiting for students to diagnose their own problems and to seek out help, a feat particularly challenging for low-income, first-generation college students who often lack the contextual knowledge to realize when they have gone off path, these new data-driven digital innovations are continuously analyzing student behaviors and, with the help of trained staff, proactively delivering personalized support[177]. The results of these data-driven digital innovations have been transformative. In fact, each of the significant data-driven innovations implemented by GSU over the past decade came not from a desire to innovate per se, but from the identification of a serious problem that demanded a solution. The data led the process all throughout from identification of the problems to their solutions[178].

6.6.3. Management Innovation Forum

Under the central leadership of the Student Success Program, GSU fosters a culture of collaborative and participatory innovation and learning. Although the Student Success Program holds the authority to evaluate, decide on, initiate, and orchestrate innovation options, ideas emerge from different levels of diverse functional units across GSU[179]. To facilitate such an organic incubation of innovation, the Student Success Program holds a mangers' meeting every week to discuss the current status, future trends, and potential innovation opportunities. Most of the data-driven decisions of the Student Success Program are made at these weekly manager meetings presided by Dr. Renick. Representatives from different functional units attend the

[177] Based on the interview with Dr. Timothy Renick
[178] Based on the interview with Dr. Timothy Renick
[179] Based on the interview with Dr. Timothy Renick

meetings to learn about the ongoing development of the Student Success Program and contribute their expert opinions on future innovation initiatives[180]. As Dr. Renick commented:

> *Every time I meet with my managers, we're looking at data. The output of that is we discover problems, you know, we discover ways in which we are not serving students well and those problems are what lead to the innovations.*

The attendees at these meetings review what data is on the table, the portfolio of ongoing projects, and potential innovations. Dr. Renick often brings topics to the table, but other people can also raise issues to discuss. Everybody gets an opportunity to voice their opinions based on their own perspective and expertise. Through these discussions they learn from each other, identify problems to be solved, propose potential solutions, and make data-driven decisions by consensus. These meetings also facilitate collaboration across functional areas[181].

For example, the attendees did not necessarily understand that the summer melt problem was growing, that GSU was losing more and more freshmen before classes even began during the summer. But they learned it from data that was presented and explained by an expert in admissions. Through discussions on the data, they realized that summer melt is a real problem. As a result, they shifted the discussions towards finding a way to address the summer melt problem. They looked at more data and discussed across the functional units. Ultimately, they decided to implement an AI chatbot to reduce or eliminate summer melt[182].

As such, even though the authority is centralized at GSU, the genesis of innovation is decentralized, emergent, and organic. The commitment of people at these meetings to student success motivates them to proactively participate in innovation and learning. GSU's culture of

[180] Based on the interview with Dr. Timothy Renick
[181] Based on the interview with a decision maker at Student Success Program
[182] Based on the interview with Dr. Timothy Renick

participatory innovation and learning generates a wider range of innovation options, reduces the time to realize innovation opportunities, and eliminates potential bureaucratic obstacles[183].

6.6.4. External Innovation Partnerships

GSU's decision and commitment to support student learning, to monitor and advise students, to engage and inform students, and to provide financial counselling to students led to a series of strategic digital innovation decisions, including how to source requisite professional expertise, how to select technology vendors, how to specify system features, how to communicate requirements to potential vendors, and how to customize and rebrand systems according to GSU requirements. Rather than developing technological solutions purely in-house, GSU outsourced most of them, creating close collaborations between technology developers and internal experts at GSU[184].

In developing ALT courseware, faculty members at GSU collaborated with publishers and courseware developers. This external partnership significantly reduced the cost and the time to develop ALT courseware, since publishers and courseware developers had years of experience and expertise[185]. In monitoring and advising students, GSU went into long-term partnership with EAB to gradually develop GPS and complementary advising systems. This decision to outsource the development of the predictive analytics technology helped GSU focus on its strategic goal of improving student success and avoid the risks associated with developing complex systems[186]. Later on, EAB extended the application of predictive analytics in financial counselling[187]. In engaging and informing students with the AI chatbot, GSU partnered with Admit Hub, who had

[183] Based on the interview with Dr. Timothy Renick
[184] Based on the interview with the Chief Innovation Officer
[185] Based on the interview with a pedagogical researcher
[186] Based on the interview with the Chief Innovation Officer
[187] Based on the interview with Dr. Timothy Renick

the technological knowledge and expertise to quickly and appropriately develop AI chatbots. By partnering with Admit Hub, GSU reduced risks and production time significantly[188]. As the CIO commented:

> *When it came to the chatbot, we knew we needed an AI platform for when a student texts in a question, digging into a knowledge base with thousands of potential answers and picking out just the right answer. We don't have that, you know, and we don't have any confidence that in a reasonable period of time we would be able to implement it. So that's when, you know, we go externally to look for these other sources. In this case Admit Hub.*

External technological expertise provided GSU with a wider range of options for digital innovation and an unrestricted focus on its principal function of delivering value based on these innovations to improve student success. This focus on building external partnerships for developing technological solutions has helped GSU continually create and share knowledge and resources with EAB, Admit Hub, and other technology vendors, while at the same time growing its own dedicated expertise in digital innovation for improved student success[189].

6.6.5. Innovation Capability Building

Apart from developing external partnerships, GSU also focused on internal capability building dedicated to student success[190]. In 2006, GSU experimented with ALT in introductory mathematics courses. To conduct the experiments, GSU established one Mathematics Interactive Learning Environment (MILE) lab. The pedagogical researchers along with faculty members conducted controlled experiments in the first MILE lab in small scale[191]. After confirming the initial positive impact of MILE lab on student learning, GSU gradually increased the number of MILE labs to offer ALT courseware in introductory mathematics courses for all undergraduate

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[188] Based on the interview with the Chief Innovation Officer
[189] Based on the interview with the Chief Innovation Officer
[190] Based on the interview with Dr. Timothy Renick
[191] Based on the interview with a pedagogical researcher

students[192]. GSU hired high-performing students as lab instructors and faculty members trained them to help MILE course instructors in conducting the MILE lab sessions[193]. In 2017, when GSU extended ALT to psychology, economics, and political science, it built ALT labs for social sciences and trained lab instructors to conduct the lab sessions[194].

In 2009, GSU established a small office of Instructional Design, which evolved and expanded into the Center for Excellence in Teaching and Learning (CETL) in 2014. CETL focuses on advancing the scholarship and practice of exemplary instruction[195]. CETL provides professional development opportunities for instructors in all the GSU's colleges and schools throughout their teaching careers and across all modalities from face-to-face to fully online. CETL works collaboratively with instructors on course design and implementation of appropriate instructional technologies to enhance student learning and engagement. CETL also partners with schools and colleges to develop, market, and deliver exceptional online programs[196]. As the Assistant Vice President of CETL commented:

> *When we started student success initiatives, we knew our students had to do better and graduate more frequently, which would not be possible without our faculty doing a very good job of teaching … And that is where CETL comes in. We provide information, resources, and training to all faculty members and course instructors and lab instructors.*

In 2012, GSU established the University Advisement Center (UAC) with a goal to provide timely academic advice to all undergraduate students to help them avoid or overcome potential problems[197]. While GSU partnered with EAB to develop the GPS predictive analytics system, it

[192] Based on the interview with a decision maker at Student Success Program
[193] Based on the interview with a MILE lab Coordinator
[194] Based on the interview with a pedagogical researcher
[195] Based on the interview with a decision maker at CETL
[196] Based on the interview with a Chief Learning Innovation Officer
[197] Based on the interview with a decision maker at the University Advisement Center

also developed its own organizational structure of UAC and trained human resources to advise students based on the analytics[198]. Before UAC was established, GSU had a problematic fragmented advising system with little coordination and no standard record keeping. The student-to-adviser ratio was 800 to 1, which was much higher than the industry-accepted ratio of 300 to 1[199]. UAC consolidated, centralized, and replaced the previous fragmented advising system by implementing a vertical governance structure for common advising systems and technologies that offer systematic tracking and record keeping, and coordination among advisers[200]. Through UAC, GSU hired new academic advisers and gradually increased the number of advisers to 70 in 2020, bringing the student-to-adviser ratio closer to the industry-accepted 300:1 level[201]. UAC also provided periodic systematic training and career paths for the advisers[202].

In 2016, with a donation from the SunTrust Foundation, GSU established the Student Financial Management Center (SFMC) and revolutionized the way financial services are delivered to students[203]. Financial counsellors were hired and trained to provide timely proactive financial counselling to students, based on early alerts by the financial predictive analytics system[204]. GSU built a model for financial interventions that helps students manage their financial requirements through graduation. These interventions look to reduce the debt students incur in college, proactively identify students who might have trouble paying their educational and living expenses and provide quality financial literacy training for students and community members[205].

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[198] Building University Infrastructure: Student Advisement
[199] 2013 Complete College Georgia Status Report: Georgia State University
[200] Building University Infrastructure: Student Advisement
[201] According to Renick (2020)
[202] Based on the interview with a decision maker at the University Advisement Center
[203] SunTrust Student Financial Management Center Year Two Report
[204] Based on the interview with a decision maker at Student Success Program
[205] Based on the interview with a decision maker at Student Success Program

SFMC had almost 60,000 student visits in its first eighteen months[206]. Moreover, SFMC continues to be the hub of financial success innovation, where students and financial counsellors meet in-person and virtually to pursue shared goals[207].

6.6.6. Chief Innovation Officer

Innovation has become engrained in the culture of GSU. As a highlight of GSU's commitment to innovation, in 2014, GSU changed the title of the "Chief Information Officer" to "Chief Innovation Officer (CIO)." GSU's passion for innovation is evident not only in changing the job title, but also in recasting the role of the CIO to be more strategic at the cabinet level, in redesigning the organizational structure under CIO, in hiring a person whose experience and expertise is more focused on innovation than technology, and in developing an organization-wide culture of experimentation and data-driven decision making. The current CIO joined GSU in April 2014. Before joining GSU, he had twenty years of industry experience in developing technological products and services, in organizational development, and in starting up new technological businesses. As such, the CIO was selected specifically for his vast experience in innovation. He led the way in shifting GSU's focus from information systems and technology to instructional innovation and technology. Under his leadership, GSU developed capabilities around new digital technologies and information systems. According to his strategy, when building external partnerships with technology developers and vendors, such as EAB, Admit Hub, and ALT courseware developers, GSU provided creative freedom to the external partners in innovating the solutions and focused primarily on applying those solutions in improving student success. His team ensured successful integration of new information technologies and systems with old ones. He has a highly capable technical team, which he refers to as an

[206] SunTrust Student Financial Management Center Year Two Report
[207] According to Renick (2020)

"integration machine" that allows GSU to quickly integrate forty to fifty new products, on average, every year primarily into the Banner platform. His philosophy is that GSU should not take the risk of developing sophisticated new systems. Rather, by developing external partnerships, GSU has access to a much broader range of fully developed solutions that are best of the breed. By getting the solutions integrated into GSU's existing platforms, GSU can onboard a new tool usually within thirty days. Although his leadership was crucial in realizing the digital innovations at GSU, the innovation culture at GSU was equally important[208]. As he commented:

> *I'm meeting with the cabinet and the president and the deans at the time and seeing how collaborative things were, how people worked together to get things done. Innovation is a team effort and its more culture than technology. It's enabled by technology, but it's definitely more culture.*

6.6.7. External Knowledge Sharing

An important ingredient for the success of GSU's transformation was its move to a culture where it was acceptable, even lauded, to publicly talk about its failings[209]. At many institutions, data are cited by campus leaders when they shine a light on accomplishments and highlight points of pride. GSU leaders intentionally began to use the data to identify what it was doing wrong. GSU believed that every self-help program begins with the sober admission of failing. GSU officials analyzed data and began to admit there were problems. That was the first step towards solving the problems through innovative solutions[210].

Since 2011, from the very beginning of digital innovations to solve its problems, GSU was vocal about its initiatives through publications and presentations[211]. GSU has been publishing about its digital innovation initiatives in the annual Complete College Georgia report. In these reports

[208] Based on the interview with the Chief Innovation Officer
[209] Based on the interview with a decision maker at Student Success Program
[210] According to Renick (2020)
[211] Based on the interview with a decision maker at Student Success Program

GSU has presented information about its past and present problems, initiatives undertaken to solve these problems, and the current status and future direction of the initiatives[212]. The SVP of the Students Success Program authored a book chapter to discuss how GSU applied predictive analytics and academic advising to improve student success[213]. Leaders of the Student Success Program also shared information with authors and academic researchers. A world-renowned British-born author and journalist, Andrew Gumbel, published an entire book on GSU's Student Success program. In the book, Gumbel focuses on the personal struggles of many students at GSU and how GSU helped them improve their lives by introducing the initiatives of the Student Success Program[214]. Leaders of the Student Success Program also shared information about their innovation initiatives with journalists frequently. As such, many top news publishers with worldwide influence and readership published news articles about the digital innovation initiatives at GSU. Washington Post commented:

> *Georgia State is a perpetual laboratory of new ideas for using 'big data' to improve higher education and to keep disadvantaged students on track toward a degree. [Washington Post, October 1, 2015]*

And, The New York Times commented:

> *Georgia State has been reimagined, amid a moral awakening and a raft of data-driven experimentation, as one of the South's most innovative engines of social mobility. [The New York Times, May 15, 2018]*

Leaders of the Students Success Program frequently gave presentations about the innovation initiatives at different conferences and seminars. GSU has been hosting Student Success Program Campus Visits since 2016[215]. Administrators, academic researchers, and faculty members from higher education institutions around the world regularly attended these campus visits. In these

[212] 2018 Complete College Georgia Status Report: Georgia State University
[213] Renick (2020)
[214] Gumbel (2020)
[215] Based on the interview with a decision maker at Student Success Program

day-long events, leaders of the Student Success Program present the history, evolution, and future direction of the innovation initiatives at GSU. They also engage in informative and insightful discussions with the attendees[216].

Finally, in 2014 GSU entered the University Innovation Alliance (UIA) as a member institution[217]. UIA was established to facilitate collaboration and knowledge sharing among its eleven members about their innovation initiatives to improve student success. UIA is the leading national coalition of public research universities committed to student success and diversity. The UIA member institutions believe that higher education needs to do a better job of graduating students across the socioeconomic spectrum, particularly first-generation students, low-income students, and students of color. Improving graduation rates is imperative for individual social mobility and global competitiveness. Higher education institutions have wasted time and resources trying to solve this graduation challenge by themselves for too long. It was ineffective and inefficient, and students paid the price. Through UIA the member institutions decided to innovate together by setting ambitious goals, opening up their data, and agreeing to share everything they learn[218].

6.6.8. Summary

The above-mentioned characteristics of the organizational change context at GSU reflected and influenced the digital innovation initiatives, their conceptualization, rationalization, and realization. Although the objective of providing education is constant across all higher education institutions, the strategic, structural, managerial, and cultural contextual characteristics discussed above significantly impacted the formulation, implementation, and outcome of the strategic

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[216] Based on the interview with a decision maker at Student Success Program
[217] Based on the interview with a decision maker at Student Success Program
[218] Based on the interview with a decision maker at Student Success Program

decisions for student success. These characteristics were also representative of and affected the way organizational intelligence was applied in and developed through digital innovations. Many higher education institutions face the same challenges as GSU. However, GSU demonstrated organizational intelligence by deciding on and embracing the above-mentioned organizational changes, which contributed to achieving its goal of improving student success.

CHAPTER 7. DISCUSSION

In the midst of the fourth industrial revolution, rapid and pervasive digitalization is changing the nature and structure of products, services, processes, and business models (Kohli and Melville 2019; Nambisan et al. 2017; Svahn and Henfridsson 2012; Yoo 2010; Yoo et al. 2010a; Yoo et al. 2012), challenging organizations to cope with dynamic business landscapes as they apply digital technologies to improve their competitive positions (Kohli and Melville 2019; Tanriverdi et al. 2010). Today, digital innovations are existentially necessary for many organizations as their businesses would no longer be competitive if they cannot become significantly more digital (Wiles 2018). In order to sustain and improve their performance in increasingly digitalized business environments, organizations sense and respond to new opportunities and threats through continuous adaptations and proactive transformations (Tanriverdi et al. 2010). As such, innovations enabled by digital technologies are not only meeting new requirements, unarticulated needs, or market demands (Maranville 1992), they also lead to disruptive transformation of sociotechnical structures (Yoo et al. 2010b).

Despite the practical relevance and theoretical significance of digital innovation, our knowledge on how organizations realize and manage digital innovations to improve performance is limited. Against that backdrop, we introduce a theory on organizational intelligence to explain how an organization's digital innovation initiatives were realized and managed to improve its performance over time. We posit that organizational intelligence enables organizations to effectively gather, process, and manipulate information and to communicate, share and make sense of the knowledge it creates, so it can increase its adaptive potential in the dynamic environment in which it operates (Glynn 1996). We conceptualize that organizational intelligence materializes along its two dimensions—analytical and relational—in figurations that bear elements of both human agency and material agency. Furthermore, we explicate how organizational intelligence both shapes and is shaped by digital innovation initiatives in the broader context of focused organizational transformation. While current research on organizational intelligence predominantly emphasizes analytic capabilities, this research puts equal emphasis on relational capabilities. Similarly, while current research on organizational intelligence focuses only on human agency, this research focuses equally on material agency.

Accordingly, based on empirical evidence from four embedded cases in GSU's Student Success Program, we advance theory on how human and material agencies come together in various figurations to help organizations effectively realize and manage digital innovations, and how these digital innovations recursively enable organizations to improve their organizational intelligence. Moreover, we present empirical evidence of application of organizational intelligence in transforming the organization that reveal the important role of organizational intelligencein digital innovation as it plays out in the broader context of organizational transformation. Our proposed theory of organizational intelligence has pronounced implications for both theory and practice and responds to recent call by Sarker et al. (2019) to position IS theories closer to the fundamental and unique characteristic of IS research as expressed in the sociotechnical perspective. Hence, through our proposed theory of organizational intelligence, we revisit the roots of IS research and offer novel scholarly discussions along the sociotechnical axis of cohesion (Sarker et al. 2019).

7.1. Contributions to Knowledge

In general, intelligence enables entities to perceive their environment and take actions that maximize their chance of successfully achieving their goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013). In our case, the entity was a higher education institution, and the goal was to improve its student success. To achieve this goal, the organization undertook a series of digital innovation initiatives and transformed itself over the span of two decades. During each of these innovation efforts, the organization explored its environment, identified, rationalized, and realized appropriate innovation opportunities, and evaluated the effectiveness of the innovations in improving student success. Following these steps for each digital innovation initiative, our analyses revealed how the organization demonstrated intelligence constituted by entanglement of analytical intelligence and relational intelligence figurations of human and material agencies, within the broader context of its focused organizational transformation. Specifically, for each innovation initiative we empirically observed (1) the role of human and material agency, (2) the entanglement of analytical and relational intelligence, and (3) the contextualist nature of organizational intelligence. The key concepts of this study are defined in Appendix C.

7.1.1. The Role of Human and Material Agency

One significant contribution to knowledge is our theoretical framing of how the different, but equally important, roles of human and material agencies entangle into observable figurations to form organizational intelligence, together with our empirical analyses that demonstrate the detailed workings of this framing. The predominant view in IS literature has been the "use" of digital technologies in performing tasks and achieving goals, giving primacy to human agency, and portraying digital technologies as passive tools (Baird and Maruping 2021). However, new forms of digital technologies, such as AI and analytics, with their increasingly influential material agency, are not just tools waiting to be used and they are not necessarily subordinate to human agents but can perform tasks on their own (Baird and Maruping 2021). As such, we theorize and empirically demonstrate that while the influence of human and material agencies may vary in performing tasks in achieving organizational goals, both are essential for organizations to demonstrate intelligence and function rationally. While current research on organizational intelligence focuses only on human agency, this research focuses equally on material agency.

In organizational practices both humans and digital technologies act as rational agents (Russell 2019; Russell and Norvig 2013) by doing what is appropriate for their circumstances and goals, being flexible to changing environments and changing goals, and making appropriate choices, all the while learning from experience (Poole and Mackworth 2010). However, as rational agents, human beings and specific technologies do not individually possess sufficient memory and have requisite time to appropriately observe the state of their environment (Poole and Mackworth 2010; Russell 2019; Russell and Norvig 2013). Organizations overcome such perceptual and computational limitations of its rational agents by employing both human agency and material agency in different figurations in organizational practices (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). In this dissertation, we empirically observed such figurations, and theoretically advanced our knowledge about the role of these figurations in forming organizational intelligence. In all four cases embedded into GSU's Student Success Program, we empirically observed how human and material agencies entangled to identify the problems, to create solutions to the problems, and to periodically evaluate the impact of the implemented solutions. While human and material agencies are ontologically separable (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013), we observed in each case how they entangled in key characteristics of organizational intelligence to achieve organizational goals, such as the ability to reason, responding to the environment, and learning from experience.

First, the ability to reason—rationality—is central to organizational intelligence (Gottfredson 1997; Neisser et al. 1996). In each of the four cases, we found that human and material agencies entangled as evidence of the organization's ability to reason (Table 10). In Case 1, we empirically observed how Banner, a digital technology, facilitated identification of problematic courses through analysis of data. The material agency of Banner was complemented by human agency of pedagogical researchers to experiment with adaptive learning technologies (ALT) as a possible solution. It was this entanglement of human and material agencies that lead to the rationalization of ALT as an appropriate digital innovation to improve student learning. After ALT was implemented, the innovation provided GSU with new capabilities to reason. Through ALT, GSU was able to monitor every student's past activities, tasks, and performance, and present new course materials accordingly. However, it was the lab instructors who helped students comprehend the course materials through discussions on the specific materials presented by ALT. Tailoring course materials for each individual student through ALT, along with transfer of knowledge from lab instructors to students, improved student performance. As such, the material agency of the digital technology, complemented by human agency, recursively improved organizational intelligence by affording GSU the ability to teach course materials in a rationally more effective way.

Second, responding to the environment by continuously sensing it and taking appropriate action is an important aspect of organizational intelligence (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013). Again, we found in each of the four cases that human and material agencies entangled as evidence of the organization's ability to respond to the environment (Table 10). In Case 2, human and material agencies entangled to constitute the capability to monitor the environment and predict potential problems. In this case, the human agency in consolidating many fragmented information systems and ensuring quality of data was complemented by the material agency in analyzing big data, identifying early indicators, and developing a predictive model for monitoring students. As such, it was the entanglement of human and material agencies that enabled GSU to rationalize and realize the digital innovation, named GPS. Moreover, after the predictive model of GPS was implemented, it started monitoring GSU's more than 20,000 undergraduate students daily across 800 early indicators. Such large-scale monitoring of each individual student daily would have been impossible without the material agency of GPS. However, predicting potential problems for students could not, on its own, ensure improvement in student success. GSU had to establish a centralized University Advisement Center (UAC) with 70 full-time advisers who monitored the alerts generated by GPS and responded with timely, proactive, and individualized advice to students. As such, GPS advising, through the entanglement of human agency of advisers and material agency of GPS system, recursively improved organizational intelligence by affording GSU an unprecedented ability to monitor and perceive its environment and take necessary action. Similarly, in Case 4, the financial predictive analytics system possessed the material agency to monitor the finances of all students daily and predict potential problems. Such large-scale monitoring and analytics would not be possible without the material agency of the financial predictive analytics system. However, based on the predictions of the financial predictive analytics system, financial counsellors applied their human agency in intervening with timely financial counselling. With the help of such counselling student success was improved. As such, through the entanglement of material agency in predicting financial problems with human agency in providing counselling to avoid or overcome those problems, GSU demonstrated organizational intelligence by perceiving the environment and taking necessary action.

Third, learning from experience is another important aspect of organizational intelligence (Gottfredson 1997; Neisser et al. 1996). In our empirical analyses of all four cases we also found evidence of the organization's ability to learn from experience based on entanglement of human and material agencies (Table 10). In Case 3, the material agency of the AI chatbot in disseminating information to students was complemented by the human agency in developing a knowledge base for the chatbot. Moreover, the AI chatbot gradually became more knowledgeable by learning the meaning of new questions posed by students and consequently the knowledge base grew from 250 answers to more than 3,000 answers with the help of human agency of the chatbot staff. As such, the AI chatbot, through the entanglement of human and material agencies, recursively improved organizational intelligence by affording GSU a capability to learn from interactions with students.

Table 10: The Role of Human and Material Agency

Aspects of Intelligence	Case 1: Digital Innovation in Teaching	Case 2: Digital Innovation in Monitoring	Case 3: Digital Innovation in Engaging	Case 4: Digital Innovation in Financing
Functioning rationally	In rationalizing and realizing ALT, the material agency of Banner entangled with the human agency of pedagogical researchers. The innovated ALT recursively afforded the ability to teach course materials in a more effective way, through the entanglement of the material agency of ALT and the human agency of the lab instructors.	The material agency of GPS to monitor all students and predict potential problems, entangled with the human agency of advisers to help students avoid or overcome such problems. Such entanglement afforded data-driven prediction and identification of potential problems, and rational ways to avoid or overcome problems.	The material agency of the chatbot afforded a capability to effectively engage thousands of students, entangled with the human agency of the chatbot staff to develop, expand, and improve the knowledge base. Such entanglement provided a rational and practical way to engage thousands of students and keep them up to date.	The human agency of SSP leaders in deciding to adopt predictive analytics for monitoring student finances, entangled with the material agency of the financial predictive analytics system to analyze 10 years of financial data and develop the predictive model. Such entanglement afforded data-driven decision making to rationally avoid or overcome financial problems.

Perceiving the environment	The material agency of ALT to keep track of past activities, tasks, and performance of all students, and to present course materials accordingly tailored to each individual student, entangled with the human agency of the lab instructors to intervene and share knowledge with the students. Such entanglement facilitated perceiving the environment and taking appropriate action.	In developing GPS, the human agency to consolidate fragmented advising systems entangled with the material agency of GPS to analyze big data, identify early indicators, and develop a predictive model. The innovated GPS advising recursively afforded an unprecedented ability to monitor thousands of students and take necessary action, through the entanglement of the material agency of GPS system with the human agency of the advisers.	The material agency of the chatbot to comprehend the informational needs students had, entangled with the human agency to populate the knowledge base with the necessary information. Such entanglement afforded a capability to perceive the environment in a rational way and inform students about the environment.	In developing the financial predictive analytics system, the material agency of technology to analyze financial data entangled with the human agency to explore and explain the early indicators. The innovated financial predictive analytics system recursively afforded an unprecedented ability to monitor finances of thousands of students and provide financial counselling for the students when necessary.
Learning from experience	The material agency of ALT to learn from past activities, tasks, and performance of students, entangled with the human agency of course instructors to train and share knowledge with lab instructors periodically. Such entanglement facilitated learning from experience. GSU also learned from applying ALT in mathematics and used that knowledge to extend ALT to social sciences.	The material agency of GPS to improve the predictive model based on new sets of indicators that grew from only a few dozen to 800 today, entangled with the human agency of the advisers to learn from experience of their own and others through records and notes kept in complementary advising systems, and through knowledge sharing at weekly meetings and periodic training.	In developing the chatbot, the human agency to Identify the root cause of summer melt entangled with the material agency of the chatbot to disseminate necessary information to students. The innovated chatbot recursively afforded the capability to learn the semantic meaning of questions posed by students, and gradually expand and improve the knowledge base.	The material agency of the financial predictive analytics system to gradually improve the accuracy of the predictive model entangled with the human agency of the financial counsellors to learn from past counselling sessions with students. Such entanglement facilitated learning from the environment and taking appropriate action.

Accordingly, GSU demonstrated organizational intelligence in its digital innovation initiatives by making decisions rationally (Gottfredson 1997; Neisser et al. 1996), by perceiving the environment and taking appropriate action (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013), and by learning from experience (Gottfredson 1997; Neisser et al. 1996). In each of these foundational aspects of intelligence, both human agency and material agency played irreplaceable roles. We have empirically observed that while human and material agencies were both necessary for the organization to act intelligently, each agency was insufficient alone. In fact, it was the entanglement of human and material agencies in different figurations (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013) that enabled the organization to demonstrate organizational intelligence in achieving its goals.

Although the rational agent perspective in AI (Russell 2019; Russell and Norvig 2013) and the recent delegation perspective in IS research (Baird and Maruping 2021) discuss the increasingly influential role of material agency in enabling organizations to function intelligently, no study has conceptualized and empirically demonstrated how human and material agencies come together in forming organizational intelligence. Moreover, while the role of human and material agencies have been studied in different contexts, namely the constitution of sociotechnical practices (Jonsson et al. 2018; Latour 2005; Leonardi 2013); organizational collaboration through flexible technologies and flexible routines (Leonardi 2011); big data analytics technologies in service-dominant logic (Lehrer et al. 2018); and autonomous decision making by digital technologies (Adomavicius et al. 2009; Glezer 2003; Nunamaker et al. 2011), no studies have yet examined the role of human and material agencies in the context of digital innovation. Against that backdrop and as discussed above, we have contributed a conceptual framing and related empirical evidence into how human and material agencies come together to drive organizational intelligence in digital innovation. Next, we discuss the entanglement of human and material agencies in two types of figurations—analytical and relational intelligence.

7.1.2. The Entanglement of Analytical and Relational Intelligence

Another significant contribution to knowledge is our theoretical framing of how organizational intelligence manifests through the entanglement of analytical and relational intelligence figurations, together with our empirical analyses that demonstrate the detailed workings of this framing. While the extant literature discusses figurations—empirically observable traces of entangled human and material agency—in the constitution of sociotechnical practices (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013), we extend the concept of figuration to an organizational capability, namely intelligence. Moreover, while current research on organizational intelligence predominantly emphasizes analytic capabilities, this research puts equal emphasis on relational capabilities. The extant literature differentiates between two types of figurations: digital representation, in which technology is used to monitor and produce a particular work space (Jonsson et al. 2018; Ramaprasad and Rai 1996), and digital mediation, in which technology is used to share and enact a particular work arrangement (Jonsson et al. 2018; Persson et al. 2009). While digital representations focus on how technology is used to monitor and produce digital content (Jonsson et al. 2018; Ramaprasad and Rai 1996), digital mediations focus on how technology is used for digitally mediated cooperative work (Jonsson et al. 2018; Persson et al. 2009). Building on this distinction, we have theorized and empirically observed (1) analytical intelligence—a capability focused on creating and analyzing representations of the real world, (2) relational intelligence—a capability focused on enabling and facilitating mediations among organizational actors, and (3) organizational intelligence as the entanglement of analytical and relational intelligence. Moreover, we have theorized and empirically observed how, through such entanglement, organizational intelligence shapes and is shaped by digital innovations.

On one hand, to function intelligently, organizations need the capability to analyze critical business data to better understand its environments and make timely, appropriate business decisions (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017). In recent years, widespread digitalization provides access to enormous amounts of data about the inner and the outer contexts of organizations (Hilbert and López 2011), a phenomenon known as big data (Breur 2016). Characterized by volume, variety, and velocity, big data poses new challenges for organizations regarding data-driven decision making (Breur 2016). Since human agency is inadequate in analyzing big data, representation-dominant technologies, such as analytics and AI, are increasingly being used in rational decision making and in learning from experience. However, although material agency of these technologies can entirely replace the need for human agency in many routinized decisions (Wu et al. 2020), in areas involving creativity and insight, human agency is still irreplaceable (March and Simon 1958; McAfee and Brynjolfsson 2017). While representation-dominant technologies possess immense computing power to analyze enormous amounts of data very quickly (Park et al. 2017; Seddon et al. 2017), humans with their cross-domain explicit and tacit knowledge interpret, derive insights from, give meaning to, and learn from such analyses (Kulkarni et al. 2017; Seddon et al. 2017). As such, analytical intelligence manifests as figurations in which human agency comes together with material agency to analyze data in decision making. Conceptualizing organizations as information processing systems (Daft and Lengel 1986; Daft and Weick 1984; Galbraith 1973; Morgan 1986; Park et al. 2017; Thomas et al. 1993), we empirically observed how human and material agencies come together in analytical intelligence figurations in all four embedded cases (Table 11).

On the other hand, to function intelligently, organizations need the capability to facilitate collaboration to support organizational practices (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012). Organizational realities are constructed, co-created, and perceived through relational processes of sensemaking among many stakeholders (Dachler 1992; Maak and Pless 2006) with varied domain knowledge and intelligence. Such relational processes of collective minding enable organizations to understand more of the complexity in their environment and to respond accordingly (Weick and Roberts 1993). These relational processes require communication, collaboration, and coordination among stakeholders mediated by digital technologies. As modern organizations digitalize work, people increasingly access and share information with others using mediation-dominant technologies, such as digital communication and collaboration technologies (Jonsson et al. 2018). Mediation-dominant technologies enable communication, collaboration, and coordination among organizational actors across spatial, temporal, organizational, and contextual boundaries (Jonsson et al. 2018). While collective minding focuses on processing information by many individuals (Weick and Roberts 1993), due to the advent of digital technologies as rational agents, such technologies also become actors in the collective thinking and decision making. As such, relational intelligence manifests as figurations in which human agency and material agency come together to enable collaborative practices in organizations. These figurations influence the emergence of new structures and capabilities in organizations in response to the evolving nature of digital technologies (Baptista et al. 2020). We empirically observed how digitally mediated collaboration and coordination forms new figurations of human and material agency (Lehrer et al. 2018; Leonardi 2011), which were essential for organizational transformation (Leonardi and Bailey 2008; Baptista et al. 2020) in all four embedded cases (Table 11).

Together, the entanglement of analytical and relational intelligence affords organizations the capability to gather, process, and manipulate information and to communicate, share and make sense of the knowledge they create. As such, organizational intelligence materializes as entanglement of analytical intelligence and relational intelligence figurations that bear elements of both human and material agency (Leonardi 2011; Saldanha et al. 2017). Organizations apply analytical intelligence to create knowledge through analyses of data and apply relational intelligence to interpret the meaning of such analyses through social interactions. The entanglement of analytical and relational intelligence enables organizations to act in a rational, purposeful, and goal-directed manner, so that they can increase their adaptive potential in the environment in which they operate (Glynn 1996). We have theorized and empirically observed organizational intelligence as entangled figurations of analytical and relational intelligence in all four embedded cases (Table 11).

In this dissertation, we studied implications of organizational intelligence specifically in digital innovation initiatives in the broader context of focused organizational transformation. Organizational intelligence is applied in decision-making at all levels: operational, tactical, and strategic (Glynn 1996), within and beyond digital innovations. However, through digital innovations organizations solve traditional business problems by innovating products, services, processes, structures, and business models (Haffke et al. 2017), leading to organizational transformations (Li et al. 2018; Vial 2019; Westerman et al. 2011). Such innovation and consequent transformation require organizations to perceive their environment, identify and rationalize appropriate innovation options, and learn from experience while innovating. As such, organizations apply organizational intelligence in their digital innovation initiatives, and the digital innovations in turn improve organizational intelligence. We theorized and empirically observed how organizational intelligence shapes and is shaped by digital innovations in all four embedded cases (Table 11).

Table 11: Entanglement of Analytical and Relational Intelligence				
Aspects of Intelligence	**Case 1: Digital Innovation in Teaching**	**Case 2: Digital Innovation in Monitoring**	**Case 3: Digital Innovation in Engaging**	**Case 4: Digital Innovation in Financing**
Analytical Intelligence	Analysis of Banner data, along with experiments of the pedagogical researchers about ALT, made the digital innovation in teaching possible. The innovated ALT possessed the capability to analyze past activities, tasks, and performances of all students.	Analysis of RPG data, along with exploration of indicators by decision makers, made the digital innovation in monitoring possible. The innovated GPS possessed unprecedented capability of analyzing academic behavior of all undergraduate students daily.	Research on summer melt conducted by academic researchers, along with analyses of digital data from various sources, made the digital innovation in engaging possible. The innovated AI chatbot possessed the capability to analyze and learn from interactions with students.	Analysis of financial data, along with exploration of early indicators by decision makers, made the digital innovation in financing possible. The innovated predictive model possessed the capability of analyzing financial data of all undergraduate students daily.
Relational Intelligence	Collaboration among pedagogical researchers, publishers, and courseware developers, enabled by digital technologies, made the digital innovation in teaching possible. The innovated ALT facilitated knowledge sharing between lab instructors and students.	Collaboration between GSU and EAB, facilitated by GPS and other digital technologies, made the digital innovation in monitoring possible. The innovated GPS facilitated conversation and communication between academic advisers and students during advising sessions.	Collaboration among academic researchers, GSU, and Admit Hub, facilitated by digital technologies, made the digital innovation in engaging possible. The innovated AI chatbot facilitated communication with and knowledge dissemination to students.	Collaboration among GSU, SunTrust, and EAB, facilitated by the predictive analytics system and other digital technologies, made the digital innovation in financing possible. The innovated system facilitated conversation and communication between financial counsellors and students during interventions.
Organizational Intelligence	Organizational intelligence was	Organizational intelligence was	Organizational intelligence was	Organizational intelligence was

	demonstrated through the entanglement of analytical and relational intelligence in understanding the root causes of student failure, and in collaboratively developing ALT courseware.	demonstrated through the entanglement of analytical and relational intelligence in exploring and selecting indicators, and in collaboratively developing GPS.	demonstrated through the entanglement of analytical and relational intelligence in understanding the root causes of summer melt, and in collaboratively developing the AI chatbot.	demonstrated through the entanglement of analytical and relational intelligence in exploring and selecting early indicators, and in collaboratively developing the predictive model.

Although Wilensky (1967) first coined the term "organizational intelligence" a long time ago, and Glynn (1996) redefined and revised the concept, our understanding of organizational intelligence is incomplete at best. Glynn (1996) focused on only human intelligence in defining and conceptualizing organizational intelligence, although many of today's agentic digital technologies (Baird and Maruping 2021) display some form of intelligence (Russell 2019; Russell and Norvig 2013). Moreover, the scarce research on organizational intelligence focuses solely on information processing capability (Akgun et al. 2007; Glynn 1996; Huber 1990; Porter 1980; Sammon et al. 1984) and discards the relational social processes involved in functioning intelligently. Against that backdrop and as discussed above, we have contributed a conceptual framing and related empirical evidence into how organizational intelligence is constituted through the entanglement of analytical intelligence and relational intelligence figurations of human and material agency. Furthermore, we have theorized and empirically observed how organizational intelligence is implicated in digital innovation initiatives in the broader context of focused organizational transformation. Although digital innovations have been studied as product innovation (Fichman et al. 2014; Lyytinen et al. 2016; McKenna 1985; Vargo and Lusch 2004), service innovation (Lusch and Nambisan 2015; Vargo and Lusch 2004; Ye and Kankanhalli 2018), process innovation (Davenport 1993; Fichman et al. 2014; Flynn et al. 1999;

Markus 2010; Pisano 1997; Swanson 1994), and business model innovation (Fichman et al. 2014; Svahn et al. 2017; Teece 2010), we know little about how digital innovations are rationalized, realized, and managed. Our theoretical framing and empirical analysis enrich knowledge about how organizational intelligence is applied in rationalizing, realizing, and managing digital innovations, and how the innovations recursively build on and improve organizational intelligence.

7.1.3. The Contextualist Nature of Organizational Intelligence

Pettigrew (1985, 1987, 1990) proposed contextualist inquiry as a theory of method to study organizational change through the interactions among the context, the content, and the process of change. Organizational intelligence in digital innovation is in this sense contextualist in nature, since organizational intelligence shapes and is shaped by digital innovations and since digital innovations bring change to organizations through interactions between context, content, and process. As such, we adapted contextualist inquiry to understand the challenges and opportunities involved in the complex organizational transformations (Pettigrew 1985, 1987, 1990; Van de Ven and Poole 2005) in which digital innovations are embedded. This adaptation of contextualist inquiry as a theoretical frame to study organizational intelligence in digital innovations in the broader context of focused organizational transformations, has been empirically validated. Through our process model (Figure 1), adapted from contextualist inquiry, we empirically observed how analytical intelligence and relational intelligence come together to form organizational intelligence in understanding the context, in innovating the content, and in evaluating the outcome of digital innovation initiatives (Table 12).

An important aspect of organizational intelligence is the ability to perceive the environment (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013).

In contextualist inquiry, the context of change refers to the environment in which organizations and stakeholders operate (Pettigrew 1985, 1987, 1990). As such, an organization demonstrates intelligence through understanding the context of its digital innovation initiatives. On the one hand, organizations need to comprehend the opportunities and constraints in the outer context constituted of social, competitive, economic, and political factors (Jemison 1981; King 1990; Pettigrew 1985, 1987, 1990; Wejnert 2002). On the other hand, organizations need to appreciate the structural, cultural, and political factors in the inner context to capitalize on the opportunities and overcome the constraints (Jemison 1981; King 1990; Pettigrew 1985, 1987, 1990; Wejnert 2002). With an understanding of both outer and inner contexts, organizations engage in digital innovations to match solutions to problems (von Hippel and von Krogh 2016). We have empirically observed how the economic, demographic, and social factors in Georgia influenced the specific challenges GSU faced. Because of factors in its outer context, the majority of GSU students is first generation college students, from low-income families, and from underrepresented demographics. As such, the specific challenges GSU faces in teaching, monitoring, engaging, and financing students, along with the underlying causes of such challenges, are very different from many other higher education institutions situated in different contexts. At the same time, the structural, cultural, and political factors in the inner context at GSU determined what changes were necessary and feasible (Armenakis and Bedeian 1999). Hence, an understanding of the factors in the inner context was critical in successfully rationalizing and realizing the observed digital innovations (Camison-Zornoza et al. 2007).

With an understanding of the context, GSU decided to appropriate various digital innovations (Table 12). Responding to the environment appropriately is an aspect of intelligence (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013), and GSU demonstrated organizational intelligence through such decisions. First, an understanding of the pedagogical context revealed that many students were failing and dropping out in some introductory courses. GSU decided to innovate the way students were taught in these courses with ALT. Second, exploration of the context revealed that many students were dropping out due to the lack of timely advising. Hence, GSU decided to proactively advise students using predictive analytics and thus developed GPS advising. Third, many students at GSU became victims of summer melt. GSU identified the root cause of summer melt to be the absence of a reliable source of information for students about the administrative processes. Consequently, GSU created an AI chatbot to disseminate necessary information to students when they need it. Finally, many students were dropping out because of financial problems. Hence, GSU decided to provide timely financial counselling for students using predictive analytics.

GSU also selected the appropriate metrics and periodically evaluated the outcome of the digital innovations to assess whether they were effective in achieving organizational goals (Table 12). Through these evaluations GSU monitored progress towards and revised its actions in achieving its goals. Since successfully achieving pre-defined goals is an aspect of intelligence (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013), GSU demonstrated organizational intelligence through these evaluations. Such periodical evaluations also facilitated learning from experience, which is another important aspect of organizational intelligence (Neisser et al. 1996). Based on the evaluation of the outcome, GSU recursively engaged in efforts to understand the context, and innovate the content.

Table 12: Adaptation of Contextualist Inquiry in Digital Innovation

Model of Digital Innovation	Case 1: Digital Innovation in Teaching	Case 2: Digital Innovation in Monitoring	Case 3: Digital Innovation in Engaging	Case 4: Digital Innovation in Financing

Understanding the context	GSU developed an understanding of the pedagogical context and identified problematic courses by analyzing Banner data in collaboration with pedagogical researchers.	GSU developed an understanding of the academic context by exploring problematic aspects in current practices through analyzing RPG data, in collaboration with academic and administrative stakeholders.	GSU developed an understanding of the administrative context and identified the underlying causes of summer melt, in collaboration with academic researchers, by analyzing data in different information systems.	GSU developed an understanding of the financial context collaboratively by analyzing financial data from office of student accounts, academic data from Banner, and RPG, and demographic data from internal and external sources.
Innovating the content	For the identified problematic courses, GSU experimented with different modes of ALT, in collaboration with pedagogical researchers, and selected the most effective mode by analyzing Banner data.	GSU decided to monitor and proactively advise students, and innovated GPS advising, in collaboration with EAB, by identifying statistically significant indictors through analyses of data in RPG, IPORT, and Banner.	GSU decided to engage and inform students, and developed an AI chatbot, in collaboration with Admit Hub, by gradually enriching the knowledge base of the chatbot while the AI kept learning the meaning of student questions and their appropriate answers.	GSU created proactive financial counselling based on predictive analytics collaboratively by analyzing financial records in student accounts, academic data in Banner, and RPG, and demographic data from internal and external sources.
Evaluating the outcome	To continually assess the efficacy of ALT, GSU selected and monitored the DFW rates, by analyzing Banner data, and by interpreting and explaining the DFW rates in collaboration with pedagogical researchers.	GSU periodically assessed the performance of GPS advising collaboratively, by selecting, monitoring, and explaining different metrics in GPS and other information systems.	To assess the efficacy of the AI chatbot, GSU selected and monitored appropriate metrics collaboratively, by analyzing data in various information systems.	GSU periodically assessed the performance of the financial predictive analytics system collaboratively by selecting, monitoring, and explaining different metrics from various information systems.

Overall, the digital innovations at GSU took place within a context of an ongoing, focused organizational transformation with characteristics as summarized in Table 13 and elaborated in the following. In 2011, leadership at GSU shared a vision and provided a clear direction through the five-year strategic plan. Although some digital innovation initiatives started before 2011, the strategic plan initiated an organization-wide concerted and heedful effort towards improving student success. Although GSU historically had been an institution with very high research activity, the strategic plan extended its focus from advancing research to improving graduation rates. Moreover, the strategic plan acknowledged the fact that the majority of GSU students is first generation college students, from low-income families, and from underrepresented demographics and that ensuring success of such students would require unprecedented innovations across the organization. As such, the strategic plan worked as an impetus for the digital innovation initiatives at GSU.

To manage the innovation initiatives, GSU consolidated resources and authority into one organizational structure, the Student Success Program. Through the establishment of the Student Success Program, GSU made a conscious decision to transform itself through digital innovations. The Student Success Program experimented with the innovation initiatives, expanded their scope, and improved their efficacy, and led the way from the top by rationalizing, initiating, and implementing each digital innovation. As such, by centralizing authority of decision making about the innovation initiatives through the Student Success Program, GSU ensured proper management of these initiatives, and reduced the time and cost in decision making. GSU demonstrated and further advanced organizational intelligence through such restructuring since it supported innovation and maximized the chance of successfully achieving pre-defined goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013).

Throughout GSU's organizational transformation, decisions were rationalized based on evidence of underlying problems rather than speculative adoption of sophisticated technologies. GSU sensed the unique economic and demographic problems in its outer context and interpreted them as opportunities to innovate its value propositions, structures, processes, and systems. Moreover, GSU had to appreciate its existing structural, processual, and cultural arrangements in its inner context to ascertain and realize possible solutions. Thus, GSU's transformation was driven by continuously analyzing data about the existing problems and about the impact of the solutions. As such, GSU demonstrated and further advanced organizational intelligence since such data-driven decision making exhibits a capability to comprehend the environment (Gottfredson 1997) and to effectively adapt to the environment (Neisser et al. 1996).

GSU's transformation, under the central leadership of the Student Success Program, was supported by a culture of collaborative and participatory innovation and learning. Although the Student Success Program held the authority to evaluate, decide on, initiate, and orchestrate innovation options, ideas emerged from different levels of diverse functional units across GSU. Management innovation forums facilitated such an organic incubation of innovation, where attendees discussed the current status, future trends, and potential innovation opportunities. Representatives from different functional units attended the forums to learn about the ongoing development of the student success program and contribute their expert opinions on future innovation initiatives. As such, GSU demonstrated and further improved organizational intelligence through such discourse, since weighing alternative options by engaging in reasoning from different perspectives displays intelligence (Neisser et al. 1996).

GSU's digital innovation initiatives led to strategic decisions on whether to develop its digital solutions in house. Rather than developing digital solutions by itself, GSU outsourced most of them, creating close collaborations between technology developers and internal experts at GSU. External technological expertise provided GSU access to a wider range of options for digital innovation and an unrestricted focus on its principal function of delivering value based on these innovations to improve student success. Such partnerships also reduced the time and cost in developing new technologies. This focus on building external partnerships for developing technological solutions has helped GSU continually create and share knowledge and resources with EAB, Admit Hub, and other technology vendors, while at the same time growing its own dedicated expertise in digital innovation for improved student success. GSU demonstrated and developed organizational intelligence through its strategic decisions to outsource digital technologies, since this strategy maximized the chance of successfully achieving pre-defined goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013).

In its organizational transformation, GSU also developed its own capabilities, not only through the digital technologies themselves, such as ALT, GPS, AI chatbot, and the financial predictive analytics system, but also by redesigning organizational structures and processes, and by retraining the people involved. Realization of digital innovations necessitated novel structural and processual configurations and development of capabilities that transcended traditional functional boundaries (Agarwal and Sambamurthy 2002). We empirically observed how GSU created and benefitted from new organizational structures, such as the Student Success Program to oversee all innovation initiatives, MILE labs to teach mathematics courses using ALT, UAC to monitor and advise students based on GPS predictions, chatbot team to continually expand the knowledge base of the chatbot, and SFMC to monitor and counsel students on financial issues. To reap the benefits of digital innovations, GSU also changed existing processes and introduced new ones, such as teaching using ALT, academic advising process using GPS predictions, expanding the knowledge base of and disseminating new information using the chatbot, and financial counselling process. GSU also improved the knowledge of the people involved in the innovation initiatives through training the ALT instructors, the academic advisers, the chatbot staff, and the financial counsellors. Since one of the critical barriers to change is the inertia and unsuitability of current organizational structures and processes to execute new strategies (Porter and Heppelmann 2015), GSU demonstrated and further advanced organizational intelligence through revising structures and processes and developing capabilities.

GSU's transformation was driven by a culture of innovation, in which GSU proactively shifted strategic focus from conventional informational activities to novel innovational efforts. As an example of its commitment to innovation, GSU changed the title of the "Chief Information Officer" to "Chief Innovation Officer (CIO)." It was not merely a change in the job title, but also a recasting of the role of the CIO to be more strategic in transforming the organization. For the reimagined CIO position, GSU hired a person whose experience and expertise were more focused on innovation than technology and who had two decades of industry experience in developing technological products and services, in organizational development, and in starting up new technological businesses. GSU's strategic shift to innovation demonstrated and supported development of organizational intelligence, since it maximized the chance of successfully achieving pre-defined goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013).

Finally, an important ingredient in GSU's transformation was its efforts to exchange knowledge with and to learn from other higher education institutions interested in improving student success. GSU annually published its Complete College Georgia report alike other institutions in Georgia. These reports highlight the rationalization, initiation, and progression of the innovation initiatives in institutions across Georgia. These institutions also shared knowledge about improving academic advising through an organization named Enhanced Advising Processes. GSU also entered the University Innovation Alliance (UIA) as a member institution, and engaged in collaboration and knowledge sharing with UIA's eleven members about their innovation initiatives to improve student success. Through such knowledge-sharing efforts GSU demonstrated and further developed organizational intelligence since these efforts display learning from the environment (Neisser et al. 1996) and from experience (Gottfredson 1997).

Table 13: Organizational Intelligence in the Context of the Broader Transformation

Characteristics of Transformation Context	Evidence of Organizational Intelligence
Restructuring to Support Innovation	GSU demonstrated organizational intelligence by gradually and incrementally consolidating resources and authority into the organizational structure named Student Success Program to better manage all digital innovation initiatives.
Data-Driven Innovation	GSU demonstrated organizational intelligence by rationalizing, realizing, and managing digital innovation initiatives based on analysis of data.
Management Innovation Forum	GSU demonstrated organizational intelligence by making decisions about the digital innovation initiatives through discussions and debates among key stakeholders with diverse perspectives, who contributed their unique knowledge and expertise.
External Innovation Partnerships	GSU demonstrated organizational intelligence by developing digital technologies through external innovation partners, which provided GSU access to their technological expertise, a wider range of options for digital innovation, and an unrestricted focus on its principal function of delivering value based on these innovations to improve student success.
Innovation Capability Building	GSU demonstrated organizational intelligence by establishing organizational structures, such as SSP, MILE labs, UAC, chatbot team, and SFMC, and by recruiting and training people for proper functioning of these structures.
Chief Innovation Officer	GSU demonstrated organizational intelligence by nurturing a culture of innovation and by shifting focus from purely informational activities to innovational efforts.
External Knowledge Sharing	GSU demonstrated organizational intelligence by sharing knowledge with and learning from other higher education institutions, Complete College Georgia, Enhanced Advising Processes, University Innovation Alliance, and other organizations.

7.2. Implications for Theory

From a theoretical perspective, this dissertation (1) contributes a revised conceptualization of organizational intelligence as the entanglement of analytical intelligence and relational intelligence figurations of human and material agency, (2) reveals the contextualist nature of organizational intelligence in digital innovation, (3) theorizes how organizations apply organizational intelligence in rationalizing, realizing, and managing digital innovations, and (4) explains how the digital innovations recursively build on and improve organizational intelligence.

First, this dissertation contributes to both the digital innovation literature and the organizational intelligence literature. While the digital innovation literature focuses on product innovation (Fichman et al. 2014; Lyytinen et al. 2016; McKenna 1985; Vargo and Lusch 2004), service innovation (Lusch and Nambisan 2015; Vargo and Lusch 2004; Ye and Kankanhalli 2018), process innovation (Davenport 1993; Fichman et al. 2014; Flynn et al. 1999; Markus 2010; Pisano 1997; Swanson 1994), and business model innovation (Fichman et al. 2014; Svahn et al. 2017; Teece 2010), there is a lack of theory about how such digital innovations are rationalized, realized, and managed. Our process theory and conceptual model explains how organizational intelligence, as a capability, is applied in rationalizing, realizing, and managing digital innovations, and how the innovations recursively build on and improve organizational intelligence. Since the inception of the term "organizational intelligence" (Wilensky 1967), research on this concept has been scarce and focused only on human agency (Akgun et al. 2007; Glynn 1996) disregarding material agency. However, with the advent of agentic digital technologies (Baird and Maruping 2021) that display some form of intelligence (Russell 2019; Russell and Norvig 2013), material agency has become an integral part of organizational intelligence. As such, this dissertation redefines organizational intelligence in terms of entanglement of analytical intelligence and relational intelligence figurations of human and material agency and presents organizational intelligence as the capability that shapes and is shaped by digital innovations.

Second, our conceptualization of organizational intelligence not only appreciates the different roles of human agency and material agency (Lehrer et al. 2018; Leonardi 2011), but also posits how they come together, as common building blocks, in the constitution of figurations (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013) that enable organizations to act intelligently. While figurations have been studied in the constitution of organizational practices (Jonsson et al. 2018; Leonardi 2011), they have not been studied in the constitution of organizational capabilities. Such figurations of human and material agency shift the focus from the predominant role of human agency in organizational practices (Akgun et al. 2007; Glynn 1996; Huber 1990; Porter 1980; Sammon et al. 1984) to the important role of material agency in constituting organizational intelligence (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013). While both human and material agency is necessary for organizations to act intelligently, each one alone is insufficient. Our conceptualization of organizational intelligence as entanglement of human and material agency brings us closer to the root of the IS discipline—the sociotechnical perspective (Sarker et al. 2019), which has historically been the axis of cohesion for the IS discipline (Avgerou et al. 2004; Bostrom et al. 2009; Chiasson and Davidson 2005; Lee 2004; Sarker et al. 2019; Sawyer and Jarrahi 2014).

Third, our theoretical framing of how organizational intelligence manifests through the entanglement of analytical intelligence and relational intelligence figurations, improves extant conceptualizations of organizational intelligence (Akgun et al. 2007; Glynn 1996; Huber 1990;

Porter 1980; Sammon et al. 1984; Wilensky 1967). The scarce research on organizational intelligence focuses solely on information processing capability (Akgun et al. 2007; Glynn 1996; Huber 1990; Porter 1980; Sammon et al. 1984) and discards the relational social processes required for organizations to function intelligently. Application of digital technologies in networking and collaboration has made relational intelligence an indispensable part of organizational practices (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012). While analytical intelligence enables organizations to analyze critical business data to better understand its environments and make timely, appropriate business decisions (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017), relational intelligence enables organizations to collaboratively make sense of and learn from the environment (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012). With such a conceptualization of organizational intelligence we theorize how organizations rationalize, realize, and manage their digital innovations, and how the innovations recursively build on and improve organizational intelligence.

Finally, we theorize that organizational intelligence in digital innovation is contextualist in nature (Pettigrew 1985, 1987, 1990), such that analytical intelligence and relational intelligence come together to form organizational intelligence in understanding the context, in innovating the content, and in evaluating the outcome of digital innovation initiatives. Organizations demonstrate intelligence by comprehending the opportunities and constraints in the outer context (Jemison 1981; King 1990; Pettigrew 1985, 1987, 1990; Wejnert 2002), and by appreciating the structural, cultural, and political factors in the inner context to capitalize on the opportunities and overcome the constraints (Jemison 1981; King 1990; Pettigrew 1985, 1987, 1990; Wejnert 2002). With an understanding of the context, organizations demonstrate intelligence by responding to the context appropriately (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013), through decisions to undertake digital innovation initiatives. Organizations also demonstrate intelligence in assessing whether initiatives are effective in achieving organizational goals, by selecting the appropriate metrics and periodically evaluating the outcome of the digital innovations (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013). Moreover, organizations demonstrate intelligence by maneuvering their digital innovation efforts within the broader context of ongoing organizational transformations.

7.3. Implications for Practice

From a practical perspective, this dissertation provides guidance on how to improve organizational intelligence. Organizations looking to improve their organizational intelligence should focus not only on data analysis but also on relational social processes that facilitate communication and collaboration among organizational actors. Organizational realities should be constructed, co-created, and perceived through such relational processes of sensemaking among many stakeholders (Dachler 1992; Maak and Pless 2006) entangled with intrinsically related analytical intelligence processes. Moreover, to improve organizational intelligence, organizations should strive to combine human and material agency in both analytical intelligence and relational intelligence figurations, so that they complement each other in achieving organizational objectives.

This dissertation also provides practitioners with a framework about how to apply organizational intelligence in rationalizing, realizing, and managing digital innovation initiatives in the broader context of organizational transformation. In rationalizing digital innovations, organizations should try to understand the specific outer and inner contexts they operate in (Pettigrew 1985, 1987, 1990). In efforts to develop such an understanding, organizations should apply and develop their intelligence through combinations of human and material agency in both analyzing the data about the context and in collaboratively exploring and explaining the context. Through such heedful collaborative sensemaking (Weick 1993), organizations can comprehend the opportunities and challenges in the outer context, and appreciate the structural, cultural, managerial, and political factors in the inner context (Pettigrew 1985, 1987, 1990). With an understanding of both outer and inner contexts, organizations can rationalize specific digital innovations by matching the opportunities and challenges with appropriate digital technologies (von Hippel and von Krogh 2016).

After identifying opportunities for specific digital innovations, organizations iteratively innovate the content. In realizing digital innovations, organizations apply combinations of human and material agency in both analytical and relational intelligence. Strategic decisions, such as whether to develop the technology in-house, are made after careful consideration. However, realizing digital innovation is far more extensive than developing the digital technology, since digital innovations transform sociotechnical structures (Yoo et al. 2010b) through reconfiguration of the arrangements of production and consumption of products and services (Eaton 2012). Organizations therefore should consider the changes in products, services, processes, and business models transformed by digital innovations (Kohli and Melville 2019; Nambisan et al. 2017; Svahn and Henfridsson 2012; Yoo 2010; Yoo et al. 2012; Yoo et al. 2010a) and effectuate structural, cultural, and managerial changes to facilitate these transformations. In such mindful efforts (Weick 1993), organizations apply and further develop their organizational intelligence.

Organizations should also periodically evaluate the outcome of the digital innovations to assess whether they are effective in achieving organizational objectives. Such efforts require application of organizational intelligence in selecting the appropriate metrics and conducting correct measurements. Again, combinations of human and material agency in both analytical and relational intelligence are essential in evaluating the outcome of digital innovations. Such periodic evaluations can help organizations to successfully achieve pre-defined goals (Legg and Hutter 2007; Nilsson and Nilsson 1998; Poole et al. 1998; Russell and Norvig 2013) and learn from experience (Neisser et al. 1996). Based on such evaluations, organizations can reexplore their context and readjust their innovation efforts.

7.4. Limitations and Future Research

This dissertation has some limitations that readers should be aware of, and future researchers should try to overcome. We conducted a qualitative case study to ground the development of a theory (Van de Ven 2007), and we substantiated our theoretical claims through empirical analysis of four embedded cases within a single case. While our qualitative process study of a single case allowed us to focus intensively and illustrate a holistic and real-world perspective on organizational intelligence, our findings are generalizable only to theoretical propositions and not to populations or universes (Yin 2009). Our case study does not represent a "sample," and our goal was to expand and generalize theories—analytic generalizations—and not to extrapolate probabilities—statistical generalizations (Lee and Baskerville 2003; Lipset et al. 1956; Yin 2009). Although research based on single case studies within a specific context may limit the ability to conduct comparisons or generalize findings to other contexts (Miles et al. 2014), the single-case study can be advantageous for its attention to context, dynamics, and multiple stakeholder perspectives (Mason 2002). Consequently, this dissertation provides a rich description of implication of organizational intelligence in the digital innovation initiatives at GSU, in the broader context of GSU's organizational transformation, that can help other researchers assess the findings and apply them in other contexts (Lincoln and Guba 1985). We made theoretical claims for the wider resonance or generalizability of our explanations which are based on the rigor of our analysis (Mason 2002). As such, although this dissertation is limited to the GSU context, there remains a possibility of generalization from description to theory (Lee and Baskerville 2003; Yin 2013). Accordingly, the theoretical generalization through our collaboration with GSU provides insight into similar research contexts where organizational intelligence shapes and is shaped by digital innovation initiatives. Hence, we encourage future research to critically examine our understanding of organizational intelligence in digital innovations and mindfully apply and further develop it in different organizational settings.

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APPENDIX A: INTERVIEW PROTOCOL

Informed Consent: Share, discuss, and explain the Informed Consent Form with the interviewee and obtain their signed consent. Ask for permission to digitally record the interview.

Objective and Scope: Discuss the objective and scope of the study. Define digital innovation, organizational intelligence, analytical intelligence, and relational intelligence. Explain our perspective of organizational intelligence as an entanglement of analytical and relational intelligence, in which human and material agencies come together. Based on the definitions and explanations, mention and discuss the overarching research question: How is organizational intelligence implicated in digital innovation initiatives in the context of focused organizational transformation?

Interviewee Background: Share with and display to the interviewee the timeline in Figure 2: GSU's Digital Innovation Initiatives (1999-2020). Ask the interviewee about when they joined GSU, and their professional experience and academic background before joining GSU. Ask the interviewee to share their career progression at GSU chronologically. Find out in which of the digital innovation initiatives in Figure 2 the interviewee participated in or contributed to.

Specific Questions: Based on the interviewee's involvement in different innovation initiatives at GSU ask the following questions –

- In what capacity did the interviewee participate in the innovation initiatives? What roles did they play? How did they contribute to the innovation initiatives?
- How did those innovation initiatives progress through time? How were they initiated, rationalized, implemented, realized, and managed?
- What was the decision-making process in those innovation initiatives? Who were the decision makers and how did they make decisions? What was the role of the interviewee in decision-making?
- What was the role of data analytics in those innovation initiatives? Specifically, what were the roles of humans and technologies in data analytics?
- What was the role of collaboration in those innovation initiatives? Specifically, what were the roles of humans and technologies in collaboration?

- How was the impact of the innovation initiatives measured? What metrics were used and how were these metrics justified and monitored?
- Who designed and developed the digital technologies involved in the innovation initiatives? Were the digital technologies insourced or outsourced? How and why were the decisions made about insourcing or outsourcing digital technologies?
- How did GSU collaborate with technology partners? What was the nature of such collaborations? What was the interviewee's role in these collaborations?
- What were some challenges or obstacles to the innovation initiatives? How were the challenges addressed and the obstacles overcome? Did GSU learn something new in overcoming the obstacles?
- How was the progress of the innovation initiatives monitored? Was there learning involved in the progression of the innovation initiatives? How did GSU keep track of the knowledge learned in these innovation initiatives?

Closing Remarks: Request the interviewee to share any documents pertaining to the innovation initiatives in which they were involved. Thank the interviewee and close the interview.

APPENDIX B: LIST OF DOCUMENTS

1 2013 Complete College Georgia Status Report: Georgia State University
2 2014 Complete College Georgia Status Report: Georgia State University
3 2015 Complete College Georgia Status Report: Georgia State University
4 2016 Complete College Georgia Status Report: Georgia State University
5 2017 Complete College Georgia Status Report: Georgia State University
6 2018 Complete College Georgia Status Report: Georgia State University
7 Association Governing Boards 2019
8 Building University Infrastructure: Student Advisement
9 Castleman, B.L. and Page, L.C. 2014. "A Trickle or a Torrent? Understanding the Extent of Summer "Melt" among College-Intending High School Graduates," *Social Science Quarterly* (95:1), pp. 202-220.
10 Data and Analytics for Student Success 2017
11 Georgia State University College Completion Plan 2012
12 GSU Strategic Plan 2011-2016/21
13 Gumbel, A. 2020. *Won't Lose This Dream: How an Upstart Urban University Rewrote the Rules of a Broken System*, The New Press.
14 Horwich, L. 2015. "Report on the Federal Pell Grant Program," NASFAA.
15 Indicators of Higher Education Equity 2015
16 Page, L.C. and Gehlbach, H., 2017. "How an Artificially Intelligent Virtual Assistant Helps Students Navigate the Road to College," *SSRN Electronic Journal* (3:4), pp. 1-12.
17 Page, L.C., Lee, J. and Gehlbach, H. 2020. "Conditions Under Which College Students Can Be Responsive to Nudging," EdWorkingPapers.Com.
18 Renick, T.M. 2020. Predictive Analytics, Academic Advising, Early Alerts, and Student Success. In *Big Data on Campus: Data Analytics and Decision Making in Higher Education*, p.177.
19 Stewart, D.L. 2020. "Twisted at the Roots: The Intransigence of Inequality in US Higher Education," *Change: The Magazine of Higher Learning* (52:2), pp. 13-16.
20 SunTrust Student Financial Management Center Year Two Report
21 Task Force on Enhanced Advising Processes: Assessment of Institutional Efforts
22 Timeline of Student Success Initiatives at Georgia State University
23 University Advisement Center Manual
24 University Advisement Center, Adviser Toolkit

APPENDIX C: DEFINITION OF KEY CONCEPTS

Definition of Key Concepts	
Concept	**Definition**
Digital Technology	Combinations of information, communication, computing, and connectivity that makes products and services reprogrammable, addressable, sensible, communicable, memorable, traceable, and associable (Bharadwaj et al. 2013; Yoo 2010; Yoo et al. 2010a).
Digital Innovation	Introduction and application of novel solutions, enabled by digital technologies, that lead to the transformation of sociotechnical structures that were previously mediated by nondigital artifacts or relationships (Yoo et al. 2010a).
Human Agency	Humans' capacity to form and realize their goals (Lehrer et al. 2018; Leonardi 2011).
Material Agency	The capacity possessed by digital technologies to act on their own apart from human intervention (Lehrer et al. 2018; Leonardi 2011).
Figuration	An empirically observable trace of how human and material agency, as common building blocks, come together in the constitution of a work practice (Jonsson et al. 2018; Latour 2005; Leonardi 2011; Leonardi 2013).
Digital Representation	A figuration in which digital technology is used to monitor and produce a particular work space (Jonsson et al. 2018; Ramaprasad and Rai 1996).
Digital Mediation	A figuration in which digital technology is used to share and enact a particular work arrangement (Jonsson et al. 2018; Persson et al. 2009).
Representation-dominant Technology	A digital technology that predominantly supports digital representation.
Mediation-dominant Technology	A digital technology that predominantly supports digital mediation.
Intelligence	A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience (Gottfredson 1997).
Rational Agent	Any entity, natural or artificial, that demonstrates intelligence by acting in an environment in a way that is appropriate for its circumstances and goals, being flexible to changing environments

	and changing goals, learning from experience, and making appropriate choices (Poole and Mackworth 2010; Russell 2019; Russell and Norvig 2013).
Analytical Intelligence	The capability of an organization to apply digital technologies to analyze critical business data (Chen et al. 2012; Jonsson et al. 2018; Saldanha et al. 2017).
Relational Intelligence	The capability of an organization to apply digital technologies to communicate, collaborate, and coordinate (Jonsson et al. 2018; Saldanha et al. 2017; Zablah et al. 2012).
Organizational Intelligence	An organization's capability to process, interpret, encode, manipulate, and access information in a purposeful, goal-directed manner (Glynn 1996).