Organizational Adoption of AI:

Risk Management and Decision Making under Conditions of Uncertainty and Information Asymmetry

Inaugural dissertation
submitted to attain the academic degree
doctor rerum politicarum
(Doktor der Wirtschaftswissenschaften)
at the

ESCP Europe Business School Berlin
by
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Berlin
2024

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Day of disputation: October 16th, 2024

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AI	Artificial Intelligence
AD	Alternative Data
B2B	Business-to-business
B2C	Business-to-customer
BDA	Big Data Analytics
BM	Business Model
BMI	Business Model Innovation
BMT	Business Model Theory
CE	Circular Economy
DAO	Decentralized Autonomous Organizations
DT	Design Thinking
Fintech	Financial Technology
IAT	Information Asymmetry Theory
IoT	Internet of Things
ML	Machine Learning
NLP	Natural Language Processing
SDG	Sustainable Development Goals

All false art, all vain wisdom, lasts its time but finally destroys itself, and its highest culture is also the epoch of its decay.

Experience without theory is blind, but theory without experience is mere intellectual play.

Immanuel Kant

1. Introduction

The development of Artificial Intelligence (AI) has achieved remarkable results over the previous decade, bearing important implications for organizations, individuals and society (Russell and Norvig, 2021; Brynjolfsson and McAfee 2017). AI has the potential to substantially support and enhance *decision making* processes that are often plagued by *uncertainty* and insufficient information (Murphy, 2022). AI can significantly expand the data basis on which decisions are being made, helping to *manage risk* and reduce *information asymmetry* (Thakor 2020; Berg, Fuster, and Puri 2022). AI is already employed by a multitude of different organizations today, helping them to optimize their *productivity* and *efficiency* (Berg et al. 2020; Djeundje et al. 2021). This helps them to gain or maintain a *competitive advantage*, supporting the profitability and survival of organizations. Therefore, this dissertation aims to gain a deeper understanding on the organizational adoption of AI and its impact on decision making under conditions of uncertainty and information asymmetry.

On Defining AI

The evolution and conceptualization of AI represent one of the most significant advancements in modern information technology (Brynjolfsson and McAfee 2017; Acemoglu et al. 2022; Kemp 2023), but what does *Artificial Intelligence* actually mean? AI, as a discipline, combines the knowledge, methods, processes and mechanisms of various fields, intersecting with aspects of computer science, linguistics, psychology, and data analysis (Russell and Norvig, 2021). This multidisciplinary approach enables

AI to continue to evolve, integrating complex functionalities that mimic human cognitive abilities. AI's significant breakthroughs in recent years demand a precise yet adaptable definition that can serve as a foundational framework for ongoing research and application.

The term *Artificial Intelligence* serves as a rather broad umbrella term that different scholars use to subsume different ideas and concepts that are often related to intelligent and self-learning computer systems. Through a carefully selected exploration of fundamental and influential definitions from leading scholars in the field, this dissertation aims to delineate the scope and implications of AI, particularly the adoption of AI within an organizational setting. The following definitions, provided by the leading scholars Stuart Russell and Peter Norvig (2021), Tom Mitchell (1997), and Erik Brynjolfsson and Andrew McAfee (2017) offer a comprehensive understanding of AI's core dimensions and its potential.

Russell and Norvig (2021) understand AI as an *intelligent agent* that receives percepts from the environment and performs actions. AI is not limited in its potential to understand, categorize and systemize vast amounts of data but to *build* intelligent entities. This requires at least basic proficiencies in (1) *natural language processing*, to allow for a language-based information exchange with a human being; (2) *knowledge representation*, to be able to collect, synthesize and systematically categorize information; (3) *automated reasoning*, to actually make use of vast amounts of often unstructured data; and (4) *machine learning*, to recognize patterns and adapt to new circumstances.

Mitchell (1997) gives the following definition of machine learning (ML): “A computer program is said to learn from experience E with respect to some class of tasks T, and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.”

Brynjolfsson and McAfee (2017) define AI as a suite of technologies capable of executing tasks that typically necessitate human intelligence, while ML is defined as a machine's ability to enhance its performance autonomously, without human guidance on completing every assigned task.

By reflecting upon these three definitions, we can observe different AI conceptualizations from specific algorithmic learning to broader cognitive capabilities. Russell and Norvig (2021) focus on the operational aspect of AI as agents interacting with their environment through sophisticated data processing and decision-making frameworks. Mitchell (1997) narrows down on the learning aspect, defining AI in terms of measurable improvements in performance based on experience. Brynjolfsson and McAfee (2017) view AI through the lens of utility and versatility, highlighting its capacity to autonomously handle tasks traditionally requiring human intellect. The convergence in these definitions lies in the recognition of AI's capability to perform and improve upon tasks traditionally requiring human intelligence, whether through *learned experience* or through *engineered intelligent behaviors*. The divergence, however, stems from the emphasis each definition places on different aspects of AI: the creation of intelligent agents, the process of learning from experience, and the economic and practical implications of AI technologies. This dissertation focuses on the practical implications of AI adoption, particularly within an organizational setting and its consequences for risk management and decision making under uncertainty.

Deep Learning and Neural Networks

Deep learning refers to a domain of ML that is based on neural networks, which are nonlinear functions with many layers of processing (Murphy, 2022). Deep learning algorithms attempt to draw similar conclusions as humans would by continually analyzing data with a given logical structure. They are used for a variety of tasks including image and speech recognition or natural language processing (NLP). The 'depth' in deep learning refers to the number of layers through which the data is transformed. More layers allow for more complex features to be extracted and used for prediction or classification (Russell and Norvig, 2021).

A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates (Murphy, 2022). The goal thereby is not to actually replicate biological brains, but merely the necessary underlying mechanisms that allow the brain to process information and apply Bayesian decision theory, which is considered to be the optimal way to make decisions under uncertainty (Murphy, 2022).

Neural networks can adapt to changing input, so the network generates the best possible result without needing to redesign the output criteria (Russell and Norvig, 2021). With the advancement of methodologies and theoretical models, the domain has reached a point where neural networks are now evaluated alongside similar methods from statistics, pattern recognition, and machine learning. This evaluation allows for the selection of the most suitable technique for different applications. Consequently, these advancements have led to the emergence of a robust new industry centered around data mining technology. The Bayesian network framework was developed to enable effective depiction and precise analysis of uncertain knowledge. Currently, it is the predominant approach in AI research concerning uncertain reasoning and expert systems (Russell and Norvig, 2021).

Organizational Adoption of AI

AI is considered to be a highly promising and relevant information technology by leading scholars (Rusell and Norvig, 2021; Murphy, 2022). The impact of AI goes far beyond the fields of information and computer science (Brynjolfsson and McAfee 2017; Acemoglu et al. 2022; Kemp 2023). That is why an increasing number of organizations are looking to leverage AI in order to gain a competitive advantage, boost productivity and solve organizational problems (Thakor 2020; Berg, Fuster, and Puri 2022). AI has the potential to not only significantly impact core entrepreneurial and managerial competencies such as decision making and risk management but further offers potential to impact important social and economic challenges such as ecological sustainability, sustainable economic growth, information transparency and justice (Lu, Zhang, and Li 2023). The oversight of the development and the adoption of AI therefore demands rigorous regulatory oversight, particularly in light of the manifold ethical challenges, some of which are discussed in this dissertation. Figure 1 shows the organizational adoption process of AI:

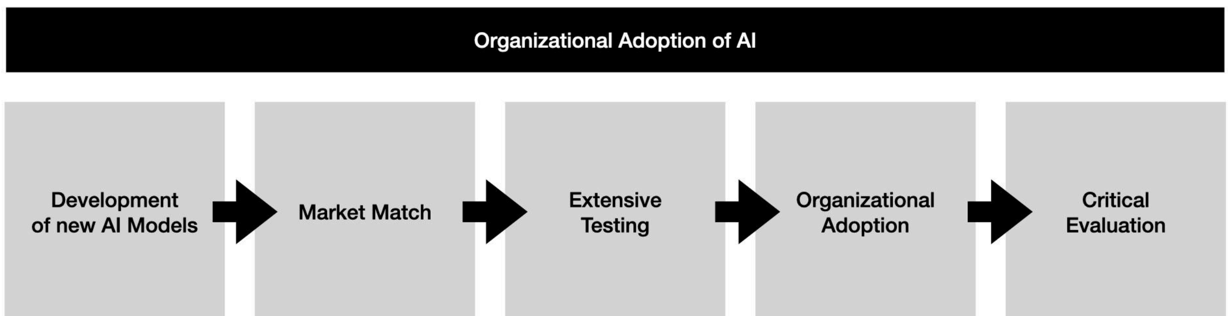

Figure 1: Organizational adoption process of AI. Author’s own contribution.

This dissertation empirically investigates the impact of AI in the fields of (1) sustainability, (2) decision making under uncertainty and idea generation and (3) risk management. Each field encompasses a highly relevant and challenging *wicked problem*, bearing important implications for organizations, economies, society and individuals. The aforementioned fields are investigated through the lens of (1) the circular economy, (2) design thinking and (3) information asymmetry theory. Each of the three phenomena studied holds important empirical findings for researchers and practitioners alike. Regulators might find the sections on ethical implications particularly interesting. Figure 2 shows the scope and focus of the dissertation.

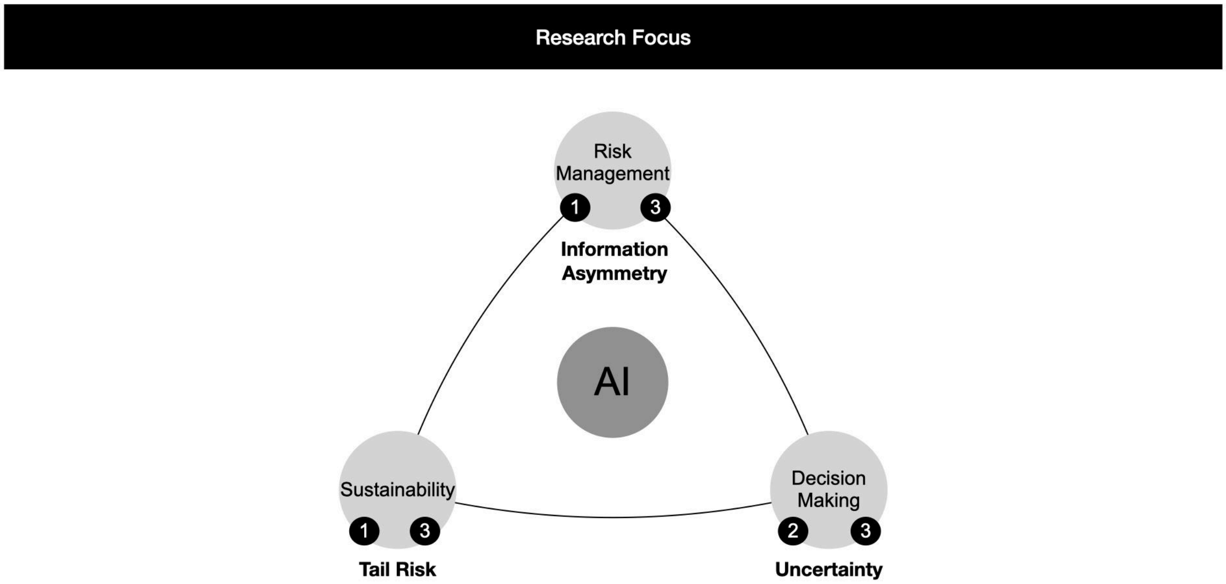

Figure 2: The focus of this dissertation. Author's own contribution.

AI-enabled Circular Economy

Climate change poses a serious risk for planet earth and therefore humanity (IPCC 2023; Lee et al. 2023). Organizational economic activities within the linear economy lack sustainability awareness and produce excess waste, contributing to ecological and climate risk (Geissdoerfer et al. 2020; Zink and Geyer 2017). The transition from the linear to the circular economy bears potential for economic growth, ecological sustainability and climate resilience. Important recent research by Geissdoerfer et al. (2020), Lüdeke-Freund et al. (2019), Bocken et al. (2014) and Zink and Geyer (2017) highlight the CE's importance in supporting economic, environmental, and technological benefits, as well as informing policy decisions. Further research points out the need to pay close attention to the *rebound-effect* (Zink and Geyer 2017; Corvellec et al. 2022). The transition to circular business models (BMs) centered around AI involves the preservation of physical stocks and resource cycles in a product's value chain, as discussed by Stahel (2016) and Lüdeke-Freund et al. (2019). These BMs, which are integral to the circular value chain, generate value through various means like repair, reuse, and recycling, with AI being a key enabler (Achterberg et al. 2016; Weber et al. 2022). Figure 3 shows the impact of AI on the CE:

The role of AI in the Circular Economy				
Waste Reduction	Close Loopholes	Circular Design	Optimal Use	Value Recovery
• Holistic footprint analysis • Active life-cycle management • Predictive maintenance • Circular recycling • Efficiency optimization	• Identify loopholes • Propose solutions • Manage flow of resources • Supply chain traceability • Support full circularity	• Informed choice of materials and resources • Sustainable manufacturing • Design for reusability • Ease of component replacement • Product longevity	• Monitoring of usage • Evaluation of key tasks • Critical time assessment • Predictive energy management • User guidance and education	• Technological openness • Disassembly and reuse • Supply chain integrability • Reutilization of operative components • Assessment of damage and remaining value

Figure 3: The role of AI in the Circular Economy. Author's own contribution, partly adapted from Achterberg et al. (2016) and Geissdoerfer et al. (2020).

Sustainable Development Goals

The integration of AI into business models (BMs) is seen as a key driver for sustainable development, particularly in enhancing circular BMs. Vinuesa et al. (2020) highlight AI's important role in achieving the Sustainable Development Goals (SDGs), a set of 17 goals and 169 targets aimed at global sustainability, covering areas like social, environmental, and economic well-being (Sachs et al. 2019). AI is likely to positively impact 134 of the 169 SDG targets, though it could negatively affect 59 targets.

Particularly, AI's relevance to the CE and its alignment with specific SDGs is noted by Schroeder et al. (2019) and the UN General Assembly and UN Economic and Social Council (2019). Five SDGs (6, 7, 8, 12, and 15) are directly linked to the CE, with SDGs 7 (affordable and clean energy), 8 (decent work and economic growth), 12 (responsible consumption and production), and 15 (life on land) being most important.

Vinuesa et al. (2020) suggest that AI could significantly contribute to these SDGs, although potential negative impacts exist. For SDG 7, AI could aid all targets, but it might also hinder 40% of them. In the case of SDG 8, AI could assist 92% of the targets but obstruct one-third. For SDG 12, AI could support 82% of the targets, with a potential hindrance to 27%. Lastly, for SDG 15, AI could bolster all targets, yet possibly impede one-third. These findings highlight the benefits of AI in promoting the CE and, consequently, ecological and economic sustainability.

Circular Business Models

Leipold et al. (2023) suggest an optimistic outlook for creating new circular business models (BMs) through technology, shedding light on the importance of understanding their development. Business Model Innovation (BMI) involves transitioning from existing business models to new ones, which can include complete overhauls or modifications of specific elements (Geissdoerfer et al. 2018, 409). Geissdoerfer et al. (2018) categorize BMI into four types: (1) creating entirely new BMs, (2) transforming existing BMs, (3) diversifying current BMs by adding new ones, and (4) acquiring and integrating new BMs. This transition to circular BMs, which Bocken et al. (2014) describe as creating value from waste, is deeply linked with technological innovation. According to Boons & Lüdeke-Freund (2013, 14), new BMs can arise from existing technologies, existing BMs can incorporate new technologies, and new technologies can lead to new BMs. AI, as an emerging technology, is expected to significantly impact circular BMs, altering aspects like value proposition, value creation, value delivery, and value capture.

AI-driven Business Model Innovation

One goal for this research was to better understand the interaction of AI with different aspects of the circular value chain, especially from a Business Model Innovation (BMI) perspective. The study builds upon recent foundational research by Bocken et al. (2014), Kirchherr et al. (2017), Lüdeke-Freund et al. (2019), and Morseletto (2020), which left several questions about this interaction unanswered. Our research makes three significant theoretical contributions to the field of circular Business Model

Innovation (BMI) for AI-driven business models (BMs), addressing gaps in the existing literature.

First, we have developed a unique circular BMI framework for AI-driven BMs, filling a gap in the literature that has largely discussed circular BMI in isolation or in the context of technology broadly, rather than specifically AI (Achterberg et al. 2016; Lüdeke-Freund et al. 2019; Bocken et al. 2014; Boons and Lüdeke-Freund 2013). Drawing from Weber et al. (2022) and Achterberg et al. (2016), we propose a 5x3 matrix that correlates four AI-driven BM types and Hybrids with three segments of the circular value chain. Our empirical findings show clear patterns in the applicability of AI-driven BMs across different value chain segments, suggesting certain AI characteristics are more suited for specific segments than for others.

Second, we define specific AI-driven BM characteristics for the Circular Economy (CE). Prior studies have either broadly addressed circular BMs or focused on the four BM layers (Achterberg et al. 2016; Geissdoerfer et al. 2020; Geissdoerfer et al. 2018; Lüdeke-Freund et al. 2019; Bocken et al. 2014). Our work goes further by detailing the configuration of AI-driven circular BMs, based on characteristics common to at least 80% of organizations within a specific AI-driven BM type. This leads to distinct configurations for circular AI-driven BMs, regardless of the specific value hill segment they apply to.

Third, we validate our findings through triangulation, involving circular organizations using AI-driven BMs and expert insights. This approach not only confirms our observations in organizations but also aligns with studies showing AI's role in enabling SDG targets related to CE (Vinuesa et al. 2020; Schröder et al. 2018). Our research extends existing knowledge by identifying specific AI applications and their utility across all segments of the circular value chain, a perspective that was previously limited in scope (Liu et al. 2022; Ghoreishi and Happonen 2020). Therefore, our study addresses important gaps in the literature by linking AI-driven BMs with circular BMI, offering detailed configurations for these BMs, and providing empirical evidence of AI's role and impact in the circular value chain.

Design Thinking and Decision Making under Uncertainty

Design Thinking (DT) is a leading concept for idea generation and decision making under uncertainty, with important implications for organizations and workflow processes (Buchanan, 1992; Dorst, 2011; Kimbell, 2011; Razzouk and Shute, 2012). AI can play an important role in enhancing the DT process (Cautela et al. 2019), however there is a current lack of understanding of AI’s manifold impact on the DT process which we aim to understand better through our research. DT is an important concept for decision making under uncertainty, enabling a broader perspective, openness, bias awareness, and innovation (Weller 2019). The concept consists of five main stages: Empathize, Define, Ideate, Prototype, and Test (Buchanan, 1992). Through our research we aim to investigate AI’s role in the DT process and its implications for each individual stage of the DT process. Figure 4 shows the DT process:

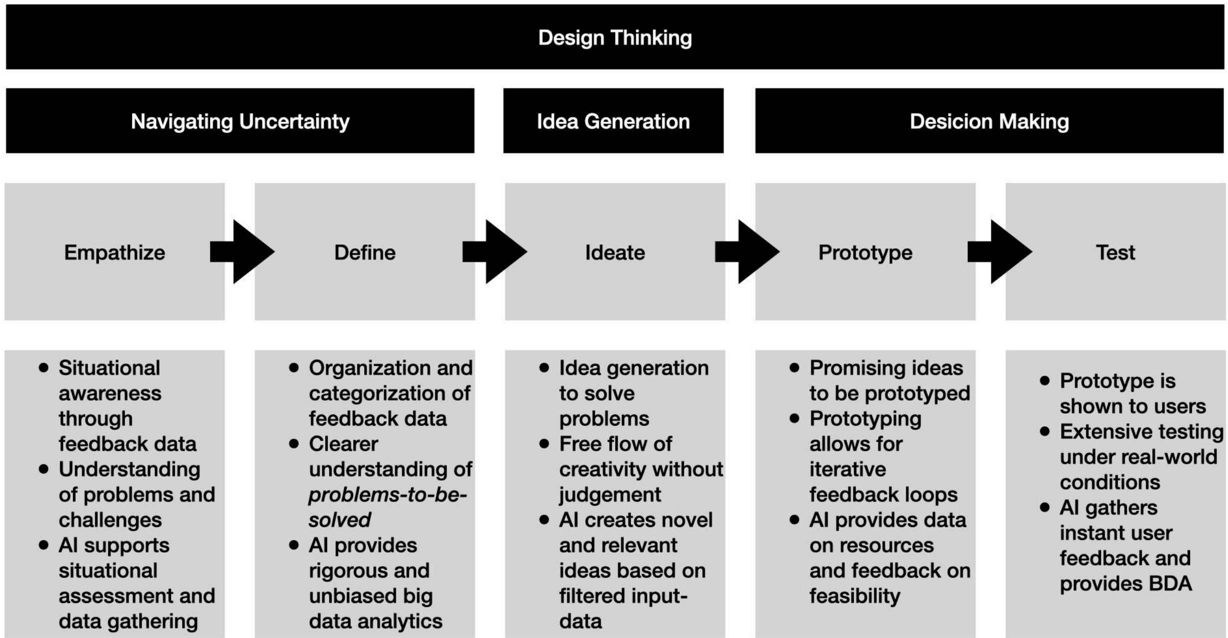

Figure 4: The Design Thinking process. Author's own contribution.

The *Empathize* stage focuses on understanding situations and gathering necessary information, involving interviews and surveys (Brown, 2008). The goal is to gain a more precise and unbiased understanding of the underlying problems at hand. AI supports this stage in accumulating and analyzing large data sets, enhancing decision-making processes (Novak et al., 2021). The data base is not only enhanced by using AI to gather and analyze additional datasets but also by integration of *alternative data* into the data pool, therefore enhancing, broadening and deepening the available data for decision making (Erhard et al., 2021). AI can extract data from various sources, such as social media, email and smartphones (Hansen and Borch, 2022), and streamline data processing, contribute to idea generation and reduce the workload for humans, allowing them to save time to focus on further pressing tasks (Cautela et al., 2019).

The *Define* stage focuses on organizing and categorizing the extensive feedback data collected during the previous *Empathize* stage (Brenner et al., 2016). AI is particularly well suited to enhance the *Define* stage, given its strength to analyze, cluster and categorize vast amounts of complex datasets in a very short time (Kimbell, 2011), either by applying inductive or deductive technologies such as neural networks, group method of data handling, statistics, inductive production rule generation, genetic algorithms or case-based reasoning (Nemati et al., 2002). AI supports the categorizations of findings, definition of problems and proposes solutions, contributing to the digitalization of traditional archival methods and overcoming issues like document loss (Rolan et al., 2019).

The *Ideate* stage focuses on the free, unrestrained flow of creativity from all participants and spontaneous idea generation without immediate judgment (Brenner et al., 2016). Future organizational DT are likely to consist of *artificial intelligent agents* as well as *human agents*. AI does provide valuable support for this stage by generating relevant ideas based on the data accumulated during the previous stages, given AI's potential in utilizing alternative data and real-time analysis (Nagorny et al., 2017) that expands the range, scale and diversity of ideas. AI therefore supports organizations in overcoming scalability-related challenges that are often confined by the amount and personal background of humans available during the *Ideate* stage (Verganti et al., 2020).

The *Prototype* stage focuses on turning ideas that were gathered during the previous stage into actionable prototypes (Cautela et al., 2019; Brown, 2008). AI does significantly impact this stage, helping to select the most promising ideas based on market data, while simultaneously considering resource limitations and costs. AI's role varies between digital/virtual and physical prototypes. While its potential is immense in digital domains, utilizing knowledge-based systems and neural networks (Pham and Pham, 1999), its impact is somewhat lesser in physical prototype construction. Nevertheless, AI aids in process automation and decision-making, enhancing tool functionality and productivity (Javaid et al., 2022) while at least contributing to the physical prototyping by selecting and purchasing resources and materials while 3D-printing may play a more important role in the years to come.

The final *Test* stage focuses on evaluating the performance of established prototypes based on user feedback (Brown, 2008; Razzouk and Shute, 2012). AI's expertise to handle large data sets plays a vital role in testing, especially for virtual and digital prototypes (Duan et al., 2019; Cautela et al., 2019). AI can increase the scale of crucial user feedback during this stage by significantly expanding the user base to which questionnaires are being sent out. By utilizing statistical methods and expanding sample sizes, AI enhances the speed and accuracy of the testing phase and can evaluate such questionnaires in no time, providing insightful dashboards and data visualizations. Given the importance of the final testing and evaluation methods, AI can substantially enhance the quality and impact of the DT process (Micheli et al., 2019; Cousins, 2018).

Therefore, AI plays an important role in supporting idea generation and decision making under uncertainty. AI does not only significantly enhance the data basis upon which decisions are made but also helps to decrease levels of uncertainty by providing market insights, evaluating user feedback and shortening feedback loops. Figure 5 shows the role of AI in decision making under uncertainty:

The Role of AI in Decision Making under Uncertainty

Big Data Analytics	Forecasting	Enhanced Automation	Oversight	Resource Management

• Analysis of large data sets
• Market analysis in real time
• Automated competition tracking
• Pricing analysis
• A/B/C/…N-Testing
	• Market trends
	• Resource allocation
	• Social norms
	• Cultural values
	• Supply chain and logistics
	• Strategic planning
		• Frees up the most important resource of all: Time
		• Emails
		• Phone calls
		• Meetings
		• Note-Taking
		• Accounting
		• Controlling
			• Real-time tracking of important resources
			• Transparency
			• Focus on key events
			• Live updates for executive dashboards
			• Action control
				• Optimized usage of
				  • Capital
				  • Labor
				  • Time
				• Regional benchmarking
				• Divisional benchmarking
				• Competitive advantage

Figure 5: The role of AI in decision making under uncertainty. Author's own contribution.

The Convergence of AI, IoT and Blockchain

While AI is already an extremely powerful information technology, as the previous chapters have shown, its convergence with the Internet of Things (IoT) and Blockchain further enhance its capabilities. Rosenberg (1963) first described technological convergence by observing that in preindustrial societies, skills and techniques were confined to specific industries, unlike in industrial societies where similar capabilities are used across a wide array of products. He coined this blending of techniques across different industries as "technological convergence". Subsequently, Adner and Levinthal (2002) exemplified this concept through the development of the CAT scanner, which integrates x-ray and computer technologies—two previously separate fields with distinct applications in medical imaging and data processing, respectively.

Hacklin et al. (2010) developed a model to explore inter-industry innovation, identifying multiple stages of convergence that are relevant to the organizational adoption processes. The initial phase, (1) knowledge convergence, involves merging different technological components. This leads to (2) technological convergence, which paves the way for applicational convergence—the harmonization of intersecting technologies to create new applications across sectors. The final stage, (3) industrial convergence, sees various industries adopting a shared technological foundation. Hacklin et al. view convergence as a dynamic process driven by knowledge spillovers that can culminate in the integration of multiple industries.

Schuelke-Leech (2018) further investigated the impact of disruptive technologies, distinguishing between *first-order disruptions*, which affect localized sectors, and *second-order disruptions*, which have broader societal impacts. She proposed that combining multiple first-order disruptive technologies might result in second-order disruptions. However, integrating technologies such as AI, Blockchain, and IoT has faced challenges, leading to some disillusionment as described by Sodhi et al. (2022) in their investigation titled “Why emerging supply chain technologies initially disappoint: blockchain, IoT, and AI?”. They suggest that initial over-expectations, analyzed through frameworks like *Gartner's hype cycle* and affordance theory, often lead to subsequent disenchantment. Blockchain technology, identified as an *institutional innovation* (Davidson et al., 2018), leading to new ways of coordinating economic activities (Lumineau, 2021), notably by introducing a decentralized architecture. Such decentralized systems allow for independent operation of traditional networks, utilizing AI, IoT, and Blockchain.

Buterin (2014) introduced the concept of Decentralized Autonomous Organizations (DAOs), envisioning organizations where technology plays a central role and humans are peripheral, a reversal of traditional organizational structures. The operational disappointments researched by Sodhi et al. (2022), as well as earlier excessive expectations researched by Centobelli et al. (2021), underscore the importance of further research into the synergistic effects of AI, Blockchain, and IoT, the strategic drivers of their integration, and the development of frameworks to ideate human-centered autonomous systems.

AI and Risk Management

AI plays an increasingly important role in risk management, specifically in the context of transactional decision making taking place under conditions of uncertainty and information asymmetry (Hansen and Borch 2022; Thakor 2020; Berg, Fuster, and Puri 2022). The financial lending sector poses a particularly well-suited ecosystem to study the adoption of AI in order to reduce uncertainty, make better informed decisions and manage risk.

In the current financial environment, credit scoring plays a crucial role in shaping access to credit, significantly impacting the flow of credit in economies globally (Anderson 2007). The financial technology (fintech) sector has undergone significant changes in the last decade (Liu, Li, and Wang 2020), sparking interest in the use of alternative data to enhance and even transform creditworthiness assessments. This interest is fueled by the convergence of fintech with AI, particularly machine learning (ML) techniques (Thakor 2020; Berg, Fuster, and Puri 2022; Hansen and Borch 2022). Traditional credit scoring models, which rely on demographics and historical financial data like credit history, income, and assets, have long been the foundation of loan underwriting processes (Anderson 2007). Yet, these models have their drawbacks, particularly in scoring borrowers who lack traditional credit histories and by not fully capturing the dynamic and complex aspects of borrowers' financial sustainability (Dastile, Celik, and Potsane 2020; Di Maggio, Ratnadiwakara, and Carmichael 2022). The advent of AI in data analysis and predictive modeling has introduced a new perspective in credit scoring. This approach aims to *improve predictive accuracy* and *broaden access to credit*. It also seeks to *reduce operational costs* and minimize type II errors in the decision-making process whether to grant or reject a loan request (Charoenwong and Kwan 2021; Ince and Aktan 2009).

AI possesses great technical capabilities for the precise and timely analysis and interpretation of extensive financial as well as alternative data from borrowers. This capability can significantly influence lenders' decisions on approving or denying loans.

As Berg et al. (2020) show, there is a notable, immediate, and strongly positive effect of alternative data on lending mechanisms. Our research builds upon previous studies that highlight the latent predictive power of alternative data in credit scoring. This data includes utility payments, rent, digital footprints (e.g., email usage, social media activities), mobile phone usage patterns, and psychometrics. Such data sources enable a multidimensional and almost real-time assessment of creditworthiness, steering towards a more customer-centric, platform-based model (Lu, Zhang, and Li 2023; Vives 2019). The effectiveness and significance of alternative data in credit scoring have been validated through various comprehensive quantitative studies (Berg et al. 2020; Djeundje et al. 2021; Óskarsdóttir et al. 2019; Iyer et al. 2016; Tan, Bhattacharya, and Phan 2016) and have been systematically reviewed in recent years (Thakor 2020; Berg, Fuster, and Puri 2022).

This shift towards using alternative data for credit scoring is driven by the broader movement towards adopting AI for big data analytics (BDA) in financial services (Agarwal and Zhang 2020). BDA provides a robust framework for integrating and interpreting large, complex, and often unstructured datasets, such as alternative data (De Cnudde et al. 2019; Fang and Zhang 2016). Although fintech companies increasingly gather extensive and diverse sets of alternative data, the quality of such data remains a critical limiting factor. The reliability and accuracy of such data can impact the adoption and economic effectiveness of fintech innovations (Romero and Fitz 2021; Cong, Li, and Zhang 2021). Figure 6 shows the role of AI in risk management:

The Role of AI in Risk Management				
Risk Assessment	Information Asymmetry	Crisis Management	Fraud Prevention	Compliance
• Un-biased rating • Benchmarking according to market norms • Competitor analysis • Focus on key risk • Mitigation strategies	• Exists between 2+ parties/ agents • Poses existential risk to organizations • Adverse selection • Moral hazard • Uncertainty and signaling	• Speed and information are decisive • Rapid response • Communicatio n control • Stakeholder management • Mediation	• Real-time monitoring • Automated data-sharing with law enforcement authorities • Precise identification of causative agent(s) • Preventive forecasting	• Automated tracking of updated regulations • Assessment of compliance • Detection of non-compliance • Communicatio n with regulators

Figure 6: The role of AI in risk management. Author's own contribution.

The aim of this research is to shed light on how the incorporation of alternative data, enabled by AI, exposes critical flaws in traditional credit scoring systems, such as *exclusivity*, *moral hazard*, and *adverse selection*. The adoption of AI and alternative data in credit scoring further supports *financial inclusion*, playing an important role in helping people to realize their *economic potential*. This expansion is particularly notable in reaching underserved or *'unbanked' populations*, especially in emerging markets (Wagdi and Tarek 2022; Goel and Rastogi 2021). Implementing such a more inclusive credit scoring approach, with careful attention to governance and bias reduction (Aitken 2017; Agarwal et al. 2019), holds the potential to improve financial inclusion metrics (Zhang et al. 2022). Furthermore, it could lead to a fairer distribution of credit resources, benefiting broader segments of society and therefore stimulating additional economic growth (Monk, Prins, and Rook 2019; Lu, Zhang, and Li 2023).

2. Information Asymmetry Theory

One of the theories that is particularly insightful for understanding the importance of AI in organizational adoption is Information Asymmetry Theory (IAT). IAT is especially relevant for understanding the impact of AI in organizational adoption because it highlights the disparities in information access and knowledge between different stakeholders. IAT, building on the foundational work of Vickrey (1961) and Mirrlees (1971) and further discussed and advanced by Akerlof (1970), Spence (1978) and Rothschild and Stiglitz (1978), provides a fitting theoretical framework that is important for understanding how AI can impact decision making under uncertainty. IAT within the scope of organizational studies discusses how information is unevenly distributed between two parties before, during and after a decision or transaction. In this dissertation, the goal is to understand if AI does have a major impact on information asymmetry and if so, why that is and what the implications are for theory.

IAT is particularly relevant for decision making under uncertainty. In this dissertation this phenomenon is discussed within the scope of the financial services industry. Financial transactions such as lending as well as credit scoring processes provide an ideal scenario to study the effect of AI on decision making under conditions of information asymmetry and uncertainty. Information asymmetry occurs when borrowers possess more exact and relevant information about their own financial behavior and creditworthiness than lenders do. Such an imbalance can have detrimental effects, leading to two primary issues: *adverse selection* and *moral hazard*.

Adverse selection refers to situations where lenders inadvertently offer loans to high-risk borrowers. In such cases, due to lenders lacking sufficient information, they are unable to accurately differentiate between low-risk and high-risk borrowers (An, Deng, and Gabriel 2011; Marquez 2002; Cressy and Toivanen 2001). Therefore, the phenomenon of adverse selection bears not only important implications for decision making under uncertainty but also for risk management and mitigation strategies.

Moral hazard refers to situations when borrowers engage in riskier behaviors after the final decision has been made and the loan has been approved (Karlan and Zinman 2009; Sufi 2007; Saito and Tsuruta 2018). After borrowers receive credit, their behavior towards risk may alter, with borrowers being under the assumption that the risk of their actions is now borne by lenders. Borrowers might take on more debt that they could safely and sustainably manage or invest in high-risk ventures, believing that the financial burden of any negative outcome will fall on lenders.

The adoption of AI in decision making processes that take place under conditions of uncertainty, particularly through the use of alternative data, holds the potential to significantly reduce such information asymmetry. This provides the decision making agent with access to a wealth of personalized and historical data on the other party, allowing them to make better informed decisions (Cassar, Ittner, and Cavalluzzo 2015). By leveraging such data in the financial sector, lenders can gain a more holistic and accurate understanding of a borrower's creditworthiness, thereby mitigating the risks associated with both *adverse selection* and *moral hazard* (Thakor 2020; Berg, Fuster, and Puri 2022). Therefore, IAT plays an important role in understanding information discrepancies between stakeholders before, during and after decision making processes.

3. Research Overview

3.1 Overview of the Manuscripts

This cumulative dissertation consists of three manuscripts. All of them address organizational adoption of AI through different perspectives. A particular focus of this dissertation lies on risk management and decision making under uncertainty and information asymmetry. Successful risk management benefits from data-based decision-making processes that yield positive results under uncertainty. The presence of uncertainty is often aggravated by information asymmetry. When parties have unequal knowledge, the decision-making process becomes more risky, as the decision-maker may not have access to all relevant information or may misjudge the reliability of the information they do have. Information asymmetry can therefore significantly influence the assessment and perception of risk. Therefore, the manuscripts aim to investigate the impact of AI on risk management and decision making under uncertainty and information asymmetry through different theoretical and conceptual lenses to gain a deeper and more holistic understanding of the phenomenon. Table 1 gives an overview of the three manuscripts that are part of this dissertation.

Manuscript	**1**	**2**	**3**
Title	New Business Models for a Circular Economy: Exploring The Promises of Artificial Intelligence for Circular Business Model Innovation	Leveraging Design Thinking towards the Convergence of AI, IoT and Blockchain: Strategic Drivers and Human-Centered Use Cases	Who gets the Money? Evidence on the Adoption of Alternative Data for Credit Scoring in Fintech Lending
Method	Empirical, qualitative	Empirical, qualitative	Empirical, qualitative
Data	55 expert interviews	40 expert interviews	26 expert interviews
Theory / Concept	Circular Economy	Design Thinking	Information Asymmetry Theory

Table 1: Research overview of the three manuscripts.

The first manuscript aims to understand how organizational adoption of AI does impact the transition to more sustainable business models. The Circular Economy (CE) concept seeks to reconcile economic growth with ecological sustainability and climate risk management. Recent empirical studies suggest a significant potential for AI to impact organizational decision making and resource utilization. However, the exact mechanisms by which AI facilitates the evolution of sustainable and circular business models remain unclear. This manuscript attempts to shed light on the impact of AI on the transition from linear to circular business models. Drawing on business model theory

(BMT), this manuscript aims to systematically analyze stakeholder behaviors and enhance business model frameworks applicable to the CE through the adoption of AI. Employing a qualitative research methodology, the manuscript contains 55 interviews, featuring 28 experts in AI and the circular economy, along with 27 organizations implementing AI in their circular business models. The research contributes to the literature by: (1) formulating a new framework for innovation in circular business models, identifying optimal AI-driven business model types for various segments of the circular value chain; (2) outlining distinct characteristics of AI-driven business models within the circular economy context; (3) providing empirical evidence regarding the application and effectiveness of AI in various segments of the circular value chain.

The second manuscript aims to understand what role AI plays within organizations in order to foster idea generation, decision making under uncertainty and knowledge management through Design Thinking (DT). Employing a qualitative research methodology, the manuscript includes 40 interviews. The DT process, enhanced by AI, supports idea generation and decision making under uncertainty across its stages. During the *Empathize* stage, AI aggregates and analyzes vast data from diverse sources including alternative data pulled from social media, blogs, smartphones and archives. This not only enriches the data pool but also saves time, allowing for a focus on more productive DT stages while maintaining a rigorous understanding of the problem at hand. AI's role in data collection, categorization, and preliminary analysis is crucial, freeing up human resources for more complex and important tasks. During the *Define* stage, AI categorizes and labels large datasets while conducting BDA, applying methods like neural networks and genetic algorithms. AI supports in distilling relevant information, defining problems, and creating structured artifacts. During the *Ideate* stage, AI's ability to analyze data with specific filters enhances idea generation. AI assists in overcoming limitations such as scalability and the availability of resources. AI's potential lies in expanding the pool of ideas and bringing diverse perspectives, contributing to the quantity and diversity of ideas. During the *Prototyping* stage, AI supports the creation of digital/virtual and physical prototypes, utilizing large databases including alternative datasets and interconnecting data silos. While its role in physical prototyping is less significant than in virtual/digital, AI still offers support through knowledge-based systems and process automation, enhancing tool functionality and research on resources and feasibility checks. During the final *Test* stage, AI supports in evaluating feedback data, particularly for digital and virtual prototypes. AI improves the quality of the feedback gathered during this stage by sending out a large amount of questionnaires to the right userbase. AI then automatically evaluates such questionnaires with near real-time speed and high accuracy, enabling faster feedback loops and iterative prototype refinements. Therefore, the organizational adoption of AI in the DT process offers a competitive advantage by positively impacting productivity, creativity and efficiency.

The third manuscript aims to understand how organizational adoption of AI does impact risk management, decision making under uncertainty and information asymmetry. The financial lending industry is an ideal ecosystem for an empirical evaluation of this matter, as granting, negotiating or rejecting loan requests typically involves high levels of uncertainty and information asymmetry. The manuscript investigates the impact of AI on credit scoring in the fintech sector and its impact on the allocation of economic opportunities. It specifically explores how the adoption of AI, particularly with the use of alternative data, is impacting credit scoring in fintech lending. The manuscript critically evaluates the impact of AI on information asymmetry that usually accompanies the credit scoring process. Employing a qualitative research methodology, the study uses the *Gioia method* to systematically gather, analyze, and categorize perspectives from a panel of 26 experts spanning fintech lending, AI, data science, and academic institutions. The findings of the research are manifold. They include the reduction of information asymmetry, improved decision making under uncertainty based on historical financial data as well as alternative data, the expansion of credit accessibility to previously ‘unbanked’ parts of the population, the development of real-time credit assessment mechanisms, and the emergence of innovative business models for entrepreneurs. Additionally, the manuscript sheds light on the increase in credit market efficiencies and their implications on the stability of financial markets. Moreover, the manuscript emphasizes the critical need for rigorous ethical oversight. It calls for the establishment of robust ethical principles to address issues surrounding data privacy, opt-in policies, transparency, traceability, responsibility and bias mitigation. These concerns encompass consent protocols, algorithmic transparency, data quality control, representativeness, and potential biases leading to discrimination. The manuscript concludes that the adoption of AI and alternative data in credit scoring holds many relevant benefits such as a more equitable, sustainable, fair and inclusive credit system but also requires a delicate balance between leveraging technological innovations and upholding the privacy rights of borrowers.

3.2 Publication Status of the Manuscripts

All three manuscripts have been submitted to peer-reviewed academic journals and are either already published or currently under review. **Table 2** gives an overview of the three manuscripts and their current publication status.

Manuscript	**Authors**	**Journal**	**Ranking (VHB)**	**Publication Status**
New Business Models for a Circular Economy: Exploring The Promises of Artificial Intelligence for Circular Business Model Innovation	Remke, Konstantin; Tigges, Maximilian; Mauer, René	Journal of Product Innovation Management	A	Revise & Resubmit (1,33 points)
Leveraging Design Thinking towards the Convergence of AI, IoT and Blockchain: Strategic Drivers and Human-Centered Use Cases	Tigges, Maximilian; Ipert, Chloé; Mauer, René	Lecture Notes in Computer Science	C	Published (0,5 points)
Who gets the Money? Evidence on the Adoption of Alternative Data for Credit Scoring in Fintech Lending	Tigges, Maximilian; Tschirner, Sebastian; Mauer, René	Technological Forecasting and Social Change	B	Revise & Resubmit (0,83 points)

Table 2: The three manuscripts and their current (March 2024) publication status.

The three manuscripts result in a total of 2,67 points, which surpasses ESCP's requirement of 2,50 points for a successful cumulative dissertation.

4. Manuscripts

4.1 Manuscript One

Title: “New Business Models for a Circular Economy: Exploring The Promises of Artificial Intelligence for Circular Business Model Innovation”

Authors: Konstantin Remke, Maximilian Tigges, René Mauer

Journal: Journal of Product Innovation Management

Status: Revise & Resubmit

4.2 Manuscript Two

Title: “Leveraging Design Thinking towards the Convergence of AI, IoT and Blockchain: Strategic Drivers and Human-Centered Use Cases”

Authors: Maximilian Tigges, Chloé Ipert, René Mauer

Journal: Lecture Notes in Computer Science

Status: Published

Citation: Tigges, M., Ipert, C., & Mauer, R. (2022). Leveraging Design Thinking Towards the Convergence of AI, IoT and Blockchain: Strategic Drivers and Human-Centered Use Cases. In International Conference on Human-Computer Interaction (pp. 147-162). Cham: Springer International Publishing.

4.3 Manuscript Three

Title: “Who gets the Money? Evidence on the Adoption of Alternative Data for Credit Scoring in Fintech Lending”

Authors: Maximilian Tigges, Sebastian Tschirner, René Mauer

Journal: Technological Forecasting and Social Change

Status: Revise & Resubmit

5. Overarching Conclusion

Summary of Key Findings

The empirical research featured in this dissertation reveals that the adoption of AI in organizations is rapidly increasing and bears important implications for economies, organizations, individuals, and society. This dissertation finds that AI enhances decision making through access to extensive and relevant data, improves risk management by applying BDA, and reduces uncertainty and information asymmetry through data-based decision making. In risk management, AI's capabilities in predictive analytics and real-time monitoring allow organizations to proactively address potential risks. Furthermore, the use of alternative data in credit scoring improves financial inclusivity and accuracy in risk assessment, benefiting both lenders and borrowers by easing credit access and enhancing financial stability. AI also significantly supports design thinking processes across various stages, enhancing creativity and efficiency in organizational decision making and problem-solving. Finally, AI contributes to sustainable economic practices by enabling the Circular Economy, particularly in enhancing resource efficiency and lifecycle management while reducing excess waste and closing existing loopholes.

Further Important Findings

Beyond aforementioned key findings, this dissertation holds further important implications for researchers, practitioners and regulators. A critical evaluation of AI adoption reveals that AI is no ‘miracle’ and will not ‘magically solve all the worlds’ multifaceted serious problems’. Neither should AI be uncritically labeled a ‘hero’ or a ‘villain’. However, the empirically grounded findings of this dissertation show that the benefits enabled by the organizational adoption of AI are important and manifold: better informed decisions grounded in additional relevant data, reduction of uncertainty, improved risk management and mitigation of information asymmetry.

Risk management is substantially improved through BDA, predictive analytics, decision making based on relevant data and real-time monitoring. Predictive analytics is enabled through AI systems that analyze large amounts of relevant data to identify patterns and trends that are difficult for humans to gather and evaluate at a comparable scale and speed. This is particularly relevant for decision makers to predict potential risks, enabling organizations to take proactive measures to manage and mitigate them. Real-time monitoring is enabled through AI that monitors systems and operations continuously, providing real-time alerts in case of anomalies or potential risks while enabling predictive maintenance. Risk is further reduced by automating tasks and processes, reducing human error rates.

Decision making under uncertainty benefits from AI in multiple ways. AI enables BDA, collects and analyzes large datasets that were previously unavailable or inaccessible to humans in order to provide insights that help in making informed decisions, which is particularly important in situations of great uncertainty. AI can model various scenarios and outcomes, helping decision-makers understand potential risks and benefits under different conditions, thus reducing uncertainty. By enabling BDA and visualizing key findings, AI allows human decision makers to save time and focus on assessing whether the solutions and recommendations provided by AI are just and reasonable.

Alternative data can be used by AI to access new, previously untapped data pools in order to reduce *uncertainty* and *information asymmetry.* The research featured in this dissertation clearly shows that using alternative data in credit scoring significantly enhances predictive accuracy, leading to major benefits: (1) It becomes easier for individuals to obtain credit, helping to realize their *economic potentialities*, (2) Lenders experience *reduced risk and uncertainty*, (3) *Economic resilience* is strengthened as lenders allocate more credit to reliable borrowers, and (4) the functionality and *stability of financial markets* improve. Furthermore, AI and alternative data serves as an enabler for people who were previously unable to apply for loans. Often, such 'unbanked' individuals are in this situation not due to ‘risky or irrational financial behavior’, but because of poverty, lack of financial knowledge, or living in remote areas. AI and alternative data not only facilitate their access to credit but also aids in enhancing their financial knowledge and credit score, by teaching them the value of responsible and proper financial decision making and risk management strategies. This approach also offers a major opportunity for fintech entrepreneurs to surpass traditional lenders in areas like cost, speed, convenience, simplicity, inclusivity and accessibility.

AI also plays an important role for *design thinking*, which is a much discussed concept in the literature in the field of innovation and creativity studies, supporting idea generation and decision making under uncertainty. While the concept features five stages as discussed in the respective manuscript, it is important to note that all five stages substantially benefit from the adoption of AI along the process. (1) the *empathize* stage is enhanced by AI through data gathering on a scale, depth and timeline that is hard to match by human agents; (2) the *define* stage is enhanced by AI through data analysis that can surpass human action by accuracy, speed and error rates; (3) the *ideate* stage is enhanced by AI through idea generation and keyword analysis; (4) the *prototype* stage is enhanced by AI through resource selection and workflow automation and (5) the final *test* stage is enhanced by AI through the creation and evaluation of feedback loops.

In regards to risk management, one of the most important tail risks currently observed is climate change. AI can make major contributions to a more sustainable and resilient economy. The CE is a promising concept for sustainable development, conciliating economic progress with ecological goals. The CE plays an important role in the current *decoupling* process, that is referring to simultaneous economic growth with falling CO2 emissions that can be observed in multiple developed economies such as the UK, France, Germany, Sweden, the US and Finland among many others (Ritchie, 2021). AI plays an important role in enabling the goals of the CE while also accelerating the transition from a linear to a circular economy. AI substantially impacts all categories of the *Value Hill* framework, as discussed by Achterberg et al. (2016). The *circular design* segment is enhanced by AI through supporting extraction, manufacturing, assembly, and retail processes. The *optimal use* segment is enhanced by AI as repair and maintenance are fueled with predictive maintenance, monitoring and anomaly detection, as well as lifecycle predictions. The *value recovery* segment is enhanced by AI through the reuse, redistribution, refurbishment, remanufacturing, and recycling of critical components and resources. This is supported and accomplished through automated disassembly, sorting, and cleaning that is constantly monitored by AI systems. Therefore AI plays an important role in closing existing loopholes and serves as a key enabler for a more sustainable economy.

Beyond such promises and benefits, *ethical concerns* remain. Key among such concerns is the matter of *data privacy*, *transparency* and *consent*, as gathering personalized data and particularly alternative data through AI often means accessing private details that people might not anticipate being used for BDA. This raises questions on how well-informed individuals of AI’s underlying processes and mechanisms are and whether they have fully understood and agreed to the collection and analysis of their private data. Moreover, the transparency of such algorithms, often referred to in the literature as the *black box* issue, is a significant concern. The algorithms processing extensive alternative data can lack clear *traceability*, which makes it difficult for both borrowers and lenders to understand how credit scores are determined and decisions are made. Such obscurity can seriously damage trust in the credit scoring system and leads to important legal and regulatory questions. The robustness and representativeness of data are equally important, as errors in alternative data can falsely portray borrowers’ creditworthiness and negatively impact decision making. Additionally, there's a *risk of bias and discrimination*. Algorithms might unintentionally echo prevailing societal prejudices, especially if the input data mirrors historical discrimination or biases. This could result in biased credit scoring outcomes that disadvantage specific groups without any individual wrongdoing. Tackling such ethical challenges is essential to ensure that the application of AI remains fair, inclusive, non-prejudicial, and transparent in order to maintain clear *accountability* and *responsibility* throughout the credit scoring process.

Implications for Research

The findings of this dissertation bear important implications for research. Through the empirically grounded findings of this dissertation, we can confirm the substantial impact of AI for decision making under uncertainty (Fuster et al. 2019; Berg et al. 2020). AI plays an important role supporting decision makers to make better decisions by reducing uncertainty through accessing and analyzing vast amounts of data while automating processes (Acemoglu et al. 2022; Berente et al. 2021; Verganti et al. 2020). We were able to independently confirm through our qualitative work the important findings of quantitative studies, that additional available data, such as *alternative data*, leads to better decision making and helps to navigate uncertainty (Berg et al. 2020; Djeundje et al. 2021; Óskarsdóttir et al. 2019; Iyer et al. 2016; Tan, Bhattacharya, and Phan 2016). Our findings also bear important implications for Information Asymmetry Theory, particularly on the information disparities that occur during transaction processes between two or more parties (Akerlof 1970; Rothschild and Stiglitz 1978). We show that lenders frequently encounter a lack of relevant data on a borrower's financial behavior and creditworthiness, which can compromise loan decisions (Karlan and

Zinman 2009). This information asymmetry can lead to two previously discussed phenomena: *adverse selection* and *moral hazard*. Adverse selection refers to the inability of lenders to differentiate between high-risk and low-risk borrowers, increasing the likelihood of approving loans for those prone to default (An, Deng, and Gabriel 2011). We show that this is an important challenge that can at least partly be overcome by the adoption of AI and alternative data into credit scoring mechanisms. Moral hazard arises after loan approval, as borrowers might adopt riskier financial practices, often without lenders' knowledge (Saito and Tsuruta 2018). We show that AI does also impact moral hazard by making it easier to understand borrowers' sustainability in regards to their financial actions. Traditional credit scoring methods, which predominantly depend on historical data like repayment records and credit usage, are often inadequate in addressing these risks (Anderson 2007). Through our work we show that there is a growing consideration for incorporating *alternative data* sources to improve the accuracy and predictive capability of credit scoring models, thereby fostering a more accessible, resilient and sustainable credit system (Berg, Fuster, and Puri 2022; Fuster et al. 2019; Thakor 2020). This bears direct implications for the IAT literature, as both major risks, *adverse selection* and *moral hazard,* are substantially reduced through the incorporation of AI and alternative data into credit scoring models. We show that AI does not only make organizations more efficient and resilient but that AI, if controlled for biases, can also contribute to the greater social good by enabling financial inclusion of previously 'unbanked' populations, helping people to realize their economic potentialities and grow out of poverty (Zhang et al. 2022; Monk, Prins, and Rook 2019; Lu, Zhang, and Li 2023).

Our work on creativity, innovation and design thinking also bear important implications for research. We have also shown that AI plays an important role in creativity and innovation, enhancing human idea generation processes within the DT process (Cautela et al. 2019). AI also serves as an enabler for the convergence with IoT and Blockchain in smart organizations, helping to deal with security and privacy issues (Mohanta et al. 2020). AI does play an important role in such a convergence, as it allows the automated real-time analysis of vast amounts of data that are an important basis for decision making, particularly in highly complex interconnected systems (Alvarez et al., 2020; Nambisan et al., 2019).

Our findings also bear important implications for the literature on sustainability and the circular economy. We show that AI serves as an important enabler to accelerate and smoothen the transition from a linear to a circular economy (Geissdoerfer et al. 2020; Bocken et al. 2014). It is currently not very well understood in the literature, what exact segments of the circular value chain will be impacted the most by AI, even though interesting work has started to appear (Achterberg et al. 2016) that we contributed to through our work. We propose a new integration of two previously discussed streams of literature by Weber et al. (2022) and Achterberg et al. (2016). Our work expands on existing research concerning circular business model innovation (Lüdeke-Freund et al. 2019) through digital technology by introducing a new 5x3 matrix. This matrix illustrates the interactions between four types of AI-driven business models and Hybrids across three segments of the circular value chain. We utilize the AI-driven business model pattern taxonomy for organizations outlined by Weber et al. (2022) and apply it within the framework of the three segments of the circular value chain described by Achterberg et al. (2016). Thus, we establish a new connection between these two distinct streams of literature.

Implications for Practice

This dissertation also bears important implications for practitioners. We show that the organizational adoption of AI is happening at an increasing rate, bearing important implications for organizations that currently consider the adoption of AI as well as organizations that choose *not* to adopt AI for normative reasons or because they are unaware of the potential benefits. AI is particularly well-suited for organizational adoption, as it directly impacts many of the core organizational tasks: Decision making, short term actions, long range planning, information gathering, task automation, error detection and market analysis. It can support the various departments of the organization such as Human Resource, Marketing, Controlling, Sales and Research and Development. There are currently already a significant number of AI solutions available to assist the aforementioned departments, so I will only mention a few brief examples: AI can help to screen candidates, generate high-quality content through LLMs, analyze vast amounts of different types of data, reach out to prospective customers, communicate value and assist with research tasks. Through our work we show that AI bears particularly important implications for tasks that require the assessment of large amounts of data in order to reduce uncertainty and information asymmetry. This is the case during credit scoring processes, where AI decreases the uncertainty that occurs during, prior and after the decision whether or not to grant a loan. Therefore, AI substantially contributes to organizational well-being and long term survivability, helping the organization to manage risky and potentially highly dangerous decision making processes through well-informed and rational decision making. However, it is important for organizations to address ethical challenges associated with AI adoption, such as ensuring consent, transparency, traceability, control for potential data biases, and protecting users' data privacy, to ensure trust and accountability.

Limitations

While the qualitative nature of this dissertation was chosen due to the novelty of the topic and in order to gain a deeper understanding of the contextual and complex impacts of organizational adoption of AI, it also comes with certain limitations, particularly in generalizability and quantification of impacts. Qualitative studies may not capture the entire breadth of AI's implications across different industries or cultural contexts due to their focus on specific cases or narratives. Furthermore, subjective elements of qualitative data analysis can lead to biases in interpreting the data, even though we tried our best to account for this by carefully and rigorously adopting the *Gioia method*. These limitations suggest the need for future studies that combine qualitative research with quantitative methods in order to provide a more balanced and comprehensive understanding of AI's impacts, enabling the validation of qualitative findings through additional quantitative empirical data and statistical analysis.

Avenues for Further Research

The scope and findings from this dissertation open several avenues for further research. We highlight the need for studies that further explore the integration of AI in risk management and decision-making processes under uncertainty. While this dissertation has a specific focus on certain fields and industries, it would be important for future scholars to investigate whether similar mechanisms and results can be found in different sectors. Also the cultural context leaves room for future research. While we carefully tried to control for potential biases by rigorously selecting interviewees with a highly diverse and international background, it must be noted that all involved researchers currently work and reside in Europe and received the majority of their education in Europe. Therefore, a more international group of researchers perhaps would take a different approach to study the same phenomenon or choose entirely different research questions altogether. Additional research could also further investigate the broader socioeconomic impacts of AI, especially in enhancing financial inclusivity and supporting sustainable development goals. Moreover, given the ethical concerns raised by AI, such as data privacy and algorithm transparency, future research should focus on developing frameworks that ensure the ethical and responsible use of AI. Such studies would benefit from interdisciplinary approaches that combine insights from informatics, philosophy, economics, sociology, political science, ethics, and regulatory perspectives to develop comprehensive guidelines for AI implementation. Concerning our work on the Circular Economy, it is important to note that even though the CE can play an important role in tackling ecological resilience, it is not a concept that will solve all problems related to sustainability and climate change and requires further critical and systematic evaluation. Special emphasis could be placed upon the *rebound effect* and its implication on digital and physical footprints. Particularly when it comes to energy production and energy systems, the CE can not solve all of the related *wicked problems*, at least not alone.

An additional promising and potentially highly rewarding opportunity is the further exploration of AI's role in enabling sustainable organizations in order to tackle *wicked problems* such as climate change, free global education, sustainable economic growth or the promotion of democratic values and well-being among organizations. Looking at climate change, further research is needed on how exactly AI can support the reduction of greenhouse gas emissions, deforestation, energy production, transportation, agricultural practices and waste management. The latter can be tackled through the promising concept of the Circular Economy, however further research needs to be done on how circular entrepreneurs can close the gap to linear entrepreneurs, who often enjoy a competitive advantage due to their products being easier and cheaper to manufacture. Another research direction could involve the detailed examination of AI's role in promoting or hindering the fair distribution of opportunities and inclusivity, particularly focusing on how AI can be designed to avoid reinforcing existing societal biases. Further research is also needed to explore the implications of AI in automating complex creative processes within organizations, that go far beyond existing decision tree models and typically involve humans at the final stages in order to *judge* the quality or feasibility of the proposed solution. Finally, additional research could address the development of robust, transparent, and accountable AI systems and control mechanisms that uphold and certify ethical standards and enhance trust among users and stakeholders.

Concluding Remarks

The empirical research featured in this dissertation clearly shows the manifold benefits of AI for organizations, individuals and society while also outlining its risks, shortcomings and dangers. AI has the potential to improve organizational processes as well as people's lives by relieving them of burdensome tasks, substantially improving risk management processes and decision making under uncertainty. Organizational adoption of AI will leverage efficiencies and increase productivity while freeing up people's most important resource, time, and relieving them of tedious and time-consuming tasks. Therefore AI has an impact that goes far beyond organizational studies and could potentially contribute to human well-being in manifold ways. By aiding individuals, AI is aiding society as a whole. This is not only done by the previously discussed automation of cumbersome manual labor that is better left to AI but also by improving public health, sustainability and economic resilience. However, there is a pressing need for policymakers, practitioners and researchers to closely collaborate in shaping an environment that maximizes the substantial and far-reaching benefits of AI while safeguarding against their risks. If such collaborative and interdisciplinary work is carried out with due diligence and the necessary regulatory vigor, AI can play a major role in contributing to ecological sustainability, organizational productivity, economic resilience and individual well-being.

6. Bibliography

Abbasi, Kaleemullah, Ashraful Alam, Min (Anna) Du, and Toan Luu Duc Huynh. 2021. “FinTech, SME Efficiency and National Culture: Evidence from OECD Countries.” Technological Forecasting and Social Change 163 (February): 120454. https://doi.org/10.1016/j.techfore.2020.120454.

Acemoglu, Daron, Ufuk Akcigit, and Murat Alp Celik. 2022. “Radical and Incremental Innovation: The Roles of Firms, Managers, and Innovators.” American Economic Journal: Macroeconomics 14 (3): 199–249.

Achterberg, Elisa, Jeroen Hinfelaar, and Nancy Bocken. 2016. Master Circular Business Models with the Value Hill. Circle Economy, Utrecht.

Adner, Ron, and Daniel A. Levinthal. "The emergence of emerging technologies." California management review 45.1 (2002): 50-66.

Agarwal, Sumit, Shashwat Alok, Pulak Ghosh, and Sudip Gupta. 2019. “Fintech and Credit Scoring for the Millennials: Evidence Using Mobile and Social Footprints.” SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3507827.

Agarwal, Sumit, and Jian Zhang. 2020. “FinTech, Lending and Payment Innovation: A Review.” Asia-Pacific Journal of Financial Studies 49 (3): 353–67. https://doi.org/10.1111/ajfs.12294.

Ahmed, Bakhtiyar, Thomas Dannhauser, and Nada Philip. "A lean design thinking methodology (LDTM) for machine learning and modern data projects." 2018 10th Computer Science and Electronic Engineering (CEEC). IEEE, 2018.

Aitken, Rob. 2017. “‘All Data Is Credit Data’: Constituting the Unbanked. Competition & Change” 21 (4): 274–300. https://doi.org/10.1177/1024529417712830.

Akerlof, George A. 1970. "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." The Quarterly Journal of Economics 84 (3): 488–500. https://doi.org/10.2307/1879431.

Alvarez, Sharon A., et al. "Developing a theory of the firm for the 21st century." Academy of Management Review 45.4 (2020): 711-716.

Amend, Clara, Ferdinand Revellio, Isabell Tenner, and Stefan Schaltegger. 2022. "The Potential of Modular Product Design on Repair Behavior and User Experience – Evidence from the Smartphone Industry." Journal of Cleaner Production 367 (September): 132770. https://doi.org/10.1016/j.jclepro.2022.132770.

Anderson, Raymond. 2007. The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation. OUP Oxford.

An, Xudong, Yongheng Deng, and Stuart A. Gabriel. 2011. "Asymmetric Information, Adverse Selection, and the Pricing of CMBS." Journal of Financial Economics 100 (2): 304–25. https://doi.org/10.1016/j.jfineco.2010.12.002.

Avison, David E., et al. "Action research." Communications of the ACM 42.1 (1999): 94-97.

Bag, Surajit, Jan Ham Christiaan Pretorius, Shivam Gupta, and Yogesh K. Dwivedi. 2021. "Role of Institutional Pressures and Resources in the Adoption of Big Data Analytics Powered Artificial Intelligence, Sustainable Manufacturing Practices and Circular Economy Capabilities." Technological Forecasting and Social Change 163 (February): 120420. https://doi.org/10.1016/j.techfore.2020.120420.

Beckman, Sara L., and Michael Barry. "Innovation as a learning process: Embedding design thinking." California management review 50.1 (2007): 25-56.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri. 2020. “On the Rise of FinTechs: Credit Scoring Using Digital Footprints.” The Review of Financial Studies 33 (7): 2845–97. https://doi.org/10.1093/rfs/hhz099.

Berg, Tobias, Andreas Fuster, and Manju Puri. 2022. “FinTech Lending.” Annual Review of Financial Economics 14 (1): 187–207. https://doi.org/10.1146/annurev-financial-101521-112042.

Berente, Nicholas, Bin Gu, Jan Recker, and Radhika Santhanam. 2021. “Managing Artificial Intelligence.” MIS Quarterly 45 (3).

Bergh, Donald D., David J. Ketchen, Ilaria Orlandi, Pursey P. M. A. R. Heugens, and Brian K. Boyd. 2019. “Information Asymmetry in Management Research: Past Accomplishments and Future Opportunities.” Journal of Management 45 (1): 122–58. https://doi.org/10.1177/0149206318798026.

Binswanger, Mathias. 2009. “Is There a Growth Imperative in Capitalist Economies? A Circular Flow Perspective.” Journal of Post Keynesian Economics 31 (4): 707–27. https://doi.org/10.2753/PKE0160-3477310410.

Borisov, Vadim, Tobias Leemann, Kathrin Seßler, Johannes Haug, Martin Pawelczyk, and Gjergji Kasneci. 2022. “Deep Neural Networks and Tabular Data: A Survey.” IEEE Transactions on Neural Networks and Learning Systems, 1–21. https://doi.org/10.1109/TNNLS.2022.3229161.

Bocken, N. M. P., S. W. Short, P. Rana, and S. Evans. 2014. “A Literature and Practice Review to Develop Sustainable Business Model Archetypes.” Journal of Cleaner Production 65 (February): 42–56. https://doi.org/10.1016/j.jclepro.2013.11.039.

Bocken, Nancy M. P., Ingrid de Pauw, Conny Bakker, and Bram van der Grinten. 2016. “Product Design and Business Model Strategies for a Circular Economy.” Journal of Industrial and Production Engineering 33 (5): 308–20. https://doi.org/10.1080/21681015.2016.1172124.

Boons, Frank, and Florian Lüdeke-Freund. 2013. “Business Models for Sustainable Innovation: State-of-The-Art and Steps Towards a Research Agenda.” Journal of Cleaner Production, Sustainable Innovation and Business Models, 45 (April): 9–19. https://doi.org/10.1016/j.jclepro.2012.07.007.

Branzoli, Nicola, and Ilaria Supino. 2020. “FinTech Credit: A Critical Review of Empirical Research Literature.” SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.3612726.

Bruckner, Matthew Adam. 2018. “The Promise and Perils of Algorithmic Lenders’ Use of Big Data.” Chicago-Kent Law Review 93: 3.

Brown, Tim. "Design thinking." Harvard business review 86.6 (2008): 84.

Buchanan, Richard. "Wicked problems in design thinking." Design issues 8.2 (1992): 5-21.

Brynjolfsson, Erik, and ANDREW Mcafee. 2017. “Artificial Intelligence, for Real.” Harvard Business Review 1: 1–31.

Buterin, Vitalik. "A next-generation smart contract and decentralized application platform." white paper 3.37 (2014): 2-1.

Cautela, Cabirio, et al. "The impact of artificial intelligence on design thinking practice: insights from the ecosystem of startups." Strategic Design Research Journal 12.1 (2019): 114-134.

Cassar, Gavin, Christopher D. Ittner, and Ken S. Cavalluzzo. 2015. “Alternative Information Sources and Information Asymmetry Reduction: Evidence from Small Business Debt.” Journal of Accounting and Economics 59 (2): 242–63. https://doi.org/10.1016/j.jacceco.2014.08.003.

Centobelli, Piera, et al. "Surfing blockchain wave, or drowning? Shaping the future of distributed ledgers and decentralized technologies." Technological Forecasting and Social Change 165 (2021): 120463.

Chalmers, Dominic, Niall G. MacKenzie, and Sara Carter. 2021. “Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution.” Entrepreneurship Theory and Practice 45 (5): 1028–53. https://doi.org/10.1177/1042258720934581.

Charmaz, Kathy. 2006. Constructing Grounded Theory: A Practical Guide Through Qualitative Analysis. Pine Forge Press.

Chauhan, Chetna, Vinit Parida, and Amandeep Dhir. 2022. “Linking Circular Economy and Digitalisation Technologies: A Systematic Literature Review of Past Achievements and Future Promises.” Technological Forecasting and Social Change 177 (April): 1–18. https://doi.org/10.1016/j.techfore.2022.121508.

Cong, Lin William, Beibei Li, and Qingquan Tony Zhang. 2021. “Alternative Data in FinTech and Business Intelligence.” In The Palgrave Handbook of FinTech and Blockchain, edited by Maurizio Pompella and Roman Matousek, 217–42. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-66433-6_9.

Corvellec, Hervé, Alison F. Stowell, and Nils Johansson. 2022. “Critiques of the Circular Economy.” Journal of Industrial Ecology 26 (2): 421–32. https://doi.org/10.1111/jiec.13187.

Cressy, Robert, and Otto Toivanen. 2001. “Is There Adverse Selection in the Credit Market?” Venture Capital 3 (3): 215–38. https://doi.org/10.1080/13691060110052104.

Csaszar, Felipe, and Thomas Steinberger. "Organizations as Artificial Intelligences: The Use of Artificial Intelligence Analogies in Organization Theory." Academy of Management Annals ja (2021).

Dastile, X., T. Celik, and M. Potsane. 2020. “Statistical and Machine Learning Models in Credit Scoring: A Systematic Literature Survey.” Applied Soft Computing 91: 106263. https://doi.org/10.1016/j.asoc.2020.106263.

De Cnudde, Sofie, Julie Moeyersoms, Marija Stankova, Ellen Tobback, Vinayak Javaly, and David Martens. 2019. “What Does Your Facebook Profile Reveal about Your Creditworthiness? Using Alternative Data for Microfinance.” Journal of the Operational Research Society 70 (3): 353–63. https://doi.org/10.1080/01605682.2018.1434402.

Dell'Era, Claudio, et al. "Four kinds of design thinking: From ideating to making, engaging, and criticizing." Creativity and Innovation Management 29.2 (2020): 324-344.

Dedehayir, Ozgur, and Martin Steinert. "The hype cycle model: A review and future directions." Technological Forecasting and Social Change 108 (2016): 28-41.

Di Maggio, Marco, Dimuthu Ratnadiwakara, and Don Carmichael. 2022. “Invisible Primes: Fintech Lending with Alternative Data.” Working Paper. Working Paper Series. National Bureau of Economic Research. https://doi.org/10.3386/w29840.

Di Vaio, Assunta, Rosa Palladino, Rohail Hassan, and Octavio Escobar. 2020. “Artificial Intelligence And Business Models in The Sustainable Development Goals Perspective: A Systematic Literature Review.” Journal of Business Research 121 (December): 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019.

Dorst, Kees. "The core of ‘design thinking’and its application." Design studies 32.6 (2011): 521-532.

Dresch, Aline, Daniel Pacheco Lacerda, and José Antônio Valle Antunes. "Design science research." Design science research. Springer, Cham, (2015). 67-102.

Duan, Yanqing, John S. Edwards, and Yogesh K. Dwivedi. "Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda." International Journal of Information Management 48 (2019): 63-71.

Elsbach, Kimberly D., and Ileana Stigliani. "Design thinking and organizational culture: A review and framework for future research." Journal of Management 44.6 (2018): 2274-2306.

Eling, Katrin, Abbie Griffin, and Fred Langerak. 2016. “Consistency Matters in Formally Selecting Incremental and Radical New Product Ideas for Advancement.” Journal of Product Innovation Management 33 (S1): 20–33. https://doi.org/10.1111/jpim.12320.

Elkington, John. 1998. “Partnerships from Cannibals with Forks: The Triple Bottom Line of 21st-Century Business.” Environmental Quality Management 8 (1): 37–51. https://doi.org/10.1002/tqem.3310080106.

Erhard, Laura, Brett McBride, and Adam Safir. "A framework for the evaluation and use of alternative data in the consumer expenditure surveys." Monthly Lab. Rev. 144 (2021): 1.

Etikan, Ilker. 2016. “Comparison of Convenience Sampling and Purposive Sampling.” American Journal of Theoretical and Applied Statistics 5 (1): 1–4. https://doi.org/10.11648/j.ajtas.20160501.11.

Fehrer, Julia A., and Heiko Wieland. 2021. “A Systemic Logic for Circular Business Models.” Journal of Business Research 125 (March): 609–20. https://doi.org/10.1016/j.jbusres.2020.02.010.

Fielding, Nigel, and Margrit Schreier. 2001. “Introduction: On the Compatibility between Qualitative and Quantitative Research Methods.” Forum Qualitative Sozialforschung / Forum: Qualitative Social Research 2 (1). https://doi.org/10.17169/fqs-2.1.965.

Gallego-Schmid, Alejandro, Han-Mei Chen, Maria Sharmina, and Joan Manuel F. Mendoza. 2020. “Links between Circular Economy and Climate Change Mitigation in the Built Environment.” Journal of Cleaner Production 260 (July): 121115. https://doi.org/10.1016/j.jclepro.2020.121115.

Garrido, Angel L., Susana Sangiao, and Oscar Cardiel. "Improving the generation of infoboxes from data silos through machine learning and the use of semantic repositories." International Journal on Artificial Intelligence Tools 26.05 (2017): 1760022.

George, Gerard, Ryan K. Merrill, and Simon JD Schillebeeckx. "Digital sustainability and entrepreneurship: How digital innovations are helping tackle climate change and sustainable development." Entrepreneurship Theory and Practice 45.5 (2021): 999-1027.

Geissdoerfer, Martin, Sandra Naomi Morioka, Marly Monteiro de Carvalho, and Steve Evans. 2018. “Business Models and Supply Chains for The Circular Economy.” Journal of Cleaner Production 190 (July): 712–21. https://doi.org/10.1016/j.jclepro.2018.04.159.

Geissdoerfer, Martin, Marina P.P. Pieroni, Daniela C.A. Pigosso, and Khaled Soufani. 2020. “Circular Business Models: A Review.” Journal of Cleaner Production 277 (December): 1–17. https://doi.org/10.1016/j.jclepro.2020.123741.

Geissdoerfer, Martin, Paulo Savaget, Nancy M. P. Bocken, and Erik Jan Hultink. 2017. “The Circular Economy – A New Sustainability Paradigm?” Journal of Cleaner Production 143 (February): 757–68. https://doi.org/10.1016/j.jclepro.2016.12.048.

Geissdoerfer, Martin, Doroteya Vladimirova, and Steve Evans. 2018. “Sustainable Business Model Innovation: A Review.” Journal of Cleaner Production 198 (October): 401–16. https://doi.org/10.1016/j.jclepro.2018.06.240.

Gephart, Robert P. 2004. “Qualitative Research and the Academy of Management Journal.” Academy of Management Journal 47 (4): 454–62. https://doi.org/10.5465/amj.2004.14438580.

Ghoreishi, Malahat, and Ari Happonen. 2020. “New Promises AI Brings into Circular Economy Accelerated Product Design: A Review on Supporting Literature.” Edited by E. Baltrėnaitė-Gedienė and C. Iticescu. E3S Web of Conferences 158: 06002. https://doi.org/10.1051/e3sconf/202015806002.

Giacomin, Joseph. "What is human centred design?." The Design Journal 17.4 (2014): 606-623.

Gioia, Dennis A., Kevin G. Corley, and Aimee L. Hamilton. 2013. “Seeking Qualitative Rigor in Inductive Research: Notes on the Gioia Methodology.” Organizational Research Methods 16 (1): 15–31. https://doi.org/10.1177/1094428112452151.

Gioia, Dennis A., Kevin G. Corley, and Aimee L. Hamilton. "Seeking qualitative rigor in inductive research: Notes on the Gioia methodology." Organizational research methods 16.1 (2013): 15-31.

Glikson, Ella, and Anita Williams Woolley. 2020. “Human Trust in Artificial Intelligence: Review of Empirical Research.” Academy of Management Annals 14 (2): 627–60. https://doi.org/10.5465/annals.2018.0057.

Goel, Akanksha, and Shailesh Rastogi. 2021. “Credit Scoring of Small and Medium Enterprises: A Behavioural Approach.” Journal of Entrepreneurship in Emerging Economies 15 (1): 46–69. https://doi.org/10.1108/JEEE-03-2021-0093.

Gregory, Robert Wayne, Ola Henfridsson, Evgeny Kaganer, and Harris Kyriakou. 2021. “The Role of Artificial Intelligence and Data Network Effects for Creating User Value.” Academy of Management Review 46 (3): 534–51. https://doi.org/10.5465/amr.2019.0178.

Hacklin, Fredrik, Christian Marxt, and Fritz Fahrni. "An evolutionary perspective on convergence: inducing a stage model of inter-industry innovation." International Journal of Technology Management 49.1-3 (2010): 220-249.

Hansen, Kristian Bondo, and Christian Borch. "Alternative data and sentiment analysis: Prospecting non-standard data in machine learning-driven finance." Big Data & Society 9.1 (2022): 20539517211070701.

Hansen, Kristian Bondo, and Christian Borch. 2022. “Alternative Data and Sentiment Analysis: Prospecting Non-Standard Data in Machine Learning-Driven Finance.” Big Data & Society 9 (1): 20539517211070701. https://doi.org/10.1177/20539517211070701.

Hartmann, Philipp Max, Mohamed Zaki, Niels Feldmann, and Andy Neely. 2016. “Capturing Value from Big Data – A Taxonomy of Data-Driven Business Models Used by Start-up Firms.” International Journal of Operations & Production Management 36 (10): 1382–1406. https://doi.org/10.1108/IJOPM-02-2014-0098.

Hevner, Alan, and Samir Chatterjee. "Design science research in information systems." Design research in information systems. Springer, Boston, MA, 2010. 9-22.

Hilb, Michael. "Toward artificial governance? The role of artificial intelligence in shaping the future of corporate governance." Journal of Management and Governance 24.4 (2020): 851-870.

Ince, Huseyin, and Bora Aktan. 2009. “A Comparison of Data Mining Techniques for Credit Scoring in Banking: A Managerial Perspective.” Journal of Business Economics and Management 10 (3): 233–40. https://doi.org/10.3846/1611-1699.2009.10.233-240.

Iyer, Rajkamal, Asim Ijaz Khwaja, Erzo F. P. Luttmer, and Kelly Shue. 2016. “Screening Peers Softly: Inferring the Quality of Small Borrowers.” Management Science 62 (6): 1554–77. https://doi.org/10.1287/mnsc.2015.2181.

Jagtiani, Julapa, and Catharine Lemieux. 2019. “The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform.” Financial Management 48 (4): 1009–29. https://doi.org/10.1111/fima.12295.

Javaid, Mohd, et al. "Artificial intelligence applications for industry 4.0: A literature-based study." Journal of Industrial Integration and Management 7.01 (2022): 83-111.

Jones, Nicola. 2017. “How Machine Learning Could Help to Improve Climate Forecasts.” Nature 548 (7668). https://go.gale.com/ps/i.do?p=HRCA&sw=w&issn=00280836&v=2.1&it=r&id=GALE%7CA501590693&sid=googleScholar&linkaccess=abs.

Kannengiesser, Udo, and John S. Gero. "Design thinking, fast and slow: A framework for Kahneman’s dual-system theory in design." Design Science 5 (2019).

Karlan, Dean, and Jonathan Zinman. 2009. “Observing Unobservables: Identifying Information Asymmetries With a Consumer Credit Field Experiment.” Econometrica 77 (6): 1993–2008. https://doi.org/10.3982/ECTA5781.

Keen, Peter, and Ronald Williams. 2013. “Value Architectures for Digital Business: Beyond the Business Model.” MIS Quarterly 37 (2): 643–47. https://doi.org/10.1007/s11301-020-00185-7.

Kemp, Ayenda. 2023. “Competitive Advantages through Artificial Intelligence: Toward a Theory of Situated AI.” Academy of Management Review, April. https://doi.org/10.5465/amr.2020.0205.

Khandelwal, Komal, and Ashwani Kumar Upadhyay. "The advent of artificial intelligence-based coaching." Strategic HR Review (2021).

Kitchin, Rob. 2014. The Data Revolution: Big Data, Open Data, Data Infrastructures and Their Consequences. SAGE.

Kirchherr, Julian, Denise Reike, and Marko Hekkert. 2017. “Conceptualizing the Circular Economy: An Analysis of 114 Definitions.” Resources, Conservation and Recycling 127 (December): 221–32. https://doi.org/10.1016/j.resconrec.2017.09.005.

Kimbell, Lucy. "Rethinking design thinking: Part I." Design and culture 3.3 (2011): 285-306.

Laasch, Oliver. 2018. “Beyond The Purely Commercial Business Model: Organizational Value Logics and The Heterogeneity of Sustainability Business Models.” Long Range Planning 51 (1): 158–83. https://doi.org/10.1016/j.lrp.2017.09.002.

Lee, Hoesung, Katherine Calvin, Dipak Dasgupta, Gerhard Krinner, Aditi Mukherji, Peter Thorne, Christopher Trisos et al. "IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland." (2023): 1-34.

Leipold, Sina, Anna Petit-Boix, Anran Luo, Hanna Helander, Machteld Simoens, Weslynne S. Ashton, Callie W. Babbitt, et al. 2023. “Lessons, Narratives, and Research Directions for a Sustainable Circular Economy.” Journal of Industrial Ecology 27 (1): 6–18. https://doi.org/10.1111/jiec.13346.

Leonardi, Paul M. "When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies." MIS quarterly (2011): 147-167.

Lichtenthaler, Ulrich. "Agile innovation: the complementarity of design thinking and lean startup." International Journal of Service Science, Management, Engineering, and Technology (IJSSMET) 11.1 (2020): 157-167.

Liedtka, Jeanne. "Perspective: Linking design thinking with innovation outcomes through cognitive bias reduction." Journal of product innovation management 32.6 (2015): 925-938.

Liu, Jiajia, Xuerong Li, and Shouyang Wang. 2020. “What Have We Learnt from 10 Years of Fintech Research? A Scientometric Analysis.” Technological Forecasting and Social Change 155 (June): 120022. https://doi.org/10.1016/j.techfore.2020.120022.

Liu, Qinglan, Adriana Hofmann Trevisan, Miying Yang, and Janaina Mascarenhas. 2022. “A Framework of Digital Technologies for the Circular Economy: Digital Functions and Mechanisms.” Business Strategy and the Environment 31 (5): 2171–92. https://doi.org/10.1002/bse.3015.

Lu, Tian, Yingjie Zhang, and Beibei Li. 2023. "Profit vs. Equality? The Case of Financial Risk Assessment and A New Perspective on Alternative Data." MIS Quarterly, Forthcoming, January. https://doi.org/10.2139/ssrn.3758120.

Lüdeke-Freund, Florian, and Krzysztof Dembek. 2017. "Sustainable Business Model Research and Practice: Emerging Field or Passing Fancy?" Journal of Cleaner Production 168 (December): 1668–78. https://doi.org/10.1016/j.jclepro.2017.08.093.

Lüdeke-Freund, Florian, Stefan Gold, and Nancy M. P. Bocken. 2019. "A Review and Typology of Circular Economy Business Model Patterns." Journal of Industrial Ecology 23 (1): 36–61. https://doi.org/10.1111/jiec.12763.

Magnani, Giovanna, and Denny Gioia. 2023. "Using The Gioia Methodology in International Business and Entrepreneurship Research." International Business Review 32 (2): 1–22. https://doi.org/10.1016/j.ibusrev.2022.102097.

Marquez, Robert. 2002. "Competition, Adverse Selection, and Information Dispersion in the Banking Industry." The Review of Financial Studies 15 (3): 901–26. https://doi.org/10.1093/rfs/15.3.901.

Massa, Lorenzo, Christopher L. Tucci, and Allan Afuah. 2017. "A Critical Assessment of Business Model Research." Academy of Management Annals 11 (1): 73–104. https://doi.org/10.5465/annals.2014.0072.

McAfee, Andrew, and Erik Brynjolfsson. 2017. Machine, Platform, Crowd: Harnessing Our Digital Future. W. W. Norton & Company.

Merriam, Sharan B., and Elizabeth J. Tisdell. 2016. "Qualitative Research: A Guide to Design and Implementation." NIDA, 147.

Misselhorn, Catrin. "Artificial systems with moral capacities? A research design and its implementation in a geriatric care system." Artificial Intelligence 278 (2020): 103179.

Mitchell, Tom. 1997. “Machine Learning”. McGraw Hill.

Monk, Ashby, Marcel Prins, and Dane Rook. 2019. “Rethinking Alternative Data in Institutional Investment.” The Journal of Financial Data Science 1 (1): 14–31. https://doi.org/10.3905/jfds.2019.1.1.014.

Montes, Gabriel Axel, and Ben Goertzel. "Distributed, decentralized, and democratized artificial intelligence." Technological Forecasting and Social Change 141 (2019): 354-358.

Morseletto, Piero. 2020. “Targets for a Circular Economy.” Resources, Conservation and Recycling 153 (February): 104553. https://doi.org/10.1016/j.resconrec.2019.104553.

Murphy, K.P., 2022. Probabilistic machine learning: an introduction. MIT press.

Nagorny, Kevin, et al. "Big data analysis in smart manufacturing: A review." International Journal of Communications, Network and System Sciences 10.3 (2017): 31-58.

Nambisan, Satish, Mike Wright, and Maryann Feldman. "The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes." Research Policy 48.8 (2019): 103773.

Nemati, Hamid R., et al. "Knowledge warehouse: an architectural integration of knowledge management, decision support, artificial intelligence and data warehousing." Decision Support Systems 33.2 (2002): 143-161.

Nishant, Rohit, Mike Kennedy, and Jacqueline Corbett. "Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda." International Journal of Information Management 53 (2020): 102104.

Novak, Andrej, Daniel Bennett, and Tomas Kliestik. "Product decision-making information systems, real-time sensor networks, and artificial intelligence-driven big data analytics in sustainable Industry 4.0." Economics, Management and Financial Markets 16.2 (2021): 62-72.

Parker, Brian, and Christian Bach. "The synthesis of blockchain, artificial intelligence and internet of things." European Journal of Engineering and Technology Research 5.5 (2020): 588-593.

Parida, Vinit, David Sjödin, and Wiebke Reim. 2019. “Reviewing Literature on Digitalization, Business Model Innovation, and Sustainable Industry: Past Achievements and Future Promises.” Sustainability 11 (2): 391. https://doi.org/10.3390/su11020391.

Pham, D. T., and P. T. N. Pham. "Artificial intelligence in engineering." International Journal of Machine Tools and Manufacture 39.6 (1999): 937-949.

Philippon, Thomas. 2015. “Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation.” American Economic Review 105 (4): 1408–38. https://doi.org/10.1257/aer.20120578.

Porter, Michael E. 1985. “Technology and Competitive Advantage.” Journal of Business Strategy 5 (3): 60–78. https://doi.org/10.1108/eb039075.

Richardson, James E. 2005. “The Business Model: An Integrative Framework for Strategy Execution.” SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.2139/ssrn.932998.

Ritchie, Hannah. 2021. “Many countries have decoupled economic growth from CO2 emissions, even if we take offshored production into account” Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/co2-gdp-decoupling' on January 18, 2024

Riedl, Mark O. "Human‐centered artificial intelligence and machine learning." Human Behavior and Emerging Technologies 1.1 (2019): 33-36.

Rolan, Gregory, et al. "More human than human? Artificial intelligence in the archive." Archives and Manuscripts 47.2 (2019): 179-203.

Romero, Peter, and Stephen Fitz. 2021. “The Use of Psychometrics and Artificial Intelligence in Alternative Finance.” In The Palgrave Handbook of Technological Finance, edited by Raghavendra Rau, Robert Wardrop, and Luigi Zingales, 511–87. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-65117-6_21.

Rosnow, Ralph L., and Robert Rosenthal. 1991. “If You’re Looking at the Cell Means, You’re Not Looking at Only the Interaction (Unless All Main Effects Are Zero).” Psychological Bulletin 110 (3): 574–76. https://doi.org/10.1037/0033-2909.110.3.574.

Rothschild, MICHAEL, and JOSEPH Stiglitz. 1978. “17 - EQUILIBRIUM IN COMPETITIVE INSURANCE MARKETS: AN ESSAY ON THE ECONOMICS OF IMPERFECT INFORMATION. In Uncertainty in Economics, edited by PETER

Diamond and MICHAEL Rothschild, 257–80. Academic Press. https://doi.org/10.1016/B978-0-12-214850-7.50024-3.

Russell, S. and Norvig, P., 2021. Artificial Intelligence: A Modern Approach. Instructor, 202105.

Sachs, Jeffrey D., Guido Schmidt-Traub, Mariana Mazzucato, Dirk Messner, Nebojsa Nakicenovic, and Johan Rockström. 2019. “Six Transformations to Achieve The Sustainable Development Goals.” Nature Sustainability 2 (9): 805–14. https://doi.org/10.1038/s41893-019-0352-9.

Saito, Kuniyoshi, and Daisuke Tsuruta. 2018. “Information Asymmetry in Small and Medium Enterprise Credit Guarantee Schemes: Evidence from Japan.” Applied Economics 50 (22): 2469–85. https://doi.org/10.1080/00036846.2017.1400651.

Sangupamba, Odette Mwilu, Nicolas Prat, and Isabelle Comyn-Wattiau. "Business intelligence and big data in the cloud: opportunities for design-science researchers." International Conference on Conceptual Modeling. Springer, Cham, 2014.

Schaltegger, Stefan, Florian Lüdeke-Freund, and Erik G. Hansen. 2016. “Business Models for Sustainability: A Co-Evolutionary Analysis of Sustainable Entrepreneurship, Innovation, and Transformation.” Organization & Environment 29 (3): 264–89. https://doi.org/10.1177/1086026616633272.

Schuelke-Leech, Beth-Anne. "A model for understanding the orders of magnitude of disruptive technologies." Technological Forecasting and Social Change 129 (2018): 261-274.

Schröder, Patrick, Kartika Anggraeni, and Uwe Weber. 2018. “The Relevance of Circular Economy Practices to the Sustainable Development Goals.” Journal of Industrial Ecology 23 (February): 77–95. https://doi.org/10.1111/jiec.12732.

Sick, Nathalie, and Stefanie Bröring. "Exploring the research landscape of convergence from a TIM perspective: A review and research agenda." Technological Forecasting and Social Change (2021): 121321.

Singh, Sushil Kumar, Shailendra Rathore, and Jong Hyuk Park. "Blockiotintelligence: A blockchain-enabled intelligent IoT architecture with artificial intelligence." Future Generation Computer Systems 110 (2020): 721-743.

Sodhi, ManMohan S., et al. "Why emerging supply chain technologies initially disappoint: Blockchain, IoT, and AI." Production and Operations Management (2022).

Spence, MICHAEL. 1978. “18 - JOB MARKET SIGNALING.” In Uncertainty in Economics, edited by PETER Diamond and MICHAEL Rothschild, 281–306. Academic Press. https://doi.org/10.1016/B978-0-12-214850-7.50025-5.

Stahel, Walter R. 2016. “The Circular Economy.” Nature 531 (7595): 435–38. https://doi.org/10.1038/531435a.

Stubbs, Wendy, and Chris Cocklin. 2008. “Conceptualizing a ‘Sustainability Business Model.’” Organization & Environment 21 (2): 103–27. https://doi.org/10.1177/1086026608318042.

Sufi, Amir. 2007. “Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans.” The Journal of Finance 62 (2): 629–68. https://doi.org/10.1111/j.1540-6261.2007.01219.x.

Tan, Tianhui, Prasanta Bhattacharya, and Tuan Phan. 2016. “Credit-Worthiness Prediction in Microfinance Using Mobile Data: A Spatio-Network Approach.” ICIS 2016 Proceedings, December. https://aisel.aisnet.org/icis2016/EBusiness/Presentations/28.

Teece, David J. 2010. “Business Models, Business Strategy and Innovation.” Long Range Planning, Business Models, 43 (2): 172–94. https://doi.org/10.1016/j.lrp.2009.07.003.

Thakor, Anjan V. 2020. “Fintech and Banking: What Do We Know?” Journal of Financial Intermediation 41 (January): 100833. https://doi.org/10.1016/j.jfi.2019.100833.

Thomas, Lyn C. 2000. “A Survey of Credit and Behavioural Scoring: Forecasting Financial Risk of Lending to Consumers.” International Journal of Forecasting 16 (2): 149–72. https://doi.org/10.1016/S0169-2070(00)00034-0.

Thoring, Katja, and Roland M. Müller. "Understanding design thinking: A process model based on method engineering." DS 69: Proceedings of E&PDE 2011, the 13th International Conference on Engineering and Product Design Education, London, UK, 08.-09.09. 2011. 2011.

Townsend, David M., and Richard A. Hunt. 2019. “Entrepreneurial Action, Creativity, & Judgment in The Age of Artificial Intelligence.” Journal of Business Venturing Insights 11 (June): 1–8. https://doi.org/10.1016/j.jbvi.2019.e00126.

Trunk, Anna, Hendrik Birkel, and Evi Hartmann. "On the current state of combining human and artificial intelligence for strategic organizational decision making." Business Research 13.3 (2020): 875-919.

Vendrell-Herrero, Ferran, Glenn Parry, Oscar F. Bustinza, and Emanuel Gomes. 2018. "Digital Business Models: Taxonomy and Future Research Avenues." Strategic Change 27 (2): 87–90. https://doi.org/10.1002/jsc.2183.

Verbeke, Alain, and Thomas Hutzschenreuter. 2021. "The Dark Side of Digital Globalization." Academy of Management Perspectives 35 (4): 606–21. https://doi.org/10.5465/amp.2020.0015.

Verganti, Roberto, Luca Vendraminelli, and Marco Iansiti. 2020. "Innovation and Design in the Age of Artificial Intelligence." Journal of Product Innovation Management 37 (3): 212–27. https://doi.org/10.1111/jpim.12523.

Vickrey, William. 1961. "Counterspeculation, Auctions, and Competitive Sealed Tenders." The Journal of Finance 16 (1): 8–37. https://doi.org/10.2307/2977633.

Vinuesa, Ricardo. 2020. "The Role of Artificial Intelligence in Achieving the Sustainable Development Goals | Nature Communications." https://www.nature.com/articles/s41467-019-14108-y.

Vinuesa, Ricardo, Hossein Azizpour, Iolanda Leite, Madeline Balaam, Virginia Dignum, Sami Domisch, Anna Felländer, Simone Daniela Langhans, Max Tegmark, and Francesco Fuso Nerini. 2020. "The Role of Artificial Intelligence in Achieving the Sustainable Development Goals." Nature Communications 11 (1): 1–10. https://doi.org/10.1038/s41467-019-14108-y.

Vives, Xavier. 2019. "Digital Disruption in Banking." Annual Review of Financial Economics 11 (1): 243–72. https://doi.org/10.1146/annurev-financial-100719-120854.

Wagdi, Osama, and Yasmeen Tarek. 2022. “The Integration of Big Data and Artificial Neural Networks for Enhancing Credit Risk Scoring in Emerging Markets: Evidence from Egypt.” International Journal of Economics and Finance 14 (January): 32. https://doi.org/10.5539/ijef.v14n2p32.

Weber, Michael, Moritz Beutter, Jörg Weking, Markus Böhm, and Helmut Krcmar. 2022. “AI Startup Business Models.” Business & Information Systems Engineering 64 (1): 91–109. https://doi.org/10.1007/s12599-021-00732-w.

Weller, Amanda J. "Design Thinking for a user-centered approach to artificial intelligence." She Ji: The Journal of Design, Economics, and Innovation 5.4 (2019): 394-396.

Williams, Michael, and Tami Moser. 2019. “The Art of Coding and Thematic Exploration in Qualitative Research.” International Management Review 15 (1): 45–72.

Zhang, Lifeng, Xiangrui Chao, Qian Qian, and Fuying Jing. 2022. “Credit Evaluation Solutions for Social Groups with Poor Services in Financial Inclusion: A Technical Forecasting Method.” Technological Forecasting and Social Change 183 (October): 121902. https://doi.org/10.1016/j.techfore.2022.121902.

Zink, Trevor, and Roland Geyer. 2017. “Circular Economy Rebound.” Journal of Industrial Ecology 21 (3): 593–602. https://doi.org/10.1111/jiec.12545.