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Industry 4.0 Technologies and Customer-centricity for Digital Supply Chains

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“The best way to predict the future is to invent it.”
— Alan Kay

To the loving memory of my partner Kilian Schindler, a truly exceptional man.
For his unconditional love, strength, and support, and who will remain my inspiration.

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Abstract

The last few years have experienced the emergence of the fourth industrial revolution (Industry 4.0, I4.0), ultra-customization, as well as the explosion of demand for ethical, fair trade and sustainable consumption. For industrial organizations, these trends offer new opportunities and challenges in order to adapt to the consumer demand evolution, and to optimize the supply chain (SC) accordingly. To cope with this, organizations have recently started a digital transformation of their SCs and production. To do so, consumers are being placed at the center of companies' strategic agenda. In the context of ultra-customization, mass customization (MC) is gaining momentum, especially with the arrival on the market of digital technologies like additive manufacturing (AM), also known as 3D-printing. This technology was originally used, since 1988, for prototyping. Due to technological advances, it is now very popular for the final part production in series, and on a large scale. AM could bring current MC practices up to date. SC performance is, among others, driven by operational excellence, information sharing and trust between the different SC stakeholders. Looking at the second trend, which is focused on new consumption patterns, organizations are now encouraged to evaluate the potential of adopting new digital I4.0 technologies. In particular, the combination of Blockchain (BC) with the Internet-of-Things (IoT) seems promising to improve SC performance and meet customer demand. Despite the recognized potential of emerging I4.0 technologies, and the transition toward digital SCs (DSCs), organizations are struggling to adapt to the trend of ultra-customization, and the ethical, fair trade, and sustainable consumption one. This is mainly due to the lack of decision support tools for these new technologies' adoption, and to the lack of user-centric approaches.

Therefore, in this thesis, we develop user-centric approaches from which we model and analyze the impact of three I4.0 digital technologies on the SC. First, we develop a new demand model, the "*HLB model*", taking into account the individual demand of heterogeneous customers. This model is the first, to our knowledge, to model both the heterogeneity of customers and the evolution of their purchasing behavior over time. It couples the *Bass diffusion* and the *Hotelling-Lancaster* models. This combination allows to incorporate the product life cycle (PLC) in the demand model. Then, building on the *HLB model*, we analyze, across the PLC, marketing and operations decisions which result from technology-switching scenarios (between AM and MC). We formulate and solve an optimization problem by jointly deciding on: technology-switching times, inventory, production quantity, pricing, and product

variety strategies. The goal is to maximize a manufacturer's profit, while addressing the individual and evolving needs of customers. We use a "*sample average approximation*" for the numerical solutions of our non-convex optimization problem. Based on an *adaptive inventory policy*, we derive a closed-form solution for the production quantity decision. Our results demonstrate that the new usage of AM with MC, and a user-centric approach, can benefit a manufacturer. Significant profit improvements can be achieved with a hybrid AM-MC-AM technology-switching production scenario, with specific dynamic pricing policies, and under certain production capacity conditions. Second, we adopt a three-step approach to discover the BC IoT success conditions for lean and agile SCs: (i) a *multivocal literature review* (MLR), (ii) a *topic modeling* to categorize the success factors (SFs) identified in the literature, and (iii) associate the categories of SFs to the *SC macro-processes* for *lean* and *agile* SCs, respectively. Our findings are summarized into a conceptual framework and research propositions. This last study is a first step toward a better understanding of BC and IoT benefits for lean and agile SCs. It offers valuable insights into when and how the sweet spots for both SC types would materialize in practice, as well as their impacts with respect to the SC macro-processes performance.

Key words: Additive Manufacturing; Mass Customization; Customer Preferences; Blockchain; Internet-of-Things; Lean and Agile Supply Chains

Résumé

Ces dernières années ont connu l'émergence de la quatrième révolution industrielle (Industrie 4.0, I4.0), de l'ultra-personnalisation, ainsi que de l'explosion de la demande pour consommer éthique, équitable et durable. Pour les organisations industrielles, ces tendances offrent de nouvelles opportunités et défis d'adaptation à l'évolution de la demande des consommateurs, et d'optimisation de la chaîne d'approvisionnement (*supply chain*, SC). Pour y répondre, les organisations ont récemment entamé une transformation digitale de leurs SCs, et de leur production. Pour ce faire, les consommateurs sont placés au centre de la réflexion stratégique des entreprises. Dans le contexte d'ultra-personnalisation, la personnalisation de masse (*supply chain*, MC) prend de plus en plus d'ampleur, notamment avec l'arrivée sur le marché de technologies digitales comme la fabrication additive (*additive manufacturing* (AM), aussi connue sous le nom d'impression 3D). Cette technologie était originellement utilisée, depuis 1988, pour faire du prototypage. Grâce aux avancées technologiques, elle est maintenant très prisée pour la production de pièces finies en série et à grande échelle. L'AM pourrait mettre au goût du jour les pratiques actuelles de MC. La performance de la SC est, entre autre, basée sur l'excellence opérationnelle, le partage d'information et la confiance entre les différents acteurs impliqués dans cette chaîne. Si l'on se penche sur la deuxième tendance qui est axée sur de nouveaux modes de consommation, les organisations sont désormais conduites à évaluer le potentiel d'adoption de nouvelles technologies digitales de l'I4.0. En particulier, la combinaison de la Blockchain (BC) avec l'Internet des objets (IoT) semble prometteuse pour améliorer la performance de la SC et répondre à la demande client. Malgré le potentiel reconnu des technologies émergentes de l'I4.0, et la transition vers des SCs digitales, les organisations peinent à s'adapter aux tendances d'ultra-personnalisation et de consommation éthique, équitable et durable. La raison étant principalement liée au manque d'outils d'aide à la décision pour l'adoption de ces nouvelles technologies, et de développements d'approches centrées utilisateurs.

Dans cette thèse, nous développons des approches centrées utilisateurs à partir desquelles nous modélisons et analysons l'impact de trois technologies digitales de l'I4.0 sur la SC. Dans un premier temps, nous développons un nouveau modèle de demande, le "*HLB model*", prenant en compte la demande individuelle de consommateurs hétérogènes. Ce modèle est le premier à pouvoir modéliser à la fois l'hétérogénéité des consommateurs, ainsi que l'évolution de leur comportement d'achat au cours du temps. Il couple le modèle de diffusion

de *Bass* et le modèle *Hotelling-Lancaster*. Ce couplage permet d'incorporer le cycle de vie du produit dans le modèle de demande. Ensuite, à partir du *HLB model*, nous analysons les décisions marketing et opérationnelles au travers de scénarios de changement de technologies (entre AM et MC) tout au long du cycle de vie du produit (PLC). Nous formulons et résolvons un problème d'optimisation en décidant simultanément : des temps de changement de technologies, d'inventaires et de quantités de production, de stratégies de prix, et de variété de produits. Le but étant de maximiser le profit d'un producteur, tout en répondant aux besoins individuels et évolutifs des consommateurs. Nous utilisons une "*sample average approximation*" pour les solutions numériques de notre problème d'optimisation non convexe. Basée sur une politique d'inventaire adaptative, nous dérivons une solution analytique pour la décision de quantité de production. Nos résultats démontrent que le nouvel usage d'AM avec l'utilisation de MC, et une approche centrée utilisateurs, peuvent être bénéfiques pour un producteur. Des augmentations significatives de profit peuvent être obtenues à partir d'un scénario de production hybride de type AM-MC-AM, avec des politiques de prix dynamiques spécifiques, et sous certaines conditions de capacités de production. Dans un second temps, nous adoptons une approche en trois étapes pour découvrir les conditions et facteurs de succès (SFs) pour l'adoption de la BC et de l'IoT pour l'amélioration de la SC. Ces étapes consistent en: (i) une "*revue de littérature multivocale*", (ii) une modélisation thématique (*topic modeling*) pour catégoriser les facteurs de succès (SF) identifiés dans la littérature, et (iii) un alignement des catégories de facteurs de succès avec les macro-process des SCs lean et agiles. Nos résultats sont résumés au sein d'un modèle conceptuel et de propositions de recherche. Cette dernière étude est un premier pas vers une meilleure compréhension des avantages d'adoption de la BC et de l'IoT pour les SCs de types lean et agiles. Elle offre des indications précieuses sur la manière dont les "sweet spots" se matérialiseraient en pratique pour les deux types de SC, ainsi que sur l'impact de ces "sweet spots" sur la performance des macro-process des SCs.

Mots clefs: Fabrication Additive; Personnalisation de Masse; Préférences des Consommateurs; Blockchain; Internet des Objets; Supply Chains Lean et Agiles

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1 Introduction

With the arrival of the fourth industrial revolution, Industry 4.0 (I4.0), organizations are facing the emergence of connected, intelligent and advanced technologies (*e.g.*, Additive Manufacturing (AM), Blockchain (BC), and Internet-of-Things (IoT)), to serve the digital transformation and disrupt traditional business models. The technological advances have implicitly led to an increase in user expectations. Consumers are therefore even more demanding. They expect their placed orders to be fully personalized, fulfilled and delivered quickly. These two related trends are forcing companies to rethink and redesign their supply chains (SCs). To gain competitiveness, productivity, cost reduction, business growth and customer satisfaction, it is therefore necessary to develop and adopt a user-centric approach, which is gradually spreading within companies. It is also crucial to evaluate the potential and relevance of these new digital technologies. To avoid a mismatch between supply and demand, customer-centric technology management decisions must be aligned with business strategies. As a result, a progressive digitalization of traditional linear supply chains is occurring, a phenomenon which is referred to as *Digital Supply Chain* (DSC). Ageron et al. (2020) define the DSC as: "the development of information systems and the adoption of innovative technologies strengthening the integration and the agility of the supply chain and thus improving customer service and sustainable performance of the organization." Hence, challenges and opportunities related to DSC are receiving considerable attention from decision makers.

The two main goals of this thesis are to investigate how to leverage: user-centric approaches and emerging I4.0 technology enablers, in order to optimize the SC performance. For this purpose, we focus on three specific I4.0 technology enablers, namely: AM, BC, and IoT, at the marketing-operations interface.

1.1 Customer-centric Demand Models

Both demand and supply perspectives are equally important to rethink the SC. To be able to react to market changes, demand modeling is an essential tool for SC design. Several types of demand models have been developed over the years. Practitioners and academics have

recently investigated customer-centric strategies, recognized to drive business value. In this context and to address product customization, demand models that tackle heterogeneity and individual needs are particularly appealing. In the marketing and operations literature, utility-based demand models are typically used to study assortment problems. In this research area, Kök et al. (2015) provide a detailed review of demand models which consider customer heterogeneity. The multinomial logit (MNL) and locational choice are the prevalent models. These models are utility-based demand functions for which consumers are assumed to be rational utility maximizers (*i.e.*, they will opt for the purchasing action that maximizes their utility). In the MNL model, the utility is decomposed into deterministic and random components. Due to its analytical properties, this model has been used to deal with pricing and assortment selection issues (Aydin and Porteus 2008). In their work, Gaur and Honhon (2006) indicate that: "the locational choice model was originally developed by Hotelling (1929) to study the pricing and location decisions of competing firms". Since then, variants of the Hotelling model have been developed, such as the *Hotelling-Lancaster* model (also known as "characteristics models" or "address models"), which assumes uniformly distributed customers on a continuous virtual product space. The Hotelling-Lancaster model transposes the Hotelling model to a context of product differentiation. Lancaster (1990) offers an excellent review of them, and Gaur and Honhon (2006) provide a comprehensive comparison between the MNL and locational choice models.

For tractability reasons, most of the demand models mentioned above do characterize consumer needs at the individual level but in a static setting. They typically do not account for forward-looking (strategic) customers, *i.e.*, customers who choose their purchasing time by trading off between the benefits of buying the product and their expectations on future product prices (Song and Chintagunta 2003). Customers are generally not only variant-sensitive in their purchasing decisions, but also time-sensitive. They do not necessarily purchase the product at the same time. This is why other demand models, such as the diffusion of innovation model known as the *Bass model* (Bass 1969), focus on modeling the product life cycle (PLC) and, thus, indirectly, the evolution of consumer needs over time. The PLC concept is a concept which was introduced in the seminal article by Dean (1976). The *Bass model* is intended to predict the continued acceptance of a new product over time (Mahajan et al. 1990). It is based on the famous "bell-shaped" normal distribution, where the curve represents the frequency of customers purchasing a product over time. Diffusion models (see detailed review by Mahajan et al. (2000)) are very popular in the marketing and operations literature and have been explored and extended in numerous studies: with discrete customer choice models (Lobel et al. 2015), with pricing strategies (Shen et al. 2013), with supply constraints (Ho et al. 2002); see Peres et al. (2010) for a thorough review. Chatterjee and Eliashberg (1990), Song and Chintagunta (2003) developed micro-modeling diffusion approach (*i.e.*, demand modeled at the individual level). They highlighted the added-value of this approach for customer segmentation in terms of purchasing times.

1.2 Hybrid Mass Customization Manufacturing Practice

Two models are commonly used to determine customer preferences (Jiang et al. 2006), namely: *vertical differentiation* (based on quality and price discrimination) and *horizontal differentiation* (based on varying customer tastes for a product, *e.g.* diversifying shapes and colors of eyeglasses). For manufacturers producing horizontally differentiated custom products, mass customization (MC) is of particular interest to them since it aims to address individual customer preferences. Manufacturers commonly use *mass production* (MP), a less flexible production technology compared to MC (Alptekinoğlu and Corbett 2008), but known to provide efficiency at lower costs. Indeed, MP offers a limited set of products while MC can, ideally, offer an infinite variety of products. MC refers to both strategies and flexible manufacturing systems. Anderson (2004) defines MC as "the ability to design and manufacture customized products at mass production efficiency and speed." In his work, (Berman 2012, Table 1) compares and contrasts AM and traditional MC systems.

Due to technological advancements, new manufacturing opportunities disrupting traditional MC systems have emerged. For instance, *additive manufacturing* (AM, also referred to as 3D-printing) is now capable of producing final parts in series, at large scale, and across different industries. This practice is known as Rapid Manufacturing (RM) (Campbell et al. 2020). AM is thus increasingly adopted for this purpose (*e.g.*, Riddell (2019), an American football equipment provider who 3D-prints custom helmet liners; see AFMG (2020) for other applications), and helps meeting higher customization requirements from customers. AM, which has been used since 1988 for rapid prototyping (Hon 2007), has the potential to rejuvenate the MC movement. Its new usage, *i.e.* RM, has increased significantly from 3.9% of AM's total market to 60.9% (Campbell et al. 2020). Although AM and traditional MC systems are both capable of producing custom final parts cost-effectively, these two processes display technology and cost-specific features, as well as different customization capabilities (Dong et al. 2020b). For this reason, AM is not likely to replace traditional MC processes, but rather to supplement them (Holweg 2015, Rogers et al. 2016, AFMG 2020). The combination of AM and traditional MC processes could lead to a cost-effective hybrid manufacturing practice to achieve MC at large scale while addressing individual customer preferences.

In addition to this hybrid manufacturing practice, hybrid production modes could emerge as a consequence. Typically, if a company offers a high product variety to the customers, a shift from a Make-To-Stock (MTS) to a Make-To-Order (MTO) production mode normally occurs (Dobson and Yano 2002). This implies taking into account inventory decisions and capacity constraints. The literature on pricing and production control under capacity constraints usually focuses on inventory control where a demand distribution is assumed to be known and stationary. Only few studies (*e.g.*, Hadley and Whitin (1961), Kurawarwala and Matsuo (1996)) consider consumer goods exhibiting non-stationary demand (*i.e.*, when the demand probability function changes over time). Later on, Graves (1999) and Yang and Kim (2018) presented *adaptive inventory* models with non-stationary demand.

1.3 Blockchain with IoT for Lean and Agile Supply Chains

In the previous section, we highlighted the rise of customer expectations over the years. After recent scandals related to the recall of contaminated or defective products, deplorable working conditions in some countries (*e.g.*, Bapna (2012)), and the awareness of climate change, customers are now more sensitive to ethical, fair trade, and green sustainability practices. Companies are therefore implementing new strategies to meet these customer demands, and to digitalize their SCs for enhanced transparency, efficiency and flexibility. DSCs operate I4.0 technology enablers. BC is one of them and the cornerstone of the emerging "trust economy", in which the SC plays a central role. Another I4.0 technology enabler is IoT, which is along BC one of the most current hot topics. BC allows digital data to be stored in a cryptographically secured and decentralized manner, leading to essentially tamper-proof transactions (Chouli et al. 2017). Globally, IoT link the physical and digital worlds together in a distributed network of devices communicating both with each other and with SC stakeholders. Pairing BC and IoT seems promising to drive SC performance. BC enables privacy, security and reliability, while IoT convert the physical world into valuable information. It is therefore not surprising that this technology combination for the SC has recently received much attention (see the thirty-five compelling use cases highlighted by Yusuf et al. (2018b)) to enhance traceability and reliability across the whole chain, both internally, upstream, and downstream in the SC.

However, not all SCs are designed to produce the same product types (functional vs. innovative products), and thus to serve the same consumer segments (Agarwal et al. 2006, PwC 2012). Different SC types have hence been developed (Fisher 1997), for which strategies specific to each type are implemented to meet the consumer demand. Two SC types are typically adopted: *lean* (also called *efficient*) and *agile* (also called *responsive*). Chopra et al. (2013) provide a comparison of lean and agile SCs. Vonderembse et al. (2006) and Agarwal et al. (2006) also mention a third SC type called *hybrid* and *leagile*, respectively. Hybrid SC is a combination of lean and agile supply chains (a comprehensive description can be found in Naylor et al. (1999)). Although SC performance relies on strategic, operational and IT alignments, no study, to our knowledge, has considered the differentiation between lean and agile SCs for the adoption of BC and IoT.

1.4 Contributions and Structure of the Thesis

The thesis is structured as follows.

Chapter 2 investigates a novel customer-centric hybrid mass customization manufacturing opportunity, both from the demand and supply sides. To broaden our understanding of how AM can complement traditional manufacturing systems, we develop an exploratory quantitative model. First, we leverage customer-centricity in a novel time-varying locational choice model of heterogeneous customers, coupling the Bass and the Hotelling-Lancaster models. Then, we investigate customer-centric marketing and operations decisions, exploring technology-

switching scenarios that interchange AM with traditional MC systems across the PLC. We formulate and solve an optimization problem by jointly deciding on technology-switching times, pricing, and product variety strategies to maximize a monopolist manufacturer's profit and meet individual customers' diverse and evolving needs. We use a validated sample average approximation approach for the numerical solution of our non-convex optimization problem, and derive analytical properties for the optimal pricing policy. The material underlying Chapter 2 originates from the following working paper.

- Rachel Lacroix, Ralf W. Seifert, Anna Timonina-Farkas. Benefiting from Additive Manufacturing for Mass Customization across the Product Life Cycle. Available at *SSRN 3719793*. Submitted to *Operations Research Perspectives*, 2021.

Chapter 3 builds on Chapter 2 to further explore the customer-centric hybrid manufacturing practice, this time with the addition of inventory decisions under MC technology, production decisions, and the consideration of capacity constraints under both AM and MC processes. We address this opportunity through a mathematical model that considers a monopolist manufacturer producing horizontally differentiated products at scale. To satisfy individual customer preferences, under PLC and capacity considerations, the firm jointly optimizes the following decisions: inventory, production quantity, product variety, optimal technology-switching times (between AM and MC), and pricing policy. Our approach can be implemented by decision-makers to leverage customer-centricity and benefit from this novel hybrid manufacturing practice. We derive a closed-form solution for the production quantity decision based on an adaptive inventory policy. We solve the resulting non-convex optimization problem using the sample average approximation framework, and derive analytical results. The material underlying Chapter 3 originates from the following working paper.

- Rachel Lacroix, Anna Timonina-Farkas, Ralf W. Seifert. Utilizing Additive Manufacturing and Mass Customization under Capacity Constraints. Available at *SSRN 3737989*. *Working paper*, École Polytechnique Fédérale de Lausanne (EPFL), 2021.

Chapter 4 sheds light on lean and agile BC IoT SC sweet spots and conditions from a SC-driven perspective. We uncover the relevance and conditions for BC and IoT adoption in lean and agile DSCs through a three-step approach: (i) we conduct a multivocal literature review, (ii) perform a topic modeling to categorize the success factors (SFs) identified in the literature, and (iii) associate the categories of SFs to the SC macro-processes for lean and agile SCs, respectively. Our results build on a holistic view of the BC and IoT SFs, stemming from a SC-driven adoption perspective. The findings are summarized through a sweet spot conceptual framework and research propositions. The material underlying Chapter 4 originates from the following working paper.

- Rachel Lacroix, Christopher L. Tucci, Ralf W. Seifert. Blockchain of Things Sweet Spot

for Lean and Agile Digital Supply Chains. *Working paper*, École Polytechnique Fédérale de Lausanne (EPFL), 2021.

Chapter 5 distills the key insights of the thesis and outlines future research directions.

1.5 Statement of Originality

I hereby certify that the content of this thesis is the product of my own work with some assistance from my supervisor Prof. Ralf W. Seifert as well as my co-authors Dr. Anna Timonina-Farkas and Prof. Christopher L. Tucci.

2 Benefiting from Additive Manufacturing across the Product Life Cycle

Additive manufacturing (AM) was initially designed for prototyping and product personalization, where high production quantities were not required. Now, it is also implemented for final part production to achieve cost-effective mass customization (MC). Thanks to its tool-less production and extreme flexibility, AM has the potential to address individual customer preferences with custom final parts. Nevertheless, despite its increased competitiveness, AM is not yet likely to replace traditional MC systems, but it can complement them, improving manufacturing efficiency. To broaden our understanding of how AM can complement traditional manufacturing systems, we develop an exploratory quantitative model. First, we leverage customer-centricity in a novel time-varying locational choice model of heterogeneous customers, coupling the Bass and the Hotelling-Lancaster models. Then, we investigate customer-centric marketing and operations decisions, exploring technology-switching scenarios that interchange AM with MC across the product life cycle (PLC). We formulate and solve an optimization problem by jointly deciding on technology-switching times, pricing, and product variety strategies to maximize a manufacturer's profit and meet individual customers' diverse and evolving needs. We use a validated Sample Average Approximation approach for the numerical solution of our non-convex optimization problem. Testing different pricing strategies, we show that decreasing and flexible trajectories are optimal. We derive analytical properties for the optimal pricing policy and demonstrate that a manufacturer can benefit from interchanging AM and MC across the PLC, in particular by adopting an AM-MC-AM scenario

2.1 Introduction

The term "mass customization" (MC) was first coined in 1987 by Davis (1990). It refers to both strategies and technologies and several definitions of MC—sometimes conflicting—have been developed over the years. To avoid confusion, we define MC as "the ability to design and manufacture customized products at mass production efficiency and speed" (Anderson 2004, p. 271) to deliver variety and customization from a certain number of product base configurations at near mass production (MP) prices (Kwok et al. 2017). MP typically refers to a

manufacturing system running at high capacity utilization and building on economies of scale to "produce and deliver more of the same design of a given product or service by defraying the fixed cost with higher production quantities" (Tseng and Jiao 2001).

For manufacturers, MC means higher product variety with traditional flexible manufacturing systems. High product variety yields increased production costs due to tooling switchovers and mold creation for each new product variant. In this chapter, we use the term "mass-customized" to refer to the parts produced with the traditional MC technology. For customers, MC implies unique products matching their personal preferences. Recently, there has been renewed interest in MC due to emerging Industry 4.0 technology enablers, such as additive manufacturing (AM) (also referred to as 3D printing), pushing into the market (Olsen and Tomlin 2020) and having the potential to drive MC forward. In this chapter, we build on Berman (2012)'s comparison between AM and MC and cover the main differences between the technology-specific fixed and variable cost structures, as well as the degree of product variety. Table 2.2 summarizes the comparison of the key features between AM and MC technologies.

AM is spreading across different industries. For instance, Carbon, the world's leading Digital Manufacturing Platform, announced a partnership with Adidas to produce 3D-printed midsoles in 2017, and Riddell, the American football equipment provider, recently began 3D-printing custom helmet liners (Riddell 2019). Historically, AM was used for prototyping, but recent technological developments have also made it appealing for rapid manufacturing (RM, described as "the use of additive manufacturing (AM) technologies for final part production" (Deradjat and Minshall 2017)). According to an industrial report by Wohlers Associates (2017), the use of AM for RM has grown massively from 3.9% to 60.6% of total product and service revenues. AM has become a common option for RM: 61% of respondents use more than 10% of AM processes to produce final parts. For simplicity, AM includes RM throughout this chapter.

Despite the advantages of AM, researchers and industry experts have concluded that it is not likely to replace traditional MC processes. Instead, according to some (Holweg 2015, Rogers et al. 2016, Sasson and Johnson 2016, AFMG 2020), it complements today's traditional manufacturing processes to increase manufacturing efficiency and product value for customers. Currently, for as long as printing speed constitutes the major barrier to AM adoption for large production volumes, MC remains the technology of choice. Utilizing the complementary features of AM and MC over the product life cycle (PLC) in a technology-switching scenario (between these two technologies) can be a solution. Therefore, we follow the AFMG (2020) industry expert recommendation to evaluate the benefits of this emerging manufacturing practice for product customization at scale. Accordingly, we formulate the following research question: *How can a manufacturer quantify the economic benefits of complementing AM for final part production with an existing traditional MC technology under PLC considerations?*

Sub-questions: (i) *How can the PLC dynamics in a demand model based on customer preferences be captured? What are the effects of accounting for the PLC on technology-switching scenarios and profit maximization?* (ii) *What is the optimal technology-switching scenario to adopt?* (iii) *Which pricing policy should be applied and what is its impact on profit?* (iv) *What is the optimal number of product variants to offer under MC?*

Since technology-switching scenarios between AM and MC do not yet exist in practice, and in light of increasing interest from academics and practitioners, we develop an exploratory quantitative model. We consider a monopolist manufacturer who aims to maximize his profit while addressing individual customer preferences over a discrete-time selling horizon and under a MC manufacturing setting. We build and solve a non-convex customer-centric optimization problem that jointly optimizes the technology-switching times (between AM and MC), pricing, and product variety decisions over the PLC. We believe that no authors to date have studied this combined problem. Our research questions require customer heterogeneity, forward-looking behavior, and PLC dynamics, all of which are decisive for firms, to be taken into account. Customers' preferences differ depending on matters of taste. Customers are also sensitive to the selling price and their purchasing behavior evolves over time. We thus consider *horizontal product differentiation* (*e.g.*, diversifying shapes and colors of eyeglasses), which is a common practice for addressing varying customer tastes.

On the demand side, we leverage customer-centricity in a novel time-varying locational customer choice model that we refer to as the *Hotelling-Lancaster-Bass* (HLB) model. The HLB model combines the Hotelling-Lancaster (HL) and Bass diffusion models. This combination offers the advantages of both modeling the demand of heterogeneous customers at the individual level and mimicking the PLC dynamics. To the best of our knowledge, no previous studies combine these two models. We believe this new demand model can add to studies that consider heterogeneous customers at the individual level when modeling the diffusion of a new product (Chatterjee and Eliashberg 1990, Song and Chintagunta 2003).

On the supply side, our approach compares two flexible manufacturing technologies (AM and MC). This study substantiates the importance of technology-switching decision making highlighted in previous works (Hayes and Wheelwright 1979, Ramasesh et al. 2010) in maintaining the compatibility between the technology choice and the PLC stage. It also contributes to the literature on the impact of AM on operations management and on MC.

We believe our model and the derived managerial insights can assist academics and practitioners in quantifying the economic benefits of new customer-centric marketing and hybrid production strategies for the disruptive application of AM in Industry 4.0. This study explores both demand and supply perspectives in a dynamic setting. To summarize, this study brings two major contributions: a new time-varying locational customer choice model that considers customer heterogeneity, forward-looking behavior, and PLC dynamics; and the joint optimization of customer-centric technology-switching times, pricing, and product variety decisions over the PLC. We adopt an innovative approach to solve our non-convex optimization problem, where the convergence of the solution is proven theoretically. Numerical experiments further confirm the validity of our solution approach and highlight the benefits of and conditions for interchanging AM and MC over the PLC.

The rest of our chapter is structured as follows. In Section 3.2 we review the related literature. We describe the model in Section 3.3, and explain the solution approach and analytical results in Section 2.4. We present our numerical findings and managerial insights in Sections 2.5 and 2.6, respectively.

2.2 Literature Review

In our research, we aim to find optimal technology-switching times, pricing trajectories, and product variety in order to maximize a manufacturer's profit. Three main research streams are relevant to our work: The first centers on analytical models that investigate the impact of AM on operations and supply chain management (SCM); the second stream examines marketing and production decisions for product line design; and the third focuses on PLC decisions and the development of new product diffusion models.

A growing body of literature examines the advantages and challenges of AM for manufacturing strategies (*e.g.*, Attaran (2017), Westerweel et al. (2018a,b), Sethuraman et al. (2018), Chen et al. (2021)). According to Weller et al. (2015), one of the main benefits of AM resides in the flexibility of production and the customization of products without manufacturing cost penalties. Several recent studies outline the potential of this technology on SCM (*e.g.*, Sodhi and Tang (2017)). Although our work is, to the best of our knowledge, the first analytical framework to quantify the economic impact of AM on joint technology-switching, pricing, and product variety decision making, there are articles that analyze other aspects of AM. We review a sample of the analytical models that investigate the impact of AM on operations and SCM. Most of this emerging literature focuses on spare parts logistics (Westerweel et al. 2018a, Song and Zhang 2020), consumer goods retailing (Chen et al. 2021), component design cost analysis (Westerweel et al. 2018b), and assortment planning (Dong et al. 2020a). The framework of Song and Zhang (2020) is among the first in the operations management literature to scrutinize the impact of AM. They show that on-demand 3D-printed parts lead to significant cost savings and inventory reduction. Westerweel et al. (2018a) numerically examine, in a continuous time setting, the impact of conventional manufacturing and AM on spare parts production and assume that printed parts are of inferior quality.

Our work also compares AM and traditional manufacturing, but instead of considering them as production systems for supplying spare parts, we model both technologies with the aim of delivering final parts. Song and Zhang (2020) and Westerweel et al. (2018a) do not consider the market value of MC, whereas our model jointly optimizes marketing and production decisions and is related to the recent work of Dong et al. (2020a), who study the impact of AM on a firm's manufacturing strategy. They analyze three types of manufacturing technologies: AM, traditional flexible, and dedicated (a process that can produce only one product variant) technologies. They focus on product assortment decisions under capacity constraints and demonstrate that the combination of AM and a dedicated technology allows wider product variety with profit improvement.

Our research focuses on AM and MC without considering a dedicated technology since it does not allow customization at a low cost and involves high setup costs. We consider the production and customization of horizontally differentiated products and use a locational model instead of the multinomial logit (MNL) model to describe customer preferences. A comparison between the MNL and locational choice models is given in Gaur and Honhon (2006). More broadly, details on demand models that can be applied to assortment planning can be found in Kök et al. (2015). In this stream of literature, our chapter extends the work of

Dong et al. (2020a) to include technology-switching and pricing decisions. We also build on the work of Chen et al. (2021), which considers two adoption cases of AM in a dual-channel retail setting (online and in-store channels) and studies the firm's joint decision about products offered, prices, and inventory. Instead of modeling heterogeneous customers' preferences via a circular model (Salop 1979), we extend the classic HL model to include PLC considerations. Contributing to the product line design and MC literature (Lancaster (1998), Ramdas (2003), Kök et al. (2015)), our work considers the perspectives of both the manufacturer and the customer. Although a large number of studies focus on the reliability and cost of 3D-printed products (*e.g.*, Thomas and Gilbert (2014), Baumers et al. (2016)), only a few articles investigate the business and operations management implications. To quantify the economic implications arising from our novel hybrid production strategy combining AM with MC, we explore a customer-centric technology-switching scenario across the PLC. The importance of satisfying individual customer needs is emphasized in the work of Merle et al. (2010).

Further, in the literature related to build-to-stock (BTS) and build-to-order (BTO) policies, some works have examined quantitative models that jointly consider marketing and production decisions (*e.g.*, Alptekinoğlu and Corbett (2008), Sethuraman et al. (2018)). Jiang et al. (2006) study a MC system consisting of an initial BTS phase and a final BTO phase, and evaluate marketing, production, and pricing decisions. They compare mass production and MC and assess the possible benefits of MC technology. Chen et al. (2021) determine, for two adoption cases, the impact of AM on a firm's product offering, and incorporate the firm's pricing and inventory decisions to show that AM increases product variety offered online and leads to a price premium for online customers. In our article, we extend the classic locational model on customers' preferences that uses willingness-to-pay and disutility functions (see Lancaster (1998)) with time-varying and utility-based demand. We also contribute to the MC literature but do not consider the competition between a mass producer and a customizer (*e.g.*, Alptekinoğlu and Corbett (2008), Mendelson and Parlaktürk (2008), Xia and Rajagopalan (2009)).

Two dimensions particularly relevant to our work are the PLC—concept introduced in the seminal article by Dean (1976)—and diffusion models. These concepts are widely used in the marketing literature (see the detailed review in Mahajan et al. (2000)). The well-known diffusion model described in Bass (1969) aims to time the purchase of new products. It is commonly used to forecast demand and has multiple extensions: For example, diffusion models with supply constraints (Ho et al. 2002), with pricing strategies (Shen et al. 2013), and with discrete customer choice models (Lobel et al. 2015); see Peres et al. (2010) for a thorough review. Our work reinforces the product diffusion literature and links production technologies to PLC. In the operations management literature, few researchers have addressed the interdependency between manufacturing processes and PLC, except for Hayes and Wheelwright (1979) with their product-process matrix, which emphasizes the need for the technology-switching to maintain manufacturing performance. Ramasesh et al. (2010) extend this literature by developing an analytical model to guide the technology-switching decision when the PLC uncertainty is included. Some papers (*e.g.*, Chatterjee and Eliashberg (1990), Van den Bulte and Stremersch (2004)) develop "micromodeling" diffusion models by specifying purchasing

decisions at the individual level. However, the work of Peres et al. (2010) outlines that *"the interface between the individual level and the aggregate level still lacks a closed formulation and needs further exploration."* In our work, we couple the HL framework with the Bass diffusion process to develop a new time-varying locational customer choice model to capture the influence of heterogeneous customer preferences on the three decisions that we aim to optimize.

Our chapter proposes original insights in several aspects. None of the papers referenced so far incorporate the PLC dimension in the utility function to handle the dynamics of the market environment. We consider both marketing and production decisions, the interdependency between the two flexible manufacturing systems (MC and AM), and the PLC.

2.3 Model Framework

In this section, we derive an analytical model that optimizes technology-switching times, pricing, and the product-variety decisions of a manufacturer in possession of AM and MC technologies over a finite horizon. We propose a customer-centric utility-based demand model able to incorporate a product misfit and mimic a PLC on a random customer population. The solution we construct combines the Bass and HL models through a specific utility function formulation. Table G.1 summarizes our key notations and parametric assumptions.

Table 2.1 – Notations and Parametric Assumptions.

Parameters		Assumptions
N	: Initial market size of potential adopters	$N \in \mathbb{N}$
Ξ	: *i.i.d.* random population of customers	$(\xi_i)_{1 \le i \le N}$
T	: Length of the finite selling horizon	$T \in \mathbb{N}$
t	: Current time period	$1 \le t \le T$
$\mathscr{T}$	: Set of technology-switching scenarios characterized by a pair of technology-switching times $(T_{A\to M}, T_{M\to A})$	$\mathscr{T} \in \{T_{A\to M}, T_{M\to A}\}^T$
$T_{A\to M}$	: Technology-switching time when the manufacturer switches from AM to MC	$0 \le T_{A\to M} < T_{M\to A}$
$T_{M\to A}$	: Technology-switching time when the manufacturer switches from MC to AM	$T_{A\to M} < T_{M\to A} < T+1$
$T_{A\leftrightarrow M}$	: Technology-switching times $T_{A\to M}$ and $T_{M\to A}$	
Φ	: Virtual space of horizontally differentiated products	$\Phi = [0,1]$
ξ	: Random customer characterized by τ and ϕ	$\xi = (\tau, \phi)$ with $\mathbb{P}_\xi = \mathbb{P}_\tau \otimes \mathbb{P}_\phi$
τ	: Customer's ideal buying time	$F_\tau(t) = \frac{F_B(t\frac{t_{max}}{T})}{(1-\varepsilon)}$
ϕ	: Customer's ideal product variant	$\mathbb{P}_\phi = \mathscr{U}([0,1])$
F_B	: Bass cumulative distribution function (cdf)	$F_B(u) = \frac{(1-\exp(-(p+q)u)}{(1+\frac{q}{p}\exp(-(p+q)u)}$
p, q	: Bass innovation and imitation coefficients, respectively	$p, q \in \mathbb{R}^+$
t_{max}	: Truncation value for the Bass infinite selling horizon	$t_{max} = F_B^{-1}(1-\varepsilon)$ where $\varepsilon > 0$ s.t. $F_B^{-1}(1-\varepsilon) \sim 1$
n	: Number of product variants to offer to customers under MC	$1 \le n \le n_{max}$
x_j	: Location of product variant j on the virtual product space	$0 \le x_j \le 1$
$\mathscr{X}$	: Set of product variants available to customers for purchase under MC technology	$\mathscr{X} = \{x_1, \dots, x_n\} \subset [0,1]^n$
w	: Customer's willingness-to-pay	$\omega : [0,T] \to \mathbb{R}^+$
p_t	: Selling price at time period t	$0 \le p_t \le max\{0, U^{\mathscr{T}}\}$, $\forall j \in \Phi$
γ	: Buying time-sensitivity coefficient	$\gamma : [0,T] \to \mathbb{R}^+$
λ	: Product variant sensitivity coefficient, incurred only under MC technology	$\lambda : [0,T] \to \mathbb{R}^+$
$U^{\mathscr{T}}(\xi, t)$	: Customer's utility at time period t, dependent on the technology-switching scenario, $\mathscr{T}$	See (3.1)

Given the complexity of the study, several assumptions are needed and explained. In Section 2.3.1, we present the manufacturing scenarios that we aim to analyze and describe MC and AM technologies. In Section 2.3.2, we outline the market demand and customer preference model. Section 2.3.3 presents the cost structures and profit functions of AM and MC. Section 2.3.4 introduces the optimization problem.

2.3.1 Mass Customization and Additive Manufacturing Description and Scenarios

(Berman 2012, Table 1) compares and contrasts AM and MC, and describes traditional MC processes as relying on: "pre-assembled modular parts in different combinations or delayed differentiation" based on individual customer specifications. Although both AM and MC are capable of producing final parts cost-effectively, AM presents a higher degree of flexibility and directly prints singular parts based on unique customer designs. Compared with MC, it also offers the advantages of reducing production costs for small production volumes (no tooling investment) and allowing individual customization of products without "per product variety" additional costs (Weller et al. 2015, Attaran 2017). In this chapter, we build on the comparison

between AM and MC and cover the following main differences: (i) the technology-specific fixed and variable cost structures, and (ii) the product variety degree. Table 2.2 reports the key features that distinguish AM from MC in our study. In particular, we make the following assumptions: (i) as argued in (Dong et al. 2020a), 3D printers and AM raw materials are expensive and, thus, AM incurs a higher setup cost during the first time period the technology is used (Alptekinoğlu and Corbett 2008); (ii) following Weller et al. (2015), the marginal cost of AM is constant, whereas the corresponding MC cost increases linearly according to the number of product variants offered to customers; (iii) AM perfectly serves its customers in terms of product variants and, thus, the manufacturer incurs no "per-product" variety cost; (iv) conversely, MC offers product variants within a limited horizontally differentiated product space since traditional flexible technologies (*i.e.*, MC here) are commonly designed to manufacture a specific set of product variants, as reported in Dong et al. (2020a); and (v) the customer's ideal product location is used to compute a product misfit penalty cost which decreases the customer's utility.

Table 2.2 – MC vs. AM technology key features comparison.

Technology production features	**MC**	**AM**
Fixed setup cost	k_M	k_A, where $k_A > k_M$
Variable production cost	$c_M(n) = c_b(1 + (n-1)\delta)$, where $c_M(n) > 0$ (identical for all product variants)	$c_A > 0$ (constant)
Product misfit penalty cost	$\lambda(\tau)d(\phi, \mathscr{X})$, see (3.1)	No product variant misfit. The customer is served perfectly in terms of product variant.

Further, we assume that each product can be produced by either MC or AM technology. Wohlers Associates (2017) report that AM is economically viable when employed for small batch sizes and custom parts. Thus, a firm could potentially receive revenues from final parts produced on AM equipment, in a series production context. AM is typically more suitable at the beginning and end of the PLC because it is typically used to manufacture products for fewer customers. As demand increases, AM becomes less profitable because the production cost of MC is lower (see Section 2.3.3). Thus, we will not consider the $MC \rightarrow AM \rightarrow MC$ strategy. Instead, we investigate the five following manufacturing scenarios to quantify the economic benefits of using AM in complement of MC systems, or alone.

Base case (BC): The manufacturer uses ***MC*** technology only;

Case 1 (C1): ***AM*** → ***MC*** scenario, which implies AM during the product launch only;

Case 2 (C2): ***MC*** → ***AM*** scenario, for which AM is only used for the PLC decline phase;

Case 3 (C3): ***AM*** → ***MC*** → ***AM*** scenario resulting from the combination of (C1) and (C2);

Case 4 (C4): ***AM*** during the whole selling horizon.

We compare (BC) with (C1) to analyze the impact of AM on the product's launch phase, when demand has not yet peaked but when "innovators" (a term coined in the Bass diffusion model to describe the first consumers to buy) are most sensitive to product variants. Then, we contrast (C2) with (BC) to scrutinize the effect of combining AM with MC in a context where the manufacturer adopts MC during the initial and growth phase of the PLC. Then, we look at (C3), where the manufacturer reverts to AM for the PLC decline phase, during which AM is less costly because demand volume is declining, but customers might still seek highly customized parts. In (C4), we investigate the use of AM being employed during the entire selling period because it is more attractive from both the manufacturer's and the customers' perspectives.
We make a number of assumptions in what follows. The 3D-printed and mass-customized goods are available equally quickly. Producing one product variant requires one unit of common raw material under both MC and AM technologies. The product quality is considered equivalent under both manufacturing systems. No price discrimination is assumed for horizontally differentiated variants of the same product (following Alptekinoğlu and Corbett (2010)). The two manufacturing systems present fundamentally different characteristics and structural product line designs as shown in Sections 2.3.2 and in 2.3.3.
Sales occur during a finite number T of selling periods. At each period $\{t\}_{t=1}^{T}$, the product price is set by the firm at $p(t)$. A pair of switching times $(T_{A\to M}, T_{M\to A})$, with $0 \le T_{A\to M} < T_{M\to A} \le T+1$, defines whether period t is under MC ($T_{A\to M} < t \le T_{M\to A}$) or AM ($t \le T_{A\to M}$ or $t > T_{M\to A}$). A switching time is defined as the last time period at which the former technology was used. We denote by $\mathscr{T}$, $\mathscr{T} \in \{T_{A\to M}, T_{M\to A}\}^{T}$, the set of technology-switching scenarios, which consists of switching times $T_{A\to M}$ (when the manufacturer switches from AM to MC) and $T_{M\to A}$ (when the manufacturer switches from MC to AM). We assume AM and MC to be flexible technologies, hence capable of customizing products with a high degree of flexibility.

Additive manufacturing: AM, which is assumed to be fully flexible, is able to offer an infinite variety of customized goods in the product space. When customers buy at the tth period with $\mathscr{T}(t) = AM$, they are served perfectly—that is their product preferences are matched. We assume that AM follows a BTO (build-to-order) production approach (Chen et al. 2021). As soon as the 3D-prints are ready, they are immediately delivered to customers with no lead time.

Mass customization: The degree of flexibility of MC technology is finite. It can only handle a limited number of product variants, n (following the assumption of Dong et al. (2020a)). Thus, at the tth period with $\mathscr{T}(t) = MC$, customers will not be served perfectly, and the firm needs to decide the number of variants to offer as well as their customization type. The maximum number of product variants, n_{max}, to offer to customers with this technology is set by the manufacturer. Based on the assumption of Chen et al. (2021), we assume that MC technology (like AM) follows a BTO (build-to-order) approach. Production capacity restrictions and inventory aspects are beyond the scope of this chapter.

2.3.2 Demand and Customer Preferences

The market size, N, represents the initial number of total potential adopters of a new product and is defined as a deterministic parameter for simplicity. We consider a discrete-time, finite selling horizon. We assume that an increase in product variety yields no additional operating costs for AM. Thus, we focus on customer tastes rather than product qualities: this leads to horizontal product differentiation. We consider forward-looking consumer heterogeneity to capture individual customer purchasing behavior, defined by a utility-based demand model. The forward-looking behavior affects the shape of the product sales pattern (see Chatterjee and Eliashberg (1990)) and has implications for managerial insights as it induces price dynamics in the market. To this end, we attribute random ideal buying time and ideal product location to each customer. Then, we generate a time-varying utility incorporating time and product misfit penalty costs (see (3.1)), which influences the customer's decision on whether or not to buy a product (see Kök et al. (2015)). Customers' decisions are independent of each other, and the manufacturer decides on a selling price for each time period, maximizing the profit.
Our model is based on a combination of (i) an HL approach to consider individual preferences in terms of product attributes, and (ii) a Bass innovation diffusion model to capture customer heterogeneity in the ideal buying time over the PLC. Hence, our model offers the advantages of both modeling the heterogeneous customers' demand at the individual level and mimicking the PLC dynamics.

HL framework: The HL model assumes the horizontal product differentiation in a virtual space and describes a customer's ideal product, in particular along a Hotelling segment (see Ulu et al. (2012) for more details). Products are characterized by the attributes most relevant to consumers. A firm offers a catalogue of product variants on this segment, sets their locations and prices, and pays a fixed cost per item. The model assumes a uniform density of customers in a continuous product space. It considers non-uniform locations of customers, who are assumed to be utility maximizers.

Bass diffusion model: This parametric approach is used to predict time-dependent demand trajectories for new durable products (Bass 1969).
In our article, we extend the HL framework by adopting the Bass diffusion model to explicitly incorporate time-dependency into the locational choice model; we refer to our model as the **HLB model**. Although some researchers (*e.g.*, Dong et al. (2020a)) use the multinomial logit (MNL) model to capture consumer purchasing behavior to plan assortments in a product category, we adopt the locational choice model, which enables us to independently specify the degree of heterogeneity in terms of product attributes and ideal buying times. This is not possible with the MNL model.
Kök et al. (2015) explain that the key difference between the locational choice and MNL models is in product substitution, which *"can happen between any two products"* in the MNL model. By contrast, the IIA (Independence of Irrelevant Alternatives) property does not hold for the

locational choice model, for which *"substitution between products is localized to products with specifications that are close to each other."* As a result, the HL model provides more parameters to control for a manufacturer deciding the number of variants to offer as well as their locations in an attribute space.

In our **HLB model**, a random customer ξ is represented by independent random variables τ and ϕ, $\xi = (\tau, \phi)$, $\mathbb{P}_\xi = \mathbb{P}_\tau \otimes \mathbb{P}_\phi$, where τ represents the ideal buying time and ϕ the ideal product of the customer. Each customer has individual attributes that make it possible to define his/her utility at each selling period, and for both AM and MC alternatives. During the AM phase, customers are served by their exact product variant (no product misfit penalty cost is incurred). Conversely, customers are served by the nearest produced variant if the MC system is employed. We set the virtual product space containing all possible ideal products to $\Phi = [0, 1]$. We do not consider other Φ structures or the distribution of ϕ, since these topics are beyond the scope of this chapter.

A customer (τ, ϕ) has a continuous willingness-to-pay $\omega(t)$, $\omega : [0, T] \to \mathbb{R}^+$, which depends only on t. The variations of ω over the discrete selling horizon distinguish the random customer's interest along the PLC. The customer's utility decreases as the distance between the selling period t and his/her ideal buying time τ increases: This represents the customer's time misfit. Similarly, the utility decreases if the customer's ideal product ϕ is far from available products under MC technology, where $\mathscr{X} = \{x_1, \ldots, x_n\} \subset [0, 1]^n$ denotes the set of mass-customized goods. The willingness-to-pay is negatively affected in both cases. Given the selling price $p(t)$, a customer purchases only if his/her utility exceeds $p(t)$ at some selling period t. The customer buys at the first instance t of this condition. Clearly, during the AM phase, the willingness-to-pay is only affected by a buying time misfit: It is modeled by defining a buying-time sensitivity $\gamma : [0, T] \to \mathbb{R}^+$.

We compute sales at the center of tth period and define the customer's utility for period t under AM as $U^A(\xi, t) = U^A(\tau, \phi, t) = \omega(\tau)(1 - \gamma(\tau)|\tau - t|/T)$. Under MC technology, the customer's willingness-to-pay is also negatively affected by a product variant misfit; it is represented by the product variant sensitivity coefficient $\lambda(t)$ multiplied by the distance, denoted by $d(\phi, \mathscr{X})$, between the customer's ideal product ϕ, and the set of available products for sale $\mathscr{X}$. The customer's utility for the period t under MC technology is $U^M(\xi, t) = U^M(\tau, \phi, t) = \omega(\tau)\big(1 - \gamma(\tau)|\tau - t|/T - \lambda(\tau)d(\phi, \mathscr{X})\big)$. Overall, depending on the production technology, a customer ξ observes the following utility at period t:

$$U^{\mathscr{T}}(\xi, t) = U(\tau, \phi, t) = \omega(\tau)\left(1 - \gamma(\tau)\frac{|\tau - t|}{T} - \lambda(\tau)d(\phi, \mathscr{X})\mathbf{1}_{MC}(\mathscr{T}(t))\right). \tag{2.1}$$

We assume a customer buys at most one product as soon as the utility condition is satisfied.

In the Bass model, which we rely on to define ideal buying times, the selling horizon is infinite. However, we normalize this horizon to the finite number of selling periods T. For this, we use the inverse transform sampling method to simulate a random variable with the cumulative distribution function F_B, where F_B is the Bass cdf. To set our finite horizon to T, we first select $\varepsilon > 0$ such that $1 - \varepsilon$ is close to one. Then, we draw u uniformly from $[0, 1 - \varepsilon]$ (truncating to

the finite horizon) and obtain $v = F_B^{-1}(u)$. Afterwards, we normalize it as $vT/F_B^{-1}(1-\varepsilon)$. Thus, our customer's ideal buying time τ has the following cdf:

$$F_\tau(t) = \frac{F_B(t\frac{t_{max}}{T})}{(1-\varepsilon)}\,, \tag{2.2}$$

where $F_B(u) = (1-\exp(-(p+q)u)/(1+\frac{q}{p}\exp(-(p+q)u)$ is the Bass distribution according to the model, p and q are the Bass coefficients of innovation and imitation, $t_{max} = F_B^{-1}(1-\varepsilon)$.
In our HLB model, similar to the HL model, each product is characterized by a single-taste attribute—an element of Φ—and can also be described by the ratio of two attributes (see Lancaster (1998)). The customer's ideal product modeled by a random variable ϕ from the manufacturer's perspective is assumed to follow uniform distribution on Φ, denoted by $\mathbb{P}_\phi = U([0,1])$. As explained previously in this section, no product misfit penalty cost is incurred by a customer when the technology employed is AM. However, for a mass-customized good, the customer's utility is negatively affected by a product variant misfit penalty cost. Hence, we aim for a trade-off between the per-unit production cost and the product misfit penalty cost. On the one hand, if not enough mass-customized variants are offered, the penalty cost is significant because many consumers' ideal products are far from the assigned mass-customized good. On the other hand, if too many mass-customized variants are offered, the per-unit production cost is high. Therefore, we aim to optimize the number of mass-customized variants—given a maximum number of variants, n_{max}, set by the manufacturer—to include in the product catalogue.

2.3.3 Cost Structures and Profits

In this section, we examine AM and MC cost structures and profits. Without loss of generality, the costs of materials and energy consumption are normalized to zero under both technologies.
The firm incurs fixed costs, $k_A(N)$ and $k_M(N)$, that reflect the AM and MC equipment costs. In our model, the setup costs are proportional to the market size, N. Alternatively, one could apply an asymptotically converging coefficient for the setup costs. In our situation, $k_M(N)$ is a one-time fixed cost for setting up the MC system. It is counted once if $T_{A\to M} < T$ ($T_{M\to A} \in \mathcal{T}$). The fixed cost $k_A(N)$ is a setup cost for AM and counted once if $T_{A\to M} > 0$ or $T_{M\to A} < T$ ($T_{A\to M} \in \mathcal{T}$). We assume $k_A(N) \geq k_M(N)$ since 3D-printers are usually more expensive than MC equipment in accordance with the assumptions of Dong et al. (2020a). As the market size N grows, $k_A(N)/N$ and $k_M(N)/N$ should converge (a reasonable hypothesis is that both ratios are positively decreasing, for reasons of efficiency and economies of scale). For simplicity, we set $k_A(N) = Nk_A$, $k_M(N) = Nk_M$.
Further, a per-unit cost of production is denoted by c_A for AM technology and by $c_M(n)$ for MC technology, where $c_A > 0$ and $c_M(n) > 0$ (identical for all product variants). Because of AM's infinite flexibility in terms of product variants, its per-unit cost of production does not depend on the product's variety and c_A is defined as a constant marginal cost. By contrast,

the marginal cost $c_M(n) = c_b(1 + (n-1)\delta)$ depends on the number n of product variants to produce, where c_b denotes a base cost and δ represents an incremental cost, which is the cost to produce an additional product variant under MC. Adding products to the assortment means additional molds, switchover, tools, etc. We model the marginal cost of MC product's variety to be proportional to the number of MC variants. Although we set the production cost per-unit lower for MC than for AM, the total production cost increases in the number of mass-customized variants available and, thus, the MC total cost will at some point exceed the AM one.

The cost structures of AM and MC yield profits that are technology-specific. We compute the respective profit functions over an *i.i.d* population $\{\xi_i\}_{i=1}^N$ of size N, $\mathbb{P}_{\xi_i} = \mathbb{P}_\tau \otimes \mathbb{P}_\phi$. For each $1 \le t \le T$, we denote by S_t the number of completed sales at this period. For AM, we take into account a constant marginal cost, c_A, which is invariant in the product variety. The profit during period t is computed as:

$$\pi_t(p) = \begin{cases} S_t(p_t - c_A) - k_A(N), \text{ if } t = 1 \text{ and } T_{A\to M} > 0, \text{ or } t = T_{M\to A} + 1 \text{ and } T_{A\to M} = 0, \\ S_t(p_t - c_A), \text{ if } 1 < t \le T_{A\to M} \text{ or } t \ge T_{M\to A} + 1 \text{ and } T_{A\to M} > 0 \text{ or } t > T_{M\to A} + 1 \text{ and } T_{M\to A} = 0, \\ S_t(p_t - c_M(n)) - k_M(N) \text{ if } t = T_{A\to M} + 1, \\ S_t(p_t - c_M(n)) \text{ if } T_{A\to M} + 1 < t \le T_{M\to A}. \end{cases}$$

Note that $\pi_t(p) = \pi_t(\{\xi_i\}_{i=1}^N, p, T_{A\leftrightarrow M}, n)$. Then $\pi(\{\xi_i\}_{i=1}^N, p) = \sum_{t=1}^T \pi_t(\{\xi_i\}_{i=1}^N, p, T_{A\leftrightarrow M}, n)$ is the total profit over the horizon T. Also, note that:

$$\sum_{t=1}^T \pi_t(\{\xi_i\}_{i=1}^N, p, T_{A\leftrightarrow M}, n) = \sum_{i=1}^N \sum_{t=1}^T \pi_t(\xi_i, p, T_{A\leftrightarrow M}, n), \tag{2.3}$$

which we refer to as the *additivity property*.

2.3.4 Optimization Problem

By combining the profit functions under both AM and MC manufacturing technologies, we can now formulate our optimization model, aiming to maximize the manufacturer's total expected profit over a finite selling horizon. The joint decision variables are (i) the technology-switching scenario as defined by the switching times $(T_{A\to M}; T_{M\to A})$ (see Section 2.3.1), (ii) the selling price over time $p(t)$, and (iii) the number of product variants n to offer under the MC technology (if this process is selected).

If the selling price exceeds the customer's utility $U^{\mathcal{T}}(\xi, t)$, the customer cannot afford the product. Hence, the maximization of the expected profit is subject to a pricing strategy constraint $0 \le p(t) \le \max(\omega)$. We restrict the MC product assortment size to $1 \le n \le n_{max}$ for some n_{max} (following the assumption of Dong et al. (2020a)).

Given a random customer ξ, a technology-switching scenario, and a pricing policy, the *additivity property* implies that a manufacturer, on average, gains profit if he determines optimal

p, $(T_{A\to M}\,;\,T_{M\to A})$, n, solving the stochastic problem in (3.21):

$$\max_{p\in\mathscr{P}} \quad \max_{\substack{T_{A\leftrightarrow M}\in\mathscr{T}\\ 1\le n\le n_{max}}} \quad \Pi(p, T_{A\leftrightarrow M}, n) \left(= \max_{\substack{T_{A\leftrightarrow M}\in\mathscr{T}\\ 1\le n\le n_{max}}} \quad \underbrace{\max_{p\in\mathscr{P}} \quad \Pi(p, T_{A\leftrightarrow M}, n)}_{\tilde{\Pi}(p)} \right), \tag{2.4}$$

where $\Pi(p, T_{A\leftrightarrow M}, n) = \mathbb{E}[\pi(\xi, p, T_{A\leftrightarrow M}, n)]$ and $\pi(\xi, p, T_{A\leftrightarrow M}, n) = \sum_{t=1}^{T} \pi_t(\xi, p, T_{A\leftrightarrow M}, n)$. Thanks to the additivity property of the expectation and profit (see (2.3)), it follows that

$$\mathbb{E}\left[\sum_{i=1}^{N}\sum_{t=1}^{T} \pi_t(\xi_i, p, T_{A\leftrightarrow M}, n)\right] = N\mathbb{E}[\pi(\xi, p, T_{A\leftrightarrow M}, n)].$$

We use the right-hand side of (3.21) for the optimization in order to avoid optimization traps. The problem in (3.21) breaks down into two maximization problems: (i) an inner one optimized over p and (ii) an obvious outer one optimized over finitely many n's and $\mathscr{T}$'s. Thus, we focus on the inner one, omitting variations on $\mathscr{T}$ and n:

$$\max_{p\in\mathscr{P}} \quad \tilde{\Pi}(p) \tag{2.5}$$

The optimization problem (2.5) is a bilinear program with a nonlinear objective function of p, *i.e.*, it is a structured quadratic problem with the total profit depending piecewise on the pricing strategy. The work of Petrik and Zilberstein (2011) shows that solving a bilinear program optimally is NP-hard. The next section examines how we solve our optimization problem (2.5).

2.4 Solution Approach

We approximate the solution of (2.5) using the Sample Average Approximation (SAA) framework (more details can be found in Shapiro et al. (2014)) and a direct local search method, *i.e.*, Pattern Search (PS). Numerical experiments show the consistency of the SAA estimators (Sections 2.4.2 and 2.4.3) and the optimal pricing policy structure for a special case (Section 2.4.4).

2.4.1 Sample Average Approximation Framework

For a given technology-switching scenario and n, the SAA function is defined by $\hat{\Pi}_N(p) = \frac{1}{N}\pi(\{\xi_i\}_{i=1}^{N}, p)$. The strong law of large numbers (LLN) yields, by boundedness of integrands:

$$\forall p,\ \hat{\Pi}_N(p) \to \tilde{\Pi}(p),\ \Xi - a.s. \tag{LLN}$$

However, the convergence

$$\max_{p\in\mathscr{P}} \quad \hat{\Pi}_N(p) \to \max_{p\in\mathscr{P}} \quad \tilde{\Pi}(p), \tag{2.6}$$

requires a stronger hypothesis: This is where the SAA framework (see Shapiro et al. (2014) and Homem-de Mello and Bayraksan (2014)) comes in. When (2.6) is satisfied, we substitute the optimal value by the approximated maximum:

$$\max_{p\in\mathscr{P}} \quad \hat{\Pi}_N(p). \tag{2.7}$$

Note that in the above equation, the maximum of the optimization problem does not necessarily exist. However, the supremum does exist, since the profit is bounded between $-\max(c+k)$'s and $\max\omega$. The optimization problem in (2.7) can be solved using heuristics, which need to be chosen balancing accuracy and efficiency. We use a direct local search method, Pattern Search (PS), commonly used for highly irregular functions (Chinneck 2015).
We follow the notations of Shapiro et al. (2014) and denote by ϑ^* and $\mathscr{S}$ the optimal value and the set of optimal solutions of the true problem (2.5), and by ϑ^*_N and $\mathscr{S}_N$ the optimal value and the set of optimal solutions of the SAA problem (2.7). The SAA approach is validated when ϑ^*_N and $\mathscr{S}_N$ converge to their counterparts of the true problem (2.6), in which case SAA convergence holds.

2.4.2 Convergence of SAA Estimators

To prove the SAA convergence, we need to answer the following questions (for subsets $A, B \subset \mathbb{R}^m$, we define $\mathbb{D}(A,B) = \sup_{a\in A} d(a,B) = \sup_{a\in A}\inf_{b\in B} d(a,b)$):

(i) Are $\mathscr{S}, \mathscr{S}_N$ non-empty?

(ii) If (i) holds, does $\vartheta^*_N \to \vartheta^*$, Ξ almost surely?

(iii) If (i) and (ii) hold, does $\mathbb{D}(\mathscr{S}_N, \mathscr{S}) \to 0$ Ξ almost surely?

To this end, we set a condition that guarantees (i), (ii) and (iii). We denote by μ_L the Lebesgue measure on real line, and by μ_ω its image under ω, $\mu_\omega := (\mu_L)_\omega$. We define $\delta(\tau,t) = \omega(\tau)(1-\gamma(\tau)\frac{|\tau-t|}{T})$ for any time period t.

Theorem 2.1. If the following conditions hold

$$\mu_\omega \ll \mu_L; \quad \forall c,t,\ \mu_L\left(\delta(\cdot,t)^{-1}(\{c\})\right) = 0, \tag{H}$$

then (i), (ii) and (iii) are verified.

Proof. The proof relies on Theorems 7.53 and 5.3 of Shapiro et al. (2014), which require $(i-iii)$ for their conclusions to hold. Conditions (i,ii) are straightforward, and hypothesis (H) is used for (iii). Complete proof can be found in Appendix A. ∎

Remark 2.2. Condition (H) holds if ω and δ have Lebesgue almost sure non-zero derivatives.

2.4.3 Validation of Numerical Approximations, and Population Sample Size

In the following, we present the results of numerical simulations performed to test the consistency of SAA estimators ϑ_N^* and $\mathscr{S}_N$. As expected, the mean profit per customer converges as N grows (starting from $N = 2,000$, see Fig. 2.1), which is in line with our formal proof of the SAA convergence (Theorem 2.1). The optimal profit decreases as N increases, which is consistent with the positive bias as shown in (Shapiro et al. 2014, Proposition 5.6).

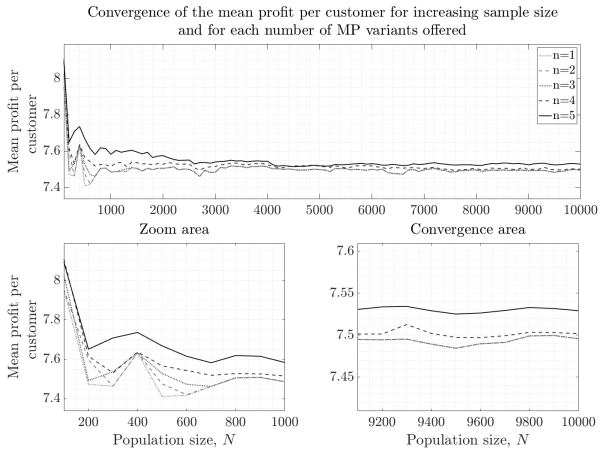


Figure 2.1 – Convergence of the mean profit per customer with the SAA framework. Parameters: $N_{max} = 10,000$, population step size = 100, $T = 12$, $p = 0.02, q = 0.6$, linear decreasing ω, $n_{max} = 5$, $k_M = 100$, $k_A = 1.5 \cdot k_M, c_b = 2, \delta = 0.06, c_A = 1.8 \cdot c_b$, flexible pricing policy.

Fig. D.1 gives additional insights for the validation of the optimal mean pricing policy and the mean sales over the selling horizon ($N = 10,000$ SAA sample paths; each population is optimized separately). The empirical cdf for normalized mean profits shows good adjustment to $\mathscr{N}(0,1)$, which, in the absence of a formal Central Limit Theorem (CLT) for the SAA approach, reinforces the validation of the sample size. We also observe similar results for the switching times $(T_{A\to M}; T_{M\to A})$ (see Fig. D.2). This justifies our choice of a population sample size $N = 10,000$, whence, the approximation of optimal strategies for the mean profit per customer is conducted on large random customer populations.

2.4.4 Policy Structure Under No Buying Time Misfit

In this subsection, we present a special case of the optimization problem, for which the analytical solution is available. It serves to analytically characterize the optimal pricing policy structure.

Lemma 2.3. Suppose $\gamma = 0$, *i.e.*, there are no buying time misfits. Given the pricing strategy p, we denote its prearrangement in decreasing order by $p^{\downarrow}$. Then, for any ξ, $\tilde{\pi}(\xi, p) \leq \tilde{\pi}(\xi, p^{\downarrow})$.

Proof. As $\gamma = 0$, the technology-switching scenario is fixed at AM and the utility is constant over all time periods. The complete proof can be found in the Appendix B. ∎

Corollary 2.4. Under the assumptions of Lemma 2.3 and if $\mu_\omega \ll \mu_L$, then Theorem 2.1 holds and the optimal pricing strategy is decreasing.

Proof. The complete proof can be found in Appendix C. ∎

2.5 Numerical Analysis

In the previous section, we proved the reliability of the SAA estimators and the pricing policy structure for a special case. For complex systems, frequent in the digital Industry 4.0, numerical approaches are necessary and very often irreplaceable methods for solution approximations.

We now aim to illustrate how our model can contribute to real-world manufacturing practice by developing technology-switching strategies addressing individual customer preferences in terms of ideal buying times and product variants across the PLC. We consider both the demand and supply sides for the design experiments. These two perspectives are essential since they affect the customer's utility (see (3.1)), our decision variables and, ultimately, the manufacturer's profit. We perform numerical experiments to study time-dependent customer-centric marketing and operations decisions across the PLC.

Accordingly, we derive managerial insights regarding our three decision variables. In Section 2.5.1, we define the parameter setup for the baseline scenario. Our goal is twofold. First, in Section 2.5.2, after performing some sensitivity analyses on customer preferences ($\gamma(\tau)$, $\lambda(\tau)$, $\omega(\tau)$), we quantify the benefits of AM across the PLC, considering customer-centric production strategies (see Section 2.3.1). Second, in Section 2.5.3, we quantify the value of pricing flexibility. The benefits of AM in bringing product variety across the PLC are discussed in the Appendix (F). Some of the results are expected, whereas others are less intuitive.

2.5.1 Parameter Setup

We overcome the lack of real data by investigating different parametric scenarios issued from our model with synthetic data, from which we derive managerial insights (see Section 2.6). For all experiments, we consider a discrete-time selling horizon with $T = 12$ (higher values of T lead to a significant computational time and do not change our managerial insights, see Fig. E.1 in Appendix E). We set Bass innovation and imitation coefficients to $p = 0.02$ and $q = 0.6$ based on the mean value and on the upper bound of the coefficients provided by Orbach (2016).

On the demand side, the numerical study focuses on the influence of buying time and product-variant sensitivity coefficients (γ and λ respectively) on our decision variables and on the profit. Customer characteristics are depicted in Fig. 2.2.

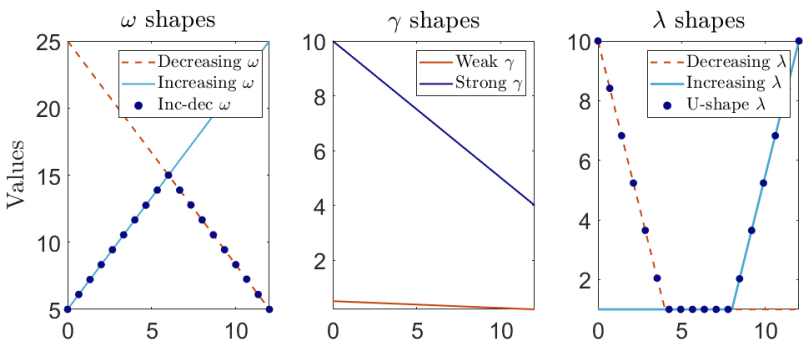


Figure 2.2 – Customer characteristics: willingness-to-pay ω, ideal buying time misfit coefficient γ, and ideal product variant misfit coefficient λ.

In particular, Fig. 2.2 illustrates possible shapes of the customer's willingness-to-pay and of the sensitivity coefficients over time. The customer's willingness-to-pay ω with a linearly decreasing profile captures its decline over the selling horizon. The consumer has high willingness-to-pay when the product is released on the market and he/she is excited about it (*e.g.*, consumer good of a well-known brand). Over time, the product loses attractiveness and the willingness-to-pay diminishes. The ideal buying time misfit coefficient γ is also modeled by a linear decreasing shape. Customers are more sensitive to their ideal buying time period at the beginning of the PLC than towards the end. The ideal product variant misfit coefficient λ can present different profiles to express high or low product variant sensitivity across the PLC.

On the supply side, our study concentrates on the maximum number of mass-customized variants, n_{max}, and on their pricing.
We set the baseline experiments as follows: 100 sample paths of a population size $N = 10,000$; the mass-customized assortment size threshold for n_{max} is 15; the fixed MC cost is $k_M = 100$; the fixed AM cost is $k_A = \rho_k \cdot k_M$, where $\rho_k = 1.5$; the unit production cost under MC is $c_M(n)$ and increases linearly with $c_M(n) = c_b(1 + (n-1)\delta)$ ($c_b = 2$, $\delta = 0.06$), which follows the form and notations given by Dong et al. (2020a); the unit production cost under AM is $c_A = \rho_c \cdot c_b$, where $\rho_c = 1.8$. The pricing policy is flexible in our baseline scenario and is optimized in our problem. Baseline parameter values are given in Table 3.3.

Table 2.3 – Baseline Parameter Values.

Parameter	p	q	N	T	n_{max}	
Value	0.02	0.6	10,000	12	15	
Parameter	k_M	k_A	c_b	δ	c_M	c_A
Value	100	150% of k_M	2	0.06	2,3.68	180% of c_b

2.5.2 Customer-centric Operations Management

Based on our baseline scenario for both the demand and supply perspectives, in this section, we discuss the implications for a manufacturer of adopting AM to complement existing MC systems. We aim to uncover whether applying a technology-switching scenario is economically viable and, hence, to assess when to switch from one technology to another. To gain additional insights into the combined problem of technology-switching, product variant, and price optimization, we first analyze the influence of customers' buying time and product variant sensitivity. Then, we analyze the influence of ω on our decision variables: These three parameters affect customers' utility (see (3.1)) and purchasing behavior, which plays a critical role in our approach.

Impact of Buying-Time Sensitivity. First, we perform a sensitivity analysis on the buying time misfit coefficient γ. We perform numerical experiments for a **"strong"** γ and a **"weak"** one, where $\gamma_{\text{strong}} = 20 * \gamma_{\text{weak}}$. Fig. 2.3 displays a shift in the sales diffusion pattern to the left, indicating that time-sensitive customers buy earlier in the PLC. As illustrated in Fig. 2.4, the buying time misfit coefficient directly impacts the manufacturer's pricing strategy. A stronger γ yields lower buying-time volatility (see the standard deviation for a "strong" γ in Table 2.4) and thus implies a lower set of potential buyers for each period. Consequently, the manufacturer charges a higher selling price in the presence of time-sensitive customers, those who are more willing to buy during the considered period. Moreover, Fig. 2.4 also

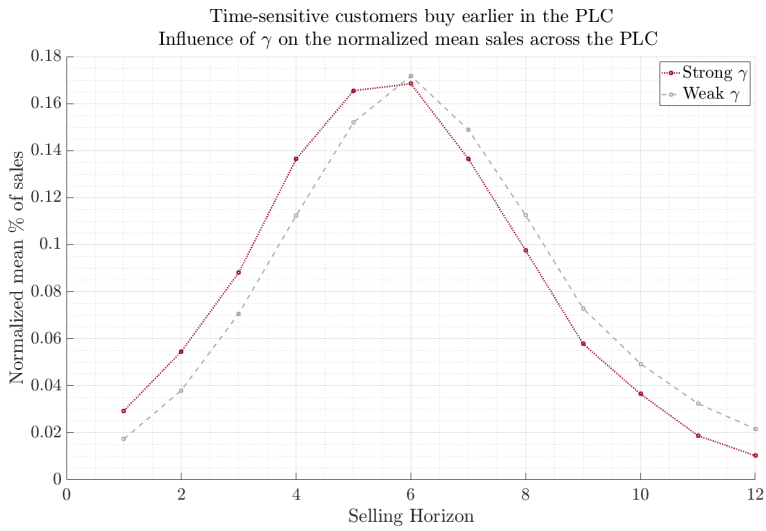


Figure 2.3 – Influence of time-sensitivity on the sales diffusion pattern.

shows that it is profitable for a firm to switch back to AM towards the end of the PLC to gain a higher profit per customer since higher selling prices are charged under this technology. Interestingly, the manufacturer switches back to AM earlier in the presence of time-sensitive adopters. Higher time sensitivity implies less volatility in the customer's buying time. Since

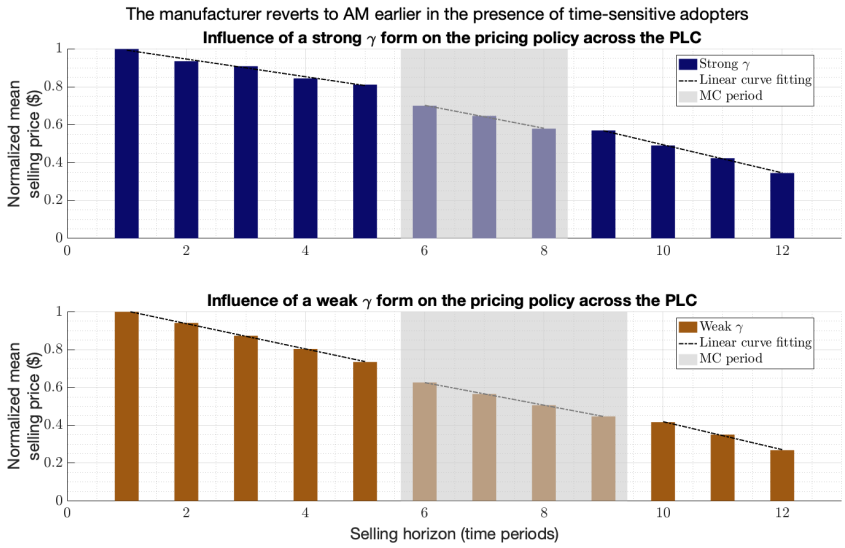


Figure 2.4 – Influence of time-sensitivity on the pricing policy trajectory across the PLC. Parameters: 100 sample paths, u-shape λ, linear decreasing ω, $n_{max} = 5$, flexible pricing policy.

the product variant misfit, λ, presents a u-shape (see Fig. 2.2) and is, thus, stronger in later periods, the utility of time-sensitive customers is profitably served under AM in these periods. Conversely, lower time sensitivity leads to more volatility in buying time periods. Therefore, some customers purchase at earlier MC production periods, at which λ is lower. Then, the observed optimal technology-switching scenarios, illustrated in Fig. 2.4, bring to light the importance of modeling the buying time misfit coefficient in the utility function to capture both customer heterogeneity and the ideal buying times. In fact, the buying time misfit strongly influences the technology-switching scenario, even though demand is endogenous.

Impact of Product-Variant Sensitivity. We now perform a sensitivity analysis on the product variant misfit coefficient λ. Since this coefficient is one of the characteristics that differentiate AM and MC (see Section 2.3.1), we aim to uncover whether it influences the technology-switching scenario and, particularly, whether it triggers the switch from one technology to another. For this purpose, we test three possible shapes of λ depicted in Fig. 2.2: (i) **decreasing**, (ii) **u-shape**, and (iii) **increasing**, where γ and ω stay decreasing as in Fig. 2.2.
According to the optimal production strategies presented in Fig. 2.5, the technology-switching decision can be triggered by the quantity $\omega\big(\lambda d(\phi, \mathcal{N})\big)$ in the customer's utility (see (3.1)) falling below the difference between the AM production cost, c_A, and the MC production cost, c_M. Indeed, there is a benefit in switching to an MC production strategy if its fixed costs $(k_A + k_M)$ are absorbed. For a u-shape and for an increasing λ, the switching times, as well as the mean profits, are identical. This is because both λs are identical during the MC period, whereas they have no influence on either pricing or sales under the AM periods.

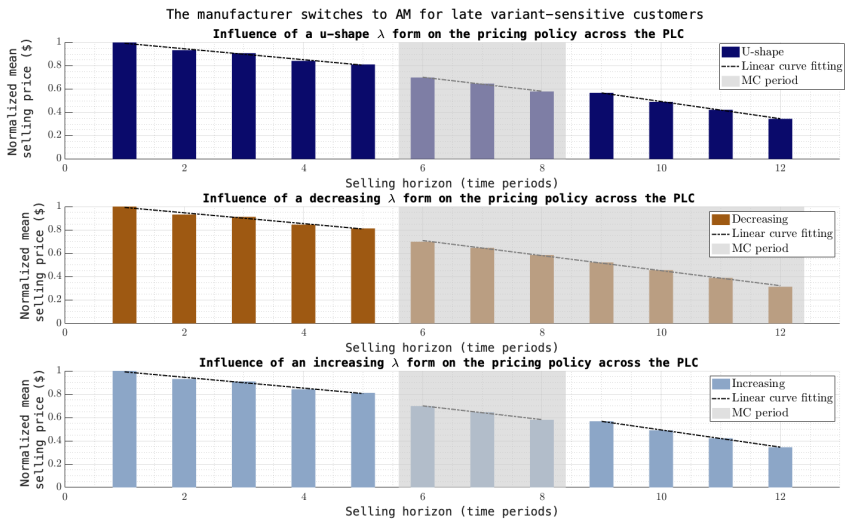


Figure 2.5 – Influence of variant-sensitivity on the pricing policy trajectory across the PLC. Parameters: 100 sample paths, strong γ, linear decreasing ω, $n_{max} = 5$, flexible pricing policy.

Fig. 2.5 clearly shows that the shape of the λ function influences the technology-switching scenario across the PLC. In the case of high λ values, it is more beneficial to produce with AM rather than with MC due to the high product variant misfit under the MC strategy. Under the u-shape and increasing λ forms, it is beneficial for the manufacturer to switch back to AM towards the end of the PLC: this captures preferences of variant-sensitive customers since they are served perfectly under AM.

Impact of the Willingness-to-Pay. We examine the influence of the willingness-to-pay ω on the pricing policy trajectory. We investigate three shapes of the function ω (Fig. 2.2): (i) **linear decreasing**, (ii) **increasing-decreasing**, or bell-shape, and (iii) **linear increasing**. Fig. 2.6 demonstrates these profiles of ω and the resulting normalized optimal pricing strategies. It clearly illustrates that ω drives the pricing policy trajectory even though the demand is endogenous.

Influence of Customer Characteristics on Production Strategy. Given our baseline scenario, Tables 2.4, 2.5 and 2.6 demonstrate that the firm can gain a mean profit increase per customer from ca. 13.3% (from 6.41 under MC to 7.26 under ***(C2)***) to 16.5% (from 6.41 to 7.47 under ***(C1)***) by adopting AM either at the end or at the beginning of the PLC, compared to the MC base case. The company can further increase the profit up to 17.5% (from 6.41 to 7.53) if it adopts a ***(C3)*** technology-switching scenario. Furthermore, the results show that strategy ***(C4)*** is around 17% (from 6.41 to 7.49) more beneficial than a MC one. However, the profit increase between the technology-switching scenario ***(C3)*** and the AM ***(C4)*** is low: the sole use of AM is around 0.5% less profitable than adopting the technology-switching strategy. Hence,

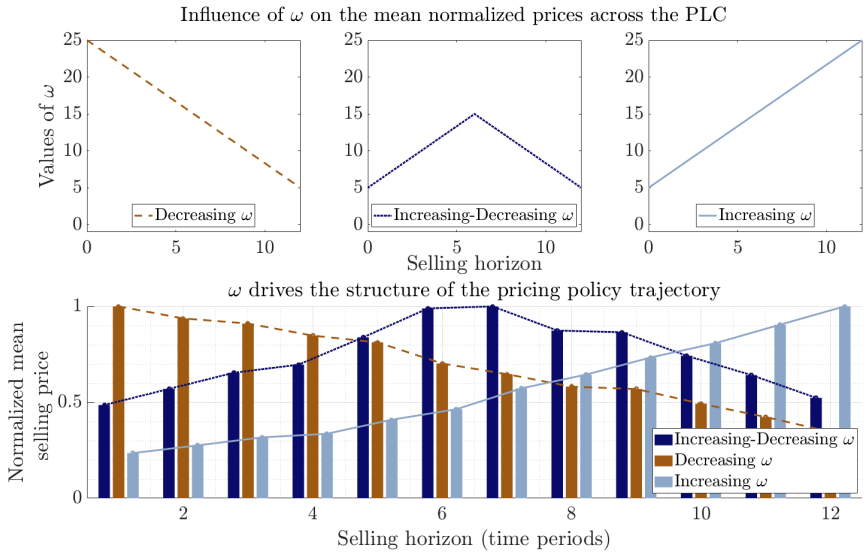


Figure 2.6 – Influence of ω profiles on the pricing policy trajectory across the PLC. Parameters: 100 sample paths, u-shape λ, strong γ, $n_{max} = 5$, flexible pricing policy.

a technology-switching strategy might be a solution for transitioning toward the sole use of AM, as MC systems become obsolescent. This finding provides additional support for the economic benefits of adopting AM in Dong et al. (2020a), Westerweel et al. (2018b), Chen et al. (2021).

These results support the decision making for the "compatibility between process choice and product life cycle stage," as highlighted qualitatively by Hayes and Wheelwright (1979) and analytically by Ramasesh et al. (2010). Hence, a firm benefits from linking AM and MC to the PLC.

2.5.3 Bringing Pricing Flexibility across the PLC

We have analyzed the impact of demand on our optimization problem outcomes. Next, we examine the value of pricing flexibility on the manufacturer's expected profit per customer. The effects of bringing higher product variety across the PLC are examined in the Appendix (see F).

We now evaluate the pricing flexibility for a manufacturer across the PLC. We perform numerical experiments on the same three shapes of ω as in Section 2.5.2 and test pricing trajectories, namely (i) **constant**, (ii) **linear decreasing**, and (iii) **flexible**, the last of which has no constraints.

Table 2.7 shows that for a linearly decreasing ω the manufacturer could gain a profit increase of 21.84% if he applied either a decreasing or a flexible pricing policy. The profits under the linearly decreasing and the flexible pricing policies are similar and the corresponding pricing

Table 2.4 – Influence of buying-time sensitivity on profit.

Technology-switching scenario	Strong γ				Weak γ			
	Mean	SD	95% CI	Range	Mean	SD	95% CI	Range
MC	6.41	0.03	6.37-6.47	6.36-6.49	10.22	0.04	10.15-10.30	10.09-10.33
$MC \rightarrow AM$	7.26	0.02	7.23-7.30	7.21-7.32	11.84	0.04	11.78-11.90	11.75-11.92
$AM \rightarrow MC$	7.47	0.02	7.43-7.51	7.42-7.53	11.92	0.04	11.85-11.98	11.79-12.00
AM	7.49	0.02	7.46-7.53	7.44-7.55	11.87	0.04	11.81-11.93	11.78-11.95
$AM \rightarrow MC \rightarrow AM$	7.53	0.02	7.50-7.56	7.48-7.57	12.00	0.04	11.93-12.05	11.88-12.07

Table 2.5 – Influence of product-variant sensitivity on profit.

Technology-switching scenario	U-shape λ				Decreasing λ				Increasing λ			
	Mean	SD	95% CI	Range	Mean	SD	95% CI	Range	Mean	SD	95% CI	Range
MC	6.41	0.03	6.36-6.46	6.34-6.49	6.56	0.03	6.51-6.60	6.50-6.63	7.41	0.03	7.36-7.46	7.35-7.49
$MC \rightarrow AM$	7.26	0.02	7.22-7.30	7.19-7.31	7.26	0.02	7.22-7.29	7.20-7.30	7.49	0.03	7.45-7.53	7.43-7.57
$AM \rightarrow MC$	7.47	0.02	7.44-7.51	7.43-7.51	7.58	0.02	7.55-7.62	7.51-7.63	7.47	0.02	7.43-7.51	7.41-7.53
AM	7.49	0.02	7.46-7.53	7.44-7.55	7.49	0.02	7.46-7.54	7.44-7.55	7.49	0.02	7.46-7.53	7.44-7.54
$AM \rightarrow MC \rightarrow AM$	7.53	0.02	7.49-7.57	7.47-7.59	7.58	0.02	7.54-7.61	7.50-7.62	7.54	0.02	7.50-7.57	7.48-7.58

Table 2.6 – Influence of the willingness-to-pay's profile on profit.

Technology-switching scenario	Decreasing ω				Increasing-decreasing ω				Increasing ω			
	Mean	SD	95% CI	Range	Mean	SD	95% CI	Range	Mean	SD	95% CI	Range
MC	6.41	0.03	6.36-6.46	6.35-6.47	4.52	0.02	4.48-4.56	4.46-4.59	5.52	0.03	5.48-5.57	5.46-5.60
$MC \rightarrow AM$	7.26	0.02	7.23-7.29	7.21-7.30	4.60	0.02	4.57-4.63	4.55-4.66	6.02	0.04	5.96-6.08	5.95-6.11
$AM \rightarrow MC$	7.47	0.02	7.44-7.51	7.42-7.52	4.63	0.02	4.59-4.67	4.56-4.69	5.63	0.03	5.58-5.68	5.56-5.69
AM	7.50	0.02	7.46-7.53	7.45-7.54	4.60	0.02	4.58-4.64	4.57-4.65	6.09	0.04	6.04-6.15	6.00-6.19
$AM \rightarrow MC \rightarrow AM$	7.53	0.02	7.50-7.57	7.48-7.58	4.72	0.02	4.69-4.76	4.67-4.78	6.14	0.04	6.08-6.20	6.07-6.23

trajectories are close to each other. Further, for an increasing-decreasing ω, the manufacturer could gain a mean profit increase of 15.12% if he adopted the flexible pricing policy. Finally, for an increasing function ω, the value of pricing flexibility is only 3.17%. Indeed, between time periods $t = 1$ and $t = 8$, the optimal prices are very close for all three pricing policies and they start to increase from time period $t = 9$ accounting for customers with a higher willingness-to-pay.

Table 2.7 – Value of pricing flexibility for manufacturing practice across the PLC.

	Mean profit per customer		
Pricing policy	**Decreasing ω**	**Increasing-decreasing ω**	**Increasing ω**
Constant	6.18	4.10	6.62
Linear decreasing	7.53	3.04	6.62
Flexible	7.53	4.72	6.83

2.6 Managerial Insights and Conclusions

The present study was designed to model and evaluate the disruptive practice of a manufacturer combining traditional MC with AM for final part production, in the Industry 4.0 era. We quantify the benefits of adopting AM as an alternative or as a complement to MC. This study lends support to the growing interest in quantifying the economic benefits of AM on

operations management and MC. Our model focuses on the operations-marketing interface and jointly optimizes customer-centric technology-switching, pricing, and product variety decisions. We show that technology-switching scenarios could help to satisfy individual customer preferences while maximizing profitability across the PLC.

Individual customer preferences and the PLC are two important aspects to consider in practice to rapidly develop and manufacture customized products. These aspects, though, have not yet been fully explored in the context of operations management for Industry 4.0. To the best of our knowledge, there is no analysis linking customer preferences and the PLC to the technology choice over time. Although the emerging literature on AM in operations and SCM compares conventional manufacturing systems with AM, it typically neglects the demand perspective and the time-dependency of customer preferences. It also commonly ignores the interdependency between manufacturing systems, the PLC, and pricing decisions. We incorporate these aspects in our pilot study to derive operational and managerial insights.

Our first contribution is the novel time-varying locational customer choice model at the individual level, called the HLB model. We extend the Hotelling-Lancaster model by using the Bass diffusion model to include the PLC dimension in the utility function. This model is the first to offer the advantages of both modeling the demand of heterogeneous customers at the individual level and mimicking the PLC dynamics. It could widen the literature on micromodeling diffusion models (*e.g.*, Chatterjee and Eliashberg (1990), Song and Chintagunta (2003)). We shed light on the importance of modeling individual customer preferences and purchasing behavior, and, in particular, buying time-sensitivity, product variant sensitivity, and willingness-to-pay. We demonstrate that these customer attributes affect the optimal technology-switching scenario and the pricing policy.

Second, we quantify the benefits of adopting AM over a finite selling horizon, considering both the demand and supply perspectives. Our results show that the firm could gain a significant profit surplus by interchanging AM and MC over the PLC. For instance, an AM-MC-AM manufacturing scenario can lead to a significant profit surplus compared with the sole use of MC. In this scenario, AM makes it possible to address product variant and time-sensitive customers at the beginning and at the end of the PLC, while MC provides economies of scale and satisfies customers during the PLC growth stage. Our study finds that the combination of AM and MC could be a temporary solution in the move toward the sole adoption of AM over the PLC, as its competitiveness increases further and as traditional MC becomes obsolescent.

Third, we quantify the value of pricing flexibility. It can be an effective lever in the presence of either "early" product variant and time-sensitive customers or "late" ones. It allows the firm to charge higher selling prices under AM. Interestingly, as shown in Fig. 2.6 and Table 2.7, our model shows that ω drives the shape of the optimal pricing policy. If the ω shape is linear, then the profits under flexible or linear pricing policies are close. When buying time-sensitivity is absent and customers' utility is constant over the PLC, the optimal pricing strategy to apply is a classic linear decreasing one.

Finally, we review the benefits of adopting AM for product variety across the PLC in the Appendix (see F). Since AM has the capability to produce infinite product variety (Reeves et al. 2011), it can be used during the PLC's introductory and decline stages. It can also

be adopted on its own over the whole PLC if the number of product variants under MC is either low or too high. Low product variety under MC means it is not possible to match customer preferences, and high product variety under MC comes at a cost. Joint product variety, technology-switching, and pricing decision making is a challenging task for the manufacturer. Our results demonstrate that AM could offer significant economic benefits in addressing time-sensitive customers and higher customer expectations in terms of product variety. This study: (i) confirms and quantifies the potential of AM for final part production in combination with existing traditional manufacturing systems, and (ii) proposes an innovative way to leverage customer-centricity to update marketing and operations decisions. We believe that companies will increasingly select this technology in the future. Further, our findings lead to the recommendation to consider both the demand and supply perspectives, as well as to link them to the PLC. Both perspectives influence the manufacturer's decisions and his expected profit. Our model can be used to help understand the impact of relative parameter values on optimal pricing, marketing, and production strategies. It is the first step toward a study of hybrid production strategies using Industry 4.0 technologies. We aim to use it to explore alternatives a manufacturer could face when implementing such strategies. It can serve as a baseline for future studies and be used by practitioners and managers to make more informed marketing and operations decisions using one of the disruptive Industry 4.0 technologies, such as AM for final part production. Fig. 2.7 illustrates a technology-switching scenario, pricing strategy, and conditions under which a manufacturer could maximize profit while satisfying individual customer preferences.

Our work offers several paths for future research. First, when data becomes available, para-

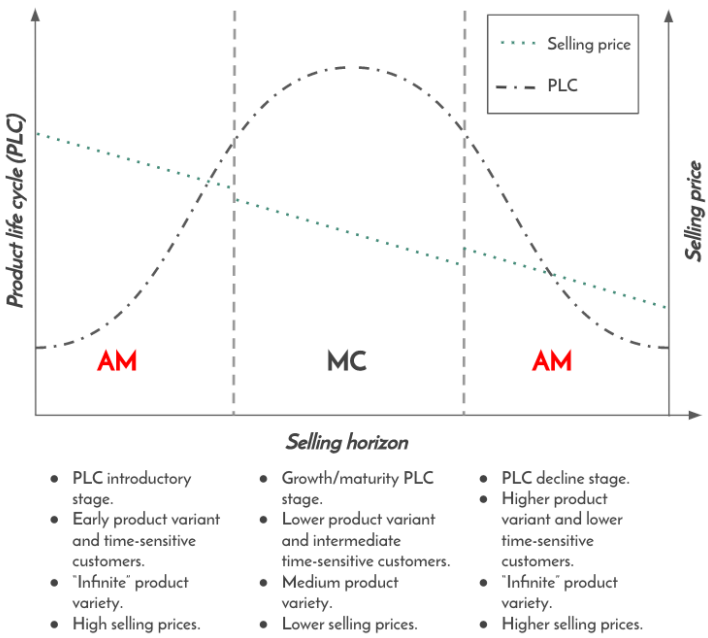


Figure 2.7 – Illustration of a beneficial technology-switching scenario and pricing strategy over the PLC.

metric estimations for customer characteristics and industrial data for production costs could be used to fit the model. Second, since one of the advantages of AM over traditional manufacturing, highlighted in the work of Attaran (2017), is the possibility to use AM for decentralized manufacturing to *"potentially reduce the need for logistics as designs could be transferred digitally"*, one could investigate how to take into account the decentralization in our model. Some papers investigate this topic in dual-sourcing literature. In a manufacturing setting, Westerweel et al. (2018a) model the replenishment and printing decisions through a Markov decision process to characterize the optimal policy structure. They focus on spare parts inventory control and show promising results for using AM at remote locations. In a retail setting, Chen et al. (2021) analyze the impact of on-demand customization in dual channels. They develop a stylized model to evaluate the impact of AM on product offering, as well as pricing for the two channels and inventory decisions. They consider the consumer point of view without incorporating technology-switching decisions or PLC considerations. It is worth investigating how our results can be extended to incorporate centralized and decentralized manufacturing under individual customer preferences and PLC considerations.

A Proof of Theorem 2.1.

Theorem 2.1. If (H) holds, then (i), (ii) and (iii) are verified.

Proof. of Theorem 2.1. The proof relies on Theorems 7.53 and 5.3 of Shapiro et al. (2014). The first guarantees that $\mathscr{S}$ is non-empty and (LLN) holds almost surely uniformly on p. The second builds on the first to deliver the desired conclusions.
According to Theorem 7.53 of Shapiro et al. (2014), $\tilde{\Pi}$ is continuous on the compact set of prices $[0, \max(\omega)]^T$, $\mathscr{S}$ is non-empty and (LLN) holds almost surely for uniform p, if 1) the set of prices p is a compact subset; 2) $\forall p_0$, the function $p \mapsto \tilde{\pi}(\xi, p)$ is $\xi - a.s.$ continuous at p_0; 3) there exists integrable h, such that for all p, $|\tilde{\pi}(\xi, p)| \leq h(\xi)$.
Conditions 1) and 3) are straightforward and, thus, we focus on proving condition 2).
We consider a random customer $\xi = (\tau, \phi)$. Recall that $\mathbb{P}_{(\tau,\phi)} = \mathbb{P}_\tau \otimes \mathbb{P}_\phi$ has density $f_\tau \times \mathbf{1}_{[0,1]}$ w.r.t. Lebesgue measure on $\mathbb{R}^2$. Given a pricing strategy $\mathbf{p}_0 = (\mathbf{p}_0(t))_{1\leq t\leq T}$, and a random customer ξ, we investigate conditions under which $\mathbf{p} \mapsto \tilde{\pi}(\xi, \mathbf{p})$ is continuous at $\mathbf{p}_0$. We distinguish two cases, either $\rho = \min_t |U(\xi, t) - \mathbf{p}_0(t)| > 0$, or not.
If $\rho > 0$, and $\| \mathbf{p} - \mathbf{p}_0 \|_\infty < \rho$, then either $\mathscr{U}(\xi, t) - \mathbf{p}_0(t) > 0$ and then $\mathscr{U}(\xi, t) - \mathbf{p}_t > 0$ (*i.e.*, a customer purchases at time t), or $\mathscr{U}(\xi, t) - \mathbf{p}_0(t) < 0$ and then $\mathscr{U}(\xi, t) - \mathbf{p}_t < 0$ (*i.e.*, no purchase at time t).
It follows that $|\tilde{\pi}(\xi, \mathbf{p}) - \tilde{\pi}(\xi, \mathbf{p}_0)| \leq \| \mathbf{p} - \mathbf{p}_0 \|_\infty$ (see (B.1)), whence the profit is locally Lipschitz at $\mathbf{p}_0$, therefore it is continuous at $\mathbf{p}_0$. From this we deduce that for ξ-a.s. continuity of $\mathbf{p} \mapsto \tilde{\pi}(\xi, p)$ to hold, it suffices to prove that for any $\mathbf{p}_0$, $\mathbb{P}(\cup_{1\leq t\leq T}\{U(\cdot, t) = \mathbf{p}_0(t)\}) = 0$, which is granted if $\forall t$, $\mathbb{P}(U(\cdot, t) = \mathbf{p}_0(t)) = 0$. We now carefully examine the case when for some t, and some positive α $(= \mathbf{p}_0(t))$, $U(\xi, t) = U(\tau, \phi, t) = \alpha$.

If production is AM at period t, then $\mathbb{P}(\{U(\tau, t) = \alpha\}) = \mathbb{P}(\omega(\tau)(1 - \gamma(\tau)|\tau - t|/T) = \alpha) = \mathbb{P}_\tau(\delta(\cdot, t)^{-1}(\{\alpha\}))$. Let us denote $A = \delta(\cdot, t)^{-1}(\{\alpha\})$. Then

$$\mathbb{P}_\tau(A) = \int \mathbf{1}_A d\mathbb{P}_\tau = \int_0^T \mathbf{1}_A f_\tau(t) dt = \int_A f_\tau(t) dt = 0$$

as $\mu_L(A) = 0$ by assumption (H). So indeed, if production is AM, $\mathbb{P}(U(\tau, t) = \alpha) = 0$.

Else, **if production is MC** at period j, then $\mathbb{P}(\{U(\tau,\phi,j)=\alpha\}) = \mathbb{P}(\omega(\tau)(1-\gamma(\tau)|\tau-j|/T - \lambda(\phi)d(\phi,\mathscr{X}))=\alpha)$. We set $A=\{\omega(t)(1-\gamma(t)|t-j|/T-\lambda(t)d(s,\mathscr{X}))=\alpha\}$. By Fubini, we have

$$\mathbb{P}(\{U(\tau,\phi,t)=\alpha\}) = \int_A d\mathbb{P}_{\tau,\phi} = \int_0^T (\int_0^1 (\mathbf{1}_A(t,s)ds) f_\tau(t)dt$$
$$= \int_{\lambda\omega=0} (\int_0^1 \mathbf{1}_A(t,s)ds) f_\tau(t)dt + \int_{\lambda\omega\neq 0} (\int_0^1 \mathbf{1}_A(t,s)ds) f_\tau(t)dt.$$

• If $\lambda\omega\neq 0$, then since $\mathscr{X}$ is finite, $\{0\le s\le 1 : d(s,\mathscr{X})=\beta\}$ is finite, therefore $\mathbb{P}(d(\phi,\mathscr{X})=\beta)=0$ for any real β, in particular if $\beta=\frac{1}{\lambda(t)}(\frac{\alpha}{\omega(t)}-1-\gamma(t)|t-j|/T)$, whence $\int_{\lambda\omega\neq 0}(\int_0^1 \mathbf{1}_A(t,s)ds)f_\tau(t)dt = 0$.

• If $\lambda\omega=0$, then if $\omega=0$, since $\mu_\omega << \mu_L$, it follows that $\int_{\omega=0}\mathbf{1}_A(t,s)d\mathbb{P}_{\tau,\phi}(t,s)=0$. Else, to conclude with the last remaining case, that is if $\lambda=0$, the result proves as if $\mathscr{T}(t)=AM$, *i.e.*, we recover the AM case: $\mathbb{P}(\{U(\tau,\phi,t)=\alpha\}\cap\{\lambda=0\})\le \mathbb{P}(U^{AM}(\tau,t)=\alpha)=0$.

Now, we recall the assumptions of Theorem 5.3 of Shapiro et al. (2014), which we need to conclude our proof: 1) $\emptyset\neq\mathscr{S}\subset C$, C compact; 2) $\tilde{\Pi}$ continuous on C; 3) (LLN) holds uniformly on C; 4) $(\xi_i)_{1\le i\le N} - a.s.$, $\emptyset\neq\mathscr{S}_N\subset C$.

If these hold, then (i), (ii) and (iii) from Section 2.4.2 follow. Obviously, $C=[0,\max\omega]^T$ is compact and we already have 2) from which 1) follows. We also already have 3), therefore only 4) requires consideration.

For fixed $(\xi_i)_{1\le i\le N}$, since $\hat{\Pi}_N$ is bounded, there exists a sequence of prices $p^{(k)}$ such that $\hat{\Pi}_N(p^{(k)})\to\vartheta_N^*$. For each $1\le i\le N$, the sequence $(t(\xi_i,p^{(k)})_{k\ge1}$ takes only a finite number of values. By compactness of C and since N is finite, we can, therefore, select a sub-sequence (which we still denote $(p^{(k)})_{k\ge1}$), which satisfies: a) $\exists p^\infty\in C \,/\, p^{(k)}\to p^\infty$; b) for some k_0 on, and all $1\le i\le N$, $t(\xi_i,p^{(k)})=t_i$ is constant.

We set $p^{(k)}(0)=0\ \forall k$. Then by b), $\forall k\ge k_0$ and all $1\le i\le N$, $\tilde{\pi}(\xi_i,p^{(k)})=p^{(k)}(t_i)-p^{(k_0)}(t_i)+\tilde{\pi}(\xi_i,p^{(k_0)})$. Then, $\hat{\Pi}_N(p^{(k)})=\frac{1}{N}\sum_{i=1}^N\tilde{\pi}(\xi_i,p^{(k)})=\hat{\Pi}_N(p^{(k_0)})+\frac{1}{N}\sum_{i=1}^N(p^{(k)}(t_i)-p^{(k_0)}(t_i))\to \hat{\Pi}_N(p^{(k_0)})+\frac{1}{N}\sum_{i=1}^N(p^\infty(t_i)-p^{(k_0)}(t_i))=\hat{\Pi}_N(p^\infty)$ by $a)$. By uniqueness of the limit, it follows that $\vartheta_N^*=\hat{\Pi}_N(p^\infty)$, which proves 4) for all $(xi_i)_{1\le i\le N}$. ∎

B Proof of Lemma 2.3.

Lemma 2.3. Suppose $\gamma = 0$, *i.e.*, there are no time misfits. Given the pricing strategy p, we denote its prearrangement in a decreasing order by $p^{\downarrow}$. Then, for any ξ, $\tilde{\pi}(\xi, p) \leq \tilde{\pi}(\xi, p^{\downarrow})$.

Proof. of Lemma 2.3. We define buying times as $t(\xi, T_{A\leftrightarrow M}, p)$, equal to 0 if the customer never purchases, otherwise to the first time period at which the customer's utility exceeds the period's price. Then

$$\tilde{\pi}(\xi_i, p) = p\big(t(\xi, T_{A\leftrightarrow M}, p)\big) - c\big(t(\xi, T_{A\leftrightarrow M}, p)\big) - k_A \mathbf{1}_{AM}(T_{A\leftrightarrow M}) - k_M \mathbf{1}_{MC}(T_{A\leftrightarrow M}), \quad \text{(B.1)}$$

where $p(0) = c(0) = 0$ and $c\big(t(\xi, T_{A\leftrightarrow M}, p)\big)$ is the production cost per-unit for time period under technology-switching scenario $\mathcal{T}$.
Given a customer ξ, $U^{\mathcal{T}}(\xi, t) = U^{\mathcal{T}}(\xi, t') =: U^{\mathcal{T}}(\xi)\ \forall\ 1 \leq t, t' \leq T$. If the customer does not purchase at price p, neither does he at prices $p^{\downarrow}$, since $U^{\mathcal{T}}(\xi) < \min p = \min p^{\downarrow}$. Conversely, if the customer purchases at period $t(\xi, p)$, then $p(1), \ldots, p(t(\xi, p) - 1) > U^{\mathcal{T}}(\xi) \geq p(t(\xi, p))$. Since the position of $p(t(\xi, p))$ in $p^{\downarrow}$ is at least $t(\xi, p)$, the customer purchases at time $t' \geq t(\xi, p)$ under $p^{\downarrow}$ with profit difference $p^{\downarrow}(t') - p((t(\xi, p)) = \tilde{\pi}(\xi, p^{\downarrow}) - \tilde{\pi}(\xi, p) \geq 0$. ∎

C Proof of Corollary 2.4.

Corollary 2.4. Under the assumptions of Lemma 2.3 and if $\mu_\omega \ll \mu_L$, then Theorem 2.1 holds and the optimal pricing strategy is decreasing.

Proof. of Corollary 2.4. Since $U^{\mathscr{T}}(\xi, t) = U^{\mathscr{T}}(\xi) = \omega(t)(1 - \lambda(t)d(\phi, \mathscr{X}))$, then, similar to the proof of Theorem 2.1, either $\tau \in \{\lambda \neq 0\}$, in which case (H) follows by independence of τ and ϕ, or $\tau \in \{\lambda = 0\}$, in which case (H) follows by the hypothesis $\mu_\omega \ll \mu_L$. Then, all elements in either $\mathscr{S}_N$ or $\mathscr{S}$ can be chosen decreasing by Lemma 2.3. ∎

D Cross-validation - SAA Framework

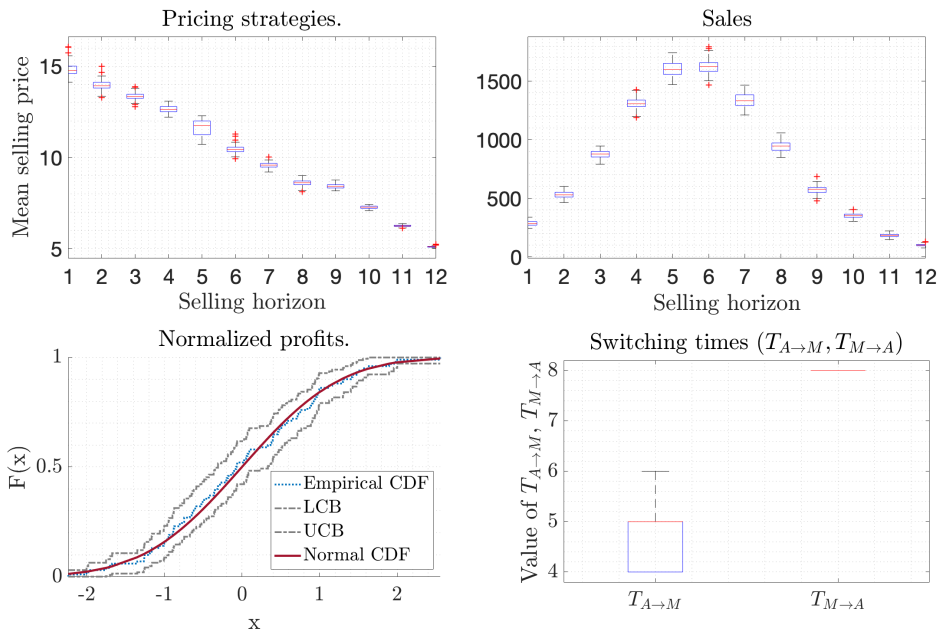


Figure D.1 – Stability of the pricing policy, sales, and profit with the SAA framework. Parameters: $N_{tot} = 10,000$, 100 sample paths for each population size N, population step size $= 100$, $T = 12$, $p = 0.02$, $q = 0.6$, linear decreasing ω, strong γ, u-shape λ, $n_{max} = 5$, $k_M = 100$, $k_A = 1.5 \cdot k_M$, $c_b = 2$, $\delta = 0.06$, $c_A = 1.8 \cdot c_b$, flexible pricing policy.

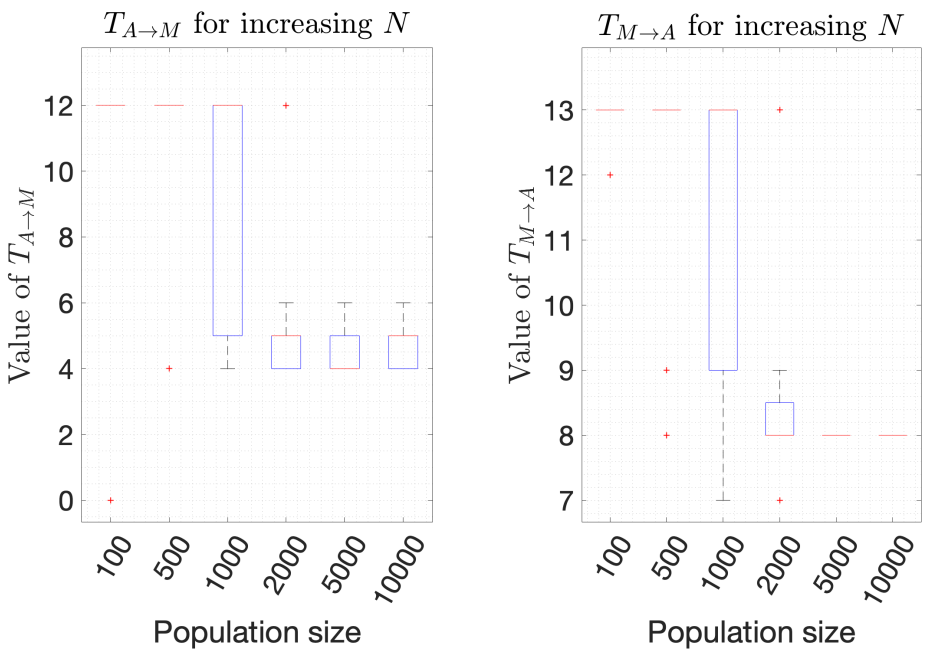


Figure D.2 – Convergence of the switching times with the SAA framework.
Parameters: $N_{tot} = 10,000$, 100 sample paths for each population size N, population step size $= 100$, $T = 12$, $p = 0.02$, $q = 0.6$, linear decreasing ω, strong γ, u-shape λ, $n_{max} = 5$, $k_M = 100$, $k_A = 1.5 \cdot k_M$, $c_b = 2$, $\delta = 0.06$, $c_A = 1.8 \cdot c_b$, flexible pricing policy.

E Selling Horizon Length

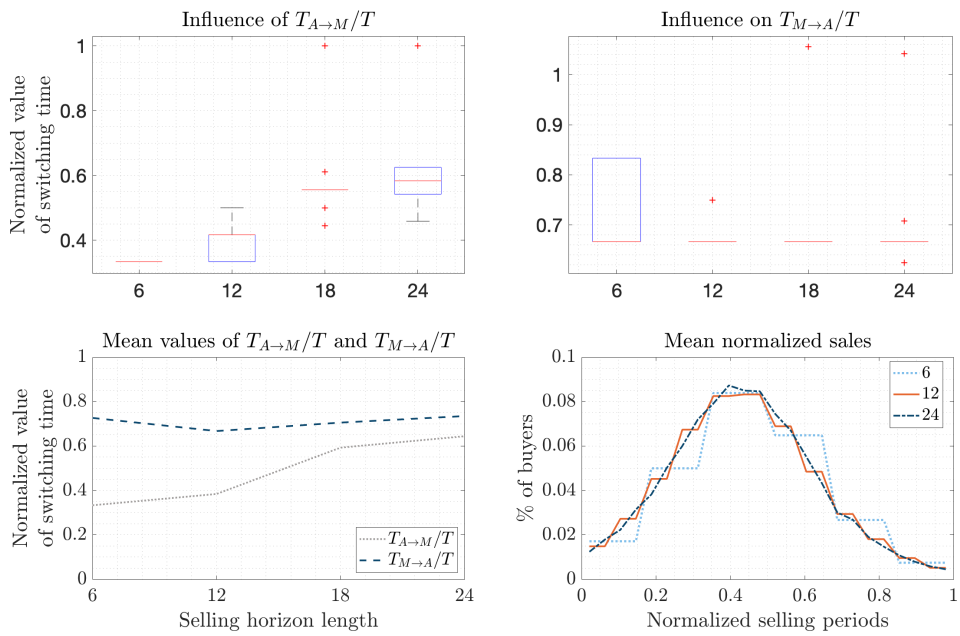


Figure E.1 – Influence of the selling horizon length, T, on the switching times, $(T_{A\to M}; T_{M\to A})$. Parameters: $\mathcal{N} = 10,000$, 100 sample paths, $T = [6, 12, 18, 24]$, $p = 0.02, q = 0.6$, decreasing ω, u-shape λ, strong γ, $n_{max} = 5$, $k_M = 100$, $k_A = 1.5 \cdot k_M, c_b = 2, \delta = 0.06, c_A = 1.8 \cdot c_b$, flexible pricing policy.

F Higher Product Variety

In this section, we assess the impact of higher product variety on the optimal technology-switching scenario and on the mean profit per customer. We vary the MC assortment size threshold n_{max} in the baseline scenario. As shown in Fig. F.1, the optimal profit per customer obtained for $n = 5$ is 0.26% lower w.r.t. the one obtained for $n^* = 6$, which is the optimal number of mass-customized variants to offer. Increasing n_{max} above $n = 5$ does not lead to a significant profit surplus but to a profit loss starting from $n = 7$. Further, it is not economically viable to switch to the technology at periods above $n = 10$. Moreover, starting with $n = 15$, the cost per MC unit exceeds the one for AM in our model, therefore there is no interest in adopting MC when offering such a large variety of products. Also, increasing n_{max} leads to a drop in efficiency of the estimators.

As n_{max} increases, the time, at which the manufacturer switches to MC technology in the technology-switching scenario, decreases. This can be explained by the dynamic identified in Section 2.5.2. Specifically, increasing the number of mass-customized variants results in a lower product variant misfit $\lambda(\tau)d(\phi, \mathcal{N})$ in the customer's utility function, but in a higher per-unit production cost c_M. This production cost can be attributed to the cost of switching itself, to the production of additional molds, and the use of tooling to manufacture supplementary variants.

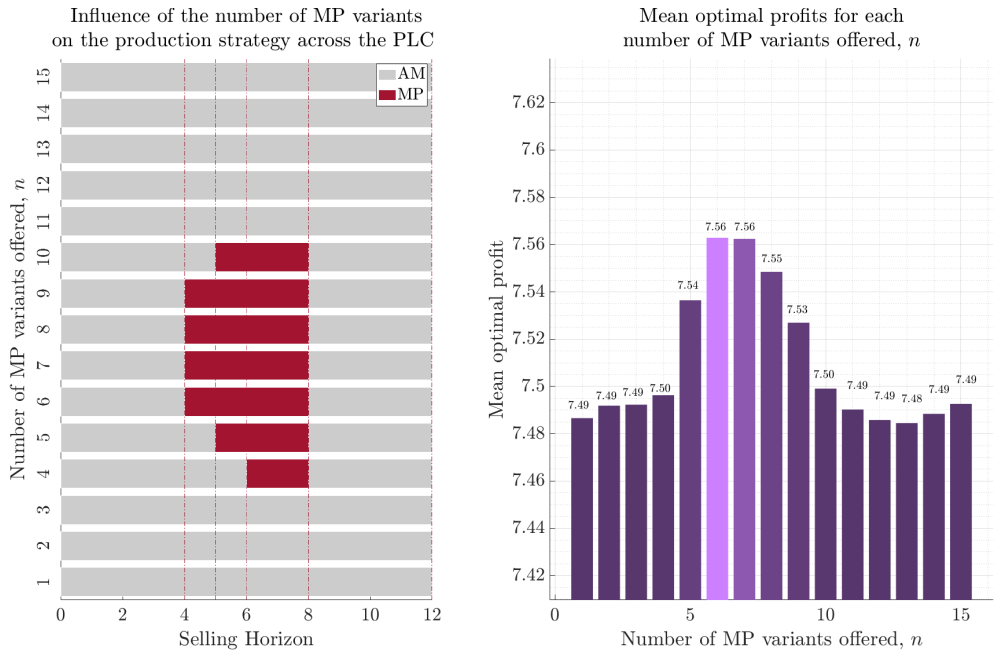


Figure F.1 – Influence of bringing higher product variety across the PLC.
Parameters: $\mathcal{N} = 10,000$, 100 sample paths, $T = 12$, $p = 0.02$, $q = 0.6$, decreasing ω, u-shape λ, strong γ, $n_{max} = 5$, $k_M = 100$, $k_A = 1.5 \cdot k_M$, $c_b = 2$, $\delta = 0.06$, $c_A = 1.8 \cdot c_b$, flexible pricing policy.

As demonstrated in the right plot of Fig. F.1, the profit difference between an AM and an $AM \rightarrow MC \rightarrow AM$ manufacturing scenario is only around 0.93%, which is close to the margin identified in Section 2.5.2. Thus, we could argue that the firm would be better off adopting solely the AM production strategy. However, if the firm offers a medium amount of product variants under the MC technology, it is beneficial to use AM both at the beginning and at the end of the PLC and to switch to MC during the middle phase of the PLC.

3 Utilizing Additive Manufacturing and Mass Customization under Capacity Constraints

Additive manufacturing (AM), originally used for prototyping, is increasingly adopted for custom final part production across different industries. This usage brings new manufacturing opportunities for mass customization (MC). However, printing speed and production volume are two barriers to AM adoption for product customization at large scale. But what if manufacturers could combine the benefits of AM for product customization with traditional MC technologies over the product life cycle (PLC)? We address this opportunity through a mathematical model that considers a monopolist manufacturer producing horizontally differentiated products at scale. To satisfy individual customer preferences, under PLC and capacity considerations, the firm jointly optimizes the following decisions: inventory, production quantity, product variety, optimal technology-switching times (between AM and MC), and pricing policy. Our approach can be implemented by decision-makers to leverage customer-centricity and benefit from this novel hybrid manufacturing practice. We derive a closed-form solution for the production quantity decision based on an adaptive inventory policy. We solve the resulting non-convex optimization problem using the Sample Average Approximation framework grounded by analytical results. Our results demonstrate that the new usage of AM with MC can benefit a manufacturer for customer-centric driven strategies. Significant profit improvements can be achieved with an AM-MC-AM technology-switching scenario, under certain capacity conditions, and with an increasing-decreasing pricing policy. Our results also indicate that the benefits of pricing flexibility are highest when capacity is unlimited, or when the firm does not hold inventory. Under capacity constraints, a simple decreasing pricing policy combined with inventory performs very well.

3.1 Introduction

The recent technological developments of additive manufacturing (AM, also referred to as 3D-printing) are shifting its original usage. Although AM has been used since 1988 for rapid prototyping (Hon 2007), only recently has it been considered for rapid manufacturing (RM, which is described by Campbell et al. (2020) as the series production of final parts). According to an industrial report by (Campbell et al. 2020), AM for RM grew significantly from 3.9% to

60.6% of the total AM market and "more and more manufacturers are interested in using 3D-printing technologies for full-scale production as they believe they can benefit from mass customization at lower costs." Throughout the chapter, AM includes RM. Mass customization (MC) typically refers to both strategies and flexible manufacturing systems. Anderson (2004) defines MC as "the ability to design and manufacture customized products at mass production efficiency and speed." In this chapter, the term "mass-customized" will refer to the parts manufactured with the traditional MC technology.

To meet higher customer expectations for MC (Deradjat and Minshall 2017), AM full flexibility has been explored. The absence of tooling requirements, geometry freedom, and inventory reduction through just-in-time operations makes AM particularly attractive over conventional manufacturing processes (Weller et al. 2015, Baumers et al. 2016). (Berman 2012, Table 1) compares and contrasts AM and traditional MC. Although AM and MC are capable of producing custom final parts cost-effectively, these two processes display technology-specific cost structures and different customization capabilities, as highlighted in (Lacroix et al. 2020, Table 2). In this chapter, we focus on these key differences. Adopting AM for final parts production has been proliferating across different industries (Berman 2012). In the automotive industry, BMW is manufacturing 3D-printed customized components for commercial vehicles. AFMG (2020) reports that "from consumer electronics to toys and sportswear, key players within the consumer goods industry are increasingly recognizing 3D-printing as a valuable addition to existing manufacturing solutions."

Yet, AM for MC is not widely deployed for large-scale production and is not expected to replace traditional MC processes. Rather, researchers and industry experts (*e.g.*, (Holweg 2015, Rogers et al. 2016, Sasson and Johnson 2016, AFMG 2020)) argue that AM will supplement existing MC processes. Currently, printing speed and production volume are preventing AM adoption at large scale (Arbabian and Wagner 2020). But what if manufacturers could combine the benefits of AM with traditional MC processes over the course of the product life cycle (PLC)? Firms currently lack quantitative decision tools to assess this opportunity. We aim to bridge this gap.

On the demand side, practitioners and academics have recently scrutinized customer-centric strategies, recognized to add business value, particularly in the context of MC. For instance, Lacroix et al. (2020) have developed a time-varying locational customer choice model that allows for customer heterogeneity and forward-looking behavior. The authors highlight the importance of linking individual customers' preferences to the PLC and to the technology (AM or MC) choice over time.

Thus, the combination of customer-centric strategies with the new usage of AM combined with MC, provide for new manufacturing opportunities. Yet, AM economic benefits over traditional MC processes, are not fully uncovered, and specifically not under capacity constraints and across the PLC. As Dong et al. (2020b) point out, AM and MC (referred to as traditional flexible manufacturing system in their work) present a different degree of flexibility and cost structures. Hence, optimal technology-switching scenarios operating AM and MC over the PLC and with limited capacity are of interest to manufacturers who aim to maximize their profit while addressing individual customer preferences. The design thinking Venn diagram (Ideo

2020) is widely spread in practice to implement a profitable customer-centric solution. Building on it (see Fig. 3.1), we can illustrate this manufacturing sweet spot that can successfully drive operational efficiency, customer satisfaction, and profit. This diagram also highlights pending questions related to this opportunity: Which pricing policy should be applied? How many product variants to manufacture to satisfy individual customer preferences? Which technology-switching scenario over the PLC (*i.e.*, combining AM with the firm's existing MC processes) would be more beneficial? What are the effects of production capacity constraints and inventory decisions on marketing and operations decisions?

In this chapter, we aim to answer the following research question: *"How can a manufacturer*

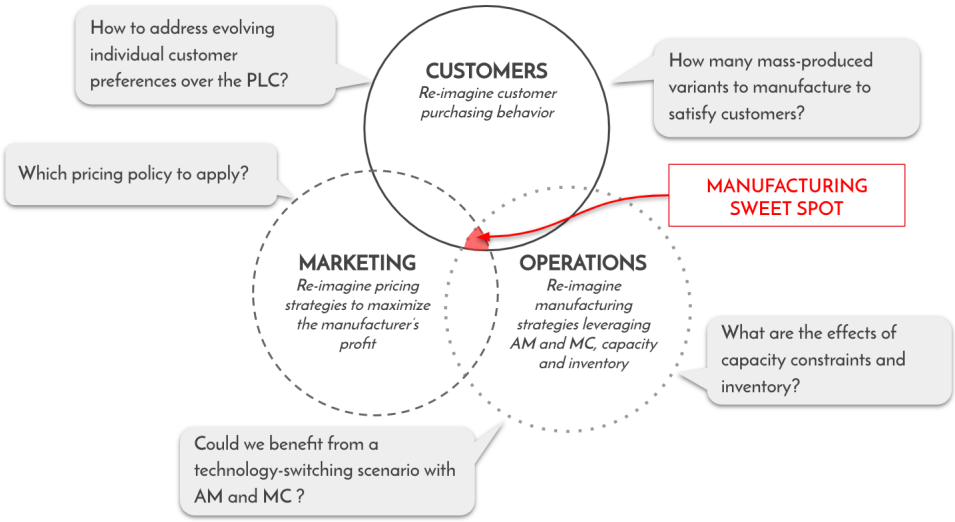


Figure 3.1 – Manufacturing sweet spot to transition toward mass customization at scale.

combine the benefits of AM with traditional MC technology under capacity constraints?" We address this opportunity through a mathematical model, where individual customer preferences and forward-looking behavior, PLC, and capacity constraints are considered. We analyze the impact of deploying AM with MC for a monopolist manufacturer producing horizontally differentiated products at scale. The manufacturer jointly decides on customer-centric strategies, namely: inventory, production quantity, product variety, technology-switching times (between AM and MC), and pricing decisions. To this end, several technology-switching scenarios, and three production capacity and inventory cases are considered.

We develop an *adaptive inventory policy* intended for an interdependent non-stationary demand. From this inventory policy follows a closed-form solution for the production quantity decision. The numerous decisions involved in our optimization problem lead to a non-convex problem. We thus analytically ground our optimization problem and successfully derive an algorithmic formulation for our objective function under various capacity and inventory scenarios. We solve our problem using the Sample Average Approximation (SAA) framework. We perform robustness tests to check the convergence of our approximation problem and validate the population sample size used in our numerical experiments.

On the operations side, given our manufacturing setting and the customers' profile, significant

profit improvements can be achieved with an AM-MC-AM technology-switching scenario. On the marketing side and under capacity constraints, our results reveal that considering both customer heterogeneity and limited production capacity requires an increasing-decreasing pricing policy. Our findings also show that the benefits of pricing flexibility are highest when capacity is unlimited, or when the firm does not hold inventory. Under capacity constraints, a simple decreasing pricing policy combined with inventory performs very well and lessens the need for pricing flexibility. Overall, our numerical results show that the combination of customer-centric marketing and operations strategies with the new usage of AM combined with MC can maximize a manufacturer's profit while addressing individual customer preferences.

The remainder of this chapter is organized as follows. In Section 3.2, we review the relevant literature. In Section 3.3, we describe our analytical model in detail. Specifically, we describe our customer choice model, introduce the manufacturing scenarios that we investigate, and the technology production characteristics that differentiate AM from MC. We then describe our demand forecasting methods and develop an adaptive inventory policy. Next, we characterize our objective function and build on the analytical properties of our demand forecasting method to ground our non-convex optimization problem. In Section 3.4, we use the (SAA) framework to approximate our optimization problem and perform robustness tests to check its validity. Section 3.5 presents our sensitivity analyses and numerical experiments. Section 3.6 summarizes our key findings and managerial insights. In the Appendix, we provide an overview of our notations and parametric assumptions (see Table G.1), as well as analytical results, algorithms, and proofs.

3.2 Literature Review

A growing body of literature has developed analytical models to evaluate the impact of AM vs. conventional manufacturing systems on operations management (*e.g.*, (Westerweel et al. 2018b,a, Sethuraman et al. 2018, Song and Zhang 2020, Dong et al. 2020b, Chen et al. 2020)). Preliminary works in this field focused primarily on spare part logistics (Westerweel et al. 2018a, Song and Zhang 2020), consumer goods retailing (Chen et al. 2020), component design cost analysis (Westerweel et al. 2018b), and assortment planning (Dong et al. 2020b). Only a few papers (*i.e.*, Dong et al. (2020b), Chen et al. (2020)) position themselves at the operations-marketing interface, considering both the demand and supply perspectives. Our work is more closely related to this literature. Chen et al. (2020) focused on AM adoption cases in a dual-channel retail setting (*i.e.*, online and in-store channels) and studied the firm's joint decision about product offers, pricing, and inventory. Our model is placed in a manufacturing setting. Dong et al. (2020b) was among the first to evaluate the impact of AM over conventional manufacturing systems on a firm's manufacturing strategy. The authors examine three manufacturing technologies (*i.e.*, AM, traditional flexible, and dedicated technologies). They focus on product assortment decisions under capacity constraints and show that pairing AM with dedicated technology allows wider product variety and profit increase. More recently,

Lacroix et al. (2020) has built on the work of Dong et al. (2020b) to add technology-switching (between AM and MC) and pricing decisions, under PLC considerations. Assuming limited capacity under AM and MC, we extend their work to consider inventory decisions under MC technology.

As we consider a monopolist manufacturer producing custom products that are horizontally differentiated, papers modeling a utility-based demand in the mass customization (MC) literature are relevant to our work. Commonly used in the marketing literature, utility-based demand models in assortment planning (see Kök et al. (2015) for a detailed review of demand models in this research area) consider customer heterogeneity. Although some researchers (*e.g.*, Dong et al. (2020b)) model customer preferences through a multinomial logit (MNL) model, we derive demand from the "*Hotelling-Lancaster-Bass*" (HLB) demand model developed by Lacroix et al. (2020). The HLB model is a novel time-varying locational customer choice model that combines the classic Hotelling-Lancaster model (Lancaster 1990) (also referred to as an "address model" by Kök et al. (2015)) and the well-known Bass diffusion model (Bass 1969). For tractability reasons, most of the above papers study marketing and operations decisions in a static setting. However, forward-looking customers are typically variant-sensitive but also time-sensitive in their purchasing decisions. Thus, as previously mentioned, we adopt the HLB demand model, which characterizes the demand of heterogeneous customers at the individual level and mimics the PLC dynamics. With respect to the operations side, few studies have been conducted on generalized Bass diffusion models (*i.e.*, those which include the selling price) (Bass 2004) with production or inventory decisions (e.g., Ho et al. (2002), Kumar and Swaminathan (2003) and Shen et al. (2013)). Ho et al. (2002) jointly analyze demand and sales dynamics in a constrained new product diffusion context where backorders and lost sales are deemed. Kumar and Swaminathan (2003) explicitly model interactions between manufacturing and marketing decisions for a firm with a fixed production capacity. Shen et al. (2013) focus on the joint impact of pricing, sales, and production decisions with limited capacity. They derive optimal policies for handling new product introductions. Unlike these papers, we do not use the Bass diffusion model as such to model the demand, but we include it through the HLB model. Furthermore, most Bass diffusion models usually consider aggregate demand which does not address the recent need of operations managers for applying customer-centric operations strategies (see M&SOM upcoming special issue on this topic). Chatterjee and Eliashberg (1990) developed an innovation diffusion model using a micro-modeling approach (*i.e.*, modeling demand at the individual level). They highlight the added-value of this approach for customer segmentation in terms of adoption times. Lacroix et al. (2020) showed the importance of modeling time-varying customer preferences at the individual level as it directly impacts the operations, marketing decisions, and a manufacturer's profit. Accordingly, since our focus is not on new product introduction timing but on evaluating the benefits of combining AM with traditional MC, we build on the work of Lacroix et al. (2020). The authors consider a monopolist manufacturer who jointly optimizes technology-switching, pricing, and product variety decisions across the PLC. Unlike their model, we consider AM and MC technologies as capacity-constrained and add inventory decisions under MC technology.

Our work is also related to the literature on pricing and production control under capacity constraints. While this line of literature primarily focuses on inventory control where a demand distribution is assumed to be known and stationary, few studies are intended for consumer goods exhibiting non-stationary demand (*i.e.*, the demand probability function changes over time) and partial information. We focus on adaptive inventory control problems for non-stationary demand and incomplete information. The earliest model investigating stochastic non-stationary demand was by Hadley and Whitin (1961). They proposed an optimal inventory model where demand is Poisson distributed. Graves (1999) developed an adaptive base-stock inventory policy for a non-stationary problem. However, in Graves' model, the firm has complete information as the demand is fully characterized by an auto-regressive integrated moving average ARIMA(0,1,1) and by the observed demand from previous periods. Kurawarwala and Matsuo (1996) presented a growth model to estimate the parameters of a non-stationary demand process over its entire PLC but do not revise these estimates using new observations. Treharne and Sox (2002) examined a periodic-review inventory model with non-stationary and partially observed demand. The demand state is estimated using the observed sales in each period. The inventory control problem is modeled as a partially observed Markov's decision process. Recently, Yang and Kim (2018) developed a joint replenishment policy characterized by a variable order-up-to level for items sold in a retail system. They adopt a multiplicative seasonal model to generate demand data to forecast the true demand and assume that the forecast errors are normally distributed. Our model forecasts the demand using a discrete-time version of a Bass diffusion model. The above-mentioned studies are different from our work in that they do not apply customer-centric manufacturing strategies, that is, they do not consider the evolving customer purchasing behavior at the individual level and most of them do not combine marketing and operations decisions. Key realistic features that distinguish our chapter from the above-mentioned ones is that we include (i) customer heterogeneity in terms of product attributes and buying times, (ii) pricing flexibility, and (iii) capacity constraints and PLC considerations at the marketing-operations interface. We jointly optimize technology-switching, pricing, product variety, and inventory decisions that are of interest to operations managers, in a context where customer-centric operations strategies have gained much attention.

3.3 Model Framework

We consider a monopolist manufacturer, who serves customers over a finite horizon composed of T periods. The customer preferences, which are heterogeneous in product attributes and buying times, are described through a time-varying locational choice model similar to the one proposed by Lacroix et al. (2020). This model is referred to as the Hotelling-Lancaster Bass (HLB) model by the authors (see Section 3.3.1). Considering customer individual preferences, the manufacturer decides whether to adopt only one production technology (AM or MC) over the PLC or, alternatively, to switch between AM and MC during the selling horizon (*i.e.*, to select a technology-switching scenario, hereafter specified by technology-switching time

decisions). We formulate an analytical model that jointly optimizes, over time $1 \leq t \leq T$, the four following manufacturer's decisions.

(i): the technology-switching times, a pair $(T_{A\to M}, T_{M\to A})$ where $0 \leq T_{A\to M} < T_{M\to A} \leq T+1$, where MC production occurs at periods $1 \leq t \leq T$ such that $T_{A\to M}+1 \leq t \leq T_{M\to A}$, only. We set $\mathscr{T} = \{(T_{A\to M}, T_{M\to A}) : 0 \leq T_{A\to M} < T_{M\to A} \leq T+1\}$ denote a set of possible technology-switching pairs, $\mathscr{T}^A = \{t \in \{0,T\} : t \leq T_{A\to M} \text{ or } t > T_{M\to A}\}$ the set of AM production periods, and $\mathscr{T}^M = \{t \in \{0,T\} : T_{A\to M} < t \leq T_{M\to A}\}$ the set of MC ones;

(ii): the pricing strategy $(p_t)_{1\leq t\leq T}$;

(iii): the product variety under MC, n;

(iv): the production quantity for each mass-customized variant j, $Q_{j,t}$.
We begin with the customer choice model, present the considered manufacturing scenarios and production technology assumptions, and, finally, describe the firms' operational decisions.

3.3.1 Customer Choice Model

Our study builds on the customer choice model described in Lacroix et al. (2020). Considering customer heterogeneity in *product preferences* denoted by ϕ, and *ideal buying time* τ, we focus on a manufacturer adopting *horizontal product differentiation* (*i.e.*, the selling price is equal for all product variants).
We consider a potential market size, N, that represents the initial number of potential adopters. Although unknown a priori, N can be estimated qualitatively via market research, or via the Delphi method (Snyder and Shen 2019). A market's *random customer* ξ is defined by his two independent attributes τ and ϕ: $\xi = (\tau, \phi)$, $\mathbb{P}_\xi = \mathbb{P}_\tau \otimes \mathbb{P}_\phi$.
The virtual product space $\Phi = [0,1]$ contains all possible ideal variants ϕ, uniformly distributed on Φ ($\mathbb{P}_\phi = \mathscr{U}([0,1])$). Given its infinite manufacturing flexibility, AM technology is assumed to serve customers perfectly in product attributes. By contrast, under MC, customers are served by the nearest mass-customized variant, one within $\mathscr{X} = \{x_1, \ldots, x_n\} \subset [0,1]^n$.
The customer's ideal buying time τ is drawn from a *truncated Bass distribution* to model the spread of customers along with the PLC (details in Lacroix et al. (2020)).
A *customer's utility* is built on several components: a *willingness-to-pay* $\omega(\tau)$, a *time disutility proportional term* representing the customer buying time misfit at t, and a *product disutility proportional term* corresponding to the customer's product variant misfit under MC. The variations of ω over the PLC display the customer's evolving interest. The time disutility factor is the product of a *time sensitivity factor* $\gamma(\tau)$ by a *normalized time distance* $|\tau - \frac{2t-1}{2}|/T$ between the selling period and the customer's ideal buying time τ. The variations of γ over the PLC represent the customer's sensitivity to the buying period. The product disutility term is equal to a *product sensitivity factor* $\lambda(\tau)$ weighted by a product misfit distance $d(\phi, \mathscr{X})$ between the customer's ideal variant ϕ and the nearest mass-customized variant from $\mathscr{X}$. The variations

of the customer's product sensitivity factor over the PLC represent the customer's product sensitivity to the product misfit under MC production. The customer's utility decreases as the weighting distances increase. The willingness-to-pay is penalized under both AM and MC, but with a higher penalization under MC due to the additional product disutility term. Overall, given a production technology, a customer ξ presents the following utility at period t:

$$U^{\mathcal{T}}(\xi, t) = U^{\mathcal{T}}(\tau, \phi, t) = \omega(\tau)\left(1 - \gamma(\tau)\frac{|\tau - (2t-1)/2|}{T} - \lambda(\tau)d(\phi, \mathcal{X})\mathbf{1}_{\mathcal{T}^M}(t)\right). \tag{3.1}$$

We assume that customers are rational utility maximizers (*i.e.*, the customers choose the product variant that yields the maximum utility for them). Furthermore, we adopt the following assumptions about the customer purchasing behavior: given the selling price p_t, (i) a customer buys at most one product as soon as his or her utility exceeds the selling price, (ii) the customer buys at the first period t at which the previous purchasing condition is satisfied, if the product is available, and leaves the market. Assumption (i) implies that the initial market size N (the set of remaining potential customers after t) is denoted by Ξ_t. Our general notations and parametric assumptions for the decision variables, the HLB customer choice model, the technology characteristics, and the inventory policy (described in Section 3.3.4) are summarized in Table G.1 (see Appendix).

3.3.2 Manufacturing and Inventory Scenarios

The key element of the model regarding the supply side is that a manufacturer can serially produce the variants using either AM or MC technologies. Therefore, given the stage of the PLC, the firm must decide when to switch from one production technology to another, to maximize a manufacturer's profit while satisfying individual customer preferences across the PLC. We analyze the five following manufacturing scenarios presented in Lacroix et al. (2020) (where produced quantities are unlimited). Unlike their model and following Shen et al. (2013), we consider manufacturing capacities under AM and MC as it can result in lost sales and perturb the PLC, and determine the potential benefits of using AM on its own or to complement MC across the PLC.

Base case (BC): The manufacturer uses ***MC*** technology only;

Case 1 (C1): ***AM*** → ***MC*** The manufacturer uses only AM during the PLC introductory stage;

Case 2 (C2): ***MC*** → ***AM*** The manufacturer uses AM toward the PLC decline stage;

Case 3 (C3): ***AM*** → ***MC*** → ***AM*** This case combines the (C1) and (C2) cases;

Case 4 (C4): ***AM*** The manufacturer uses only AM over the PLC.

The following assumptions characterize AM and MC.

(A1) AM and MC are both considered flexible manufacturing systems – they can easily adapt to changes in the product variant and in the quantity being manufactured (Dong et al. 2020b).

(A2) The lead time is zero, that is the product variants are produced instantaneously.

(A3) The product quality is similar under both AM and MC technologies.

(A4) AM and MC technologies both require one unit of common raw material to produce one product variant.

(A5) The selling prices and unit production costs are assumed to be identical for all variants offered during the same period.

(A6) The manufacturing capacity per period K^A resp. K^M, under AM resp. MC is constant over the PLC, following Dong et al. (2020b).

(A7) Consequently to assumption (A6), we assume that, up to the capacity limit, customer orders are served on a First-Come First-Served (FCFS) basis.

(A8) On the one hand, AM is used as a Make-To-Order (MTO) production process – even though production capacity is limited, the manufacturer does not hold inventory as products are tailor-made and shipped directly to customers. Producing ahead of time under AM would require prior knowledge of customer preferences, which is not the case in our model. On the other hand, MC is typically composed of two stages: an initial Make-To-Stock (MTS) phase for base product variants and a final MTO phase to customize them. In this chapter, we focus on one-dimensional product customization and thus concentrate on the initial stage of MC, that is, the MTS one (see the assumption of Jiang et al. (2006)). Product modularity falls outside the scope of this chapter. As production capacity and the assortment size (set to n_{max}) are limited, the manufacturer may need to produce ahead of time to meet demand during the upcoming periods.

The firm incurs one-time fixed costs, $k^A(N)$, and $k^M(N)$, which are independent of the production quantity, though depending on the market size, N. This reflects investment expenses on AM and MC equipment. The fixed cost $k^M(N)$ is counted once if $T_{A\to M} < T$. The fixed cost $k^A(N)$ is also incurred once if $T_{A\to M} > 0$ or $T_{M\to A} < T$. Following the assumption of Dong et al. (2020b), we assume $k_A(N) \geq k_M(N)$ since 3D-printers are typically more expensive than MC equipment. Based on the assumption of Lacroix et al. (2020) and, for simplicity, the authors set $k^A(N) = N\tilde{k}^A$, $k^M(N) = N\tilde{k}^M$, where $\tilde{k}^A = k^A/N$ and $\tilde{k}^M = k^M/N$.
Further, per unit production costs denoted by c^A for AM technology and by $c^M(n)$ for MC technology are defined, where $c^A > 0$ and $c^M(n) > 0$ (identical for all variants). Due to AM's infinite flexibility in terms of product variants, c^A does not depend on the product's variety and is set constant. By contrast, $c^M(n) = c_B(1 + (n-1)\delta)$ depends on the number n of mass-customized variants to offer, where c_B denotes a base cost and δ represents an incremental cost (following the form and notations in Dong et al. (2020b)).

Besides the production framework (MTS and MTO), the product misfit penalty cost and the cost structure, AM and MC distinguish from each other in terms of production capacities (in line with Shen et al. (2013) and assumption (A6)). We assume the total production capacity under MC per period and variant, K^M/n, is equally distributed among the mass-customized variants and is greater than the production capacity under AM per period, K^A: we set $K^A = \kappa * \frac{N}{T} > 0$, with $K^A \leq \sum_j K_j^M := K^M = \frac{\kappa}{\rho} \times \frac{N}{T}$, where κ denotes the production capacity magnitude, and $\rho = \frac{K^A}{K^M}$ the production capacity ratio between AM and MC. To adapt the production capacities to the market size, we set them proportional to N. We introduce proportionality coefficients $\tilde{K}^M = K^M/N = \kappa/(\rho T)$, and $\tilde{K}^A = K^A/N = \kappa/T$. The manufacturing technologies characteristics' are summarized in Table 3.1.

Table 3.1 – MC and AM Technology Characteristics Comparison.

	Production Technology Comparison	
Characteristic	**MC**	**AM**
Production framework	MTS	MTO
Production period	$\mathcal{T}^M$	$\mathcal{T}^A$
Assortment size	$n \in [1; n_{max}]$	$n \in [1; +\infty[$
Unit production cost	$c^M(n) = c_B(1 + (n-1)\delta) > 0$	$c^A = \text{constant} > 0$
Setup cost	$k^M = \text{constant} > 0$	$k^A = \text{constant} > 0$
Production capacity	$K_j^M > 0, \forall j \in \{1, \ldots, n\}$	$K^A > 0$, $K^A \leq \sum_j K_j^M := K^M$
Total production capacity	$K^M = \sum_j K_j^M = N\tilde{K}^M$	$K^A = N\tilde{K}^A$, $K^A \leq K^M$
Holding cost	h	0 (no inventory under AM)
Salvage value	$v = 0.8 \times p_{T_{M\to A}}$	0 (no inventory under AM)

As described earlier, we consider a capacity-constrained manufacturer using two flexible manufacturing systems, namely AM and MC. We investigate three production capacity and inventory scenarios: (i) the **MTO uncapacitated** (MTOUC) scenario, where production capacities under AM and MC are assumed to be unlimited, and the firm does not hold inventory. This scenario serves as our reference case. Further, we consider (ii) the **MTO capacitated** (MTOC) scenario, where the production capacities under AM and MC are constant over time, and the firm does not hold inventory. Finally, (iii) the **MTS capacitated** scenario (MTSC) is similar to the MTOC scenario and allows the firm to hold inventory. The lead time is zero, that is, the variants are produced instantaneously. We assume that the manufacturer can face a non-stationary demand for which the information distribution is not necessarily accessible. Therefore, in the MTSC scenario, the manufacturer carries an inventory for an assortment of mass-customized variants, sold to end-users. The inventory is controlled using an *adaptive inventory policy*, described later in Section 3.3.4.

3.3.3 Demand and Forecasting Model

In the MTSC scenario, at each period, the objective is to control the inventory of each mass-customized variant, facing a non-stationary demand. We first introduce our demand forecasting methods. To select the production quantity for each mass-customized variant offered to customers, $Q_{j,t}$, we build on Snyder and Shen (2019) to forecast the demand trajectory, over

the PLC. Let $D_{j,t}$ denote the demand of variant j at time t. Following our notations,

$$\begin{cases} D_{j,t} &= \sum_{i\in\Xi_{t-1}} \mathbf{1}_{\{U^{\mathcal{T}}(\xi_i,t)>p_t\}} \cap \{d(\phi_i,\mathcal{X}) = d(\phi_i,x_j)\} \text{ if } \mathcal{T}(t) = MC;\ D_t = \sum_j D_{j,t} \\ D_t &= \sum_{i\in\Xi_{t-1}} \mathbf{1}_{\{U^{\mathcal{T}}(\xi_i,t)>p_t\}} \text{ if } \mathcal{T}(t) = AM; \text{ we set } D_{j,t} = 0 \text{ for homogeneity of notations.} \end{cases} \tag{3.2}$$

We aim to adopt a meaningful forecasting demand method from the viewpoint of the manufacturer, who has partial information about the customer attributes, such as the Bass distribution. We propose two alternatives to define the demand forecast, ${}_*D'_{j,t}$. The first one corresponds to a *censored* information case, that is, the firm only has access to the Bass distribution information, not to the full demand distribution. We define for it a left subscript c (for *censored*) and obtain the demand forecast by approximating the Bass distribution as if it were representing the demand in our model. The second alternative corresponds to an *uncensored* information case, in which the firm can statistically estimate the customer attributes: ω, λ, γ, through market research. The demand forecast, in this case, is characterized by a left subscript u (for *uncensored*), computed for a given pricing strategy, and is based on the exact mean value of the demand in our random customer choice model. This second forecast alternative plays a central role in analytically grounding results (see (i) in Lemma 3.2, Theorems 3.3,3.8) for our optimization problem in Section 3.4.1.
By independence of τ and ϕ for a population of size N, the first demand forecast is written as:

$$\begin{cases} \left.\begin{aligned} {}_cD'_{j,t} &= N \times \overbrace{\mathbb{P}(\{t \le \tau < t+1\} \cap \{d(\phi,\mathcal{X}) = d(\phi,x_j)\})}^{{}_c\mathbf{d'_{j,t}}} = \tfrac{N}{n}(F_\tau(t+1) - F_\tau(t)) \\ {}_cD'_t &= \textstyle\sum_j {}_cD'_{j,t};\ (:= \mathbf{N_c d'_{j,t}} = \tfrac{\mathbf{N}}{\mathbf{n}}\mathbf{c d'_t}) \end{aligned}\right] & \text{if } \mathcal{T}(t) = MC; \\ \left.\begin{aligned} {}_cD'_t &= N \times \underbrace{\mathbb{P}(\{t \le \tau < t+1\})}_{{}_c\mathbf{d'_t}} = N(F_\tau(t+1) - F_\tau(t)) \end{aligned}\right] & \text{if } \mathcal{T}(t) = AM. \end{cases} \tag{3.3}$$

If the second forecast alternative is predicted by accurate model parameter estimations, then

$$\begin{cases} \left.\begin{aligned} {}_uD'_{j,t} &= N \times \overbrace{\mathbb{P}\left(\{U^{\mathcal{T}}(\xi,t) \ge p_t\} \cap (\cap_{1\le g<t}\{U^{\mathcal{T}}(\xi,g) < p_g\}) \cap \{d(\phi,\mathcal{X}) = d(\phi,x_j)\}\right)}^{{}_u\mathbf{d'_{j,t}}} \\ {}_uD'_t &= \textstyle\sum_j {}_uD'_{j,t};\ (:= \mathbf{N_u d'_{j,t}} = \tfrac{\mathbf{N}}{\mathbf{n}}\mathbf{u d'_t}, \text{ see (3.5) below}) \end{aligned}\right] & \text{if } \mathcal{T}(t) = MC; \\ \left.\begin{aligned} {}_uD'_t &= N \times \underbrace{\mathbb{P}\left(\{U^{\mathcal{T}}(\xi,t) \ge p_t\} \cap (\cap_{1\le g<t}\{U^{\mathcal{T}}(\xi,g) < p_g\})\right)}_{{}_u\mathbf{d'_t}} \end{aligned}\right] & \text{if } \mathcal{T}(t) = AM. \end{cases} \tag{3.4}$$

Indeed, independence and a change of variable ($y' = x_{j'} - x_j + y$) in the following integral

$${}_ud'_{j,t} = \int_0^T \left(\int_{x_j - \frac{1}{2n}}^{x_j + \frac{1}{2n}} \left(\prod_{g=1}^{t-1} 1_{]-\infty,p_g[}(U^{\mathcal{T}}(x,y,g)) \right) 1_{[p_t,+\infty[}(U^{\mathcal{T}}(x,y,t)) f_\tau(x)\,dy \right) dx \tag{3.5}$$

yield, under MC technology: $\forall j, j',\ {}_u d'_{j',t} = {}_u d'_{j,t}$. As a consequence of the uniform distribution in the Hotelling-Lancaster model, the independence of τ and ϕ, and (3.3, 3.4):

$$ {}_* D'_{j,t} = {}_* D'_t / n,\ {}_* D'_{j,t} = N_* d'_{j,t},\ {}_* D'_t = N_* d'_t,\ {}_* d'_t = {}_* d'_{j,t} / n, \text{ where "}*\text{"equals to } c \text{ or } u. \quad (3.6) $$

3.3.4 Adaptive Inventory Policy

We develop an *adaptive inventory policy* that shows key features that differ from most inventory models in operations management: (i) the demand forecast is interdependent across the PLC, due to the production capacity influencing the customer ability to purchase; (ii) the policy is adaptive over time and relies on a backward-forward process (as explained below). We set the current time point as the beginning of period t. The on-hand inventory (*i.e.*, the variants that are available on stock), $I_{j,t}$, is monitored periodically at the beginning of each period, and set initially to 0 at the first period under MC, for all variants (*i.e.*, $I_{j,T_{A\to M+1}} = 0$). The ending inventory level in period t is equal to the starting inventory level in period $t+1$.
In detail, our policy proposes a first step, called the *backward step*, and a second step, termed the *forward step*. The *backward step* is based on the demand forecast, ${}_* D'_{j,t}$ (see (3.3), (3.4)). For each $t \in \mathcal{T}^M$ and going backward across periods (i.e., starting at $t = T$), the manufacturer aims to estimate the target inventory level for each period and variant, $I'_{j,t}$. For this, we develop a *Water Filling Scheme* (WFS) which is an algorithm typically used in information theory (Yu and Cioffi 2001). It provides equalization strategies on communications channels. We do not use this algorithm but only refer to its concept of water level compensations between channels (periods in our case). Our WFS algorithm can be analogically described as follows: if the water level (*demand forecast*) in the lock chamber (*period t*) exceeds the maximum water level (*MC production capacity*), we open the valve separating the current lock chamber from the next one (*period* $t-1$) to only allow the excess water level (*target inventory level - MC production capacity*) to be moved to the next lock chamber. We repeat the operation, going backward from one lock chamber to the next one until the excess water level does not surpass the maximum water level anymore. Figure 3.2 displays the water filling analogy.

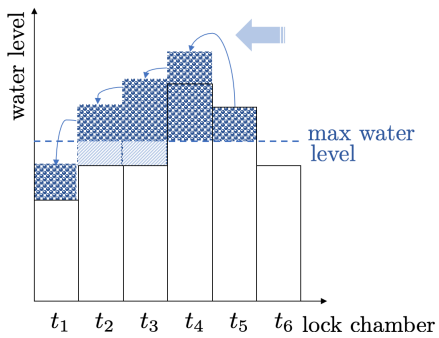


Figure 3.2 – Water filling scheme analogy.

From the (WFS), we also evaluate the mean total target inventory level per period, i'_t. This quantity is required in Section 3.3.6 for the formulation of our objective function.

Next, for the *forward step*, the goal is to determine the optimal production quantity, $Q_{j,t}$, after observing the actual demand, $D_{j,t}$, such that the on-hand inventory level, $I_{j,t}$, matches the target one, $I'_{j,t}$ (from the *backward step*), as much as possible (*i.e.*, $I'_{j,t} \overset{!}{=} I_{j,t}$). This time going forward across periods (*i.e.*, starting at $t = 1$), this step consists of the following actions: we first initialize to zero the inventory level for each mass-customized variant j. Then, for each t, we observe the actual demand and compute the optimal production quantity for each variant.

Remark 3.1. Note that we provide a closed-form solution of $Q_{j,t}$ under MC (see (3.8)). □

Once the production quantity is determined, we compute the on-hand inventory level per variant, $I_{j,t+1}$. This is the inventory that remains at the end of the considered period, or equivalently that is the starting inventory level for the upcoming period, $t+1$. We iterate this sequence of actions until we reach the end of the PLC.
We define hereafter the *backward* (step 1) and *forward* (step 2) steps:
Step 1: *Backward step.* We define the target inventory level for each period and variant $I'_{j,t}$, $1 \le j \le n$, $1 \le t \le T+1$, the mean target inventory level per period and variant $i'_{j,t}$, $1 \le j \le n$, $1 \le t \le T+1$, the total target inventory level per period I'_t, $1 \le t \le T+1$, and the mean total target inventory level per period i'_t, $1 \le t \le T+1$, using the above-mentioned **Water Filling Scheme** and (3.3, 3.4, and 3.6):

$$\boxed{(\mathtt{I}'_1,\ldots,\mathtt{I}'_{\mathtt{T}+1}) = \mathtt{WFS}(\mathscr{T},\mathtt{n},({}_*\mathtt{D}'_1,\ldots,{}_*\mathtt{D}'_{\mathtt{T}}))\,:}$$

$$\begin{aligned}
&\boldsymbol{t = T,\ I'_{T+1} = i'_{T+1} = I'_{j,T+1} = i'_{j,T+1} = 0}\\
&\mathtt{while}\ \ \boldsymbol{t > 0}\\
&\quad \mathtt{if}\ \ \boldsymbol{t > T_{A\to M}}\\
&\qquad \boldsymbol{I'_{j,t} = \max((_*D'_{j,t} - K^M_j)\mathbf{1}_{\{\mathscr{T}(t)=MC\}} + I'_{j,t+1}, 0)}\\
&\qquad \boldsymbol{i'_{j,t} = \tfrac{1}{N} I'_{j,t} = \max((_*d'_{j,t} - \tilde{K}^M/n)\mathbf{1}_{\{\mathscr{T}(t)=MC\}} + i'_{j,t+1}, 0)}\\
&\qquad \boldsymbol{I'_t = \textstyle\sum_j I'_{j,t}}\\
&\qquad \boldsymbol{i'_t = \textstyle\sum_j i'_{j,t} = I'_t/N}\\
&\qquad \boldsymbol{t = t-1}\\
&\quad \mathtt{else\ if}\ \ \boldsymbol{\le T_{A\to M}}\\
&\qquad \boldsymbol{i'_t = 0}\\
&\qquad \boldsymbol{t = t-1}\\
&\quad \mathtt{end}\\
&\mathtt{end}
\end{aligned} \tag{WFS}$$

Note that in the above algorithm, for all t periods, such that $\mathscr{T}(t) = AM$, $I'_t = i'_t = I'_{j,t} = i'_{j,t} = 0$, because under AM, the probability of demand for a specified finite number of variants is 0, by continuity of $\mathbb{P}_\phi$ $({}_*D'_{j,t} = 0)$. Whence, this is consistent with the notations introduced previously.

Step 2: *Forward step.* We then compute the on-hand inventory per variant and period

$(I_{j,t})_{\substack{1\le j\le n,\\ 1\le t\le T+1}}$, the mean inventory level per period and variant $(i_{j,t})_{\substack{1\le j\le n,\\ 1\le t\le T+1}}$, the total inventory level per period $(I_t)_{1\le t\le T+1}$, and the mean total inventory level per period $(i_t)_{1\le t\le T+1}$:

1. Set $t = 1$, and initialize the inventory level for each mass-customized variant j:

$$I_{j,1} = 0 \tag{3.7}$$

2. While $t \le T$

   (a) Observe the actual demand $D_{j,t}$ (3.2)

   (b) Determine the production quantity for each variant j:

$$Q_{j,t} = \mathbf{1}_{\{\mathcal{T}(t)=MC\}} \min\{K_j^M, \max\{0, I'_{j,t} - I_{j,t} + D_{j,t}\}\},\ Q_t = \sum_j Q_{j,t} \tag{3.8}$$

   (c) Compute the inventory levels per variant for the upcoming period $t+1$:

$$I_{j,t+1} = \max\{0, I_{j,t} + Q_{j,t} - D_{j,t}\},\ I_{t+1} = \sum_j I_{j,t+1} \tag{3.9}$$

   (d) Set $t = t+1$

3. For later analytical requirements (in Section 3.3.6), set $i_{j,t} = I_{j,t}/N$, $i_t = I_t/N$.

Proceeding with the customers' model, we note that they choose the nearest—to their ideal one—product variant available, without observing the inventory levels, and do not make a second choice if the first choice is not available due to production capacity shortage. In this case, unmet demand during the period is considered lost for which the firm incurs a stockout cost, denoted by s. The corresponding lost customers are then canceled out of the customers' population. The excess inventory is salvaged at value v, at the end of the last MC period. The salvage value corresponds to a fraction of the selling price of the last period under MC. It is incurred at the end of this period, which is at $T_{M\to A}+1$. As for the on-hand inventory, the firm incurs a holding cost h per unit per period. The holding cost is assumed to be lower than the stockout cost, $h < s$, otherwise there would be no incentive for the firm to stock the variants. Also, to ensure the profitability of the manufacturer the following condition should hold: $p_t > v > c^M(n)$. The notations are summarized in Table G.1 (see Appendix).

3.3.5 Manufacturer's Profit

We can now compute the manufacturer's technology-specific profits under AM and MC for each period, denoted by $\Pi_t^{\mathcal{T}}$. Based on the cost structures of AM and MC described in Section 3.3.2, we formulate the profit function and recall that we do not carry inventory under AM. Hence, no holding costs are incurred under this technology. Note that the actual demand

at time t under AM is equal to

$$D_t = \sum_{i \in \Xi_t} \mathbf{1}_{\{U^A(\xi_i,t) > p_t\}}, \text{ and that } D_t = S_t + L_t \tag{3.10}$$

where the materialized sales, S_t, and the lost sales, L_t, for each period are given respectively by

$$S_t = \min\{D_t, K^A\},\ L_t = \max\{0, D_t - K^A\}. \tag{3.11}$$

Thus, focusing on AM technology first, the profit under this technology at period t, if $\mathcal{T}(t) = AM$, is given by (for clarity, we subtract the fixed cost later in the profit function (see 3.15))

$$\Pi_t^{\mathcal{T}}(p) = p_t S_t - c_A S_t - s L_t. \tag{3.12}$$

Similarly, we define the profit function for MC periods, which is given by (again, we subtract the fixed cost later in the profit function (see 3.15))

$$\Pi_t^{\mathcal{T}}(p) = \sum_j \left(p_t S_{j,t} - c_M(n) Q_{j,t} - h I_{j,t+1} - s L_{j,t} + v I_{j,T_{M\to A}+1} \mathbf{1}_{\{t = T_{M\to A}\}} \right), \tag{3.13}$$

where the materialized sales, $S_{j,t}$, and lost sales, $L_{j,t}$, for each period under MC are given respectively by

$$S_{j,t} = \min\{D_{j,t}, K_j^M + I_{j,t}\},\ L_{j,t} = \max\{0, D_{j,t} - I_{j,t} - Q_{j,t}\}. \tag{3.14}$$

For each mass-customized variant and each period, the production quantity, $Q_{j,t}$, and the starting inventory level for the upcoming period, $I_{j,t+1}$, are given by (3.8) and (3.9).
By combining the profit functions (3.12) and (3.13), and incorporating the once-incurred fixed costs of AM and MC technologies, we formulate the manufacturer's total profit across periods and for all customers

$$\Pi^{\mathcal{T}}(\{\xi_i\}_{i=1}^N, p) = \left(\sum_t \Pi_t^{\mathcal{T}}(p) \right) - k^A(N) \mathbf{1}_{\{t:\mathcal{T}(t)=AM\} \neq \emptyset} - k^M(N) \mathbf{1}_{\{t:\mathcal{T}(t)=MC\} \neq \emptyset}. \tag{3.15}$$

In the work of Lacroix et al. (2020), an *additivity property* enabled the authors to formulate their objective function as a *mean profit per customer*, independent of the random population. They formulated and added the profit per customer—which could be defined independently of each other and set the *mean profit per customer* to be the expected profit per customer attained by the Law of Large Numbers (LLN). However, in our case, no *additivity property* holds (under the MTOC and MTSC scenarios) in the profit function. Indeed, by restriction of production capacities, potential buyers may fail to buy because some products might no longer be available. For instance, if two customers have a positive utility and are interested in the same product variant, if only one product variant is available, one customer will end up

not purchasing. In general,

$$\Pi^{\mathcal{T}}(\{\xi_i\}_{i=1}^N, p) \neq \sum_{i=1}^N \Pi^{\mathcal{T}}(\{\xi_i\}, p). \tag{3.16}$$

If we define the *mean profit per customer* as

$$\pi^{\mathcal{T}}(\{\xi_i\}_{i=1}^N, p) = \frac{1}{N}\Pi^{\mathcal{T}}(\{\xi_i\}_{i=1}^N, p), \tag{3.17}$$

how can we prove the existence of the limit in (3.17)? The LLN no longer holds straightforwardly. We address this question in Section 3.3.6. In particular, we describe algorithmically the limit of (3.17) and prove *a.s.* convergence. To further validate our optimization approach, we prove the validity of the SAA approach (see Section 3.4.1).

3.3.6 Theoretical Mean Profit per Customer

As observed in (3.16), we can no longer use the arguments from Lacroix et al. (2020) to prove *a.s.* convergence in (3.17) to some limit. If such a limit existed, we would call it the *theoretical mean profit per customer* for the given pricing, variety, and production strategies, and denote it by $\tilde{\pi}(\mathcal{T}, n, p)$. In this section, we develop a precise algorithmic formulation of $\tilde{\pi}(\mathcal{T}, n, p)$, and prove the aforementioned *a.s.* convergence. Note that, for the ${}_u d'_t$, we have an integral form (3.5):

$${}_u d'_t = \int_0^T \left(\int_0^1 \left(\prod_{g=1}^{t-1} 1_{]-\infty, p_g[}(U^{\mathcal{T}}(x,y,g)) \right) 1_{[p_t,+\infty[}(U^{\mathcal{T}}(x,y,t)) f_\tau(x)\, dy \right) dx. \tag{3.18}$$

Lemma 3.2. By the Law of Large Numbers (LLN), for all t, j, we obtain the $(i-ii)$ *a.s.* convergence of the mean actual demand to the mean uncensored demand. From this follows the *a.s.* convergence of the quantities involved in the profit function, that is the mean: $(iii-iv)$ target and $(v-vi)$ on-hand inventory levels, $(vii-viii)$ production quantity, $(ix-x)$ sales, and $(xi-xii)$ lost sales, $(xiii-xiv)$ on-hand inventory for the next period, and, finally, (xv) profit per period (see Appendix H for more details).

Proof. of Lemma 3.2. See Appendix H. ∎

We observe that the mean limiting total target inventory level per period, $(i'_1, \ldots, i'_{T+1})$ is also obtained from $({}_* d'_1, \ldots, {}_* d'_t)$ by a water filling algorithm (wfs) that resembles the (WFS), described in 3.3.4. Using this key observation and Lemma 3.2, we can now formally define the *theoretical mean profit per customer*, and its algorithmic formulation.

Theorem 3.3. Mean profit per customer, *a.s.* convergence. If $(\xi_i)_{1\leq i\leq N}$ is i.i.d., then

$$\Pi^{\mathcal{T}}(\{\xi_i\}_{i=1}^N, p) \,/\, N \to_{a.s.} \tilde{\pi}(\mathcal{T}, n, p), \tag{3.19}$$

$$\text{where} \quad \tilde{\pi}(\mathcal{T}, n, p) = \pi_1^{\mathcal{T}} + \ldots + \pi_T^{\mathcal{T}} - \tilde{k}^A \mathbf{1}_{\{T_{A\to M}>0 \text{ or } T_{M\to A}<T\}} - \tilde{k}^M \mathbf{1}_{\{T_{A\to M}<T\}}, \tag{3.20}$$

and the $\pi_t^{\mathcal{T}}$'s are obtained from algorithm (A-MTS) (see Appendix J).

Proof. of Theorem 3.3. The proof follows from Lemma 3.2 (see Appendix H). ∎

The two following corollaries are proved using arguments similar to those detailed for proving Lemma 3.2 and Theorem 3.3. They provide algorithmic computations of the theoretical mean profits per customer derived again from the ${}_u d_t'$s, in the MTOC and MTOUC scenarios.

Corollary 3.4. Mean profit per customer – the MTOC scenario. In the presence of production capacity constraints, in the MTOC setting, a similar *a.s.* convergence holds and the limit of the *mean profit per customer* is obtained by a simplified version of the (A-MTS) algorithm (see Appendix K).

Corollary 3.5. Mean profit per customer – the MTOUC scenario. Still reducing complexity, without inventory and production capacity limitation, we recover the case in Lacroix et al. (2020), for which we obtain *a.s.* convergence of the mean profit, with a different and algorithmic formulation for the limit (see Appendix L).

Remark 3.6. Absence of mass-customized variants at the limit. We observe that in all three cases –MTSC, MTOC, MTOUC, the limit of the *mean profit per customer* is expressed through a formula where the reference to mass-customized variants has completely disappeared, except in the term $c_{\mathcal{T}(t)}$. This is a consequence of two factors, namely: the product variants' uniform distribution from the Hotelling-Lancaster model and the independence of the customer attributes τ and ϕ.

3.4 Solution Approach to Maximize Profit

In a discrete-time setup, the manufacturer aims to maximize its total expected profit by jointly deciding on (i) the technology-switching times $(T_{A\to M}, T_{M\to A})$, (ii) the pricing strategy p_t, (iii) the product variety n, and (iv) the production quantity Q_t under MC. Given the capacity and the inventory scenario, we formulate our optimization problem using the *theoretical mean profit per customer* as previously described in (A-MTS, A-MTOC, A-MTOUC) algorithms. Since the optimal production quantity is written in closed-form (3.8), we do not include this decision variable in the formulation of our optimization problem:

$$\pi^* := \max_{\substack{\mathcal{T} \\ 1\le n\le n_{max}}} \max_{p\in\mathcal{P}} \tilde{\pi}(\mathcal{T}, n, p). \tag{3.21}$$

Here, special attention is required for the inner maximization, which is a non-convex optimization problem:

$$\tilde{\pi}(\mathscr{T}, n) := \max_{p \in \mathscr{P}} \tilde{\pi}(\mathscr{T}, n, p). \tag{3.22}$$

The solution approach to estimate this maximum is similar to the one described in Lacroix et al. (2020), uses the SAA framework (Shapiro et al. (2014)), and a direct local search method, in particular Pattern Search (PS). Note, that the PS heuristic is commonly used for nonlinear programming problems with discontinuous non-smooth objectives (Chinneck 2015). By Theorem 3.3 and Corollaries 3.4, 3.5, we numerically estimate $\tilde{\pi}(\mathscr{T}, n, p)$ from (wfs, A-MTS, A-MTOC, A-MTOUC) algorithms. The (A-MTS, A-MTOC, A-MTOUC) algorithms rely on calculating ${}_u d'_t$ (3.4). The calculation requires, given $\mathscr{T}, n, p$, the computation of T integrals (3.18), of highly irregular functions, which is computationally expensive. Therefore, we proceed with optimizing $\pi^{\mathscr{T}}(\{\xi_i\}_{i=1}^N, p)$ (3.17) as formulated in our SAA problem (3.21). The method generates estimates of the maximum mean profit per customer and an associated pricing strategy for a fixed production and a product variety strategy. After a finite number of evaluations of these pricing strategies, we obtain an estimate π^* and the associated optimal strategies p^*, $\mathscr{T}^*$, n^*.
We prove that the SAA convergence holds even in the absence of the additivity property (3.16). To determine a sufficient sample population size for our SAA optimization problem, we conduct a robustness test in Section 3.4.2 .

3.4.1 SAA Convergence

As explained in Section 3.3.5, we cannot formulate our objective function by adding the profit per customer. Under capacity constraint, the demand becomes interdependent across the PLC. Thus, this approach fails for the MTS and MTOC cases, given the lack of additivity property in the profit function. We have nonetheless observed in Lemma 3.2 (see H) and Theorem 3.3, that the mean profit per customer can be derived algorithmically from the integrals defining the value of ${}_u d'_t$ (3.4). Also, the *a.s.* convergence of any involved quantities in Lemma 3.2 relies on that of the D_t/N's or $D_{j,t}/N$'s. The SAA approach purely relies on the existence of a p-uniform a.s. convergence (UASC) (Shapiro et al. 2014).

Lemma 3.7. Uniform a.s. convergence of $\mathbf{D_{j,t}/N}$'s. If (UASC) holds in Lemma 3.2, (i,ii) (for the D_t/N's and the $D_{j,t}/N$'s), then

$$\pi^{\mathscr{T}}(\{\xi_i\}_{i=1}^N, p) \longrightarrow_{a.s.} \tilde{\pi}(\mathscr{T}, n, p) \text{ uniformly in } p \in \mathscr{P} \tag{UASC}$$

where $\mathscr{P} = [0, \max_{x \in [0,T]} \omega(x)]^T$.

We can prove (UASC) for the $D_{j,t}/N$'s, and D_t/N's using the same assumption as in (Lacroix et al. 2020, Theorem 1).

Theorem 3.8. SAA convergence of the mean profits. If $(\xi_i)_{i\geq 1}$ is i.i.d., and if

$$\mu_\omega \ll \mu_L; \text{ and } \forall c, t,\ \mu_L\left(\delta(\cdot, t)^{-1}(\{c\})\right) = 0, \tag{H}$$

then a (UASC) holds for the $D_{j,t}/N$'s and $D_{j,t}/N$'s. As a consequence of Lemma 3.7, if

$$\begin{cases} p^{(*,N)} \text{ achieves } \max_{p\in\mathscr{P}} \pi^{\mathscr{T}}(\{\xi_i\}_{i=1}^N, p) := \pi^{(*,\mathscr{T})}(\{\xi_i\}_{i=1}^N, p^{(*,N)}), \\ p^* \text{ achieves } \max_{p\in\mathscr{P}} \tilde{\pi}(\mathscr{T}, n, p)\ (= \tilde{\pi}(\mathscr{T}, n) = \tilde{\pi}(\mathscr{T}, n, p^*)), \end{cases} \tag{3.23}$$

then

$$\begin{cases} p^{(*,N)} \to p^*; \\ \pi^{(*,\mathscr{T})}(\{\xi_i\}_{i=1}^N, p^{(*,N)}) \to_{a.s.} \tilde{\pi}(\mathscr{T}, n). \end{cases} \tag{SAA}$$

Proof. of Theorem 3.8. See I. ∎

3.4.2 Robustness Test and Population Sample Size Choice

We proceed by assessing that a sample population size of 10,000 is sufficient for approximating $p^*, \pi^*, \mathcal{T}^*, n^*$. To this end, we test 100 optimization strategies for 100 independent sample population paths of size 10,000. We then evaluate variations on the obtained optimal quantities. We maximize the mean profit for each sampled population and optimization strategies. The profit is computed from materialized sales. Figure 3.3 illustrates and validates the robustness by comparing the normalized mean profits with the normal distribution, in the MTOC and MTS cases. We observe very low standard deviations for the mean optimal profits.

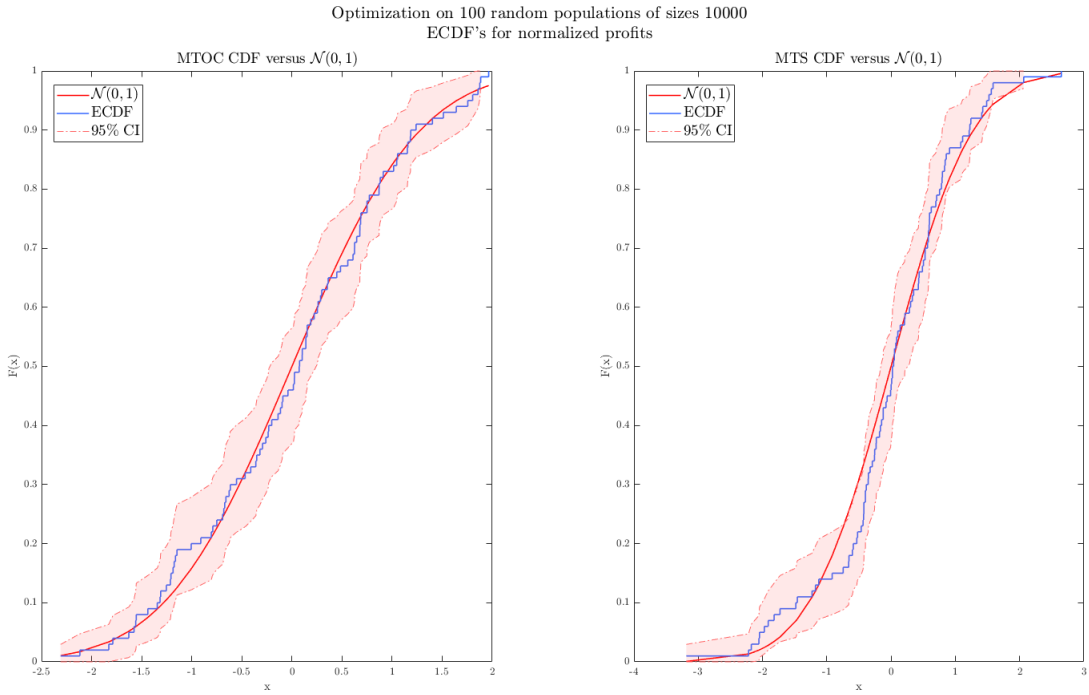


Figure 3.3 – SAA validation

Table 3.2 – SAA mean profit variations, sample size 10^4

Statistical estimators	**MTOC**	**MTS**
mean(mean profits)	5.79	5.91
std(mean profits)	0.025	0.027

3.5 Numerical Experiments

We now perform numerical experiments to highlight the benefits of and conditions for interchanging capacitated AM and MC over the PLC. Specifically, we aim to understand the effect of capacity constraints and inventory decisions on this new manufacturing opportunity. In all

experiments, we use the PS algorithm.

3.5.1 Parameter Setup

Due to the lack of real-world data, we first perform sensitivity analyses (see Section 3.5.2) and investigate several parametric scenarios issued from our model with synthetic data (see Sections 3.5.3 and 3.5.4). The baseline setup is similar to (Lacroix et al. 2020, Table 4), while we set additional capacity and the inventory parameters as follows: the fixed production capacity magnitude and ratio are $\kappa = 0.5$ and $\rho = K^A/K^M = 0.5$ respectively; the holding cost is $h = 0.5$; the stockout cost is $s = 0.8$ per unit of unsatisfied demand; the potential remaining inventory at the end of MC period is salvaged at $v = 0.8p_{T_{M\to A}}$. Table 3.3 reports the baseline parameters.

Table 3.3 – Baseline Parameter Values.

Parameter	p	q	N	T	n_{max}	k_M	k_A	δ
Value	0.02	0.6	10,000	12	15	100	150% of k_M	0.06
	c_b	c_M	c_A	κ	ρ	h	s	v
	2	2.48	180% of c_b	0.5	$\frac{K^A}{K^M} = 0.5$	0.5	0.8	$0.8 \times p_{T_{M\to A}}$

3.5.2 Sensitivity Analyses

Before investigating the potential benefits of adopting a technology-switching scenario under capacity constraints, we perform sensitivity tests.

Production Capacity – Ratios and Magnitude – Sensitivity

Analyzing several production capacity ratios between AM and MC, namely $\frac{K^M}{K^A} \in \{10; 4; 2; 1.33; 1\}$, we fix the production capacity per period under AM and vary the total production capacity under MC. We use the assumption (A6) which implies $K^A \leq K^M$.

For each production capacity ratio, we analyze *low, medium,* and *high* production magnitudes. In particular, we correspondingly fix the values for K^A, with $K^A \in \{41; 208; 416\}$, and determine the values for K^M through the production capacity ratios.

Firstly, Fig. 3.4 demonstrates the behavior of the optimal pricing strategy p. We observe that the selling price is not monotonically decreasing as it would be in the uncapacitated case (Lacroix et al. 2020). It exhibits an increasing-decreasing pattern when the demand tends toward the production capacity under AM and MC. Thus, to avoid potential lost sales from capacity shortage, the firm charges high upfront prices by an increasing pricing policy. This strategy helps the firm to boost short-term profits from the most eager and interested initial customers. Compared with the case with *high* production magnitude, the firm charges higher selling prices during the products' introduction for the *low* and *medium* capacity magnitudes. This is because the firm can offer fewer products due to the capacity constraint, and, consequently, tries to attract fewer customers but those with higher product valuation.

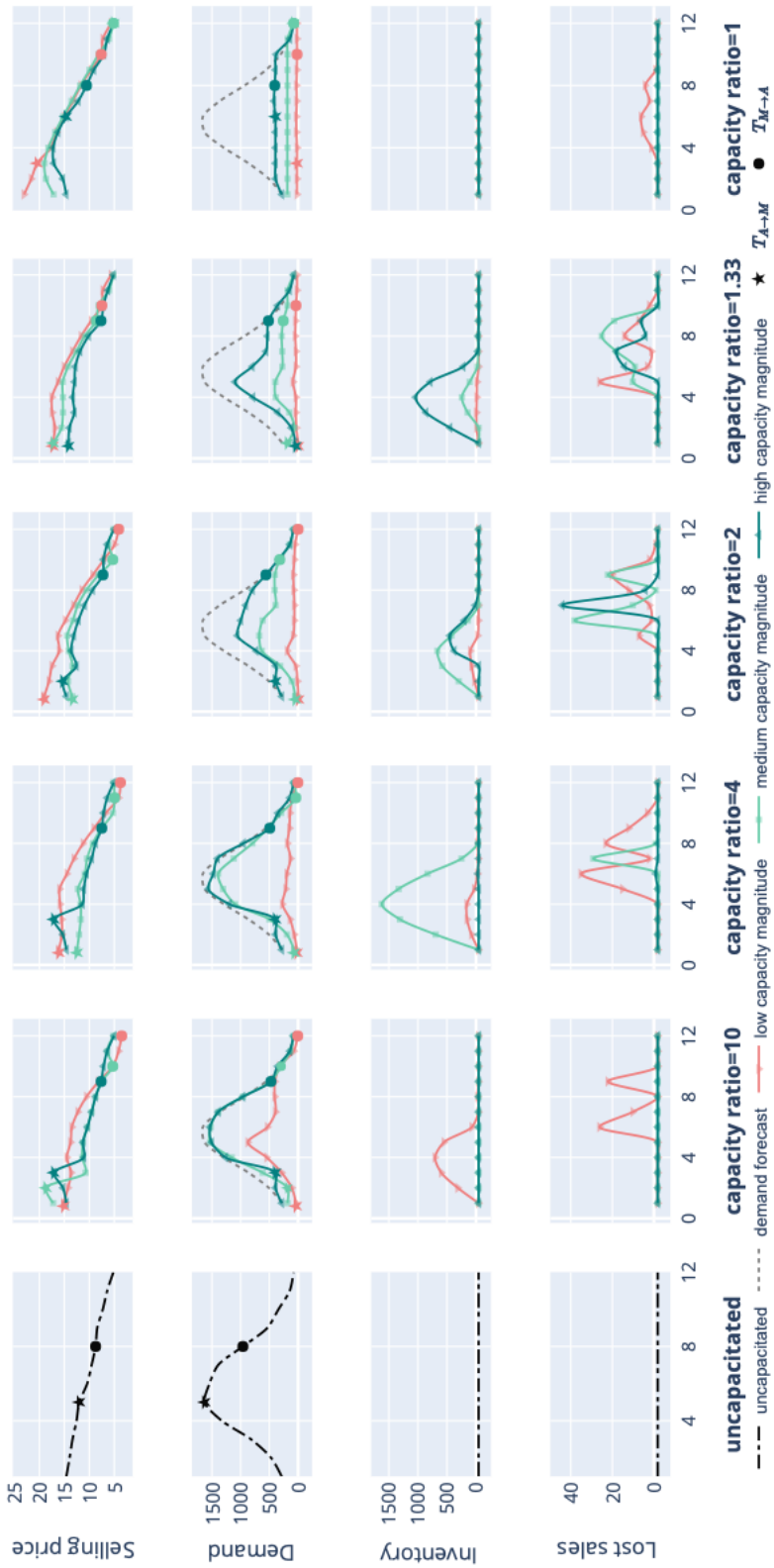


Figure 3.4 – Sensitivity analysis of production capacity ratios and magnitude under AM and MC technologies, in the MTS scenario.

This also leads to higher profit and reduced lost sales which come at a cost. Furthermore, the effect is strengthened due to the forward-looking behavior of customers since they have a decreasing willingness-to-pay (see (3.1)). Secondly, Fig. 3.4 shows the demand process D_t. As we model customers through a utility-based demand, the selling price has a direct impact on the demand diffusion pattern. In the MTOUC case, we recover the traditional bell-shaped curve of the demand. In the MTS case, the demand patterns and demand forecast are also bell-shaped for *high* capacity magnitudes under MC (see demand for *medium* and *high* capacity magnitudes and $\frac{K^M}{K^A} = 10$). As the production capacity ratio diminishes, the demand trajectory tends to flatten. At the beginning and the end of the PLC, there are fewer customers due to their ideal buying time distribution. Less product quantity is sufficient to meet the demand. The demand grows and the firm can sell at full production capacity toward the middle of the PLC. Thirdly, Fig. 3.4 depicts the on-hand inventories to satisfy the demand. For low capacities, we observe that the inventory decreases as the production capacity ratio diminishes. This is due to opposite trends of the selling price and the demand patterns. Next, we see that the lost sales are negligible.
Lastly, for similar production capacities and as the production capacity magnitude increases, AM technology is used more often by the manufacturer. Fig. 3.4 illustrates this through the technology-switching times. However, for the low capacity magnitude case, and when K^A is much lower than K^M, the manufacturer does not switch to AM (see the technology-switching times for $\frac{K^M}{K^A} = 10$). During the introduction and decline stages of the PLC, higher production capacity magnitudes allow the firm to offset the higher fixed and production costs of AM compared with those of MC. Overall, the manufacturer could benefit from adopting AM at the beginning and the end of the PLC in the MTS scenario. Switching to MP in the middle of the product life cycle could be profitable provided a high production capacity magnitude and similar production capacities under AM and MC.

Holding Cost Sensitivity

Considering the MTSC scenario, we now examine the sensitivity of our results to the holding cost as it impacts the profit. Fig. 3.5 shows that the firm charges a higher selling price as the holding cost value increases. If the holding cost is lower, the firm decides to stock more inventory to satisfy the demand and, oppositely, to stock less when it is more expensive. Moreover, it is more beneficial to start producing with AM instead of MC when the holding cost is high, and when the production capacity of this technology allows meeting the demand. Table 3.4 reports the holding cost impact on the technology-switching scenario as well as on the *mean profit per customer*. As expected, a lower holding cost yields a higher mean profit per customer and as the holding cost becomes expensive it is beneficial to start producing with AM at the beginning of the PLC when there are fewer but more excited customers (*i.e.*, with a higher utility).

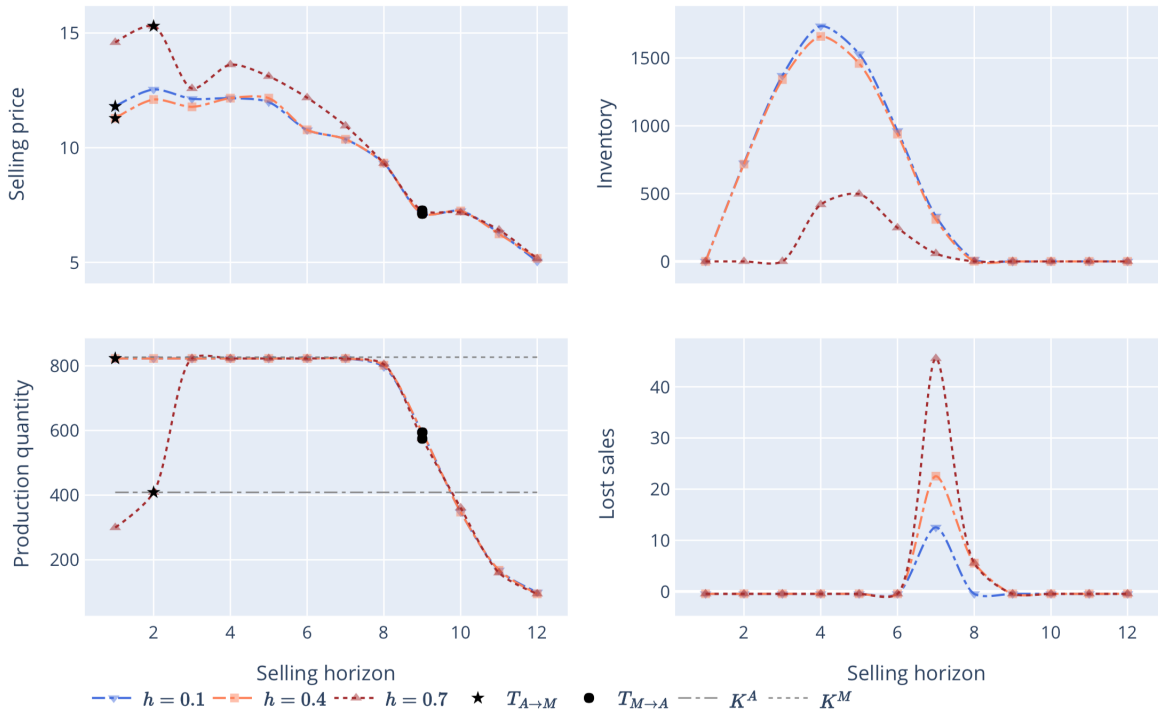


Figure 3.5 – Holding cost sensitivity.

Table 3.4 – Holding cost impact on the mean profit per customer.

	Mean profit per customer for each holding cost value		
Production strategy	$h = 0.1$	$h = 0.4$	$h = 0.7$
MC	6.06	5.85	5.66
$MC \to AM$	6.12	5.93	5.68
$AM \to MC$	5.91	5.82	5.74
AM	4.02	3.81	4.04
$AM \to MC \to AM$	5.99	5.92	5.88

3.5.3 Value of Holding Inventory

To identify the value of holding inventory across the PLC, we examine three capacity and inventory scenarios, namely MTOUC (which serves as our reference case), MTOC, and MTSC. For each of these scenarios, we extract the optimal mean profit per customer for every production strategy and highlight the highest among them. Considering our reference case (MTOUC), Table 3.5 shows that, as expected, capacity constraints generate a 24% profit loss under the MTOC scenario, and a 22% profit loss under the MTSC scenario (see the MTOC and MTSC scenarios). Furthermore, holding inventory and adopting an $AM \to MC \to AM$

technology-switching scenario allows a 3% profit gain compared with the MTOC scenario.

Table 3.5 – Capacity and inventory strategies impact on the mean profit per customer.

	Mean profit per customer		
Production strategy	**MTOUC**	**MTOC**	**MTSC**
MC	6.42	5.08	5.79
MC → *AM*	7.22	5.16	5.87
AM → *MC*	7.46	5.62	5.80
AM	7.48	4.05	4.06
AM → *MC* → *AM*	7.55	5.72	5.90

3.5.4 Value of Pricing Flexibility

Next, we investigate the impact of pricing flexibility on the manufacturer's expected mean profit per customer. We perform numerical experiments and study three selling price trajectories, namely constant, linear decreasing, and flexible.
In line with our findings in Section 3.5.2, Fig. 3.6 reveals that there is a tendency to increase selling prices if they must stay constant over the time horizon. By contrast, the firm charges lower prices in the MTSC case (compared with MTOUC and MTOC cases) up to the middle of the PLC when the pricing pattern must be linear decreasing. Technology-switching times can explain this phenomenon. Although MTOUC and MTOC scenarios only employ AM during the whole PLC, the MTSC scenario uses MC technology on its own. To offset the product misfit penalty cost only incurred under MC and to attract more customers, the firm relies on lower upfront prices until the demand peak. The flexible pricing strategy results in an optimal non-convex path. Interestingly, we observe "reversed" selling prices set at $t = 3$ and $t = 9$ in our flexible pricing trajectories. This can be explained by technology-switching and production capacity effects on the selling price, and, consequently, on demand. AM is used up to period $t = 3$ in the MTOC scenario whereas it is used until period $t = 2$ in the MTSC scenario. The price is thus set higher for the third period under AM in the MTOC scenario. In both the MTOC and the MTSC scenarios, when the firm switches to AM at the end of the PLC, the selling price first increases before decreasing as demand is close to the production capacity under AM. We define the relative gain of the flexible, versus the constant pricing strategy, as $(\pi^*_{flex} - \pi^*_{const}) \cdot (\pi^*_{const})^{-1}$ and, similarly, the one of flexible versus linear decreasing pricing strategy as $(\pi^*_{flex} - \pi^*_{dec}) \cdot (\pi^*_{dec})^{-1}$. Table 3.6 summarizes the results. We observe a significant gap between a constant and a flexible pricing policy (highest under the MTOC case). Next, we notice that the gap is small (+1.5%) between the flexible and decreasing pricing policies when the firm has an infinite capacity (MTOUC case). Therefore, in this case, it might be more cost-effective to apply a simple decreasing pricing policy as suggested by the marketing literature. It works well in practice and can avoid unobserved fees. However, under capacity constraints, the gap strongly increases (+11.5% in the MTOC scenario) and the firm can benefit from a flexible pricing policy displaying an increasing-decreasing pattern. The

ability to increase prices during the PLC helps the manufacturer to better align supply and demand. Our results are consistent with those of Shen et al. (2013). The authors report that an increasing-decreasing pricing strategy, combined with optimal production/inventory policies, is profitable under capacity constraints. The value of pricing flexibility is highest (+11.5%) under the MTOC scenario, and decreases when the firm carries inventory (+3.7%). Holding inventory might lessen the need for pricing flexibility. In other words, holding inventory allows the firm to have higher profits by itself.

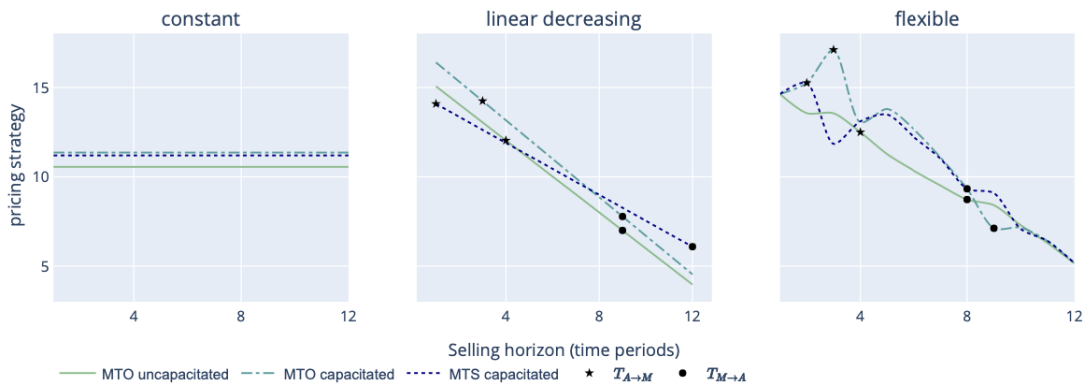


Figure 3.6 – Selling price trajectory for each production and inventory scenario.

Table 3.6 – Impact of the pricing trajectory on profit and technology-switching scenario.

Pricing trajectory	π^* (\$)	$T_{A\to M}$	$T_{M\to A}$	Production strategy
		MTOUC		
constant	6.19	3	6	$AM \to MC \to AM$
linear decreasing	7.44	12	13	AM
flexible	7.55	4	8	$AM \to MC \to AM$
		MTOC		
constant	4.11	2	7	$AM \to MC \to AM$
linear decreasing	5.14	12	13	AM
flexible	5.73	3	9	$AM \to MC \to AM$
		MTSC		
constant	5.04	0	7	$MC \to AM$
linear decreasing	5.65	0	12	MC
flexible	5.86	2	8	$AM \to MC \to AM$

Our results can help operations managers to understand this new manufacturing opportunity. Furthermore, our findings allow the firm to evaluate the potential marketing and operations benefits of combining the new manufacturing usage of AM with MC technology. Facing forward-looking customers and their individual preferences, adopting AM, in combination with MC, under capacity constraints, could improve a manufacturer's profit if the production capacity magnitude is high enough and close to the one of MC technology.

3.6 Conclusion and Managerial Insights

This chapter investigated the conditions under which a capacity-constrained monopolist manufacturer could combine the benefits of AM, for product customization, with the traditional MC technology to achieve product customization at scale. Given the stage of the PLC, the firm jointly decides on marketing (pricing policy, product variety) decisions and on operations (technology-switching times, production quantity, inventory) decisions, to maximize profit while addressing individual customer preferences. Our model positions itself at the marketing-operations interface. It considers not only the supply side with the technology choice in a dynamic setting across the PLC, but also the demand side to consider customer heterogeneity and forward-looking behavior. We provide an innovative methodology to leverage customer-centricity and optimize operations and marketing strategies.

First, we investigated several technology-switching scenarios, and three production capacity and inventory cases. In the scenario where the firm holds inventory under MC, we developed a customer-centric *adaptive inventory policy* intended for an interdependent non-stationary demand. We built the first step of this inventory policy on a *water filling algorithm*, which is typically used in information theory. We adapted it to fit our manufacturing context. From this inventory policy follows a closed-form solution for the production quantity decision. We then formalize the resulting non-convex optimization problem exploiting the analytical properties of our *uncensored* demand forecast. Furthermore, we successfully derived an algorithmic formulation for our objective function under our three capacity and inventory scenarios. We solved our optimization problem using the so-called (SAA) framework. We performed robustness tests to check the convergence of our approximation problem, and that the population sample size used in our numerical experiments was sufficient enough. Our numerical results demonstrate that the combination of customer-centric strategies with the new usage of AM combined with MC could benefit a manufacturer. In particular, on the operations side, significant profit improvements could be achieved with an AM-MC-AM technology-switching scenario, given certain capacity and inventory conditions. To be profitable, the following conditions are required: a sufficient enough production capacity under AM, similar production capacities under AM and MC, a high holding cost under MC. When the firm has the option to hold inventory, facing *low* or *medium* production capacity magnitudes implies increasing the selling price, and thus to stock more. This strategy helps in preventing lost sales and meeting the demand peak during the growth stage of the PLC. On the marketing side and under capacity constraints, applying an increasing-decreasing pricing policy yields a higher profit. Indeed, this pricing policy facilitates capturing interested customers with a high product valuation at the beginning of the PLC. As demand gets closer to the production capacity limit, the firm offers fewer products and increases the selling price to diminish lost sales. Then, as demand grows toward the middle of the PLC, the firm starts decreasing the selling price. Our findings also show that the benefits of pricing flexibility are highest when capacity is unlimited, or when the firm does not hold inventory (+11.5% under capacity constraints vs. +3.7% profit gain when holding inventory and under capacity constraints). Under capacity constraints, a simple decreasing pricing policy combined with inventory performs very well and lessens

the need for pricing flexibility. Although there are limitations due to the lack of real-world data availability, we believe that our work sheds light on this new manufacturing opportunity. Our approaches could be implemented by decision-makers to leverage customer-centricity and benefit from this novel technology-switching manufacturing practice, which operates an Industry 4.0 technology such as AM for product customization.

G Notations and Parametric Assumptions

Table G.1 – Notations and Parametric Assumptions.

Parameters		Assumptions
N	: Initial market size of potential adopters	$N \in \mathbb{N}$
Ξ_t	: Remaining potential adopters at period t	$\{\cup_{m=t}^{T} \Xi_m\}_{t=1}^{T}$
T	: Length of the finite selling horizon	$T \in \mathbb{N}$
t	: Subscript denoting period	$\{t\}_{t=1}^{T}$
$\mathscr{T}$	: Set of production strategies characterized by $(T_{A\to M}, T_{M\to A})$	$\mathscr{T} \in \{T_{A\to M}, T_{M\to A}\}^T$
$T_{A\to M}$	: Technology-switching time when the manufacturer switches from AM to MC	$0 \le T_{A\to M} < T_{M\to A}$
$T_{M\to A}$	: Technology-switching time when the manufacturer switches from MC to AM	$T_{A\to M} < T_{M\to A} < T+1$
Φ	: Virtual space of horizontally differentiated products	$\Phi = [0,1]$
ϕ	: Customer's ideal product variant	$\mathbb{P}_\phi = \mathscr{U}([0,1])$
τ	: Customer's ideal buying time	see Lacroix et al. (2020)
p, q	: Bass innovation and imitation coefficients, respectively	$p, q \in \mathbb{R}^+$
ξ	: Random customer characterized by τ and ϕ	$\xi = (\tau, \phi)$ with $\mathbb{P}_\xi = \mathbb{P}_\tau \emptyset$
n	: Number of mass-customized variants to offer to customers under MC	$1 \le n \le n_{max}$
$\mathscr{X}$	: Set of mass-customized product variants offered under MC	$\mathscr{X} = \{x_1, \ldots, x_n\} \subset [0,1]^n$
j	: Subscript denoting the mass-customized variant	$j \in \{1, \ldots, n\}$
x_j	: Location of product variant j on the virtual product space	$\forall j \in \{1, \ldots, n\}$
$w_t(\tau)$	: Customer's willingness-to-pay at period t	$\omega(\tau) \in \mathbb{R}^+$
$\gamma(\tau)$	: Buying time-sensitivity coefficient	$\gamma \in \mathbb{R}^+$
$\lambda(\tau)$	: Product variant sensitivity coefficient, incurred only under MC technology	$\lambda \in \mathbb{R}^+$
$U^{\mathscr{T}}(\xi, t)$	: Customer ξ's utility at period t, dependent on the production strategy $\mathscr{T}$ (3.1)	
p_t	: Selling price at period t	$0 \le p_t \le max\{0, U^{\mathscr{T}}\}, \forall j \in \Phi$
$*$	: Subscript denoting the demand forecast method	$* =_{c,u}$
${}_*D'_{j,t}$	: Demand forecast of variant j at time t	
Dj,t	: Observed demand for product variant j at time t	
$I'_{j,t}$	: Target inventory level of variant j at time t	
Ij,t	: Observed inventory level of variant j at time t	
K^A	: Constant production capacity under AM	
K^M	: Constant production capacity under MC	equally distributed among n
κ	: Production capacity magnitude	$\kappa \in \mathbb{R}^+$
ρ	: Production capacity ratio between AM and MC	$\rho \in \mathbb{R}^+$
S_t	: Sales at period t	
L_t	: Lost sales at period t	
$Q_{j,t}$	: Optimal production quantity for each variant j at time t	
c^A	: Constant marginal production cost under AM	$c^A = \text{constant} > 0$
c^b	: Unit production base cost under MC	$c^b = \text{constant} > 0$
$c^M(n)$	: Unit production cost under MC depending on n	$c^M(n) = c_b(1 + (n-1)\delta) > 0$
k^A	: One-time fixed cost for AM technology	$k^A = \text{constant} > 0$
k^M	: One-time fixed cost for MC technology	$k^M = \text{constant} > 0$
h	: Inventory holding cost per unit per period, common to all product variants	$h \in \mathbb{R}^+$
s	: Stockout cost incurred when excess demand is lost per unit of unmet demand, common to all product variants	$h < s$
v	: Salvage value of remaining inventory at the end of MC period	$p_t > v > c^M(n)$

H Proof of Lemma 3.2.

Lemma 3.2. By the Law of Large Numbers (LLN), for all t, j,

$$\begin{cases}
(i) & D_{j,t}/N & \to_{a.s.} & {}_u\boldsymbol{d'_{j,t}} \\
(ii) & D_t/N & \to_{a.s.} & {}_u\boldsymbol{d'_t} = \sum_j {}_u\boldsymbol{d'_{j,t}} \\
(iii) & I'_{j,t}/N & \to_{a.s.} & \boldsymbol{i'_{j,t}} \\
(iv) & I'_t/N & \to_{a.s.} & \boldsymbol{i'_t} = \sum_j \boldsymbol{i'_{j,t}},\ \boldsymbol{i'_{j,t}} = \boldsymbol{i'_t/n} \\
(v) & I_{j,t}/N & \to_{a.s.} & \boldsymbol{i_{j,t}} \\
(vi) & I_t/N & \to_{a.s.} & \boldsymbol{i_t} = \sum_j \boldsymbol{i_{j,t}} \\
(vii) & Q_{j,t}/N & \to_{a.s.} & \begin{cases} \boldsymbol{q_{j,t}} = \mathbf{min}(\tilde{\boldsymbol{K}}^{\boldsymbol{M}}/\boldsymbol{n}, \mathbf{max}(\boldsymbol{i'_t/n} - \boldsymbol{i_{j,t}} + {}_u\boldsymbol{d'_{j,t}})) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}, \\ \boldsymbol{q_{j,t}} = \mathbf{0} \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{AM}, \end{cases} \\
(viii) & Q_t/N & \to_{a.s.} & \begin{cases} \boldsymbol{q_t} = \mathbf{min}(\tilde{\boldsymbol{K}}^{\boldsymbol{M}}, \mathbf{max}(\boldsymbol{i'_t} - \boldsymbol{i_t} + {}_u\boldsymbol{d'_t})) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}, \\ \boldsymbol{q_t} = \mathbf{0} \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{AM}, \end{cases} \\
(ix) & S_{j,t}/N & \to_{a.s.} & \boldsymbol{s_{j,t}} = \mathbf{min}({}_u\boldsymbol{d'_{j,t}}, \boldsymbol{q_{j,t}} + \boldsymbol{i_{j,t}}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}, \\
(x) & S_t/N & \to_{a.s.} & \begin{cases} \boldsymbol{s_t} = \sum_j \boldsymbol{s_{j,t}} = \mathbf{min}({}_u\boldsymbol{d'_t}, \boldsymbol{i_t} + \boldsymbol{q_t}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}, \\ \boldsymbol{s_t} = \mathbf{min}(\tilde{\boldsymbol{K}}^{\boldsymbol{A}}, {}_u\boldsymbol{d'_t}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{AM}, \end{cases} \\
(xi) & L_{j,t}/N & \to_{a.s.} & \boldsymbol{l_{j,t}} = \mathbf{max}(\mathbf{0}, {}_u\boldsymbol{d'_{j,t}} - \boldsymbol{i_{j,t}} - \boldsymbol{q_{j,t}}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}; \\
(xii) & L_t/N & \to_{a.s.} & \boldsymbol{l_t} = \begin{cases} \mathbf{max}(\mathbf{0}, {}_u\boldsymbol{d'_t} - \tilde{\boldsymbol{K}}^{\boldsymbol{A}}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{AM}; \\ \sum_j \boldsymbol{l_{j,t}} = \mathbf{max}(\mathbf{0}, {}_u\boldsymbol{d'_t} - \boldsymbol{i_t} - \boldsymbol{q_t}) \text{ if } \mathcal{T}(\boldsymbol{t}) = \boldsymbol{MC}; \end{cases} \\
(xiii) & I_{j,t+1}/N & \to_{a.s.} & \boldsymbol{i_{j,t+1}} = \mathbf{max}(\mathbf{0}, \boldsymbol{q_{j,t}} + \boldsymbol{i_{j,t}} - \boldsymbol{s_{j,t}}) \\
(xiv) & I_{t+1}/n & \to_{a.s.} & \boldsymbol{i_{t+1}} = \sum_j \boldsymbol{i_{j,t+1}} = \mathbf{max}(\mathbf{0}, \boldsymbol{q_t} + \boldsymbol{i_t} - \boldsymbol{s_t}) \\
(xv) & \Pi_t^{\mathcal{T}}/N & \to_{a.s.} & \begin{aligned} \boldsymbol{\pi_t^{\mathcal{T}}} = {} & \boldsymbol{s_t}(\boldsymbol{p_t} - \boldsymbol{c_{\mathcal{T}(t)}}) - \boldsymbol{sl_t} \\ & -\mathbf{1}_{\mathcal{T}(t)=MC}\boldsymbol{hi_{t+1}} + \mathbf{1}_{t=T_{M\to A}}\boldsymbol{i_{t+1}}(\boldsymbol{vp_{T_{M\to A}}} - \boldsymbol{c^M(n)}) \end{aligned}
\end{cases} \tag{H.1}$$

We observe that $(i'_1, \ldots, i'_{T+1})$ is also obtained from $({}_*d'_1, \ldots, {}_*d'_t)$ by a water filling algorithm

(wfs) that resembles the (WFS), described in 3.3.4:

$$(\mathtt{i}'_1,\ldots,\mathtt{i}'_{\mathtt{T}+1}) = \mathtt{wfs}(\mathcal{T},\tilde{K}^{\mathtt{M}},({}_*\mathtt{d}'_1,\ldots,{}_*\mathtt{d}'_{\mathtt{T}})):$$

$$\begin{aligned}
&\boldsymbol{t = T,\ i'_{T+1} = 0}\\
&\mathtt{while}\ \ \boldsymbol{t > 0}\\
&\quad\mathtt{if}\ \ \boldsymbol{t > T_{A\to M}}\\
&\qquad\boldsymbol{i'_t = \max((_*d'_t - \tilde{K}^M)1_{\{\mathcal{T}(t)=MC\}} + i'_{t+1}, 0)}\\
&\qquad\boldsymbol{t = t - 1}\\
&\quad\mathtt{else\ if}\ \ \boldsymbol{\leq T_{A\to M}}\\
&\qquad\boldsymbol{i'_t = 0}\\
&\qquad\boldsymbol{t = t - 1}\\
&\quad\mathtt{end}\\
&\mathtt{end}
\end{aligned} \tag{wfs}$$

Proof. of Lemma 3.2. It follows by induction on t, starting with $t = 1$. The convergence of the mean demand $D_{j,t}/N$ and D_t/N follows by the law of large numbers (see Eq. 3.18, 3.5). The convergence of the mean target inventories results from the fact that the WFS algorithm and capacities are positively homogeneous (WFS, wfs), and therefore the target mean inventories are deduced from the mean demand forecast by (wfs). From (3.8,3.9) and the convergence of demand, we deduce the convergence of the mean production quantities and inventories, and the limit formulas in $(vii, viii)$ follow readily. Then, from (3.11,3.14) and the preceding convergences follow $(ix - xii)$. The convergence and the equation in $(xiii)$ follow from (3.9). To conclude, (xv) follows from the summand expressions in (3.12,3.13). ∎

I Proof of Theorem 3.8.

Theorem 3.8. SAA convergence of the mean profits. If $(\xi_i)_{i\geq 1}$ is i.i.d., and if

$$\mu_\omega \ll \mu_L; \text{ and } \forall c, t,\ \mu_L\left(\delta(\cdot, t)^{-1}(\{c\})\right) = 0, \tag{H}$$

then a p-uniform strong law of large numbers holds for the ${}_u d'_{j,t}$'s and ${}_u d'_t$'s. In other words, if

$$\begin{cases} p^{(*,N)} \text{ achieves } \max_{p\in\mathscr{P}} \pi^{\mathscr{T}}(\{\xi_i\}_{i=1}^N, p) := \pi^{(*,\mathscr{T})}(\{\xi_i\}_{i=1}^N, p^{(*,N)}), \\ p^* \text{ achieves } \max_{p\in\mathscr{P}} \tilde{\pi}(\mathscr{T}, n, p)\ (= \tilde{\pi}(\mathscr{T}, n) = \tilde{\pi}(\mathscr{T}, n, p^*)), \end{cases} \tag{I.1}$$

then

$$\begin{cases} p^{(*,N)} \to p^*; \\ \pi^{(*,\mathscr{T})}(\{\xi_i\}_{i=1}^N, p^{(*,N)}) \to_{a.s.} \tilde{\pi}(\mathscr{T}, n). \end{cases} \tag{SAA}$$

Proof. of Theorem 3.8. All we need to prove, according to Lemma 3.7, is that $D_{j,t}/N \to_u d'_{j,t}$ and $D_t/N \to_u d'_t$ uniformly in $p \in \mathscr{P}$. The proof of these uniform convergences can be conducted strictly as in (Lacroix et al. 2020, proof of Theorem 1). The only change is in that instead of considering the *mean profit per customer* there, we consider the mean demand here. ∎

J Profit Algorithm (A-MTS) for Theorem 3.3.

The mean profit per customer per period, $\pi_t^{\mathscr{T}}$, is obtained algorithmically as follows

$$
\begin{aligned}
&(\mathtt{i}'_1,\ldots,\mathtt{i}'_{\mathtt{T}+1}) = \mathtt{wfs}(\mathscr{T},\tilde{K}^{\mathtt{M}},({}_*\mathtt{d}'_1,\ldots,{}_*\mathtt{d}'_{\mathtt{T}}))\\
&\boldsymbol{i_1 = 0;}\\
&\boldsymbol{t = 1;}\\
&\boldsymbol{\tilde{\pi}(\mathscr{T},n,p) = 0}\\
&\mathtt{while}\ \boldsymbol{t \le T}\\
&\quad \mathtt{if}\ \boldsymbol{\mathscr{T}(t) = MC}\\
&\qquad \boldsymbol{q_t = \min(\tilde{K}^M, \max(i'_t - i_t +_u d'_t));}\\
&\qquad \boldsymbol{s_t = \min({}_u d'_t, i_t + q_t);}\\
&\qquad \boldsymbol{l_t = \max(0,_u d'_t - i_t - q_t);}\\
&\qquad \boldsymbol{i_{t+1} = q_t + i_t - s_t;}\\
&\quad \mathtt{else}\\
&\qquad \boldsymbol{q_t = 0;}\\
&\qquad \boldsymbol{s_t = \min(\tilde{K}^A,_u d'_t);}\\
&\qquad \boldsymbol{l_t = \max(0,_u d'_t - \tilde{K}^A);}\\
&\qquad \boldsymbol{i_{t+1} = i_t;}\\
&\quad \mathtt{end}\\
&\quad \boldsymbol{\pi_t^{\mathscr{T}} = s_t(p_t - c_{\mathscr{T}(t)}) - sl_t - 1_{\{\mathscr{T}(t)=MC\}} hi_{t+1}}\\
&\qquad\qquad\qquad\qquad \boldsymbol{+1_{\{t=T_{M\to A}\}} i_{t+1}(vp_{T_{M\to A}} - c_{\mathscr{T}(t)})}\\
&\quad \boldsymbol{\tilde{\pi}(\mathscr{T},n,p) = \tilde{\pi}(\mathscr{T},n,p) + \pi_t^{\mathscr{T}};}\\
&\quad \boldsymbol{t = t + 1;}\\
&\mathtt{end}\\
&\boldsymbol{\tilde{\pi}(\mathscr{T},n,p) = \tilde{\pi}(\mathscr{T},n,p) - \tilde{k}^M 1_{\{T_{A\to M}<T\}} - \tilde{k}^A 1_{\{T_{A\to M}>0 \text{ or } T_{M\to A}<T\}}}
\end{aligned}
\tag{A-MTS}
$$

K Profit Algorithm (A-MTOC) for Corollary 3.4.

The limit of the *mean profit per customer* is obtained by a simplified version of the (A-MTS) algorithm (see J):

$$
\begin{aligned}
&\boldsymbol{t = 1;}\\
&\boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = 0;}\\
&\texttt{while } \boldsymbol{t \leq T}\\
&\qquad \boldsymbol{s_t = \min({}_u d'_t, \tilde{K}^{\mathcal{T}(t)});}\\
&\qquad \boldsymbol{l_t = \max(0, {}_u d'_t - \tilde{K}^{\mathcal{T}(t)});}\\
&\qquad \boldsymbol{\pi_t^{\mathcal{T}} = s_t(p_t - c_{\mathcal{T}(t)}) - sl_t;}\\
&\qquad \boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = \tilde{\pi}(\mathcal{T}, n, p) + \pi_t^{\mathcal{T}};}\\
&\qquad \boldsymbol{t = t + 1;}\\
&\texttt{end}\\
&\boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = \tilde{\pi}(\mathcal{T}, n, p) - \tilde{k}^M \mathbf{1}_{\{T_{A\to M} < T\}} - \tilde{k}^A \mathbf{1}_{\{T_{A\to M} > 0 \text{ or } T_{M\to A} < T\}}}
\end{aligned}
\tag{A-MTOC}
$$

L Profit Algorithm (A-MTOUC) for Corollary 3.5.

Similarly, the limit of the *mean profit per customer* is obtained by a simplified version of the (A-MTS) algorithm (see J):

$$
\begin{aligned}
&\boldsymbol{t = 1;}\\
&\boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = 0;}\\
&\texttt{while } \boldsymbol{t \leq T}\\
&\qquad \boldsymbol{s_t =_u d'_t;}\\
&\qquad \boldsymbol{\pi_t^{\mathcal{T}} = s_t(p_t - c_{\mathcal{T}(t)})}\\
&\qquad \boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = \tilde{\pi}(\mathcal{T}, n, p) + \pi_t^{\mathcal{T}};}\\
&\qquad \boldsymbol{t = t + 1;}\\
&\texttt{end}\\
&\boldsymbol{\tilde{\pi}(\mathcal{T}, n, p) = \tilde{\pi}(\mathcal{T}, n, p) - \tilde{k}^M \mathbf{1}_{\{T_{A\to M} < T\}} - \tilde{k}^A \mathbf{1}_{\{T_{A\to M} > 0 \text{ or } T_{M\to A} < T\}}}
\end{aligned}
\tag{A-MTOUC}
$$

4 Blockchain of Things Sweet Spots for Lean and Agile Supply Chains

Recently, the combination of Blockchain (BC) with the Internet-of-Things (IoT) has been promising a sustainable competitive advantage for supply chains (SCs). However, the relevance and conditions for these two technologies' adoption in this context remain unclear. Therefore, we adopt a three-step approach to discover the BC IoT success conditions for lean and agile SCs: (i) we conduct a multivocal literature review, (ii) perform a topic modeling to categorize the success factors (SFs) identified in the literature, and (iii) associate the categories of SFs to the SC macro-processes for lean and agile SCs, respectively. Our results build on a holistic view of the BC and IoT SFs, stemming from a SC-driven adoption perspective. The findings are summarized through a sweet spot conceptual framework and research propositions. This study is a first step towards enhancing both academics and practitioners' understanding of BC and IoT benefits for lean and agile SCs. It offers valuable insights into when and how the sweet spots for both SC types would materialize in practice, as well as their impacts with respect to the SC macro-processes performance. We believe that this study is the first to holistically structure and present the BC and IoT SFs, taking into account the SC characteristics (lean or agile), and strategic objectives.

4.1 Introduction

With the emergence of advanced digital technologies and an increasing focus on customer needs, the digitalization of supply chains (SCs) has been gradually increasing. This practice is referred to as *digital supply chain* (DSC), progressively replacing traditional linear SCs (Schrauf and Berttram 2018). Ageron et al. (2020) define DSC as: "the development of information systems and the adoption of innovative technologies strengthening the integration and the agility of the supply chain and thus improving customer service and sustainable performance of the organisation." DSC operates Industry 4.0 technology enablers such as Internet-of-Things (IoT) devices and Blockchain (BC) to collect, digitize, and store information, physical, and financial flows both intra and inter-firms.

Turning to the IoT, Dorsemaine et al. (2015) define it as a "group of infrastructures intercon-

necting connected objects and allowing their management, data mining and the access to data they generate." This creates a distributed network of devices communicating both with each other and with SC stakeholders. IoT devices cover passive, semi-passive (or semi-active), and active Radio Frequency ID tags (RFID) (see further details in Gaukler and Seifert (2007), Delen et al. (2007), Lee and Özer (2007)), sensors, and other connected devices on a distributed network (Rejeb et al. 2019).

As for increasingly popular BC technology, it was originally thought to support transactions in the cryptocurrency field (Nakamoto 2008). BC can be described as a subset of distributed ledger technology (DLT) that allows digital data to be stored in a cryptographically secured and decentralized manner, leading to essentially tamper-proof transactions (Chouli et al. 2017). The major feature of DLTs is to provide secure, reliable, non-repudiable online transactions between parties (Dumas et al. 2019). Different types of BCs exist. Hellwig et al. (2020) report that they: "differ in the way new network participants (nodes) join a network." The main BC types can be classified as: public (permissionless), private (permissioned), or consortium (permissioned). Consortium BCs are typically used in a SCM context because they offer a balance of both public and private BC functions (Dutta et al. 2020).

Thus, the combination of BC and IoT blurs the boundary between the physical and digital worlds to improve SC efficiency and accelerate B2B integration. As a consequence, traditional and linear SCs are evolving towards a connected, intelligent, scalable, and customizable ecosystem to gain efficiency, agility, customer satisfaction, and, ultimately, to increase SC surplus (*i.e.*, "the difference between the final value of the product or service perceived by the customer and the SC costs generated to create this product or service" (Chopra et al. 2013)). It is therefore not surprising that, in the last five years, pairing BC and IoT for the SC has received much attention and has led to compelling use cases (see the thirty-five use cases highlighted by Yusuf et al. (2018b)). Other use cases that arise from the current COVID-19 pandemic applications are of particular interest today for SC stakeholders. Specifically, BC and IoT are being used to improve the efficiency, reliability, safety and transparency of pharmaceutical supply chains, and, in particular, those dedicated to the vaccine distribution. The technologies are used in the SC to track, monitor (*e.g.*, temperatures and conditions) and authenticate COVID-19 vaccines, testing kits, personal protective equipment (PPE) (Smartrac 2019, Abrams Kaplan 2020).

However, while the benefits of adopting BC with IoT have been thoroughly articulated by academics and practitioners (*e.g.*, (Yusuf et al. 2018a, Aich et al. 2019, Dai et al. 2019, Rejeb et al. 2019, Banerjee 2019, Kumar and Pundir 2020, Dedeoglu et al. 2020)), the question for practitioners of systematically deciding when and how to adopt newer digital technologies to improve SC performance arises. Specifically, according to Vyas et al. (2019), when it comes to nascent technologies such as BC, most people still do not fully understand how it works. Furthermore, executives wonder what return on investment they might expect. Interestingly, and in line with this questioning, the consideration of adopting BC and IoT for the SC is typically focused on technological advantages rather than on the needs and business aspects

of the supply chain. The focus on technological advantages is more prevalent than the focus on the SC business advantages. Although legitimate, the technology-driven perspective might fail to address the alignment between SC strategic objectives and information technology (IT), which is a key SC driver (Chopra et al. 2013).

A revised perspective, *i.e.* SC-driven, is therefore needed to help practitioners navigate through the digital technology landscape — in this case composed of both BC and IoT, depending on the strategic objectives targeted, to define their relevance for SC performance improvement. Some authors (*e.g.*, Hackius and Petersen (2017), Banerjee (2018), Kshetri (2018), Angelis and da Silva (2019), Viriyasitavat et al. (2019), Vyas et al. (2019), Cole et al. (2019), Saberi et al. (2019), van Hoek (2019), Yang (2019), Durach et al. (2020), Dutta et al. (2020), Hastig and Sodhi (2020), Kumar et al. (2020)), have investigated this SC-driven perspective to adopt BC for supply chain management (SCM).

This study documents several key contributions made to the field of DSC: first, to identify the success factors (SFs) favoring the adoption of BC and IoT in SCM with two perspectives: technology and SC-driven; and second, to derive from the SFs, the BC and IoT-enabled SC sweet spots and requirements depending on the organization's SC type, *i.e.*, lean or agile.

The rest of this chapter is organized as follows: Section 4.2 provides a background literature regarding the SC context and the relevance of using BC and IoT in SCM. Section 4.3 details our research methodology. Section 4.4 discusses the results and reports our sweet spot conceptual framework as well as research propositions. Finally, Section 4.5 specifies theoretical and managerial implications for lean and agile SC performance, and empirical research implications.

4.2 Background Literature

4.2.1 Supply Chain Context

Supply chain optimization is one of the primary objectives pursued by companies. Within each SC, the "supply chain surplus" is maximized (Chopra et al. 2013). With globalization, the advent of new communication techniques, and technologies to meet increasingly demanding customer requirements, SCs are becoming even more complex and fragmented.

To achieve a strategic fit between supply and demand, and, thus, to increase the SC surplus, companies adopt different SC types to accommodate different customer segments (PwC 2012). Companies do not adopt the same SC type depending on the product type offered (Agarwal et al. 2006). Indeed, a lean SC (also called *efficient*) will be adopted to produce rather functional products with a predictable demand, and generating low product margins (*e.g.*, commodities). The objective of this SC type is to satisfy demand by optimizing internal resources and minimizing SC costs (product design, production, inventory, and suppliers' costs) as much as possible (Fisher 1997). In contrast, an agile SC (also called *responsive*)

will be designed for more innovative products with uncertain demand (*e.g.*, fashion goods), generating high product margins. The efforts of an agile SC are focused on responding to consumer demand as quickly as possible by offering a high service level (Fisher 1997). Vonderembse et al. (2006) and Agarwal et al. (2006) developed frameworks to categorize SC types (lean, agile, and hybrid; and lean, agile, and leagile, respectively) and explore the relationship between the different SC type features. In this chapter, we focus on lean and agile SCs (hybrid (also called leagile) SCs are a combination of lean and agile SCs).

The determinants as well as the strategic objectives targeted by these two SC types are known to be different. Several studies have been carried out on the evaluation of SC performance. The use of metrics from the SCOR® (Supply Chain Operation Reference) model (APICS 2017) as criteria for evaluating SC performance is widespread. According to Lima and Carpinetti (2016), this model: "has been developed to map the business activities related with all phases of fulfilling a customer's demand. The model contains four sections: process, practices, people and performance. The reference model [...] is based on six primary management processes: plan, source, make, deliver, return and enable." For instance, Vyas et al. (2019) developed a framework that associates BC capabilities with SCOR performance metrics. However, unlike our study, the authors do not consider IoT, nor do they distinguish the SC type. We thus employ another method to map SC strategic objectives to BC and IoT capabilities. To this end, we associate the SFs of BC and IoT in the SC (identified in the literature) to the three SC macro-processes defined by Chopra et al. (2013), namely: *Supplier Relationship Management* (SRM), *Internal Supply Chain Management* (ISCM), and *Customer Relationship Management* (CRM). As explained by the authors, all SC activities can be listed in these macro-processes and in the *Transaction Foundation Management* (TMF). For simplicity, in the remainder of this chapter, we will consider the TMF as a fourth SC macro-process. These four SC macro-processes are considered as essential for optimizing SC performance activities. They manage the main flows of a SC (information, products, and financial flows) to meet customer demand, regardless of the SC type. Furthermore, Chopra et al. (2013) state that: "Good supply chain management [...] attempts to grow the supply chain surplus, which requires each firm to expand the scope beyond internal processes and look at the entire supply chain in terms of the three macro processes to achieve breakthrough performance."

4.2.2 Emerging Technologies

IoT and BC promise many benefits for the digitalization of the SC. These technologies are likely to reduce internal management costs, improve the efficiency of SC activities, and ensure a sustainable competitive advantage. BC and IoT are expected to do so especially through the digitalization and integration of external networks (Korpela et al. 2017). In this DSC context, the authors argue that the main benefits of these new technologies are therefore based on: "cost-effectiveness of services and value-creating activities that are advantageous to many actors in the ecosystem, including firms and their suppliers, employees and customers."

IoT has gone through a hype phase and is currently becoming a mainstream option within SCs. IoT is of special interest to SC stakeholders because it allows remote (or from an automated process) data capture and sharing, which is not otherwise possible (Banerjee 2019). However, IoT as a standalone solution for DSCs faces challenges such as security, privacy, and data reliability (Dedeoglu et al. 2020), but also decentralization, and poor data interoperability (Dai et al. 2019). In the work of Dai et al. (2019), the authors argue that BC has the potential to complement IoT systems as follows: (i) enhanced interoperability of IoT systems through the conversion and storing of IoT data in a BC; (ii) improved security; (iii) traceability and reliability; and (iv) automated interactions of IoT systems operated by smart contracts (*i.e.*, computer protocols and autonomous programs that facilitate, verify, and execute a contract whose conditions are defined and stored beforehand in the BC (Dumas et al. 2019)). Therefore, BC enables transactional security while IoT combines the physical and digital world with sensors (Kumar and Pundir 2020). As a result, recent studies have examined the opportunity of pairing IoT with BC to solve SC challenges.

Zhang and Sakurai (2020) offer an exploratory study that identifies the works and industrial cases of well-known companies that have adopted IoT and BC for DSCs. Aich et al. (2019) highlight the benefits of implementing BC- and IoT-based SCs in four industries: automotive, pharmaceutical, food industry, and retail. Dai et al. (2019) provide a comprehensive survey of the integration of BC technology with IoT, that they refer to as "Blockchain of Things" (BCoT), discuss the insights and industrial applications of this kind of implementation. Seifert and Markoff (2019) review RFID implementation in various companies (particularly retailers), derive learnings from past success/failure implementations of RFID, and use those learnings to inform managerial decisions about BC implementation. van Hoek (2019) builds on the framework of Reyes et al. (2016) to extend it using managers' insights. In particular, the author compares and contrasts RFID and BC implementation considerations. As Seifert and Markoff (2019), the goal was also to inform managerial decisions about adopting BC for the SC.

To summarize, the combination of these two technologies enables the digitalization of the physical world data and stores it in a distributed ledger accessible to multiple stakeholders, thereby bridging the trust gap. The IoT-BC combination can drive value in different ways to address SC challenges, such as adding value to products, call upon trust among partners, reduce SC costs, improve SC efficiency, and empower customers (Banerjee 2019).
Key features that distinguish our chapter from the above-mentioned ones is that we include (i) the viewpoint of both academics and practitioners by performing a multivocal literature review (MLR); (ii) both the commonly found technology-driven perspective for the adoption of digital technologies and a revised one, which is SC-driven; (iii) the considerations of both BC and IoT SFs; and (iv) the differentiation of lean and agile SCs.

4.3 Methodology

To investigate and structure the BC IoT success factors (SFs) in SCM, we used a three-fold methodology: (i) a MLR, (ii) a topic modeling approach, and (iii) a mapping of BC IoT SF categories to lean and agile SCs. From these three steps, we developed a conceptual framework (that we refer to as the "sweet spot" throughout this chapter) and research propositions.

4.3.1 Multivocal Literature Review

We rely on the SFs identified in the literature that favor the adoption of the BC IoT technology combination in SCs. Systematic Literature Reviews (SLR) have been increasingly used in different fields (*e.g.*, software engineering, social sciences, supply chain management) to collect evidence and structure findings in a specific research area. However, this kind of literature review does not include "gray" literature, defined by Garousi et al. (2019) as "non-published, nor peer-reviewed sources of information." Gray literature is typically provided by industrial practitioners, companies and the government (Butijn et al. 2020). It allows accounting for practical insights. SLRs that include both the academic and the gray literature are referred to as Multivocal Literature Reviews (MLR) by Ogawa and Malen (1991). According to Elmore (1991): "another potential use of multivocal literature reviews is in closing the gap between academic research and professional practice." The MLR approach seems particularly relevant to go beyond the BC hype in SCM, for which an abundance of academic papers have recently emerged, but where the bridge between academia and real-world practice has not yet been explored in full. Therefore, we performed a MLR and followed the approach of Shoaib et al. (2020), who apply this method to identify and prioritize the factors positively influencing the adoption of BC in the SC. Unlike their work, we do not only consider BC but also IoT. Furthermore, we first consider the SC type (lean or agile) that the company employs and the SC performance objectives that are specific to it. Once this is acknowledged, we associate the SFs with the different SC objectives and types. To summarize, instead of starting from the technological advantages that BC could bring to the SC (a common approach in the academic literature) and deducing recommendations from them in the form of a taxonomy, we start with analyzing the SC type and its corresponding performance objectives. There are several ways of examining application cases of emerging technologies such as BC. The stand in this study is to adopt a SC user-centric business logic rather than a technical-driven one. Indeed, depending on SC performance objectives, stakeholders will tend to favor one solution over another. We then deduce under which cases and conditions BC coupled with IoT could be beneficial for practitioners and in which other cases another more traditional database (TD) technology could be sufficient.
Below, we detail the MLR, first for the academic literature, and, then, for the gray literature. We invite the reader to refer to the work of Garousi et al. (2019), which presents a detailed analysis of this approach. It consists mainly of three phases: "planning the review," "conducting the review," and reporting the results. First, our goal is to identify the primary sources that allow us to answer the following research question:

- *Under which conditions could organizations benefit from BC and IoT adoption in SCs?*

and, secondly, to collect evidence from the identified sources to address our second research question:

- *How do SC characteristics factor into successful BC and IoT adoption?*

We begin with the academic literature.

Academic literature: The selection of data sources was carried out through search engines and specialized digital libraries, namely: Google Scholar, IEEE Explore, ISI Web of Science, ACM Digital Library (see Tables M.1 and M.2 in Appendix M which detail the selection of sources).

We used boolean operators (AND and OR) to develop our search strings: ("Factors" OR "Aspects" OR "Items" OR "Elements" OR "Characteristics" OR "Motivators" OR "Variables" OR "Determinants") AND ("RFID" OR "Internet of Things" OR "IoT") AND ("Blockchain" OR "Distributed" OR "Decentraliz*") AND ("Ledger" OR "Technology" OR "Database") AND ("Implementation" OR "Execution" OR "Adoption") AND ("Supply chain" OR "Supply chain management" OR "Logistics" OR "Operations Management"). Once this step was realized, a **search stopping criterion** was determined. Garousi et al. (2019) present three main search stopping criteria: "theoretical saturation, *i.e.*, when no new concepts emerge from the search results anymore; effort bounded, *i.e.*, only include the top N search engine hits; and evidence exhaustion, *i.e.*, extract all the evidence." In our case, given the large number of data sources found (more than $487'000$ results as of this writing, March 2021), we relied on the search engine page rank algorithm (Langville and Meyer 2011), and retained only a certain number of hits. We thus chose the stopping criterion called "effort bounded."

Next, **inclusion and exclusion criteria** were chosen in order to select the sources for our study. The inclusion criterion corresponds to the source type: journals, conference papers, and books. The inclusion criteria are similar to those developed in the study by Shoaib et al. (2020), especially for the journal impact factor threshold set by the authors to 2.53. We adopted the following exclusion factors: papers published in journals with an impact factor < 2.53, public BC, and industries not applicable to passive RFID tags (as most most retail applications operate with passive tags, which do not need a power supply (Delen et al. 2007, Gaukler and Seifert 2007)).

To filter the selected literature, we conducted a **quality review** of the selected literature using question-based quality assessment (QA) criteria and a "tollgate" approach (as suggested by Afzal et al. (2009) and Akbar et al. (2019)). This approach typically consists of five phases: "search using search terms," "exclusion based on title and abstract," "exclusion based on introduction and conclusions," "exclusion based on full text," and "final selection of primary studies." For the sake of simplification, we grouped the first two phases together and the next

two together, giving us only three phases instead of five. For the last phase of the "tollgate" approach, entitled "final selection of primary studies," we developed nine quality assessment criteria, specific to our study (depicted in Table 4.1). For each source, each of these criteria was evaluated as 0 when the criterion was not addressed, and as 1 otherwise. The sum of the nine evaluated criteria resulted in a score, which was normalized and used to select the relevant literature. The selection requirements were: a score greater than 0.5, and the quality criteria n°4 equal to 1 (score > 0.5, and $Q4 = 1$). Table M.1 in the Appendix shows that 89 sources from the academic literature were selected for our study.

Table 4.1 – Selected QA criteria for the academic literature.

QA questions	Checklist questions
Q1	Are the research methods justified with respect to the research questions?
Q2	Does the literature report the SFs of BC or IoT, or both?
Q3	Does the literature report the BC type: permissionless (public), permissioned (consortium), or private (centralized)?
Q4	Does the literature report the SFs depending on the BC type?
Q5	Does the literature report the SC type: lean, agile, or hybrid?
Q6	Does the literature report the technology adoption perspective, that is technology-driven or supply chain-driven?
Q7	Does the literature discuss the background and applications of BC or IoT, or both?
Q8	Are the gathered data associated with BC or IoT, or both in SCM?
Q9	Are the research questions justified by our research methods?

Gray literature: In the same fashion as for the academic literature, we identified and selected the sources of the gray literature. This type of literature allows us to answer our research question, this time, with the "voice" of practitioners. Due to the source types' nature, the **search engines and platforms** used for data selection differed from those used for the academic literature: Google, Bing, Yahoo, Arxiv, SSRN (see Table M.2 in Appendix M for more details). Then, as for the academic literature, we also used the **stopping criterion** called "effort bounded." However, the **inclusion and exclusion criteria** for the gray literature were different from those used for the academic literature. The approved source types were white papers, annual reports, magazines, technical reports, and preprints. In terms of exclusion criteria, data sets, tweets, email, and audio-video materials about BC and IoT were excluded.

Once the inclusion and exclusion criteria were defined, we proceeded with **evaluating the quality** of the gray literature. For this purpose, since some of the quality criteria used for the academic literature were no longer valid to assess the gray literature (*e.g.*, the journal impact factor threshold), we adopted and adapted the quality criteria proposed by Garousi et al. (2019) and Butijn et al. (2020), which are organized into several categories such as the publisher authority, or the methodology employed (see Table 4.2). These criteria were then evaluated using the same evaluation procedure as for the academic literature. The score obtained for each study had to be greater than 0.5 to be retained (score > 0.5). Table M.2, in Appendix M, shows that 86 sources from the gray literature were selected in the end.

Table 4.2 – Quality assessment criteria for gray literature

Category	Assessment criteria
Publisher authority	Publishers must have deep awareness about blockchains, and the organization must be trustworthy
Study objectivity	The objectives and conclusion of the report must be mentioned
Study relevance	The SFs of BC or RFID, or both must be mentioned in a SCM context
Methodology	The document must contain goals, methodology, references, limits, and specific questions
Date	Mentioned date
Sources	Must contain linked sources
Novelty	Adds something unique to the research, adds a sharp point or discusses weaknesses
Impact	Has citations and backlinks to support its statements

4.3.2 Topic Modeling

From the MLR (see Section 4.3.1), we extracted a large number of SFs for the adoption of BC and IoT in the SC. How could we now automatically group these numerous SFs into categories? Understanding a large corpus of text through topic clustering is a recurring subject in Natural Language Processing (NLP), defined by Liddy (2001) as: "a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications." To deliver on the aforementioned goal, an NLP method named *topic modeling* is typically used. It is an unsupervised machine-learning model for text-mining. Topic modeling discovers hidden semantic structures by outputting topics that best describe a given text document.

We used the Latent Dirichlet Allocation (LDA) algorithm (see Blei et al. (2003) for a detailed explanation of the method). The LDA algorithm takes documents as inputs (here the documents correspond to the sources of information we collected from the MLR) and finds topics (our desired SF categories) as outputs. A topic is represented as a collection of weighted words. The weight reflects how frequent, and, thus, important the SF is to that topic.

We followed Prabhakaran (2020)'s procedure and used the Gensim package in Python, along with the Mallet's implementation (via Gensim). According to the authors, the Mallet version is known to run faster and gives better topics segregation. We now describe the main steps of the topic modeling, which consists of: designating the preprocessed text to be analyzed (*i.e.*, our sources from the selected academic and gray literature during the MLR); tokenizing each sentence into a list of keywords; creating bigram and trigram models (*i.e.*, two or three words, respectively, frequently occurring together in the text); lemmatizing and stemming the text (*i.e*, keeping only noun, adjectives, verbs, and adverbs); creating the dictionary (the list of keywords from our sources) and the corpus (the keywords' frequency in the sources) from the text, as well as the number of topics. The dictionary, corpus, and number of topics are the input parameters subsequently required for the LDA algorithm.

Once the topic model is built, we run it and analyze the output topic coherence score, which

provides a measure for judging the quality of the given topic model (see Suaysom and Gu (2018) for further details). Typically, papers report coherence scores in the [0.35;0.65] range (Chehal et al. 2020). The higher the coherence score, the more consistent the topic is.

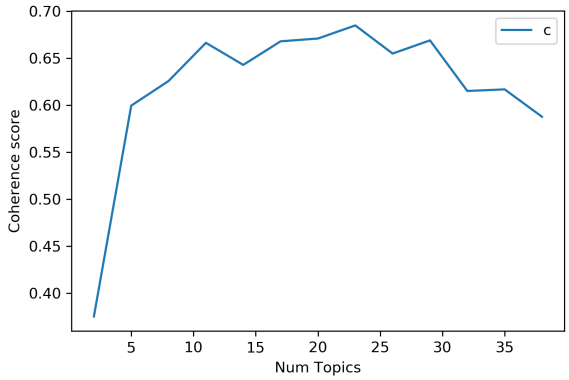


Figure 4.1 – Coherence scores for the LDA Mallet model.

Last, we analyzed the results and optimized the number of categories. For our study, the number of categories, n, retained was 14, a number from which the coherence score only slightly increased (as depicted by Fig. 4.1). The SFs were grouped into categories numbered from $n = 1$ to 14. A topic inferring phase was then carried out in order to name each SF category. The categories' name was chosen based on the top ten relevant keywords from each topic.

4.3.3 Success Factors Mapping to Supply Chain Macro-Processes

We recall that the purpose of this study is to propose a SC user-oriented sweet spot by considering, first, the SC objectives, and not the potential benefits of emerging technologies such as BC and IoT for the SC. The idea is then to define, according to these objectives, whether the need for these technologies is still high, or not.

Through the previous topic modeling (see Section 4.3.2), the key SFs for the adoption of BC and IoT were grouped into categories (see results in Section 4.4.2). By combining these categories from all types of literature (academic and gray) and perspectives (technology and SC-driven), we obtained SF macro-categories (see column "SC macro success factors" in Tables O.1 and O.2 of Appendix O). These macro-categories allowed us to associate them more easily with the SC objectives, as explained later.

Now, the question of mapping these SC macro SFs to SC objectives arises. Drivers and performance objectives for a lean and agile supply chains are known to be different. So how can we associate the SC strategic objectives of these two SC types with the SFs identified in the literature?

Vyas et al. (2019) combine the capabilities of BC with SCOR performance metrics. However, unlike our study, the authors do not consider IoT, nor do they distinguish the SC type used, and adopt a technology-driven perspective. If we were to follow their procedure, it would be difficult to discern which SFs could be attributed to a lean or agile SC type. Therefore, to overcome this challenge, we chose to map the identified SF categories to the SC macro-processes defined by Chopra et al. (2013) (see details in Section 4.2.1).

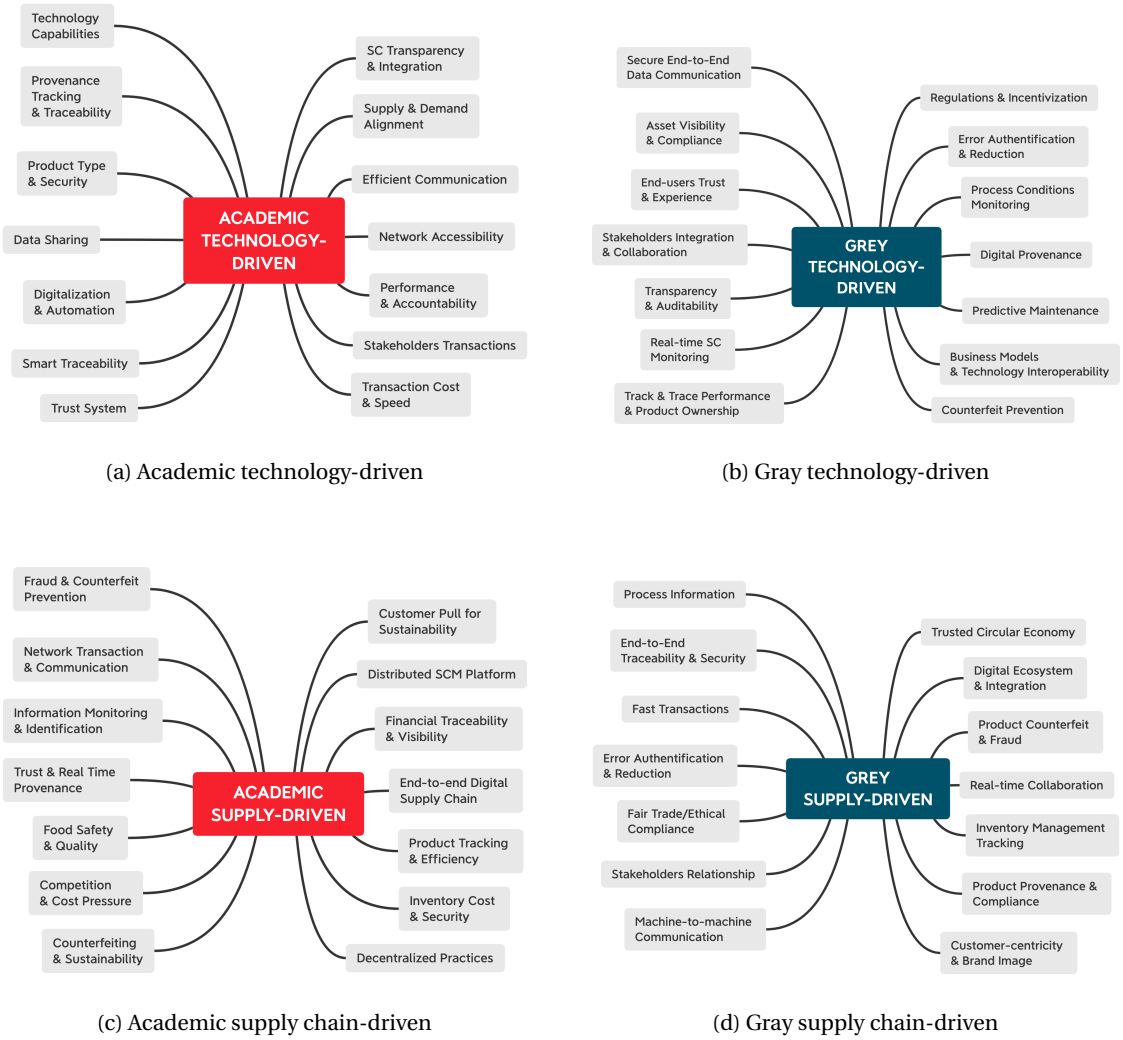
Once the mapping between the key SFs and the SC macro-processes was completed, we separated the SFs that are lean or agile-specific from those that are related to the required database type. This step permitted an identification of the sweet spot for the adoption of BC and IoT in SCM. To achieve this objective, we built on previous studies that differentiate between lean and agile supply chains. In their study, Vonderembse et al. (2006) provide a description and characteristics of lean, agile, and hybrid supply chains. As mentioned above, for simplicity, we do not consider hybrid supply chains, which are a combination of lean and agile supply chains (a comprehensive description can be found in Naylor et al. (1999)). (Chopra et al. 2013, Table 2-4, p30) propose an adaptation of the SC types comparison table, developed originally by Fisher (1997). These studies allow us to classify the SFs as pertaining to a lean or agile SC. For instance, the SF entitled "streamlined operations and product recall" characterizes a lean SC. This SC type mainly focuses internally on the continuous improvement of operational processes. Another example is the attribution of the SF "inventory, operations, and working capital costs" to this SC type. Indeed, another important objective of a lean SC usually lies in cost reduction. An example for an agile SC is the combination of the "real-time information sharing, monitoring, access" factor, whose objective is to respond quickly to consumer demand with a high service level. Access to data, as well as product information sharing in real-time, are therefore important. This logic is applied to each SF. We present the findings of our three-fold method in the next section.

4.4 Results

4.4.1 Technology- vs Supply Chain-driven Success Factors

The topic modeling approach (see Section 4.3.2) highlighted the SF categories identified in the academic and gray literature. Fig. 4.2 presents, in the form of mind maps, the SFs from the two literature types, depending on the technology-driven, and SC-driven perspectives.

Table N.1 in Appendix N summarizes the differences between the academic and gray literature. The shaded cells in Table N.1 indicate topics not covered by the academic literature.
First of all, we can see that the gray literature, with a technology-driven perspective, reveals SFs of BC and IoT adoption for the SC that are covered very little, if at all, in the academic literature. These include human and organizational factors such as: stakeholder incentivization, end-users experience, process or human error authentification and reduction, business-model enabler; and product-related factors, as follows: product ownership, product conditions



(a) Academic technology-driven

(b) Gray technology-driven

(c) Academic supply chain-driven

(d) Gray supply chain-driven

Figure 4.2 – Academic and gray topics depending on the perspectives.

monitoring, and product digital identity. For instance, in the academic literature, (Kshetri 2018, Table 2) reports comprehensive BC roles and mechanisms involved in achieving strategic SC objectives such as cost, speed, dependability, risk reduction, sustainability, and flexibility. However, human or business SFs are not predominant in their work (except for the food provenance consumer awareness). Typically, customer-facing SFs have not been covered in most academic papers. This confirms the value of considering the gray literature that extends our understanding of adopting the Blockchain and IoT combination for the SC, from the perspective of increasing customer value.

Next, turning to the SC-driven gray literature, we observe the following additional factors that are not covered in the academic literature: digital product passport, digital twin, and brand image. Then, comparing the SC-driven and technology-driven perspectives, the results indi-

cate that the first one covers three additional SFs, namely customer-facing, SC performance, and digital maturity.

In conclusion, these results confirm the need to perform a MLR, and demonstrate the synergy of collecting evidence from the two literature types. This helps uncover additional SFs from real-world practices. It also shows that perspective matters. Indeed, the revised SC-driven perspective builds on the technology-driven one. In particular, it facilitates aligning SC performance objectives with the right IT and operational capabilities. This supports SC evolution and business strategies across the entire SC.

4.4.2 Success Factor Macro-Categories

The SFs identified previously can be sorted into eight categories—all types of literature and perspectives combined: IT capabilities, data management, SC efficiency and digitalization, smart systems, SCM integration and relationships, regulatory compliance, cost savings and opportunities, and customer-facing. Applying the mapping approach described in Section 4.3.3, we obtained for each SC type (lean or agile) the mapped SFs to the eight corresponding macro SFs; the SC macro-processes they impact; the corresponding requirements, but also the necessary conditions constituting the BC and IoT sweet spot in SCM (explained later in Section 4.4.3). Tables O.1 and O.2 in Appendix O summarize the results.

Shoaib et al. (2020) developed a taxonomy of key factors organized into eleven main categories, specifically: "overall efficiency," "policies and laws," "reliability and ecoreconciliation," "data management," "sustainability," "integrate SCM," "customer satisfaction," "accessibility," "overall cost," "smart system," and "system strength." Two of our macro SFs can also be found in their work, which are: "data management" and "smart system." Although some of our categories are different from those identified by the authors, overall, they are aligned with them. We considered supplementary factors compared to their work, such as: IoT SFs, the SC-driven perspective and SC types. Therefore, our SF categories encompassed further aspects related to SC transaction management; governance of partnerships; product conditions, regulatory compliance, and product life cycle; and customer-facing. We named our categories accordingly.

4.4.3 Sweet Spot Conceptual Framework and Research Propositions

If we now take a closer look at the SFs (see column "Success factors" of Tables O.1 and O.2 in Appendix O), we notice that some of them characterize the SC type, while others are related to the database technology (BC or a TD). We are interested in knowing the conditions under which BC would be beneficial compared to using a TD. We thus only retain the decisive SFs for the database type to be considered. The other SFs, related to the SC types (see shaded cells in Tables O.1 and O.2), are discarded for the development of our conceptual framework, as these non-decisive SFs are already known in the literature to characterize lean or agile supply

chains. This led us to Fig. 4.3 and 4.4, which structures the SFs around the SC macro-processes according to the SC type.

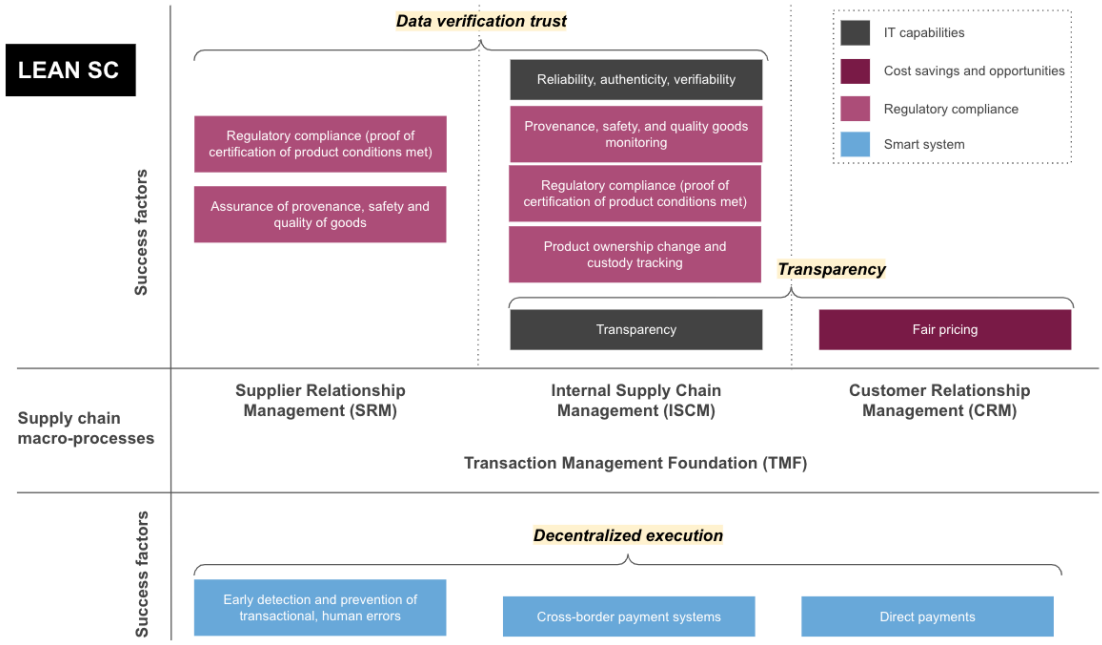


Figure 4.3 – Success factors of a lean Blockchain IoT supply chain sweet spot.

We then noted that the SFs could be grouped into three requirements: “data verification trust,” “transparency,” and “decentralized execution,” which are common to both SC types but whose respective SFs differ. The two-by-two associations of these requirements: “data verification trust-transparency,” “data verification trust-decentralized execution,” and “transparency-decentralized execution,” enabled the identification of scenarios for which the BC technology would be a preferable option compared to a TD. These scenarios are portrayed in Fig. 4.5, due to limitations in visualizing four dimensions simultaneously.

It is important to note that this comparison is only based on the IT capabilities of the database technologies (BC and TD). It would be interesting to include the short-, medium-, and long-term installation and maintenance costs of these two technologies in future research. For instance, Kumar et al. (2020) compare three inter-organizational systems (IOS), namely: BC, EDI (electronic data interchange) and SOA (service-oriented architectures) technologies. Specifically, the authors compare BC features, such as the cost, with EDI and SOA technologies. They argue that BC presents higher transaction costs and setup costs compared to the two other IOS technologies, due to the validation overhead cost and duplicated storage.
We now describe the interaction effect of the three requirements and illustrate them in Fig. 4.5.

Transparency and data verification trust scenario: We examine the case of a high level of data verification trust sought and a need of transparency (whether high or low) in the SC. The

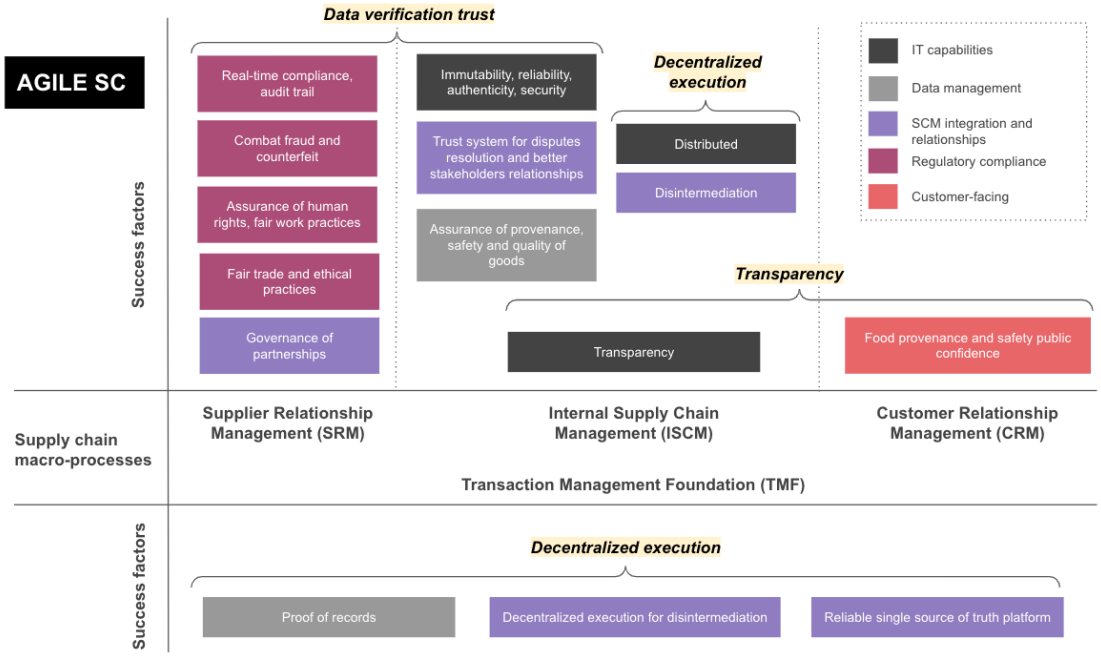


Figure 4.4 – Success factors of an agile Blockchain IoT supply chain sweet spot.

BC technology, because of its infrastructure, would meet these needs, unlike a TD. In other cases, a TD would suffice, especially for a high need of transparency (to achieve operational efficiency) but a low level of product data verification trust. This scenario could correspond to a need of common materials traceability (*e.g.*, plastics), whose provenance verification would not be paramount for SCM. On the contrary, provenance verification would be crucial for high-end valuable goods (*e.g.*, luxury goods) to combat counterfeit and losses.

Data verification trust and decentralized execution scenario: Here, the choice of BC would be appropriate to meet the high data verification trust and decentralized execution requirements in the SC. Indeed, due to its infrastructure, a TD is not originally designed for secure decentralized execution. A TD would allow, coupled with IoT sensors, data verification but in a less secure and reliable way compared to the BC. However, for low requirement levels of these two aspects, a TD may be sufficient.

Decentralized execution and transparency scenario: Again, on one hand, when the need for decentralized execution is high (as in the previous scenario), the adoption of BC would be preferable to a TD. On the other hand, a TD would be recommended when the need of decentralized execution in the SC is not important, regardless of the transparency level sought.

BC technology, paired with IoT sensors, is therefore recommended when high expectations in product data verification trust or decentralized execution are pursued in the SC. Contrary to expectations, the transparency factor is not a determinant for the adoption of BC in the

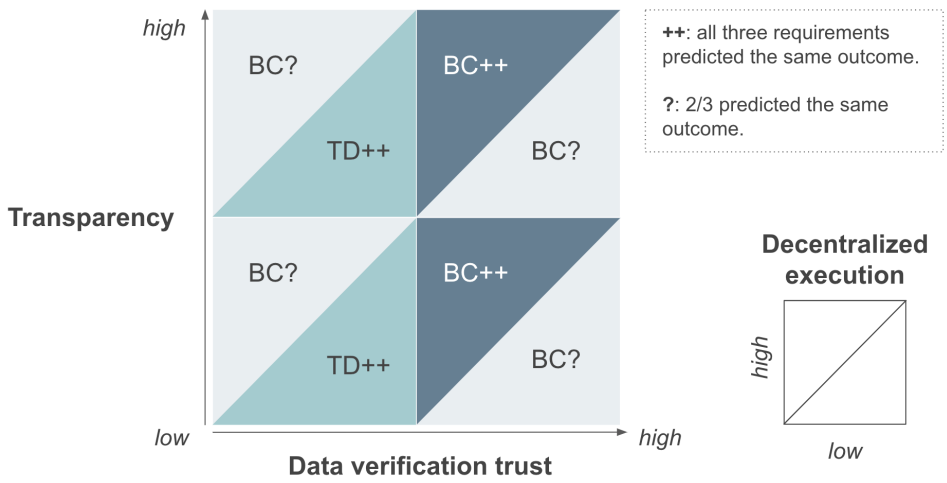


Figure 4.5 – Success factor requirements.

SC. It only becomes so when combined with a desired high level of data verification trust or decentralized execution. This can be explained by the fact that some SFs categorized under the attribute "transparency" can be addressed by a TD. If we refer to a lean SC, typically, visibility within the SC related to the traceability of raw materials can be achieved by means of IoT sensors and a TD. On the other hand, proof of compliance with respect to product transport conditions can only be achieved by means of a BC technology. The reason behind it lies in the BC IT capabilities: this technology is known to be immutable (data stored on the distributed ledgers cannot be changed, be it intentionally or accidentally). These results widen our knowledge of the BC adoption in SCM.

To summarize, we successfully determined the SFs for the adoption of BC and IoT in lean and agile supply chains, together with their conditions (see Fig. 4.5). As mentioned previously, the conditions are of three kinds: "high data verification trust and decentralized execution," and/or "high decentralized execution and transparency," and/or "high data verification trust and transparency," depending on the targeted SC's strategic objectives. Usually, not all SC macro-processes are simultaneously improved in the SC. According to the targeted SC objectives, a lean SC can be characterized by four macro SFs, namely: *regulatory compliance, IT capabilities, smart system*, and *cost savings and opportunities*. An agile SC can be featured by five macro SFs: *regulatory compliance, IT capabilities, data management, SCM integration and relationships*, and *customer-facing*. Our findings led us to our sweet spot conceptual framework and research propositions summarized in Table P.1 (see Appendix P).

Although previous work has identified SFs for the adoption of BC in SCM, our propositions include: the "voice" of practitioners (through factors identified from the gray literature), the SC-driven perspective, the BC technology as well as IoT, and the SC type. These aspects influence the definition of the sweet spot.

In subsequent sections, we argue that BC and IoT adoption are expected to improve the

performance of the four SC macro-processes: SRM, ISCM, CRM, and TMF, under certain conditions which vary depending on the SC type (lean or agile). Since all SC macro-processes are not simultaneously improved in the SC, we highlight below, for both SC types, the SC macro-processes that would likely be impacted by the favorable conditions of BC and IoT adoption. This considerations are synthesized into research propositions below.

Lean Blockchain IoT SC sweet spot - research propositions

The "high data verification trust and decentralized execution" requirement for the SC could impact the SRM and TMF macro-processes. First, looking at the SRM macro-process, the following categories and corresponding SFs (see factors in parentheses) have been identified and determine the "high data verification trust" requirement: *regulatory compliance* (proof of certification of product conditions met, assurance of provenance, safety, and quality of goods). Then, for the TMF macro-process, the category and SFs required to manage a "decentralized execution" are: *smart system* (early detection and prevention of transactional or human errors, cross-border payment systems, and direct payments):

> **P1.** *When the strategic objectives of a lean SC are geared toward the optimization of SRM and TMF macro-processes, then a* ***high level of data verification trust*** *and* ***decentralized execution*** *are likely to drive BC and IoT adoption in the SC.*

Then, the "high data verification trust and decentralized execution" requirement for the SC could also impact the ISCM and TMF macro-processes. First, looking at the ISCM macro-process, the following categories and corresponding SFs have been identified and determine the "high data verification trust" requirement: *IT capabilities* (reliability, authenticity, verifiability), and *regulatory compliance* (proof of product conditions certification met, assurance of provenance, safety and quality of goods monitoring, and product ownership change and custody tracking). Second, for the TMF macro-process, the categories and SFs required to handle a "decentralized execution" are the same as in *(P1)*:

> **P2.** *When the strategic objectives of a lean SC are geared toward the optimization of ISCM and TMF macro-processes, then a* ***high level of data verification trust*** *and* ***decentralized execution*** *are also likely to drive BC and IoT adoption in the SC.*

Next, the "high level of decentralized execution and transparency" requirement for the SC could impact the TMF, ISCM, and CRM macro-processes. First, looking at the TMF macro-process, the categories and SFs required to handle a "high level of decentralized execution" for transaction automation and disintermediation are the same as in *(P1)*. Then, for the ISCM macro-process, transparency in the SC constitutes the key SF. Second, for the CRM macro-process, the category named *cost savings and opportunities* and its "fair pricing" SF have been identified and additionally determine the "transparency" requirement:

P3. *When the strategic objectives of a lean SC are geared toward the optimization of ISCM, CRM, and TMF macro-processes, then a* ***high level of decentralized execution*** *and* ***transparency*** *are likely to drive BC and IoT adoption in the SC.*

The "high data verification trust and transparency" requirement for the SC could impact the SRM, ISCM, and CRM macro-processes. First, looking at the SRM macro-process, the category and corresponding SFs to address the "high data verification trust" requirement are the same as in *(P1)*. Then, for the ISCM macro-process, the critical categories and corresponding SFs to also address this requirement are equivalent to those reported in *(P1)*. As for the "transparency" requirement, the categories and corresponding SFs are the same as in *(P2)*. Lastly, to achieve "transparency", the categories and SFs required for the CRM macro-processes are the same as in *(P3)*:

P4. *When the strategic objectives of a lean SC are geared toward the optimization of SRM, ISCM, and CRM macro-processes, then a* ***high level of data verification trust*** *and* ***transparency*** *are likely to drive BC and IoT adoption in the SC.*

Agile Blockchain IoT SC sweet spot - research propositions

Turning now to the agile SC, the "high data verification trust and decentralized execution" requirement for the SC could impact the SRM, ISCM, and TMF macro-processes. First, looking at the SRM macro-process, the following categories and corresponding SFs have been identified and determine the "high data verification trust" requirement: *regulatory compliance* (audit trail, combat fraud and counterfeit, assurance of human rights and fair work practices), *SCM integration and relationships* (governance of partnerships). Then, for the ISCM macro-process, the categories and SFs required to manage "high data verification trust" are: *IT capabilities* (immutability, reliability, authenticity, and security), *SCM integration and relationships* (trust system for disputes resolution and better stakeholders relationships), and *data management* (assurance of provenance, safety, and quality of goods). As for successfully achieving "decentralized execution" requirement in this SC macro-process, the following categories and SFs have been identified: *IT capabilities* (distributed), and *SCM integration and relationships* (disintermediation). Lastly, for the TMF macro-process, the categories and SFs required to handle "decentralized execution" are: *data management* (proof of records), and *SCM integration and relationships* (decentralized execution for disintermediation, and reliable single source of truth platform):

P5. *When the strategic objectives of an agile SC are geared toward the optimization of SRM, ISCM, and TMF macro-processes, then a* ***high level of data verification trust*** *and* ***decentralized execution*** *are likely to drive BC and IoT adoption in the SC.*

Then, the "high level of decentralized execution and transparency" requirement for the SC could impact the ISCM, CRM, and TMF macro-processes. Looking at the ISCM macro-process, the same categories and SFs identified in *(P4)* help address the "high level of decentralized execution," and transparency in the SC constitutes the key SF. Then, for the CRM macro-process, the categories and SFs required to achieve "transparency" are: the category named *customer-facing*, and its "food provenance and safety public confidence" SF. Lastly, for the TMF macro-process, the categories and SFs required to handle a "high level of decentralized execution" for transaction automation and disintermediation are the same as in *(P5)*:

> **P6.** *When the strategic objectives of an agile SC are geared toward the optimization of ISCM, CRM, and TMF macro-processes, then a* ***high level of decentralized execution*** *and* ***transparency*** *are likely to drive BC and IoT adoption in the SC.*

Lastly, the "high level of data verification trust and transparency" requirement for the SC could impact the SRM, ISCM, and CRM macro-processes. Again, looking at the SRM and ISCM macro-processes, the same categories and SFs identified in *(P5)* help address the "high level of data verification trust," and transparency in the SC constitutes the key SF. Then, to meet the "transparency" requirement in the CRM macro-process, the same categories and SFs identified in *(P6)* are required:

> **P7.** *When the strategic objectives of an agile SC are geared toward the optimization of SRM, ISCM, and CRM macro-processes, then a* ***high level of data verification trust*** *and* ***transparency*** *are likely to drive BC and IoT adoption in the SC.*

4.5 Discussion and Conclusions

In this chapter, we have achieved three main objectives and thus contribute to the literature on supply chain management in a digital technology context. First, we collected SFs for the adoption of BC and IoT in the SC. These factors have been identified not only in the academic literature but also in the literature derived from industrial practices (gray literature) to bridge the gap between theory and practice. We used a topic modeling approach to create a holistic and structured view of these factors. The SFs were sorted into eight categories: *IT capabilities, data management, SC efficiency and digitalization, smart system, SCM integration and relationships, regulatory compliance, cost savings and opportunities,* and *customer-facing*. Then, according to the literature, the benefits and use of BC often go hand in hand with IoT sensors for automation, and improved SC efficiency (Kshetri 2017, Yusuf et al. 2018a, Viriyasitavat et al. 2019, Banerjee 2019). Therefore, we not only collected SFs related to BC but also those related to IoT. Only a few studies to date have considered the SFs' combination of these two technologies for improving SC performance. Our findings could therefore provide visibility for decision makers on the benefits of adopting BC with IoT in the SC.

Second, in order to adopt a SC user-centric approach, we have associated the SFs identified

in the literature with the SC macro-processes proposed by Chopra et al. (2013). These macro-processes have the merit of including all SC activities. This revised SC-driven perspective enables SC performance objective alignment—not only internally, but also externally with suppliers and customers—with digital technologies such as BC and IoT. Interestingly, this perspective is rarely used in the literature. A common perspective found in previous works is the technology-driven one, which starts from the identified technological advantages of BC and IoT. Recommendations according to this approach are then formulated from the advantages to identify compelling use cases in SCM. Although legitimate, this approach potentially risks neglecting the business aspect, in this case the SC performance objectives targeted by the stakeholders. Therefore, we believe that our SC-driven perspective, which is focused on the needs of SC stakeholders, allows us to highlight specific SFs which were not highlighted by the technology-driven perspective. For instance, SFs for BC and IoT adoption in the SC that are related to customer-facing, SC performance, and digital maturity are revealed by our perspective, but commonly omitted in a technology-driven one.

Third, no one to the best of our knowledge has considered analyzing the SFs of BC and IoT adoption by distinguishing the SC type (lean or agile). Depending on the needs of the targeted customers, the company must define the responsiveness or efficiency of the SC (Chopra et al. 2013). This characterization is thus critical to ensure the growth of the SC surplus. Therefore, our study provides valuable insights into the BC IoT SC sweet spot depending on the SC type. Our results show that the lean BC IoT sweet spot differs from the agile one. In particular, the lean sweet spot is characterized by SFs that revolve around regulatory compliance, cost savings and opportunities, smart system, and IT capabilities (with an emphasis on reliability and authenticity requirements). In contrast, the agile sweet spot is characterized by SFs that revolve around data management, SCM integration and relationships, regulatory compliance (this time with a focus on counterfeiting, fair trade and ethical practices), customer-facing, and IT capabilities (with an emphasis on immutability, security, and distribution).

Overall, in this chapter, we have uncovered lean and agile BC IoT SC sweet spots from a SC-driven perspective. Our results are summarized in a conceptual framework and research propositions that are consistent with previous findings in the literature related to BC IoT adoption for SCM. We believe that our study could be useful for both practitioners and academics to address SC performance strategies with aligned technologies' adoption. The uncovered sweet spots have implications for lean and agile SC performance, and empirical research. We discuss each of these implications below.

Managerial Implications for Lean and Agile SC Performance

This chapter has conceptualized key elements in favor of BC and IoT adoption in the SC, which are likely to improve SC performance, be it lean or agile. This study provides a foundation for future research on the impact of these factors on SC performance.

First, we turn our attention to lean SCs. The SFs related to the requirements of *high data verification trust* and *decentralized execution* are likely to have a positive impact on various

SC strategies. With more reliable, verifiable IT capabilities, increased regulatory compliance, tracking of products and raw materials, we expect to see an improved SRM macro-process and suppliers' selection. Also, transaction automation and decentralized execution allow for automated and cross-border direct payments between SC stakeholders, as well as early detection of human or transactional errors. Thus, we expect to witness enhanced and cheaper manufacturing, inventory, and lead time strategies for the ISCM and TMF macro-processes.

The SFs related to the requirements of *high decentralized execution* and *transparency* are likely to have a positive impact on the ISCM and CRM macro-processes performance, and, in particular, on pricing and product design strategies. As for the pricing strategy, the "fair pricing" factor is likely to increase consumer confidence in their purchases and consequently their loyalty to the brand in the future. For product design strategy, we expect a decreased time to market and a maximization of product performance.

Turning now to agile SCs, the SFs related to the requirements of *high data verification trust* and *decentralized execution* are likely to have a positive impact on the SRM, ISCM and TMF macro-processes. Fairer and more ethical practices are expected to increase the quality level of suppliers and to lead to trustworthy manufacturing strategies. Furthermore, the trust system for dispute resolution brought by BC technology and IoT sensors is likely to reduce lead time strategies, bring higher collaboration between stakeholders, and enhance relations with suppliers.

The SFs related to the requirements of *high decentralized execution* and *transparency* are likely to positively influence the SRM and ISCM macro-processes. They are expected to speed up the lead time, inventory, and manufacturing strategies through disintermediation, better data sharing in real-time, and transparency over the whole SC.

Implications for Empirical Research

Once empirically verified, the research propositions advanced in this chapter (see Section 4.4.3) provide important insights into when and how the lean and agile BC IoT SC sweet spots materialize in practice, and their impact on SC performance. Several companies have already adopted BC and IoT to improve the SC performance, some of which are very successful (*e.g.*, Bocek et al. (2017), OpenSC (2019), Smartrac (2019), Waltonchain (2021), IBM (2021)).

Limitations and Future Research

It is important to note that our results are based on the assumption of a favorable regulatory framework for the use of BC within a SC ecosystem. Given the growing number of successful worldwide companies adopting BC and IoT for their SC, this should not be a major issue.

Our conceptual framework offers research propositions to be empirically validated. This study is a first step towards enhancing our understanding of BC and IoT benefits for lean and agile SCs. Consequently, this empirical validation is reserved for future studies, which could lead to a number of SC performance implications. For instance, our conceptual model could

be tested with companies for which we have identified sweet spots of BC and IoT adoption. In particular, as a first step, an empirical analysis of the impacts of SFs on the company's SC strategies could be evaluated. As a second step, it would be interesting to identify potential obstacles to the successful implementation of BC and IoT technologies according to SC type.

Conclusion

To conclude, in this chapter we have identified the SFs and favorable conditions for the use of BC and IoT depending on the SC type existing in companies. Even if some scenarios have been highlighted in order to improve the SC performance, other scenarios for which a simple database could be sufficient have also been identified. Depending on the SC type used, we invite the SC stakeholders to align their SC objectives with the required IT technologies. We also recommend taking into account potential barriers to the implementation of new technologies such as technical, organizational, and operational challenges (as identified in the literature by Dutta et al. (2020), for instance). As a matter of time, the development of BC skills and standards, and the decrease of installation and maintenance costs of this technology, it is expected that the pairing of BC with IoT will bring significant improvements of the SC performance as well as the emergence of new business models.

M Tollgate Approach: Final Selection of Sources

Table M.1 – Academic literature selection through the tollgate approach and quality assessment criteria

Electronic databases	Phase 1	Phase 2	Final selection	Technology-driven	Supply chain-driven
Google Scholar	170	132	71	33	38
IEEE Xplore	22	18	12	6	6
ISI Web of Science	24	12	5	2	3
ACM Digital Library	111	3	1	0	1
Total	**327**	**165**	**89**	**41**	**48**

Table M.2 – Gray literature selection through the tollgate approach and quality assessment criteria

Electronic databases	Phase 1	Phase 2	Final selection	Technology-driven	Supply chain-driven
Google	80	100	81	36	45
Bing	40	3	4	0	4
Yahoo	50	3	1	1	0
Total	**170**	**106**	**86**	**37**	**49**

N Topic modeling: Academic vs. Gray Topic Comparison

Table N.1 – Academic vs. gray literature topic comparison.

Topics	Academic technology-driven	Gray technology-driven
Technology Capabilities	x	x
Secure End-to-End Data Communication	x	x
Asset Provenance Tracking, Traceability Visibility	x	x
Product Compliance	x	x
Product Ownership		x
Product Types	x	x
End-users Experience		x
Trust System	x	x
Stakeholders Integration Collaboration	x	x
Operations Customer Analytics		x
Transparency Auditability	x	x
Digitalization Automation	x	x
Real-time SC Monitoring	x	x
Technology Operations Performance	x	x
Accountability	x	x
Stakeholders Incentivization		x
Error Authentification Reduction		x
Process/Product Conditions Monitoring		x
Network Accessibility	x	x
Digital Provenance Identity		x
Predictive Maintenance		x
Transactions	x	x
Business Model-enabler		x
Regulations Counterfeit/Fraud Prevention	x	x
Topics	**Academic supply-driven**	**Gray supply-driven**
Fraud/Counterfeit Prevention, Security	x	x
Network Transaction Communication	x	x
End-to-End Traceability Security	x	x
Information Monitoring Identification	x	x
Provenance Trust, Tracking Compliance	x	x
Real Time Monitoring Collaboration	x	x
Error Authentification Reduction	x	x
Product Safety Quality	x	x
Fair Trade/Ethical Compliance	x	x
Competition Cost Pressure	x	x
Stakeholders Relationship	x	x
Sustainability	x	x
Machine-to-machine Communication	x	x
Trusted Circular Economy	x	x
Digital Passport, Digital Twin		x
Financial Traceability Visibility	x	x
End-to-end Distributed Integrated Digital Supply Chain	x	x
Real-time Collaboration	x	x
Process Efficiency	x	x
Inventory Management Tracking	x	x
Cost Savings	x	x
Decentralized Practices	x	x
Customer-centricity	x	x
Brand Image		x

O Lean and Agile Blockchain IoT Supply Chain Success Factors

Table O.1 – Lean Blockchain IoT-enabled SC success factors and conditions.

SC type	SC macro-processes	SC macro success factors	Success factors	Requirements
Lean	SRM	Regulatory compliance	Regulatory compliance (proof of certification of product conditions met)	Data verification trust
			Assurance of provenance, safety and quality of goods	Data verification trust
		Smart system	Traceability of raw materials	Data verification trust
			IoT track trace for product conditions transportation	Transparency
		IT capabilities	Transparency	Transparency
			Reliability	Data verification trust
			Authenticity	Data verification trust
			Verifiability	Data verification trust
	ISCM	Regulatory compliance	Traceability	Data verification trust
			Durability	Data verification trust
			Feasibility	Data verification trust
			Provenance, safety, and quality goods monitoring	Data verification trust
			Product ownership change ~custody tracking	Data verification trust
			Regulatory compliance (proof of certification of product conditions met)	Data verification trust
		Smart system	Predictive maintenance	Transparency
		Supply chain efficiency and digitalization	Streamlined operations and product recall	Transparency
			Business efficiency through automation	Decentralized execution
			Smart tracking through IoT to identify SC inefficiencies and improve performance	Data verification trust
			Streamlined administrative processes and paperwork	Decentralized execution
			Streamlined data management	Data verification trust
		Cost savings and opportunities	Inventory, operations, working capital costs	Transparency
			Administrative paperwork costs	Transparency
	CRM	Cost savings and opportunities	Fair pricing	Transparency
		Supply chain efficiency and digitalization	Product recall efficiency	Transparency
			Warranty programs	Transparency
		Customer-facing	Commodities, healthcare and pharmaceutical products	Transparency
	TMF	Smart system	Early detection of transactional, human errors	Decentralized execution
			Cross-border payment systems	Decentralized execution
			Direct payments	Decentralized execution
		Data management	Smart contract for process automation	Decentralized execution
			Interoperability with existing systems	Decentralized execution

Table O.2 – Agile Blockchain IoT-enabled SC success factors and conditions.

SC type	SC macro-processes	SC macro success factors	Success factors	Requirements
Agile	SRM	Regulatory compliance	Fair trade ethical practices	Data verification trust
			Real-time compliance, audit trail	Data verification trust
			Combat fraud counterfeit	Data verification trust
			Assurance of human rights fair work practices	Data verification trust
		SCM integration and relationships	Governance of partnerships	Transparency
		Smart system	IoT tracking for product conditions transportation	Transparency
	ISCM	IT capabilities	Transparency	Transparency
			Immutability	Data verification trust
			Reliability	Data verification trust
			Authenticity	Data verification trust
			Security	Data verification trust
			Distributed	Data verification trust
		Data management	Trackability	Data verification trust
			Scalability	Decentralized execution
			Assurance of provenance, safety and quality of goods	Data verification trust
			Real-time information sharing, monitoring, access	Decentralized execution
			Business rules cooperation to agree common standards	Decentralized execution
		SCM integration and relationships	Decentralized execution	Decentralized execution
			Trust system for disputes resolution and better stakeholders relationships	Data verification trust
		Smart system	Multiple stakeholders engagement and collaboration	Decentralized execution
			Horizontal and vertical network integration	Transparency
			Inventory capacity management	Transparency
			End-to-end SC monitoring, product life cycle management	Transparency
		Regulatory compliance	Policies and laws	Data verification trust
			Privacy, anonymity protection	Data verification trust
	CRM	Customer-facing	Food provenance and safety public confidence	Transparency
			High-value durable consumer goods	Data verification trust
			Brand image	Transparency
			Customer satisfaction, experience, loyalty	Data verification trust
			Customer-facing sustainability (*e.g.*, social, green, circular economy)	Transparency
		Cost savings and opportunities	Licensing services	Data verification trust
			Competitive advantage and trading pressure	Transparency
			New business models	Decentralized execution
	TMF	Data management	Proof of records	Decentralized execution
		SCM integration and relationships	Disintermediation for decentralized execution	Decentralized execution
			Reliable single source of truth platform	Decentralized execution
			Trading partner pressure for accountability	Transparency
		Smart system	Direct faster payments	Decentralized execution
		Data management	Interoperability with existing systems	Decentralized execution
			Transaction scalability	Decentralized execution

P Conceptual Framework and Research Propositions

Table P.1 – Conceptual framework and research propositions.

Lean SC sweet spot and SFs conditions			**Agile SC sweet spot and SFs conditions**		
High data verification trust and decentralized execution			High data verification trust and decentralized execution		
Impacted SC macro-processes		***SC macro SFs involved***	***Impacted SC macro-processes***		***SC macro SFs involved***
SRM	x	Regulatory compliance (P1)	SRM	x	Regulatory compliance (P5), SCM integration and relationships (P5)
ISCM	x	IT capabilities (P2), regulatory compliance (P2)	ISCM	x	IT capabilities (P5), SCM integration and relationships (P5), data management (P5)
CRM			CRM		
TMF	x	Smart system (P1, P2)	TMF	x	SCM integration and relationships (P5), data management (P5)
High decentralized execution and transparency			High decentralized execution and transparency		
Impacted SC macro-processes		***SC macro SFs involved***	***Impacted SC macro-processes***		***SC macro SFs involved***
SRM			SRM		
ISCM	x	Transparency (P3)	ISCM	x	IT capabilities (P6), regulatory compliance (P6), transparency (P6)
CRM	x	Cost savings and opportunities (P3)	CRM	x	Customer-facing (P6)
TMF	x	Smart system (P3)	TMF	x	SCM integration and relationships (P6), data management (P6)
High data verification trust and transparency			High data verification trust and transparency		
Impacted SC macro-processes		***SC macro SFs involved***	***Impacted SC macro-processes***		***SC macro SFs involved***
SRM	x	Regulatory compliance (P4)	SRM	x	Regulatory compliance (P7), SCM integration and relationships (P7)
ISCM	x	IT capabilities (P4), regulatory compliance (P4), transparency (P4)	ISCM	x	IT capabilities (P7), SCM integration and relationships (P7), data management (P7), transparency (P7)
CRM	x	Cost savings and opportunities (P4)	CRM	x	Cost savings and opportunities (P4), customer-facing (P7)
TMF			TMF		

5 Conclusion

In the age of digitalization and I4.0, SC stakeholders are facing new challenges related to SC flexibility and efficiency, information sharing, and trust. On the one hand, they have to respond to individual consumer needs in terms of customization. This urges manufacturers to adopt user-centric approaches, as well as to evaluate emerging I4.0 technologies. AM, for instance, would allow them to gain higher operational efficiency and flexibility, while limiting manufacturing costs. On the other hand, there is a growing demand from consumers for transparency on the origin of products, but also for more ethical and sustainable practices within companies. This demand encourages SC stakeholders to consider investments in advanced digital technologies, such as BC and IoT. I4.0 technologies and the transition from traditional linear SCs to DSCs seem to provide solutions to the above mentioned challenges. They offer the prospect of improving SC performance and customer satisfaction.

Chapter 2 of this thesis was designed to model and evaluate the disruptive practice of a monopolist manufacturer switching between traditional MC processes and AM for final part production. We quantified the benefits of adopting AM as an alternative, or as a complement, to MC and optimized the resulting marketing and operations decisions in a dynamic setting. We focused on the operations-marketing interface and jointly optimized customer-centric technology-switching, pricing, and product variety decisions. We showed that leveraging AM through technology-switching scenarios (in particular an AM-MC-AM scenario) could help satisfying individual customer preferences while maximizing profitability across the PLC. Testing different pricing strategies, we showed that decreasing trajectories are almost optimal and flexible ones are optimal. We then derived analytical properties for the optimal pricing policy. On the demand side, we extended the literature on micromodeling diffusion models (*e.g.*, Chatterjee and Eliashberg (1990), Song and Chintagunta (2003)) by developing a novel time-varying locational customer choice model at the individual level, called the *HLB model*. To our knowledge, the *HLB model* is the first to offer the advantages of both modeling customer heterogeneity demand, at the individual level, and mimicking the PLC dynamics. On the supply side, we substantiated the importance of technology-switching decision in maintaining the compatibility between the technology choice and the PLC stage

(Hayes and Wheelwright 1979, Ramasesh et al. 2010). We adopted an innovative approach to solve our non-convex optimization problem, where the convergence of the solution is proven theoretically. Numerical experiments further confirmed the validity of our solution approach and highlighted the benefits and conditions of interchanging AM and MC over the PLC.

Chapter 3 extended Chapter 2 to investigate the conditions under which a capacity-constrained monopolist manufacturer could combine the benefits of AM with the traditional MC technology. We considered not only the supply side with the technology choice (AM or MC) in a dynamic setting across the PLC, but also the demand side to account for customer heterogeneity and forward-looking behavior. Similarly to Chapter 2, the model was also designed to jointly optimize marketing and operations decisions. In this Chapter though, we added two additional operations decisions, namely: inventory and production quantity decisions under the MC technology. Compared to the model of Chapter 2, AM and MC technologies were both capacity-constrained. We investigated several technology-switching scenarios, and three production capacity and inventory cases. In the scenario where the firm held inventory under MC, we developed a customer-centric *adaptive inventory policy* intended for an interdependent non-stationary demand. From this inventory policy followed a closed-form solution for the production quantity decision. The numerous decisions involved in our optimization problem led to a non-convex problem. We again analytically grounded our optimization problem and successfully derived an algorithmic formulation for our objective function, under our three capacity and inventory scenarios. We solved our problem using the sample average approximation framework. Lastly, we performed robustness tests to check the convergence of our approximation problem and validated the population sample size used in our numerical experiments. On the operations side and as in Chapter 2, significant profit improvements could be achieved with an AM-MC-AM technology-switching scenario. On the marketing side and under capacity constraints, our results revealed that considering both customer heterogeneity and limited production capacity required an increasing-decreasing pricing policy. Our findings showed that the benefits of pricing flexibility are highest when capacity is unlimited, or when the firm does not hold inventory. Under capacity constraints, a simple decreasing pricing policy combined with inventory performed very well and lessened the need for pricing flexibility.

Overall, Chapters 2 and 3 showed that the combination of customer-centric marketing and operations strategies with the new usage of AM paired with traditional MC processes could maximize a manufacturer's profit while addressing individual customer preferences.

In Chapter 4, we conceptualized the SFs and conditions which are likely to improve the SC performance, and favoring BC and IoT adoption in lean and agile SCs. To this end, we adopted a three-step approach. First, through a MLR, we collected SFs for the adoption of BC and IoT in the SC. These factors have been identified not only in the academic literature, but also in the literature derived from industrial practices (gray literature) to bridge the gap between theory and practice. We not only collected SFs related to BC but also those related to IoT. Second, we used a topic modeling approach to create a holistic and structured view of these

factors into categories. Third, we leveraged user-centricity of the SC. For this, we associated the SFs identified in the literature with the SC macro-processes proposed by Chopra et al. (2013). This revised SC-driven perspective enabled SC performance objective alignment—not only internally, but also externally with suppliers and customers—with digital technologies such as BC and IoT. Lastly, we analyzed the SFs of BC and IoT adoption by distinguishing the SC type (lean or agile), which, as far as we know, have not been performed previously. We summarized our findings into a conceptual framework and research propositions. We offered valuable insights into when and how the sweet spots for both SC types would materialize in practice, as well as their impacts with respect to the SC macro-processes performance.

5.1 Future Research Avenues

While preparing the material of Chapters 2 to 4, we identified several promising paths for future research. For instance, for both Chapters 2 and 3, and when data becomes available, it would be interesting to use parametric estimations for customer characteristics and industrial data related to production costs to fit the models. Second, one could investigate how to take into account a decentralized manufacturing scenario in the models of Chapter 2 and 3 (*e.g.*, see the work of Attaran (2017) which outlines the decentralized feature of AM to reduce logistics costs, and Westerweel et al. (2018a) who focus on spare parts inventory control, and show promising results while using AM at remote locations). Thus, it would be worth examining how our results can be extended to incorporate centralized and decentralized manufacturing scenarios, under individual customer preferences and PLC considerations. Still in the context of the production scenario analysis, it would also be worthwhile to explore scenarios where AM and MC processes are operated in parallel. Finally, in Chapter 4, our conceptual framework offers research propositions to be empirically validated. Our conceptual model could be tested with companies for which we have identified sweet spots of BC and IoT adoption. In particular, a first step could consist in empirically analyzing the impacts of SFs on the company's SC strategies. A second step could identify potential obstacles to the successful implementation of BC and IoT technologies according to SC type.

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List of Abbreviations

AM	Additive Manufacturing
BC	Blockchain
BTO	Build-to-order
BTS	Build-to-stock
CLT	Central limit theorem
CRM	Customer Relationship Management
DLT	Distributed ledger technology
DSC	Digital supply chain
FCFS	First-Come First-Served
HL	Hotelling-Lancaster model
HLB	Hotelling-Lancaster-Bass model
I4.0	Fourth industrial revolution, Industry 4.0
IoT	Internet-of-Things
ISCM	Internal Supply Chain Management
LDA	Latent Dirichlet Allocation algorithm
LLN	Law of large numbers
MC	Mass customization
MLR	Multivocal literature review
MNL	Multinomial logit model
MP	Mass production
MTO	Make-To-Order
MTOC	Make-To-Order capacitated
MTOUC	Make-To-Order uncapacitated
MTS	Make-To-Stock
MTSC	Make-To-Stock capacitated
NLP	Natural Language Processing
PLC	Product life cycle
PS	Pattern Search
RFID	Radio Frequency Identification
RM	Rapid manufacturing
SAA	Sample average approximation

SC	Supply chain
SCM	Supply chain management
SCOR	Supply Chain Operation Reference model
SF	Success factor
SLR	Systematic literature review
SRM	Supplier Relationship Management
TD	Traditional database
TMF	Transaction Foundation Management
WFS	Water Filling Scheme algorithm

RACHEL LACROIX

Optimistic, solution-oriented, endowed with creative and analytical skills. Developed complex, cross-disciplinary models integrating digital technologies and a customer-centric approach. Gained exposure to user-experience design, industrial, R&D, and business areas, at the intersection of innovation, operations management, economics, and marketing. My objective is to use these polyvalent skills to help building a better future for companies and their customers in the digital era — and by extension for our economy, society, and the environment.

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SKILLS

Technical

Sketch, Balsamiq, Invision, Milanote

HTML, CSS, Javascript, Keynote

Canva, MS office, Python, C++, Matlab

INTERESTS

Design Thinking, Sketching, Blockchain, Teaching, Hiking, Social/Sport events, Mindfulness, Running, Theatre, Photography, Windsurfing, Swimming, Cooking

WORK EXPERIENCE

Ph.D. Candidate | Digital Supply Chain Management

Ecole Polytechnique Fédérale de Lausanne (EPFL)

03/2017 – present — ***Lausanne, Switzerland***

Thesis: *Industry 4.0 technologies and customer-centricity for digital supply chains*. Supervisor: Prof. Ralf W. Seifert - Chair of Technology & Operations Management.

Papers:

- Lacroix, R., Tucci, C., Seifert, R. W. (2021). Blockchain of Things Sweet Spot for Lean and Agile Digital Supply Chains. Working paper, Ecole Polytechnique Fédérale de Lausanne (EPFL).
- Lacroix, R., Seifert, R. W., Timonina-Farkas, A. (2020). Utilizing Additive Manufacturing and Mass Customization under Capacity Constraints. Submitted to *ASMBI*, 2021.
- Lacroix, R., Timonina-Farkas, A., Seifert, R. W. (2020). Benefiting from Additive Manufacturing for Mass Customization across the Product Life Cycle. Submitted to *Operations Research Perspectives*, 2021.

Teaching assistantship: *Supply Chain Management* | Prof. Ralf W. Seifert | Spring 2018, 2019, 2020. *Design Thinking: Real Problems, Human-focused Solutions* | Prof. Christopher L. Tucci | Fall 2019. *Strategic Marketing & Technology Commercialization* | Prof. Thilo Eckardt | Fall 2017, 2018.

Doctoral courses: Supply Chain Management (SCM) | Mathematical Models for SCM| Design Thinking: Real Problems, Human-focused Solutions | Blockchain | Machine Learning | Microeconomics | Econometrics | Panel Data Linear Analysis | Data Analysis for Management Research | Optimization and Simulation.

Master thesis co-supervision: *SCM performance dashboard: replenishment policy at different reference scopes,* for Richemont, by Clément Barberis. *Variety-induced complexity cost framework*, for EyeOn, by Enrique de La Fuente Favela.

Conferences: INFORMS Annual Meeting | Washington State Convention Center, Seattle, USA |October 2019. Workshop "Transitioning 3D Printing from Niche to Mainstream Markets" | École Polytechnique, Palaiseau, France | June 2018. POMS 28th Annual Conference | Hyatt Regency Bellevue, Seattle, USA | May 2017.

Consultant | Business Project Management Support

AERIAL | Strategy and Management Consulting

03/2016 – 11/2016 — ***Paris, France***

- Assisted projects, risks and budget management support for the digital transformation of the public sector and its modernization. Communication to stakeholders, strategic decisions support.

R&D Assistant Engineer | Master Thesis

CENBG - CNRS/IN2P3 | Nuclear Physics Research Center

04/2015 – 09/2015 — ***Gradignan, France***

- **Thesis**: *Cellular dosimetry by Monte Carlo methods in Geant4 simulator*.
- Successfully designed a medical beam for Bergonié Institute applied to irradiating tumor cells containing nanoparticles.

R&D Assistant Engineer | CERN Summer Student Program

CERN | European Organization for Nuclear Research

07/2014 – 08/2014 — ***Meyrin, Switzerland***

- Successfully designed, built and tested a "UCx fission targets oxidation test stand", within the ISOLDE project team, completed in 2 months instead of 6.

RACHEL LACROIX

AWARDS

Best Teaching Assistant Award
October 2019 *Lausanne, Switzerland*
Awarded annually by the graduating Master student cohort, EPFL.

AMJE-Orange Business Game
September 2013 *Cluny, France*
Awarded annually by a jury for the best Junior Enterprise project.

VOLUNTEERING

Team leader | Figaro's 10km corporate challenge, charity event
10/2016 – 11/2016 *Paris, France*
Organized the event for the company, Aerial. Team composed of 10 people, ranked 12/60. Designed technical T-shirts for the team.

President | AMJE
01/2013 – 02/2014 *Cluny, France*
Arts et Métiers Junior Enterprise. Managed a team of 12 persons - 6 projects handled.

Teacher | OPTIM Program
10/2012 – 06/2013 *Cluny, France*
Program designed to support the education of young people from modest backgrounds. Tutored maths for senior high school students.

LANGUAGES

French *(native)*
English *(fluent)*
Italian *(basics)*
Spanish *(basics)*

SKILLS

Design & UX Research

- UX/UI Methods
- Design Thinking method, mindset
- Human-Computer interaction
- Client/user interviewing
- User, Market Research, Data Visualization Conceptualization
- Wireframing, protoyping, sketching
- Creativity, empathy, and problem-solving

Professional

- Communication, presentation and teaching
- Decentralized technologies: Blockchain, Cryptocurrencies, applications
- Business, strategy and marketing know-how, project management
- Supply Chain Management, Technology Management, Operations Research, Optimization
- Collaboration with multi-disciplinary team
- Adaptability, critical thinking, autonomy

EDUCATION & CERTIFICATES

University of Iasi | Udemy online certificate
SPSS for Research
Ongoing *Online learning platform*

- Advanced statistical analysis with SPSS, advanced multivariate techniques like logistic regression, multidimensional scaling or principal component analysis.

Interaction Design Foundation | IDF online certificate
User Experience (UX) Designer - Design Thinker
Ongoing *Online learning platform*

- UX Designer learning path. Skills: Design Thinking, User Experience, Human-Computer Interaction, User-Research Methods, Emotional Design, Mobile User Experience Design, Accessibility, and Usability.

SuperDataScience | Udemy online certificate
Blockchain A-Z™: Learn How To Build Your First Blockchain
Ongoing *Online learning platform*

- Blockchain, Cryptocurrency, Smart Contracts, Initial Coin Offerings, Decentralized Applications (DApps), Digital Wallet, Distributed P2P Network. Learnt the theory behind, and created, Blockchain (BC), cryptocurrency transactions, and smart contracts.

Johns Hopkins University | Coursera online certificate
HTML, CSS, and Javascript for Web Developers
Fall 2020 *Online learning platform*

- HTML, JavaScript, Css frameworks, Cascading Style Sheets (CCS). Implemented modern responsive web pages with HTML and CSS, using Javascript and Ajax.

EDHEC Business School | Master's (M.Sc) module
Top-ranking Business School | Strategic Brand Management
09/2015 – 01/2016 *Lille, France*

- "Strategic Brand Management" module from the Marketing Management M.Sc.

Arts et Métiers ParisTech (ENSAM) | Master's Degree (M.Sc)
Top-ranking Mechanical Engineering School
09/2012 – 01/2016 *Cluny, France*

- Industrial Engineering and Management, Operations Research, Production Management, Key Account Management, Strategic Management.

References available on request.