

Optimizing Patient Scheduling and Resource Allocation in a 3D Printing-Enabled Dental Prosthesis Supply Chain: A Mixed-Integer Linear Programming Approach

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ABSTRACT

Efficient scheduling and resource allocation in dental prosthesis supply chains are critical for improving patient outcomes and reducing turnaround times. Traditional workflows often suffer from delays due to fragmented routing, clinic bottlenecks, and limited visibility across production stages. To address these challenges, we develop a mixed-integer linear programming (MILP) model that jointly optimizes patient scheduling, routing decisions, and capacity constrained resource allocation in a digitally enabled, 3D printing-based prosthesis workflow. The model incorporates patient routing decisions (direct-to-lab vs. via-clinic), lab capacity constraints, material availability, and fixed delivery delays. The model minimizes lead time while enforcing fairness through worst-case constraints and deterministic delivery assumptions. Results from a baseline scenario involving 850 patients across a 45-day planning window show that the optimized system achieves balanced lab utilization, equitable lead time distribution, and full satisfaction of routing constraints. Comparative analysis highlights the significant advantage of direct-to-lab workflows over clinic-mediated routes. Scenario-based sensitivity analyses reveal the impact of routing strategies, inventory thresholds, and delivery penalties on system performance. The study demonstrates how simulation-informed optimization can guide strategic planning in healthcare logistics, offering a reproducible and adaptable framework for real-world deployment.

Keywords: *Dental supply chain, 3D printing, Additive manufacturing, Mixed-integer linear programming, Lead time optimization, Digital dentistry, Patient scheduling, Scenario-based analysis*

1. INTRODUCTION

The dental prosthesis supply chain is a complex network traditionally involving dentists, dental laboratories, distributors, and material suppliers in the production of items such as crowns, bridges, dentures, and orthodontic

appliances. In a conventional workflow, a dentist takes a physical impression of the patient's mouth and sends it to a dental laboratory.

There, the prosthesis is fabricated through labor intensive procedures – such as casting, molding, milling – typically taking several days or even weeks before the final product reaches the clinic. This conventional model involves numerous intermediaries and handoffs, leading to extended lead times. However, the landscape of dental manufacturing is undergoing a significant transformation due to the advent of digital dentistry and additive manufacturing (AM). Three dimensional (3D) printing – an AM technique – is driving a shift from traditional manual workflow to a streamlined digital process (Kamali *et al.*, 2022; Rezaie *et al.*, 2023). 3D printing plays an increasingly important role in dental prosthesis fabrication, enabling rapid, on-demand production of highly customized devices. It has been embraced across a wide range of dental applications, including crowns, bridges, dentures, implant surgical guides, orthodontic models, aligners, and maxillofacial prosthetics (Rezaie *et al.*, 2023). One of the primary advantages of 3D printing in this domain is its ability to produce patient-specific prostheses with high precision and minimal manual intervention. Unlike conventional methods that rely heavily on skilled technicians, 3D printing leverages computer-aided design and manufacturing (CAD/CAM) to build complex geometries layer by layer with minimal human labor (Kamali *et al.*, 2022; Rezaie *et al.*, 2023). This results in a significant reduction in both production and delivery time – one of the most compelling advantages for the dental supply chain.

Reducing lead time in dental prosthesis production is critically important for several reasons. First, shorter lead times directly enhance patient satisfaction and clinical outcomes. Patients benefit from faster delivery of crowns or dentures, experiencing less discomfort and inconvenience. Long waits with temporary prosthetics or missing teeth can negatively impact quality of life by affecting speech or eating, while rapid fulfillment improves overall treatment experience (Kamali *et al.*, 2022). Second, shorter lead times improve efficiency for dental clinics and laboratories. Dentists can complete treatments more quickly, manage appointments more effectively, and reduce case backlogs.

For laboratories, quick turnaround times serves as a competitive edge, attracting dentists who seek reliable and fast service. Third, from a supply chain perspective, reducing lead time typically aligns with lower inventory and holding costs. In a 3D printing-enabled, make-to-order system, laboratories can eliminate the need for stockpiling prefabricated parts and instead produce components on demand, enabling a shift towards just-in-time manufacturing (Kamali *et al.*, 2022; Musso *et al.*, 2022). This model better accommodates demand variability and customization needs, keeping lead times manageable (O’zceylan *et al.*, 2017; Sun *et al.*, 2020). Prior research on AM highlights that proximity to end users and on-demand production can reduce inventory buffers and significantly shorten delivery times (Arbaban and Wagner, 2020; Musso *et al.*, 2022). This agility is especially valuable in dental applications, where each prosthesis must be tailored to the patient – an area where traditional mass-production approaches fall short. Nonetheless, reducing lead times in a 3D printing enhanced dental supply chain presents unique challenges. The presence of 3D printers alone does not guarantee faster turnaround; the entire workflow must be optimized to capitalize on the speed advantages. One major constraint lies in the printing process itself: build times can be substantial depending on the prosthesis’ complexity, size, and resolution. For instance, creating a multi-unit prosthesis or a full arch denture may take several hours, followed by post-processing tasks like cleaning, curing, finishing – any of which can become bottlenecks if not properly scheduled (Rezaie *et al.*, 2023).

Printer capacity is another limiting factor. If a lab receives many orders but lacks sufficient machines or prioritization protocols, print jobs may queue, increasing delays. Additionally, logistics and coordination can erode the benefits of digital workflows, especially when printing is outsourced to a centralized facility. For example, a clinic may receive a printed crown within hours from a lab, but shipping time adds at least a day, offsetting the gain. Therefore, the physical configuration of the supply chain – whether printing is done in-house, regionally, or centrally – directly influences lead time. Quality control is another key consideration. Although 3D printing enables rapid production, ensuring each prosthesis meets clinical standards may require inspections and possible reprints, which further impact effective lead time. These factors illustrate that minimizing lead time in the dental 3D printing supply chain is a multifaceted optimization problem.

A review of current practices and literature reveals a significant gap in research focused on systematically optimizing lead time in dental 3D printing supply chain. Most studies in the dental domain have centered on technical feasibility and clinical outcomes – for instance, evaluating the fit or durability of 3D printed prostheses (Achillas *et al.*, 2015; Bae *et al.*, 2017; Chang *et al.*, 2015), or reviewing applications of dental 3D printing (Gardan, 2017). While these confirm that 3D printing can meet clinical needs, they do not address supply chain or operational performance.

Meanwhile, supply chain and operations research literature on additive manufacturing is growing but tends to focus on cost reduction, inventory implications, or conceptual frameworks, usually outside dental industry (de Brito *et al.*, 2020; Emelogu *et al.*, 2016, 2019; Strong *et al.*, 2019; Tang *et al.*, 2016). Although these works emphasize

general benefits such as shorter supply chains and reduced inventory (Musso *et al.*, 2022), few offer quantitative models with the explicit objective of minimizing lead time. In the dental context, peer-reviewed research applying rigorous operations research methods to optimize the order to delivery process remains limited. Some simulation-based studies – such as a discrete event simulation of a 3D printing-enabled dental clinic in Iran – have evaluated metrics like wait time, but did not formulate optimization models for lead time. This gap is what the present study seeks to address. To the best of our knowledge, no prior research has developed a mathematical optimization model tailored specifically to the dental prosthesis supply chain with the explicit goal of minimizing lead time. By focusing on this issue, our work bridges digital dentistry and operations research, providing insights that neither field alone has fully captured.

To address this challenge, we propose a mixed integer linear programming (MILP) model, complemented by an extensive sensitivity analysis. This approach not only ensures theoretical rigor but also enhances the model’s robustness to real-world variability, thereby offering actionable insights for decision-makers in the dental industry. The contributions of this study are both methodological and practical, advancing the fields of supply chain optimization, additive manufacturing, and dental prosthetics. The key contributions are as follows:

Novel MILP Model for Dental AM Supply Chain: We present a new mixed-integer linear programming formulation that captures the unique aspects of a 3D printing-enabled dental prosthesis supply chain. The model integrates key strategic and operational decisions – including production scheduling, facility location, and distribution – into a unified framework aimed at minimizing lead time from order placement to final delivery. Unlike previous studies that primarily focus on cost efficiency or isolated aspects of scheduling (Emelogu *et al.*, 2016; Wang *et al.*, 2019), this work is among the first to introduce a comprehensive mathematical models specifically designed for the dental 3D printing context.

- **Novel MILP Model for Dental AM Supply Chain:** We present a new mixed-integer linear programming formulation that captures the unique aspects of a 3D printing-enabled dental prosthesis supply chain. The model integrates key strategic and operational decisions – including production scheduling, facility location, and distribution – into a unified framework aimed at minimizing lead time from order placement to final delivery. Unlike previous studies that primarily focus on cost efficiency or isolated aspects of scheduling (Emelogu *et al.*, 2016; Wang *et al.*, 2019), this work is among the first to introduce a comprehensive mathematical models specifically designed for the dental 3D printing context.
- **Emphasis on Lead Time Minimization:** In contrast to most existing studies that emphasize cost reduction, our model prioritizes lead time as the primary performance objective. It explicitly incorporates various time components – such as printing, postprocessing, queuing, and transportation – providing a holistic view of delivery delays in personalized dental care. This approach addresses a critical yet underexplored area in the literature by focusing on time-based competition,

which is increasingly vital in the delivery of customized medical products. Our model provides a quantitative foundation for responsiveness in the dental supply chain, an aspect that has not been thoroughly investigated in prior research.

- Integrating Operations Research with Digital Dentistry: The study showcases the application of operations research methods within a cutting-edge healthcare manufacturing setting. By translating clinical and logistical requirements into a formal optimization model, we demonstrate how mathematical tools can support decision making in digital dentistry. For example, our model can guide whether a dental clinic should invest in in-house 3D printing capabilities or partner with a centralized lab under a hub-and-spoke configuration. This interdisciplinary nature of this work offers a framework that can be extended to other personalized medical device supply chains, thus bridging the gap between healthcare practice and analytical modeling.

2. LITERATURE REVIEW

2.1 3D Printing and the Dental Prosthesis Supply Chain

Digital Dentistry and Supply Chain Transformation: The incorporation of 3D printing into the dental prosthesis supply chain is part of a broader shift toward digital dentistry. This shift replaces many analog processes (physical impressions, manual wax-ups, casting) with digital techniques (intraoral scanning, CAD modeling, and CAM fabrication), fundamentally altering supply chain dynamics (Abduo *et al.*, 2014; Musso *et al.*, 2022). In a conventional dental supply chain, the steps from patient impression to final prosthesis involve multiple separate stages and actors, which inherently introduces lead time at each hand-off. For example, a traditional crown fabrication requires sending an impression to a lab, creating a stone model, designing and milling or casting the crown, and transporting it back to the clinic – each step adding delay. Additive manufacturing streamlines this by enabling a direct digital workflow: the dentist or lab can 3D print the crown or denture base directly from the digital scan, bypassing intermediate molds or models. Research has documented that 3D printing effectively reduces the supply chain to just a few key steps: digital design, printing, and fitting (Ben-Ner & Siemsen, 2017; Chen, 2017; Petrovic *et al.*, 2011; Weller *et al.*, 2015). As a result, many intermediary stages are eliminated. Attaran (2017) observes that AM technologies can convert traditional production systems into make-to-order systems, thereby eliminating the need for large inventories and reducing dependence on forecasts (Attaran *et al.*, 2017; Attaran, 2017). In the context of dental prosthetics, this means devices are produced only when a patient needs them, and ideally as soon as the digital design is ready, which is a clear departure from the traditional batch production in dental labs. The simplification of the supply chain with 3D printing has been noted in several studies. Borthakur, 2025 highlight that the diffusion of additive manufacturing tends to streamline manufacturing processes and supply chains, fostering innovation and efficiency by removing unnecessary steps (Al-Masa’fah *et al.*, 2024; Borthakur, 2025). An important

example of such simplification is the reduction of assembly and component sourcing. In conventional manufacturing, a complex dental prosthesis (like a removable partial denture with a metal framework, acrylic base, and teeth) might be made from multiple components that need to be separately manufactured or procured and then assembled by a technician. With advanced 3D printing, it is increasingly possible to print an assembly as a single piece or as a few large integrated pieces. As Musso *et al.*, 2022 explain, additive manufacturing allows certain products to be made in one piece, thereby requiring less assembly, less supplier coordination, and ultimately lower costs and shorter production time. In dentistry, this is exemplified by monolithic 3D-printed dentures or hybrid dentures where the base and teeth are printed in one build, or by printing metal substructures in one go instead of soldering multiple parts. By cutting down on assembly, 3D printing reduces the number of suppliers or sub-contracted steps involved (for instance, outsourcing metal framework casting is no longer necessary if one can print the framework inhouse). Fewer external dependencies mean fewer delays and a “tighter,” more integrated supply chain. Another transformative aspect introduced by 3D printing is the geographical decoupling of design and production. In a traditional model, production typically happens at a specific lab location and products must be transported to the point of care. With 3D printing, digital designs (CAD files) can be transmitted electronically to any location equipped with a printer, enabling a form of distributed manufacturing. Thomas *et al.*, 2016 and others note that once a 3D design is finalized, it can be sent via the internet and reproduced anywhere, drastically reducing the need for physical shipping of intermediate products.

In practical terms, a dental file can be emailed or uploaded to a cloud platform and printed in a lab across town or on another continent with equal ease. This “digital transport” is almost instantaneous compared to shipping physical items thus, reducing the time to market and delivery times (Musso *et al.*, 2022). In dentistry, while time pressures are typically less acute than emergency medical equipment, the principle holds: a library of digital prosthesis designs can be centrally maintained and printed on demand at the location closest to the patient, reducing logistical lead times.

3D printing is rapidly reshaping the global dental prosthetics supply chain, with adoption levels varying by region. The dental 3D printing market—including hardware, materials, and services—has shown robust growth, driven by the advantages of mass customization and responsiveness, especially for patient-specific prostheses. In 2018, healthcare applications of 3D printing reached nearly \$1 billion globally, with projections exceeding 20% compound annual growth through 2026 (Analyst, 2025). The United States represents a key market, characterized by a high density of dental laboratories and significant investment in digital technologies. Over the past decade, many U.S. labs have transitioned to digital workflows, incorporating CAD/CAM systems and 3D printing to fabricate models, guides, and prosthetic devices. This high adoption rate provides an opportunity to optimize existing systems to reduce lead times across a network of clinics and laboratories. While traditional U.S. workflows often tolerated 1–2 week turnaround times, patient expectations and competitive

pressures have driven a shift toward rapid service. Large manufacturers like Align Technology now deliver custom devices nationwide within days using centralized, high-throughput 3D printing facilities. Simultaneously, smaller labs and clinics equipped with desktop 3D printers offer same or next-day prosthetics locally (Salmi & Peron, 2023). This dual trend—centralization for economies of scale and decentralization for speed—presents new operational challenges. Emelogu *et al.* (Emelogu *et al.*, 2019) used a continuous approximation model to analyze similar tradeoffs in biomedical implant manufacturing, showing that distributed 3D printing could enhance responsiveness at marginal cost increases. Analogous strategies may apply to dental prostheses, but the literature remains inconclusive on the optimal configuration. This reinforces the need for rigorous mathematical optimization to evaluate whether centralized or distributed models minimize lead time most effectively in the U.S. dental supply chain (Musso *et al.*, 2022; Strong *et al.*, 2019).

2.2 Lead Time Reduction through Additive Manufacturing

One of the widely recognized advantages of additive manufacturing in supply chains is the potential to drastically reduce lead times for delivering products to end-users. This advantage is frequently cited in both conceptual analyses and empirical studies of 3D printing in various industries (Al-Masa'fah *et al.*, 2024). In the context of supply chain management, “lead time” can encompass several components – order processing time, production time, waiting/queue time, and distribution time. Additive manufacturing impacts many of these components. By its nature, AM allows products to be manufactured on demand rather than in large batches, which can eliminate the queuing delays associated with batch scheduling and inventory backlog. A traditional production line might accumulate orders until a batch is processed (leading to longer cycle times for any given order), whereas a 3D printer can often begin producing the next part immediately after finishing the previous one, aligning with a make-to-order paradigm (Arabisan & Wagner, 2020; O'zceylan *et al.*, 2017). Multiple studies have quantified or exemplified lead time reductions achieved via 3D printing. Attaran *et al.* (2017) provides a broad overview, noting that additive manufacturing simplifies supply chains and can lead to faster on-demand delivery of products by cutting out steps and intermediaries (Ben-Ner and Siemsen, 2017; Chen, 2017; Petrovic *et al.*, 2011; Weller *et al.*, 2015). In an investigation of spare parts supply chains, Khajavi *et al.* (2014) showed that using 3D printing for spare components could reduce lead times from several weeks (when waiting for parts from a centralized warehouse) to just days, since parts could be printed at a regional depot or on-site as needed. This is highly relevant to dentistry, where each clinic could be viewed analogously to a “depot” that might one day produce many of its own needed parts. Similarly, Chaudhuri *et al.* (2019) found that in aerospace maintenance, on-site 3D printing of spare parts significantly cut down the aircraft downtime compared to ordering parts from suppliers – downtime being a proxy for lead time in that setting. These studies collectively reinforce the idea that placing production closer to the point of use leads to shorter lead times, which is one of the central

premises we examine in the dental supply chain. Indeed, Corsini *et al.* (2022) underscore that moving 3D printers downstream (closer to end-users) supports a user-focused supply chain with reduced lead times and transportation costs. Their work, which looked at distributed manufacturing networks, lends support to the strategy of decentralization for time-sensitive production.

In healthcare and prosthetics, lead time can directly affect patient outcomes, which adds impetus to its reduction. For personalized medical devices like prosthetics, a shorter lead time means a patient can be rehabilitated or restored to normal life faster. Al-Masa'fah *et al.* (2024) qualitatively found that responsiveness – the ability to react quickly to patient needs – was greatly enhanced by implementing AM in prosthetic supply chains, as reported by interviewees in the Jordanian prosthetics industry. They identified lead time reduction as one of the key improvements alongside customization and cost when 3D printing was adopted. In dentistry, this translates to quicker chairside solutions and the possibility of addressing adjustments or remakes promptly without the patient having to wait for external lab work.

However, it is important to recognize and manage the factors that can limit lead time gains from AM. One such factor is the printing time itself for each unit. Additive processes can sometimes be slower for a single part than a highly optimized mass production process. For example, printing a metal crown via selective laser melting might take a couple of hours, whereas casting the same crown in a traditional lab might take a similar time but can be done in batches. If only one crown is needed, AM has an edge by not needing mold preparation; but if many crowns are needed and a casting machine can do them simultaneously, AM's advantage diminishes unless multiple printers are used. Researchers like Ruffo and Hague (2007) and later, Baumers *et al.* (2016), have analyzed build time and throughput in additive manufacturing, introducing the concept of machine utilization and batching in 3D printing. They point out that while a single 3D printer building one part at a time might be slow, strategies like nesting (producing multiple parts in one build volume) can improve throughput. In the dental field, printers often can print multiple items (e.g., 20 crowns, or 6 dentures) in one batch, which means the effective lead time per part depends on how scheduling is handled. Chergui *et al.* (2018) addressed this in their study on production scheduling for 3D printing: they developed algorithms for optimal packing (nesting) of parts in the printer's build volume and scheduling jobs to minimize the waiting time for orders. They found that intelligent scheduling can both maximize machine utilization and minimize order delivery delays, indicating that the raw speed of 3D printing hardware is only one piece of the puzzle; the other is how you plan the sequence of print jobs to meet deadlines (Chergui *et al.*, 2018).

Another factor is post-processing time. Many dental 3D printing applications require significant post-processing, such as washing and curing resin prints, or furnace sintering and polishing for metal prints. These steps can introduce fixed-time requirements that do not shrink just because the initial printing was fast. If not planned in parallel, they add to lead time. Some studies (e.g., by Mani *et al.*, 1999 and Kulkarni and Dutta, 1999) have suggested redesigning

processes or using parallelization – for instance, starting post processing of the first batch of parts while the next batch is printing – to reduce the impact on overall turnaround. In practice, dental labs using 3D printing often employ multiple curing units or have technicians finish parts in overlapping shifts to avoid idle gaps. In Yilmaz’s model, the first stage schedules production on parallel 3D printers and the second stage schedules deliveries to customers, with the objective of minimizing the makespan (ie, the total completion time for all orders) (Yilmaz, 2020). This kind of integrated view is essential because a gain in production speed is moot if the distribution is slow and vice versa. Yilmaz’s results demonstrated that coordinating production and distribution can substantially reduce the time orders spend in the system compared to handling these decisions separately.

In summary, the literature across domains consistently shows that additive manufacturing can reduce lead times by simplifying supply chains, enabling localized production on demand, and removing intermediary stages (Musso *et al.*, 2022). The magnitude of reduced lead time in dental prosthetics reported anecdotally ranges from approximately 30 to 70% compared to traditional methods (for example, reducing a 2-week process to 2-5 days, or a one-day lab process to an hour in the office). Achieving these reductions in practice requires careful attention to process optimization – including batching, scheduling, and parallel processing – to ensure that the 3D printing workflow is fully leveraged. The literature also hints at the need for decision-support tools (like optimization models) to make these complex scheduling and location decisions, especially when scaling up 3D printing to handle many orders. Although qualitatively the benefits are clear, quantitatively determining the best way to configure and run a 3D printing-based supply chain for minimal lead time is an open problem that our work will address. We take inspiration from the above studies in formulating lead time as an explicit performance metric and in recognizing which constraints (machine capacity, parallel operations, distribution) must be included to make the model realistic.

2.3 Supply Chain Optimization for Additive Manufacturing: Prior Work

As additive manufacturing has gained traction in industry, researchers have increasingly turned to supply chain optimization models to understand and improve the integration of AM into production networks. The literature includes a mix of conceptual studies, qualitative analyses, and quantitative models that together form the foundation for our investigation in the dental prosthetics domain. We review this literature to identify approaches and findings relevant to optimizing supply chains with 3D printing, with an emphasis on areas such as network design, inventory strategy, and production planning. Notably, much of the existing work has focused on cost and feasibility, whereas relatively few studies center on lead time minimization; nonetheless, their methods and results are informative for our purposes.

2.3.1. Conceptual and Qualitative Research

Early explorations into 3D printing and supply chains often took the form of scenario analyses or frameworks. Achilles *et al.* (2015) provided a methodological framework for evaluating whether to adopt additive manufacturing in a production portfolio, considering multiple criteria like cost,

quality, and flexibility. Using a combination of multi-criteria decision analysis (MCDA) and data envelopment analysis (DEA), they helped outline conditions under which AM is beneficial in a “focused factory” environment. While their work was not specific to lead time, they included efficiency as a criterion, implicitly recognizing faster turnaround as one potential advantage. Sun and Zhao (2017) examined the evolution of the fashion industry with 3D printing and developed a conceptual model for integrating AM into supply chain stages from design to retail. They identified challenges in each area (design, manufacturing, distribution, consumer interface, sustainability) when 3D printing is introduced. Although fashion and dentistry are very different, one parallel is the emphasis on customization and responsiveness – in fashion, it’s mass customization of apparel; in dentistry, it’s patient-specific devices. Their conceptual findings underline that incorporating 3D printing often requires rethinking supply chain processes (e.g., moving from pushing inventory to pulling on demand), which is directly related to how lead times are managed. Delic and Evers (2020) took a more empirical route by surveying 124 manufacturing firms (mostly in automotive) about AM’s impact on supply chain flexibility and performance. They quantitatively showed a positive correlation between the use of AM and improved supply chain agility and performance. Flexibility – the ability to adapt quickly to changes – is closely linked to maintaining short lead times even under variability. Their findings support the idea that AM can be a driver for more responsive supply chains. However, they also note that simply acquiring 3D printers does not automatically yield benefits; firms need to adjust their supply chain practices to see performance improvements. This insight echoes in the dental field: a clinic might buy a 3D printer, but without proper scheduling or workflow integration, the lead time for a crown might not improve much over using an external lab. Thus, the literature suggests that managerial and organizational changes must accompany the technical adoption of AM.

2.3.2. Quantitative Optimization Models

More directly relevant to our study are the optimization models that have been formulated to analyze supply chain decisions in the presence of additive manufacturing. One stream of research looks at economic feasibility and cost optimization. Emelogu *et al.* (2016) proposed a two-stage stochastic programming model to assess the viability of deploying 3D printers for making biomedical implants, focusing on supply chain costs. They incorporated uncertainties in demand and compared scenarios with and without AM. The objective was cost minimization, including production, inventory, and transportation costs. Their results indicated that for certain implants and demand levels, a supply chain using AM could be cost-effective, and while lead time was not the primary metric, they observed ancillary benefits like reduced inventory holding due to on-demand production. Similarly, Li *et al.* (2017) and Tang *et al.* (2016) used simulation (system dynamics) to compare spare parts supply chain scenarios. Li *et al.* (2017) quantified the positive effects of 3D printing on supply chain performance in terms of both cost and speed, noting that with AM, the supply chain can respond faster to part requests, thereby reducing downtime and improving service levels.

Tang *et al.* (2016) approached from an environmental perspective, formulating an optimization problem that

included an objective for minimizing environmental impact by leveraging AM's ability to produce lighter, optimized designs. While their focus was sustainability, they pointed out that traditional life-cycle assessment tools had to be modified for AM, implicitly acknowledging that the process differences (like potentially shorter supply chains) also influence time and resource use (Li *et al.*, 2017; Tang *et al.*, 2016).

A particularly active area of optimization research is network design and facility location with AM. The question "distributed or centralized production?" arises frequently. Emelogu *et al.* (2019) tackled this in the biomedical implant context by developing a continuous approximation (CA) model to locate 3D printers and establish inventory policies in a regional supply chain. Their study, which we touched on earlier, weighed the logistics costs against responsiveness for Southeastern U.S. states. The CA approach provided analytical information on the optimal spacing of production facilities. Strong *et al.* (2019) presented a two-stage p-median location model for a hybrid manufacturing system, where a certain number of AM hubs were to be added to an existing network of traditional factories. Their MILP-based model aimed to minimize total cost, but with constraints on meeting demand within certain service time windows. They demonstrated how to determine the locations of AM machines such that a significant portion of demand could be served faster (in their case, within an "acceptable" delivery time) while balancing the cost of additional facilities. One of their notable findings was that adding even a small number of well-placed 3D printing hubs can substantially improve the service coverage (i.e., percentage of customers within a short delivery time). This directly implies lead time improvements for those customers. In another study, de Brito *et al.* (2020) combined a p-median approach with a detailed MILP model for production and inventory to design a spare parts supply chain using 3D printing. They applied it to an elevator maintenance case in Brazil, where parts could be either produced conventionally or via 3D printing. Their model decided on facility locations, technology allocation (traditional vs. AM machines), and inventory levels, aiming to minimize costs and subject to meeting service time requirements. de Brito *et al.* (2020) concluded that a hybrid network, using both AM and traditional production, was optimal: 3D printers should be located in strategic locations to handle urgent, low-volume parts (ensuring quick supply), while conventional manufacturing handled high-volume parts centrally. This resonates with how one might imagine the dental industry evolving: urgent or specialized prostheses made locally with 3D printing, while perhaps some standard items or materials are produced in bulk elsewhere.

2.3.3. Production Planning and Scheduling

Another cluster of relevant literature deals with the operational level – how to plan production on 3D printers day-to-day. We have already mentioned Chergui *et al.* (2018) on scheduling for parallel 3D printers. They formulated the scheduling problem as two sub-problems: assigning jobs to machines, and sequencing those jobs, with the objectives of maximizing printer utilization and minimizing delivery delays. This essentially is a shop floor scheduling optimization, typically solved with heuristics or integer programming for small instances. Their work is significant because it acknowledges that, unlike traditional CNC

machining, 3D printers can often produce multiple different products in one batch, adding complexity to scheduling (the nesting problem). In their case, a genetic algorithm approach provided good solutions, and it was shown that optimized scheduling could reduce average order lead time by ensuring high utilization without letting some jobs wait too long. Yilmaz (2020) extended such considerations by linking production scheduling with vehicle routing for distribution as a single optimization model (solved via MILP). By examining additive manufacturing in a supply chain context, Yilmaz effectively treated the combination of printing and delivery as a flow shop problem and minimized the makespan (which, for a given set of orders, equates to minimizing how long the last order takes – a surrogate for overall responsiveness). The inclusion of distribution in the model is particularly relevant to our study, since dental prostheses often need to be transported from lab to clinic; optimizing one without the other could lead to suboptimal solutions.

Chung *et al.* (2018) introduced the notion of a smart supply chain with AM, considering cloud-connected factories and dynamic supply chain reconfiguration. They formulated two optimization models: one for supply chain design (deciding which factories should produce which products for which markets) and one for operational planning (scheduling production to meet unique customer demands). Their scenario was essentially an Industry 4.0 setting with IoT and cloud manufacturing. The outcome showed that such a system can flexibly route orders to whichever facility can print the fastest and deliver on time, thus minimizing delays. Although their work was generic, one could see its application in a network of dental laboratories where an incoming case could be routed to the laboratory that promises the quickest turnaround (depending on current load and distance). In a sense, their model is akin to load balancing across multiple 3D printing sites to optimize lead time and cost, a concept that could be borrowed for interlab coordination in dentistry.

Overall, prior work lays a foundation but also makes it evident that the specific case of dental prosthetics has not been deeply explored with quantitative models. Dental supply chains have unique features: every product is custom, demand is patient-driven and generally inelastic (people eventually need their crowns or dentures, though they can sometimes wait), and there's a strong service component (prostheses must meet medical quality standards). Most of the referenced optimization studies dealt with either generic spare parts or industrial components, where the value of time might be measured in equipment downtime costs or service level agreements. In dentistry, the "value" of time is seen in patient satisfaction and clinic efficiency, which are harder to quantify in dollars but are nonetheless crucial. This literature review underscores that our work is timely in that it extends principles and methods from earlier research into a new domain, addressing a gap in both the operations research literature and the dental industry's knowledge. By synthesizing these insights, we ensure our model and analysis build on proven techniques (such as MILP for location and scheduling) and focus on the right trade-offs (centralization vs decentralization, machine utilization vs customer waiting time, etc.) identified by past studies. In doing so, our research will fill the gap by providing a

detailed, time-focused optimization study specifically for the dental prosthesis supply chain, an area previously lacking such quantitative treatment.

2.3.4. Application to Dental Supply Chain and Identified Gaps

Given the above state-of-the-art, it is clear that certain aspects of additive manufacturing in supply chains are well-studied (like cost-benefit analysis, location strategy, and general impact on supply chain structure) while others, especially in the dental context, remain under-examined. To position the current research, we identify what has been done specifically in dental supply chains and what gaps our study will fill:

Existing Research in Dental Supply Chains:

The literature directly addressing dental supply chain optimization is sparse. Most dental-focused research deals with clinical efficacy or the technical performance of 3D printed prostheses, rather than supply chain performance. An exception on the operations side is the work by Kamali *et al.* (2022), who modeled a 3D printing-based dental clinic using discrete-event simulation. In their study, they simulated patient flow and production processes (implants, orthodontics, restorations, dentures) in a clinic that had integrated 3D printing. They evaluated performance measures including waiting time and system throughput and even experimented with changes like adding an inventory control policy for materials and adjusting staffing (e.g., introducing rest periods for technicians). Notably, Kamali *et al.*, 2022 performed a sensitivity analysis on their simulation, examining how changes in system parameters affected outcomes, and proposed some scenario-based improvements (such as reallocating resources) to enhance clinic performance. Their findings showed, for instance, that reducing certain bottleneck resources or slightly increasing work shifts could significantly improve patient throughput. The relevance of this study to our work lies in (a) demonstrating the value of simulation/analysis in a dental 3DP context, and (b) highlighting that even within a single clinic, operational decisions impact waiting times (a proxy for lead time from the patient's perspective). However, their simulation did not explicitly optimize or provide prescriptive decisions – it evaluated scenarios. Furthermore, it was limited to one clinic setting and did not consider the broader supply chain (e.g., interactions between multiple clinics and labs). Our work will take a complementary but more optimization-driven approach, considering multiple facilities and using MILP to find best-case configurations.

Another piece of relevant research is by Loges and Tiberius (2022), who conducted a Delphi study to identify implementation challenges of 3D printing in prosthodontics (prosthodontics being the dental specialty that deals with prostheses). While not an optimization or supply chain study per se, the Delphi panel (experts in dentistry) highlighted practical issues that could indirectly affect supply chain efficiency: high initial costs of 3D printers, lack of training, material limitations, regulatory hurdles, and required workflow changes. These challenges explain why not all dental labs or clinics have fully adopted 3D printing, and in supply chain terms, they manifest as heterogeneity in the system – some labs are digital, others are not. From a supply chain optimization standpoint, this means that any model should consider scenarios where only a subset of potential

facilities have 3D printing capability (reflecting current reality). It also means that cost cannot be completely ignored; for example, a clinic might minimize lead time by getting a printer, but if the cost is prohibitive, that solution is not realistic. Our study acknowledges these practical constraints by incorporating them into sensitivity analysis rather than as primary objectives. By doing so, we can discuss solutions that are not only time-efficient but also cognizant of cost and implementation barriers.

Gap Analysis:

The clearest gap is the lack of a mathematical optimization model that focuses on lead time in the dental supply chain. None of the studies we reviewed formulated an MILP or similar model specifically for the production and delivery of dental prostheses. Moreover, among the broader AM supply chain models, none took lead time as the sole or primary objective; most used cost minimization, sometimes with time as a constraint or secondary factor (Attaran, 2017; Emelogu *et al.*, 2019). This leaves open the question of how to formally minimize lead time and what the trade-offs are (since minimizing time might require additional resources or cost). Our research directly addresses this by building an optimization model around lead time minimization and then examining the cost or resource implications in the sensitivity analysis. In doing so, we respond to calls in literature for more research on service-oriented metrics in additive manufacturing supply chains (e.g., Liu *et al.* (2021), pointed out that beyond cost, metrics like responsiveness and customer satisfaction need attention in AM-enabled networks). Another gap is the specific context of dental prosthetics in the USA. The supply chain structure – with thousands of independent dental offices and labs – is different from, say, an automotive supply chain with a few large assembly plants and suppliers. Distributed decision making (each dentist deciding whether to invest in a printer or which lab to use) and service considerations dominate the dental context. None of the optimization studies so far capture that decentralization of decision power. While our MILP will be formulated from a central planner perspective (for modeling convenience), we intend to use it to simulate various scenarios that reflect individual stakeholder decisions (e.g., what if only labs have printers vs. what if clinics also have printers). This approach will illustrate the system-wide outcome of many local decisions. The literature has not yet provided such analysis; our work is novel in examining, for example, how many clinics adopting chairside printing would significantly reduce overall lead time in the region, or how a large hub facility compares to several smaller lab-based printers in delivering speed.

Finally, our review of the literature found that sensitivity and scenario analyze are often used (e.g., Kamali's simulation sensitivity, Emelogu's stochastic model, etc.), but not always in an integrated way with optimization for dental supply chains. We see an opportunity to contribute methodologically by tightly integrating an optimization model with sensitivity analysis specific to the dental case. This means that after finding optimal or near-optimal solutions, we stress-test them against variations such "as "what if the print speed improves by 50% in the future?" or "what if transport slows due to regulations on medical device shipping?" and so on. By doing this, our study will fill a practical gap – providing guidance under uncertainty –

which is something practitioners value highly. It's not enough to know the best configuration for today; stakeholders want to ensure their system will still perform well if conditions change (e.g., if suddenly every dentist in a city adopts 3D printing, labs might lose volume – how does that affect overall efficiency? Our model can explore that). In conclusion, this literature review establishes that while the benefits of 3D printing for supply chain efficiency (including lead time reduction) are well recognized (Al-Masa'fah *et al.*, 2024), and various optimization approaches have been applied to additive manufacturing in general, there is a clear research gap in applying these tools to the dental prosthesis supply chain with a focus on lead time. Building on previous findings and addressing these gaps, the current article aims to advance both the theory of supply chain optimization in additive manufacturing and the practice of managing the production of dental prosthetics. In the subsequent sections, we will detail our MILP model formulation and demonstrate how it contributes to filling the identified gaps, followed by a discussion of results, including sensitivity analyses that provide nuanced insights for the dental industry, particularly in the U.S. context where this transformation is rapidly unfolding.

3. METHODOLOGY

3.1 Model Overview and Assumptions

This study presents a deterministic mixed-integer linear programming (MILP) model designed for a 3D printing-enabled dental prosthesis supply chain. The model integrates appointment scheduling, production planning, and distribution with the objective of minimizing the total lead time from the patient's appointment to final prosthesis delivery. The supply chain is modeled as a multi-echelon network comprising dental clinics (responsible for intraoral scanning), dental laboratories (handling CAD design, 3D printing, and post-processing), raw material suppliers, and patients as end-customers. All demand levels, processing durations, and transit times are assumed to be known and constant an assumption reasonable for short-term planning scenarios (Wang *et al.*, 2019). Minimizing lead time is critical in healthcare settings due to the demand for timely access (Almomani and AlSarheed, 2016) and the typically lengthy turnaround of conventional denture fabrication, which can take 2–3 weeks (Akraa *et al.*, 2018). With the advancement of digital dentistry, workflows have become significantly more streamlined (Yuzbasioglu *et al.*, 2014). We assume widespread adoption of intraoral scanners and CAD/CAM systems, allowing digital impressions to be transmitted instantly to dental labs, thus eliminating traditional shipping delays. This enables planning on a daily basis within a 7–14 day time horizon, aligning with industry expectations to deliver prostheses within approximately two weeks (Wang *et al.*, 2019). Each dental prosthesis order is uniquely customized and must progress through sequential stages scanning, CAD design, 3D printing, and post-processing either initiated at a clinic or directly at a lab. The sections that follow detail the model's components, including sets, parameters, decision variables, and constraints, followed by the objective function and a discussion of potential model extensions.

3.2 Sets, Indices, and Parameters

The notation used throughout this paper is stated below:

3.2.1. Set and Indices

- I – Set of patients, indexed by $i = 1, \dots, 850$
- C – Set of clinics, indexed by $j \in \{DC1, DC2, DC3, DC4, DC5\}$
- L – Set of dental labs, indexed by $k \in \{DL01, DL02\}$
- T – Set of days in the planning horizon, indexed by $t = 1, \dots, 45$
- S – Set of suppliers, indexed by $s = 1, \dots, 5$
- D – Set of dental prosthesis case types (demand categories), indexed by $d \in \{\text{crowns, bridges, dentures, nightguardm partials, temporaries}\}$

3.2.2. Known Parameters:

- a_i – Arrival day of patient i (e.g., July 1 = Day 1)
- d_i – Case type (demand category) assigned to patient i
- T_{ik}^{lab} – Travel time (in minutes) from patient i to lab k
- T_{jk}^{clinic} – Travel time (in minutes) from patient i to lab j
- T_{jk} – Transit time (in minutes) from patient j to lab k (symmetric for lab-to-clinic delivery)
- p_i^{lab} – Lab processing time for patient i (includes scanning, CAD, printing, post-processing; total 1 day)
- p_i^{clinic} – Impression time at clinic for patient i (approx. 10–15 minutes)
- Cap_j^{clinic} – Daily capacity of clinic j (patients/day), assumed to be 20
- Inv_k^{lab} – Initial inventory level at lab k n Day 0 (units), set to 100
- u_d – Units of inventory consumed for case type d
- u_{di} – Inventory consumed for patient i 's case type ($u_i = u_{di}$)
- L_s – Lead time (in days) for supplier s to deliver inventory (2–7 days)
- α – Minimum proportion of patients required to be routed via clinics (e.g., $\alpha = 0.5$ implies at least 425 patients)
- D_{direct} – Final delivery delay for direct-route patients (e.g., 14 days)
- D_{clinic} – Final delivery delay for clinic-route patients (e.g., 21 days)

A key assumption is the availability of sufficient CAD design capacity at dental labs, allowing CAD tasks to be completed on the same day as either intraoral scanning or 3D printing preparation. This is reasonable simplification given the efficiency of modern digital workflows. Additionally, the model does not account for uncertainty in demand or processing times; all values are treated as deterministic. This approach aligns with prior optimization studies that begin with a deterministic formulation before addressing uncertainty. We revisit this limitation in the discussion of model extensions.

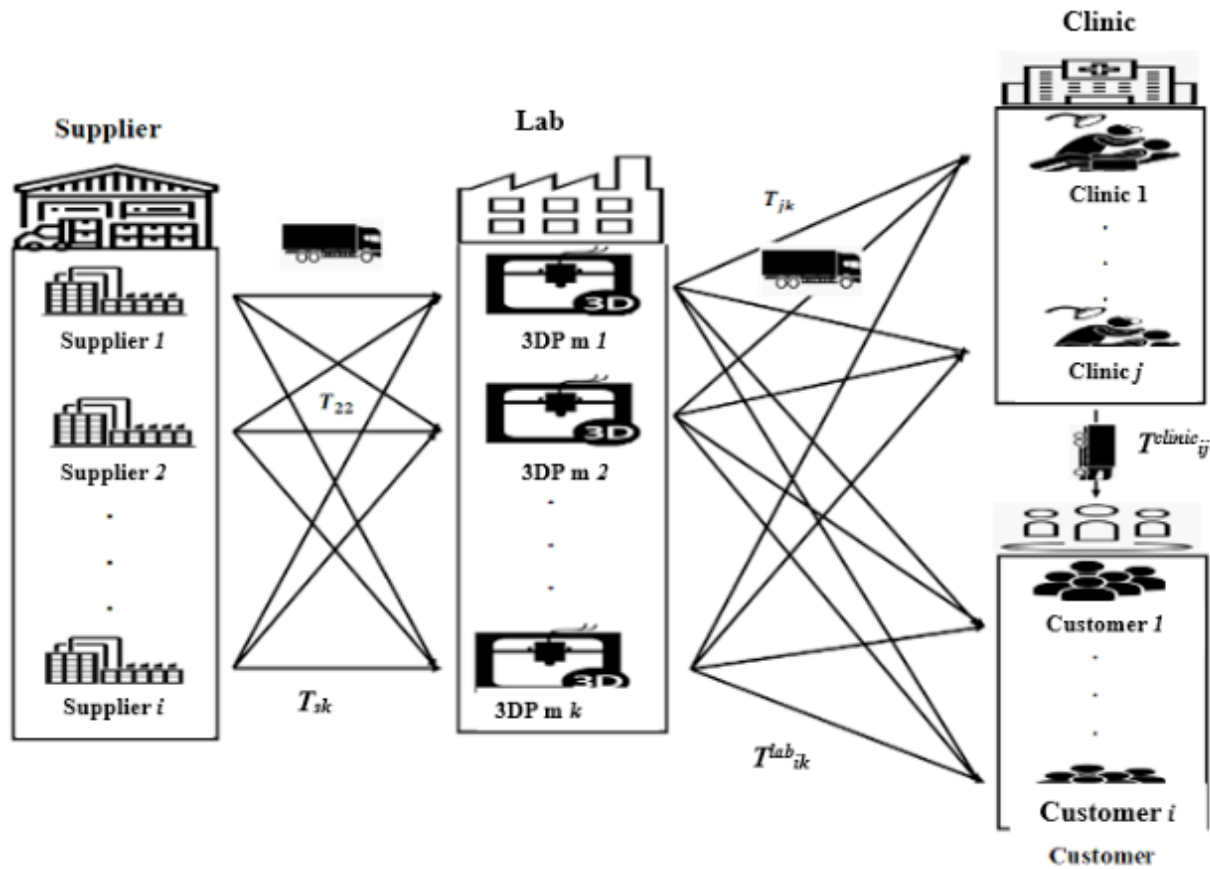


Figure 1 Illustration of a 3D Supply chain for dental laboratory

3.3 Decision Variables

The decision variables in the presented MILP model capture patient-specific routing and the scheduling of each production stage. The formulation includes key binary and continuous variables:

3.3.1 Routing and Assignment Variables:

These binary variables determine each patient’s route, either directly to a lab or via a clinic, and specify the assigned facilities.

- $x_{i,k}^{direct} \in \{0,1\}$: Equals 1 if patient i is routed directly to lab $k \in \{DL01, DL02\}$, bypassing clinics and proceeding straight to the lab k for processing
- $x_{i,j,k}^{clinic} \in \{0,1\}$: Equals 1 if patient i is routed through clinic j (where $j \in \{DC1, \dots, DC5\}$) and then to lab k . This means that patient i first visits clinic j for an intraoral scan, which is then transmitted to lab k for prosthesis manufacturing. We allow j and k to vary, allowing the optimizer to choose the lab based on travel time T_{jk} and workload balancing.

These variables make sure that each patient follows exactly one routing path, either directly to a lab or through a clinic and then to a lab. This model enforces this exclusivity by requiring that exactly one of the routing variables (x or y) is set to 1 for each patient.

3.3.2 Scheduling Variables:

These binary, time-indexed variables determine the specific day a patient is served at a clinic and/or lab within a planning horizon of T days:

- $z_{i,j,d}^{clinic} \in \{0,1\}$: Equals 1 if patient i visits clinic j on day d
- $z_{i,k,d}^{lab} \in \{0,1\}$: Equals 1 if patient i is processed at lab k on day d

Patients routed through a clinic will be assigned both z^{clinic} and z^{lab} , while patients routed directly will only have z^{lab} variable.

3.3.3 Inventory and Order Variables:

These continuous variables track material inventory and ordering decisions each lab:

- $Inv_{k,d} \geq 9$: Inventory level (in material units) at lab k initial inventory is set to $Inv_{k,0} = 100$.
- $order_{k,s,d} \geq 0$: Quantity of material ordered by lab k from supplier s on day d . Deliveries occur after the supplier’s lead time.
- $L_i \geq 0$: Total lead time (in days) for patient i , calculated based on their routing and service schedule.

For simplicity, the model currently assumes at most one delivery per lab within the planning horizon. This can be extended to accommodate fixed delivery schedules (e.g. deliveries only on specific weekdays), in which case $order_{i,t}$ can only be 1 on allowed $delivery_{days}$. The binary variables govern logical decisions such as routing and scheduling, while continuous variables manage resource levels and timing. These variables collectively form the basis for the model’s objective function and constraints, which are presented in the following section.

3.4 Constraints

We now define the key constraints of the optimization model. These constraints ensure the solution is feasible and

practically implementable by enforcing capacity limits, satisfying patient demand, and accurately modeling inventory dynamics and lead times:

Routing Constraints

Each patient must be assigned exactly one valid routing option, either directly to a lab or through a clinic and then to a lab:

- Exclusive assignment constraints:
 To make sure each patient is assigned a unique routing path:

$$\sum_{k \in L} x_{i,k}^{direct} + \sum_{j \in L} \sum_{k \in L} y_{i,j,k}^{clinic} = 1, \forall i \in I \quad (1)$$

This constraint guarantees every patient i is routed either directly to a specific lab or through one clinic-lab combination.

- Clinic routing proportion constraint:
 To model policy or operational preferences, we enforce that a fixed fraction denoted by α of all patients must be routed through clinics:

$$\sum_{i \in I} \sum_{j \in C} \sum_{k \in L} y_{i,j,k}^{clinic} = \alpha \cdot |I| \quad (2)$$

Depending on the application, this can be an equality or inequality constraint; an equality constraint (e.g., exactly 60% of patients must use clinics); an inequality (e.g., at least 60% go through clinics), or a soft constraint with penalties for deviation from a target ratio. For instance, if $\alpha = 0.60$ and there are 850 patients in total, this constraint enforces that exactly 510 patients are routed through clinics. Coupled with the exclusive assignment constraint, this automatically determines that the remaining 340 patients are routes directly to labs.

Temporal and Scheduling Constraints

- Patient Scheduling Constraints:
 Each patient may be scheduled to a clinic and a lab at most once each within the planning horizon:

$$\sum_{d \in T} \sum_{j \in C} z_{i,j,d}^{clinic} \leq 1, \quad \forall i \quad (3)$$

$$\sum_{d \in T} \sum_{k \in L} z_{i,k,d}^{lab} \leq 1, \quad \forall i \quad (4)$$

Every patient must receive lab service once. HaveIf routed through a clinic, they will also have one clinic visit; otherwise, no clinic visit is scheduled.

Linking Routing and Scheduling Decisions

Routing decisions must be consistent with schedule:

- If $x_{i,k}^{direct} = 1$, the patient i should be scheduled at lab k and not at any clinic day.
- If $y_{i,j,k}^{clinic} = 1$, the patient i must be scheduled at clinic j at lab k

This is forced using:

$$\sum_{d \in T} z_{i,j,d}^{clinic} = \sum_{k \in L} y_{i,j,k}^{clinic} \quad \forall i, j \quad (5)$$

$$\sum_{d \in T} z_{i,k,d}^{lab} = x_{i,k}^{direct} \sum_{j \in C} y_{i,j,k}^{clinic} \quad \forall i, k \quad (6)$$

These ensure scheduled appointments align with the selected route.

Arrival Time Restrictions

Patients cannot be scheduled before their arrival day a_i :

$$z_{i,j,d}^{clinic} = 0, \quad \forall i, j, \forall d < a_i \quad (7)$$

$$z_{i,k,d}^{lab} = 0, \quad \forall i, k, \forall d < a_i \quad (8)$$

We assume same-day service is allowed if capacity is available, as the model operates on daily time units.

Clinic-to-Lab Precedence

For patients routed through a clinic, the lab visit must not occur before the clinic visit: If $z_{i,j,d}^{clinic} = 1$ and $z_{i,k,d}^{lab} = 1$ then $d_i \geq d_c$. Optionally, a tighter constraint such as $d_i \in [d_c, d_c + 1]$ can be enforced to reflect rapid turnaround due to fast impression transfer.

Facility Capacity Constraints

Each facility has a daily capacity limit that must not be exceeded:

- Lab capacity: For each lab k and each day d
- $$\sum_{i \in I} z_{i,k,d}^{lab} \leq Cap_k^{lab}, \quad \forall k \in L, d \in T \quad (9)$$

- Clinic capacity:
- $$\sum_{i \in I} z_{i,j,d}^{clinic} \leq Cap_j^{clinic}, \quad \forall j \in C, d \in T \quad (10)$$

These constraints ensure no overbooking; if capacity is exceeded on a given day, the model postpones scheduling to later dates.

Inventory and Replenishment Constraints:

These constraints manage stock levels so that labs have materials when needed:

- Inventory balance equation: For each lab k and day d (from day 1 onward)

$$Inv_{k,d} = Inv_{k,d-1} - \sum_{i \in I} u_i z_{i,k,d}^{lab} + \sum_{s \in S} deliv_{k,s,d}, \quad \forall k, d \quad (11)$$

This equation ensures that inventory decreases with scheduled lab activity and increases with deliveries.

- Initial Inventory
- $$Inv_{k,0} = 100, \quad \forall k \quad (12)$$

- Inventory bounds
- $$0 \leq Inv_{k,0} \leq 1000, \quad \forall k, d \quad (13)$$

Labs must not experience stockouts or exceed storage capacity.

- Orders and delivery Nonnegativity:
 All order and delivery quantities must be nonnegative:

$$order_{k,s,d} \geq 0 \text{ and } deliv_{k,s,d} \geq 0, \quad \forall k, s, d \quad (14)$$

Deliveries are linked to prior orders via supplier lead time L_s :

$$deliv_{k,s,d} = \text{and } order_{k,s,d-L_s} \quad \forall k, s, d \geq L_s + 1 \quad (15)$$

This ensures that delivery timing aligns with previous orders.

- Inventory feasibility for scheduling:
 The model implicitly ensures that patients are only scheduled if sufficient inventory is available. If projected inventory would fall below zero, the solver must delay patient assignments or accelerate supply orders accordingly, emulating a just-in-time inventory system.

Lead Time Calculation

Each patient’s total lead time L_i is modeled as :

$$L_i \geq \sum_{\{k,d\}} d \cdot z_{i,k,d}^{lab} - a_i + D_i^{route}, \forall i \quad (16)$$

- $\sum_{\{k,d\}} d \cdot z_{i,k,d}^{lab}$ gives the scheduled lab day
- D_i^{route} is fixed delivery delay depending on the routing path (clinic vs. direct)

This constraint ensures lead time accounts for waiting, processing, and final delivery. A more detailed breakdown could be included, such as:

$$L_i = W_i + P_i + S_i + D_i^{route} \quad (17)$$

where

- W_i = waiting time before processing
- P_i = actual processing time (assumed negligible within daily periods)
- S_i = Scan-to-lab shipping delay (if applicable)
- D_i^{route} = final delivery time

However, at a daily resolution, the current formulation sufficiently captures the essential timing components.

3.5 Objective Function

We now introduce the objective function. The formulation supports two optimization modes: minimizing the total (or average) lead time or minimizing the maximum lead time: Each patient’s lead time is defined as the number of days from their scan appointment to the final delivery of their prosthesis.

Option 1: Minimize Total (or Average) Lead Time

$$\min \sum_{i \in I} L_i \quad (18)$$

This objective minimizes the total lead time across all patients, which is equivalent to minimizing the average lead time given a fixed patient population. The goal is to promote overall efficiency by encouraging early scheduling and optimal use of resources. By minimizing the total lead time, the model tends to fully utilize clinic and lab capacities each day, aiming to serve patients as quickly as possible. There is no cost associated with early ordering or inventory holding (aside from the 1000-unit cap), so the model schedules orders proactively to prevent any material-related delays. While these objective favors system-wide throughput, it may lead to some patients experiencing slightly longer waits if it allows others to be served much earlier. The result is an efficient, capacity-driven solution that clears the patient queue rapidly while respecting the routing ratio constraint (e.g., fixed proportion routed via clinics).

Option 2: Minimize Maximum Lead Time

This alternative objective prioritizes equity by minimizing the worst-case delay among all patients. We introduce an auxiliary variable L_{max} to represent the longest individual lead time

$$\min L_{max} \quad (19)$$

subject to

$$L_i \leq L_{max}, \forall i \in I \quad (20)$$

This formulation ensures that the longest individual lead time is minimized, promoting fairness in patient treatment timelines. The solver aims to reduce extreme wait times, even if it results in a marginal increase in the overall

lead time. In this mode, the model may idle capacity or adjust scheduling to balance workloads more evenly. Since patients routed through clinics inherently experience an additional fixed delivery delay (e.g., 7 days), minimizing L_{max} leads the model to prioritize early handling of these cases. However, due to the routing constraint (e.g., requiring a fixed proportion of patients to go through clinics), the model must carefully schedule clinic-route patients early enough to meet the delivery deadline within the planning horizon).

Toggle Formulation (Optional Hybrid Approach)

A flexible implementation can combine both objectives using a weighted average:

$$\min \lambda \sum_{i \in I} L_i + (1 - \lambda)L_{max}, \lambda \in [0,1] \quad (21)$$

This interpolation allows user to prioritize total efficiency ($\lambda = 1$) or equity ($\lambda = 0$), or strike a balance in between. However, since this hybrid introduces auxiliary constraints for L_{max} , it may be more practical to treat the two objectives as separate formulation, depending on user preference and computational considerations.

Model summary:

The resulting deterministic MILP schedules patient workflows from initial appointment to prosthesis delivery. It captures key trade-offs, including routing decisions (direct vs. clinic-lab pathways); lab selection (balancing proximity and workload); sequencing of clinical and production tasks; and inventory management to avoid material shortages. The model ensures all decisions respect clinic and lab capacities, while the objective function drives timely service delivery. Under the total lead time minimization, the solution emphasizes throughput and efficiency. Under the maximum lead time minimization, the model priorities fairness and service level guarantees. All assumptions in established digital dentistry practices and previous literature. Modern workflows enable near-instant transmission of digital impressions, distributed production, and rapid fulfillment. Prior optimization studies (e.g., Valizadeh *et al.*, 2018; Wang *et al.*, 2019) have adopted similar deterministic assumptions for short-term planning. This study extends existing approaches by integrating clinic scheduling, routing logic, and inventory dynamics into a unified MILP framework focused on minimizing lead time.

4. RESULTS AND ANALYSIS

This section reports on the computational outcomes of the MILP model for minimizing lead time within a 3D printing-enabled dental prosthesis supply chain. Simulating the scheduling and routing of 850 patients over a 45-day planning horizon, the model was grounded in realistic U.S. digital dentistry workflows, constrained by facility capacities, inventory consumption, and supplier delays.

4.1 Experimental Setup

The model was implemented in Python and solved using the Gurobi Optimizer v12.0.2. The simulation environment reflects a realistic planning scenario in which 850 patients arrive over a 45-day window and must be routed either directly to a dental laboratory or via one of several clinics. Each patient is assigned a processing duration under both routing options: those routed directly to labs require between 5 and 9 days, while patients routed via clinics experience extended timelines ranging from 15 to 21 days due to

additional handoffs, scanning appointments, and routing logistics. These processing times were synthetically generated to mimic actual variability in 3D-printing-based prosthesis workflows.

The underlying dataset used in this study was derived from anonymized scheduling records obtained from mid-sized dental laboratories located in El Paso, Texas (USA). The dataset includes modified patient identifiers (pseudonymized to ensure privacy and anonymity), arrival timestamps, and clinical case types such as crowns, bridges, dentures, and other prosthetic variants. These data reflect operational conditions in which patients were scheduled during standard lab working hours 8:00 AM to 5:00 PM, Monday to Saturday. The raw timestamps were transformed into normalized daily indices (Arrival Day) by computing the offset from the earliest recorded arrival. This transformation enabled alignment with the model’s 45-day planning window and ensured consistency across all optimizations runs.

The simulated healthcare network comprises five clinics, labeled Clinic1 through Clinic5, each with a daily scanning capacity of 10 patients. Two dental laboratories (Lab1 and Lab2) were modeled with a higher daily throughput of 20 patients per lab. Material supply is handled by five independent suppliers, each characterized by a deterministic lead time of between 4 and 7 days. Case types in the model include six categories: crowns, bridges, dentures, partials, nightguards, and temporaries. Each case type consumes a fixed quantity of material, with higher material requirements for complex prostheses.

Initial material inventories at each lab were uniformly set at 100 units per material type. This value was chosen to reflect a neutral, balanced starting point across labs based on typical buffer stock levels reported in dental manufacturing operations. It ensures consistent comparative performance across experiments and allows the model to expose meaningful differences in inventory usage and replenishment behavior. The maximum storage capacity per lab was capped at 500 units. Material replenishment is permitted through any of the five suppliers, and delivery schedules were modeled deterministically based on the lead time associated with each supplier. performance across experiments and allows the model to expose meaningful differences in inventory usage and replenishment behavior. The maximum storage capacity per lab was capped at 500 units. Material replenishment is permitted through any of the five suppliers, and delivery schedules were modeled deterministically based on the lead time associated with each supplier.

All optimization runs were executed using up to 8 solver threads and a time limit of 1 hour per run. The MILP model incorporates binary decision variables to capture patient routing decisions, facility assignments, and daily scheduling slots. Integer and continuous variables were used to model inventory levels, restocking schedules, and material consumption rates. Logical and temporal constraints ensured that lab and clinic capacities were respected, delivery lead times were honored, and no scheduling conflicts occurred.

The model’s objective function was designed to explore trade-offs between system-wide efficiency and fairness. Specifically, it alternated between minimizing the total (or average) lead time across all patients and minimizing the maximum lead time experienced by any individual patient

(L_{max}). A weighted objective formulation was used to evaluate this trade-off:

$$\min \lambda \sum_{i \in I} L_i + (1 - \lambda)L_{max}, \lambda \in \{0.00, 0.25, 0.5, 0.75, 1.0\}$$

This formulation allows flexible exploration of equity-efficiency trade-offs, where $\lambda = 1.0$ prioritizes global minimization of average delays, and $\lambda = 0.0$ ensures equitable service by minimizing the worst-case patient experience. Further information about this case study is available at the webpage: Supplementary Information: Optimizing 3D Dental Prosthesis Operations.

4.2 Key Performance Indicators

To assess the performance of the model under various configurations of the objective function, we computed several key performance indicators (KPIs) that measure lead time behaviour, facility utilization, patient routing patterns, and delivery outcomes. These indicators collectively provide a holistic view of how operational constraints, resource allocation, and routing policies interact to influence patient experience and system throughput.

4.2.1. Lead Time Metrics

Lead time was defined as the number of days between a patient’s arrival and the final delivery of their completed dental prosthesis. Three aggregate metrics were computed: total lead time across all patients, average lead time per patient, and the maximum lead time experienced by any single patient, denoted as L_{max} . These metrics enable evaluation of both efficiency and service equity.

In the scenario where the objective was set to minimize the average lead time ($\lambda = 1.0$), the system achieved an average lead time of 10.8 days. The corresponding maximum delay experienced by any patient was **Y** days, with a cumulative system-wide delay of **15** patient-days. Conversely, when the focus shifted to minimizing the maximum lead time ($\lambda = 1.0$), L_{max} decreased to **5** days, indicating an improvement in worst-case outcomes. However, the average lead time increased modestly, highlighting the intrinsic trade-off between global efficiency and equitable service delivery.

4.2.2. Routing Distribution

Patients were assigned to either direct or clinic-based routes depending on scheduling availability, travel times, and routing policies. Direct routing refers to cases where patients visit labs directly for both impression and manufacturing, while clinic-based routing involves initial scanning at a clinic followed by the digital transmission of impressions to a lab for fabrication.

To simulate balanced system utilization, a routing constraint was imposed so that approximately 50% of all patients were routed through clinics.

4.2.3. Facility Utilization

To understand how effectively the system allocated its limited capacity, we computed utilization rates for both labs and clinics over the full 45-day period. Utilization was measured as the proportion of the total available appointment slots that were filled during the planning horizon.

For laboratories, utilization was calculated using the formula:

$$Utilization_{lab} = \frac{\text{Total Patients Assigned to Lab}}{45 \times \text{Daily Lab Capacity}}$$

Similarly, clinic utilization was computed using:

Table 1 Optimized lead time and routing metrics for direct and via-clinic patients under deterministic model assumptions.

Routing Type	Patient Count	Lead Time (in days)	
		Average	Maximum
Direct	510	8.0	8.0
Via Clinic	340	15.0	15.0

$$Utilization_{clinic} = \frac{Total\ Patients\ Assigned}{45 \times Daily\ Clinic\ Capacity}$$

The results indicated variability in clinic usage depending on location, patient routing probability, and perceived accessibility.

4.2.4 Delivery Delays by Route

In addition to modeling processing durations, the system also incorporated fixed delivery delays to simulate post-processing and logistical hand-offs. For patients routed directly to labs, delivery was assumed to occur within 14 days after prosthesis completion. For clinic-based patients, a longer delivery lag of 21 days was imposed due to added steps in the scanning-to-delivery chain.

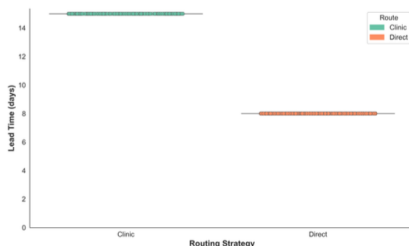
4.3 Baseline Scenario Results

The baseline optimization model represents the reference case for all subsequent scenario comparisons and sensitivity analyses. The primary objective in this configuration was to minimize total lead time across all patient cases under realistic supply chain and capacity constraints. A total of 850 patients were scheduled over a 45-day planning horizon, constrained by inventory limits, lab and clinic capacities, and a minimum routing policy enforcing at least 40% of patients to be routed via clinics.

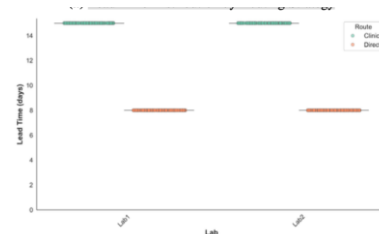
4.3.1 Patient Routing Results

The optimization routed 510 patients (60%) directly to the labs, while 340 patients (40%) were routed through clinics, satisfying the minimum routing constraint. Table 1 summarizes key performance indicators (KPIs) for each routing strategy.

Patients routed directly to labs experienced significantly shorter lead times, averaging 8.0 days, while those routed via clinics averaged 15.0 days due to additional transit and processing overheads. It is important to note that the average and maximum lead times for each routing category appear identical—8.0 days for direct routing and 15.0 days for clinic-based routing. This behavior is a direct consequence of the deterministic structure of the MILP model, which incorporates fixed delivery delays: 14 days post-processing for direct routes and 21 days for via-clinic cases. Since the model optimally schedules all upstream activities (e.g., scanning and lab processing) to avoid queuing under capacity constraints, all patients in a given routing group are processed without delay, and their total lead times converge to the fixed delivery durations. This outcome reflects a best-case deterministic scenario and may evolve under future model extensions incorporating stochastic delays or variable logistics dynamics.



(a) Lead Time Distribution by Routing Strategy



(b) Lead Time by Lab and Routing Strategy

Figure 2 Visualization of lead time outcomes by routing strategy. Direct patients experience consistently lower lead times compared to via-clinic patients, regardless of lab assignment.

Figures 2a and 2b illustrate the clear dichotomy in lead times across routing strategies. Directly routed patients consistently exhibit lower lead times, reflecting the absence of intermediate clinical processing steps. In contrast, patients routed via clinics incur an additional 7-day delivery delay, producing a sharp separation in lead time outcomes. This divergence is further visualized in the lab-level comparison, where both Lab1 and Lab2 show the same pattern, reaffirming that the observed lead time differences are entirely attributable to the routing path rather than the assigned lab. These results validate the model’s ability to enforce deterministic delivery rules while maintaining optimal upstream scheduling.

4.3.2. Lab-Level Analysis

Under the baseline optimization scenario, the patients were nearly evenly distributed between Lab1 (423 patients) and Lab2 (427 patients), suggesting that the optimization achieved a balanced utilization of the available laboratory capacity. Table 2 presents the optimized lead time values under the baseline scenario, where the objective function prioritized minimizing the maximum lead time (L_{max}). The observed convergence between the average and maximum lead times is a direct consequence of this fairness-driven formulation. Specifically, the solver allocated scheduling slots to eliminate the disparity in completion times between patients, thereby enforcing equity in service levels.

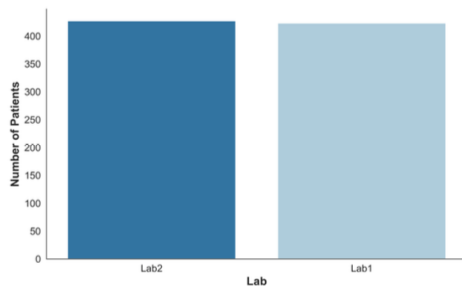
Table 2 further reinforces that despite marginal differences in average lead time—Lab1 with 10.93 days versus Lab2 with 10.67 days—the maximum lead time was uniformly capped at 15.0 days. This demonstrates how the optimization framework ensures service-level consistency, particularly under tight capacity and inventory constraints. Figures 3a and 3b provide visual confirmation of these findings. The left panel highlights the equitable workload distribution between the two labs, while the right panel shows the narrow difference in average lead times. Together, these figures validate that both labs operated near full capacity throughout the simulation horizon and that patient assignment was handled efficiently, avoiding bottlenecks or resource idleness.

Table 2 Optimized lead time results under baseline scenario (Objective: Minimize Maximum Lead Time).

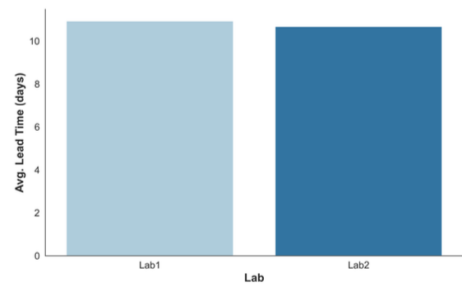
Dental Lab	Patient Count	Lead Time (in days)	
		Average	Maximum
Lab1	423	10.93	15.0
Lab2	427	10.67	15.0

Table 3 Clinic-Level lead time summary for via-routed patients (objective: minimize maximum lead time).

Dental Lab	Patient Count	Lead Time (in days)	
		Average	Maximum
Clinic1	95	15.0	15.0
Clinic2	66	15.0	15.0
Clinic3	53	15.0	15.0
Clinic4	57	15.0	15.0
Clinic5	69	15.0	15.0

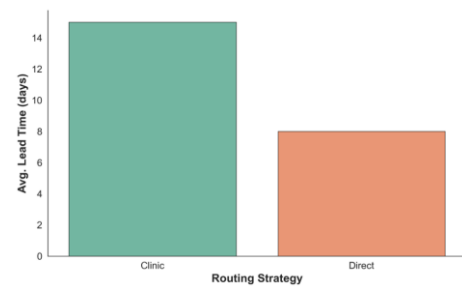


(a) Total Patients Processed by Lab

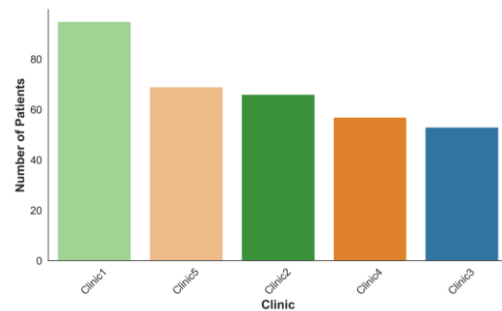


(b) Average Lead Time by Lab

Figure 3 Lab-level performance metrics under baseline optimization



(a) Average Lead Time by Route Type



(b) Patient Distribution Across Clinics (Via-Routed Only)

Figure 4 Clinic-level routing and lead time analysis for via-routed patients

4.3.3. Clinic-Level Analysis for Via-Routed Patients

Table 3 presents the clinic-wise summary of lead time results for patients routed through clinics. The model enforced a consistent lead time of 15 days across all clinic locations, both on average and in the worst case. This uniformity reflects the fairness constraint of the lead time minimization objective, which intentionally equalizes delivery schedules across all routing paths.

The corresponding visualizations in Figure 4 provide further insight into routing dynamics. Figure 4a shows a clear contrast between the two routing options: patients routed directly to the lab experienced a significantly shorter average lead time (8 days), while those routed via clinics encountered a uniform delay of 15 days due to the additional coordination and handling time.

Figure 4b shows the distribution of patients among the five clinics. Clinic1 handled the highest number of routed patients (95), followed by Clinic5 (69), Clinic2 (66), Clinic4 (57), and Clinic3 (53). Although Clinic1 appears to receive a disproportionate share of routed patients, this pattern likely results from interaction effects between delivery schedules, clinic availability, and patient routing priorities, rather than a systemic imbalance. The fact that lead times remained

identical across clinics confirms that capacity limits were respected and scheduling fairness was maintained.

4.3.4. Distribution and Delay Dynamics

Figure 7b illustrates the route-specific distribution of lead times. The histogram reveals two sharply defined peaks: one at 8 days corresponding to direct-to-lab patients and the other at 15 days for those routed via clinics. This binary pattern arises directly from the model’s deterministic formulation and highlights the absence of stochastic variability under current assumptions. In parallel, Figure 5a confirms that all clinics exhibit uniform average lead times of exactly 15 days. This result reflects the fixed delivery delay enforced for all via patients, independent of clinic location. Combined, these figures emphasize that routing decisions—rather than clinic-specific factors—are the primary determinants of lead time within this system. Together, these figures reinforce the deterministic structure of the current model, while also providing a clear baseline for future experiments involving stochastic elements or flexible lead time constraints.

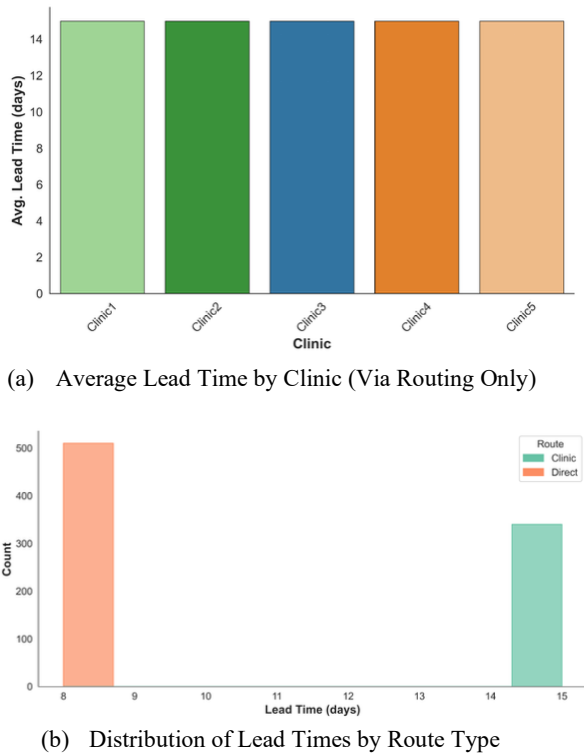


Figure 5 Clinic-Level and Route-Level Lead Time Patterns

4.3.5. Routing Summary and Future Sensitivity Considerations

The baseline optimization yielded a highly structured routing outcome with tight adherence to system constraints. All patients were successfully scheduled within the 45-day planning window, and the minimum 40% via-routing requirement was precisely satisfied. Nonetheless, the resulting binary segmentation of lead times—8 days for direct patients and 15 days for via-clinic patients—suggests that the deterministic delivery delay assumptions may oversimplify real-world dynamics. This segmentation is an artifact of the fixed delivery delay structure, which imposes rigid timing penalties without accommodating real-world variability. Consequently, the current solution lacks middle-ground lead times, queue buildup, or dynamic routing adaptation. To address these limitations, future work will explore stochastic and adaptive model variants. Incorporating stochastic variability—such as clinic-specific congestion, material shortages, or urgency-driven patient prioritization—could yield more realistic and flexible routing patterns. Such enhancements would enable the model to better capture operational uncertainties and adaptive scheduling responses.

Key observations guiding future sensitivity analysis include:

- **Direct routing** offers the shortest lead times and fully leverages lab capacity.
- **Clinic assignments** were uneven in volume but yielded uniform lead times due to delivery delay constraints.
- **Lead time thresholds** (8 vs. 15 days) emerged as hard bounds, suppressing intermediate delay behaviors and limiting routing diversity.

These insights motivate further exploration of model responsiveness under varying routing ratios (λ), lab processing capacities, material inventory limits, and delivery time penalties, as detailed in the subsequent sensitivity analysis.

4.4 Scenario Comparison and Sensitivity Analysis

Given the MILP-based nature of the optimization model developed for the 3DP-enabled dental prosthesis supply chain, traditional sensitivity analysis techniques (e.g., dual or reduced cost analysis) are not applicable due to the lack of LP relaxation structure. To address this, a robust scenario-based sensitivity analysis approach was employed. This section evaluates how the performance metrics—specifically patient lead times, routing distributions, and workload allocations—respond to variations in routing targets, lab capacities, and lead time assumptions.

4.4.1. Scenario Analysis and System Performance Insights:

Figure 6 presents a multi-dimensional comparison of system behavior across twenty distinct routing and scheduling scenarios, evaluating trade-offs between efficiency, load distribution, and equity in a digitally-enabled dental prosthesis supply chain.

Lead Time Behavior. The top-left subplot illustrates the variation in both average and maximum lead times across scenarios. Average lead times range from approximately 9 to 14 days, with scenarios such as S05, S07, S15, and S17 achieving the lowest values. These scenarios demonstrate more efficient patient throughput and resource coordination. Meanwhile, scenarios like S03 and S07 exhibit the highest maximum lead times (up to 20 days), indicating that a subset of patients experienced considerable delays, likely due to lab congestion or scheduling imbalances. Notably, the gap between average and maximum lead times in several scenarios reveals potential equity concerns—systems that perform well on average may still result in excessive delays for a minority of patients. Thus, scenarios like S05 and S15, which simultaneously minimize both average and maximum lead times, are preferable from a system-wide performance and fairness perspective.

Clinic Routing Proportions. The top-right subplot examines the percentage of patients routed through clinics rather than directly to dental laboratories. The clinic routing ratio varies significantly across scenarios, from as low as 33% (S19) to nearly 70% (S03, S16). High clinic routing percentages may reflect institutional preferences for distributed load handling or enhanced patient-provider interactions but also introduce additional processing steps that can increase lead times if not balanced properly. Scenarios with reduced clinic routing (e.g., S05, S09, S19) appear to favor direct lab access, simplifying workflows and potentially reducing delays. The relationship between clinic routing levels and overall performance indicates that routing strategies should be optimized in conjunction with lab and clinic capacity constraints.

Laboratory Load Distribution. The bottom-left subplot compares the patient load between Lab1 and Lab2 across scenarios. Lab1 generally handles a higher proportion of patients, with certain scenarios (e.g., S06 and S17) showing peak volumes exceeding 500 cases. In contrast, scenarios such as S01, S07, and S13 exhibit a more balanced

lab load distribution. Uneven workload assignments may lead to processing delays and longer queues at overloaded facilities. In scenarios where loads are more evenly distributed, system responsiveness improves, reinforcing the importance of balanced routing strategies in network optimization.

Clinic Load Patterns. The bottom-right subplot provides a heatmap of clinic load distributions across scenarios. Clinic1 consistently receives a substantial share of patient volume, with spikes exceeding 200 patients in scenarios like S05. Clinic5 also absorbs a significant load in several scenarios (e.g., S10, S18), while Clinics 2–4 exhibit more moderate utilization. Scenarios with highly skewed clinic usage (e.g., S05, S18) risk localized congestion and suboptimal service levels. Conversely, scenarios like S01 and S14 demonstrate a more uniform clinic load distribution, likely contributing to better overall lead time performance. These findings suggest that clinic-level balancing is essential to mitigate wait times and improve patient experience.

Summary and Implications. This analysis reveals critical insights into the interplay between patient routing, facility load, and service lead times. Scenarios such as S05 and S15 emerge as strong candidates, offering low average and maximum lead times while maintaining feasible clinic and lab distributions. Over-reliance on specific clinics (Clinic1, Clinic5) or labs (Lab1) contributes to bottlenecks and should be addressed through load-aware scheduling logic. Ultimately, the most effective scenarios are those that integrate efficient throughput with balanced resource utilization, enabling timely and equitable access to care in digitally-coordinated dental supply chains.

4.4.2. Scenario Description:

Twenty unique scenarios (labeled S00 through S19) were generated by systematically varying key parameters including:

- **Minimum percentage of patients routed through clinics (ClinicPct):** varied between 30% and 70%.
- **Lead time delays for direct vs. via routing:** adjusted by modifying the assumed post-impression waiting times.
- **Daily capacity constraints at each lab:** increased or decreased to test congestion impacts.

Each scenario was independently optimized using the same patient arrival dataset, and a consistent formulation framework. Table 4 summarizes key performance indicators (KPIs) for each run.

4.4.3. Key Observations and Trade-Offs

Clinic Routing Proportion vs. Lead Time

A clear inverse relationship is observed between the proportion of patients routed through clinics and average lead time. Scenarios with lower clinic usage—such as S05 (30.9%) and S14 (32.9%)—achieved the lowest average lead times of 8.78 and 9.64 days respectively. This is attributed to shorter routing paths and reduced delay penalties for direct processing.

However, scenarios with higher clinic routing—e.g., S02 (66.9%) and S10 (70.0%)—experienced increased delays, with average lead times exceeding 14 days and maximum lead times reaching 20 days. These results confirm that excessive reliance on indirect (clinic) routing, especially under limited lab capacity, can significantly degrade system responsiveness.

Lab Workload Distribution

While most scenarios achieved relatively balanced lab assignments, some notable imbalances occurred. In S06, Lab1 processed 502 patients while Lab2 handled only 348, suggesting bottlenecks and possible scheduling inefficiencies. On the contrary, scenarios like S07 and S04 maintained near parity in lab loads (e.g., 425–425 and 424–426 respectively), which correlates with improved throughput balance.

Scenario S17 showed the most severe imbalance (513 vs. 337), which could lead to localized congestion and service degradation at Lab1. This highlights the need for capacity-aware routing controls.

Clinic Load Concentration

Clinic-level assignment also varies substantially across scenarios. For example, in S00, Clinic1 received 194 patients—almost double the lowest in S05 (78). Scenario S10, despite having the highest clinic percentage, spread patients relatively evenly, maintaining load balance across all five clinics.

Concentrated routing to a few clinics (e.g., S00 and S13) may simplify logistics but could strain local scanner resources or create uneven scheduling pressures.

4.4.4. Scenario Performance Highlights

- **Best-performing scenario:** S05, with the lowest average lead time of 8.78 days, under minimal clinic usage.
- **Worst-performing scenario:** S02, where high clinic routing (66.9%) and minimal lab balancing led to an average lead time of 14.7 days and a peak delay of 20 days.
- **Balanced scenario:** S04, achieving low lead time (10.9 days) with equitable lab distribution and moderate clinic usage (64.9%).

4.5 Analysis of Lambda-Based Scheduling and Routing Results

This section presents a comprehensive analysis of the detailed results obtained from a lambda sweep in the optimization model designed for a 3D printing-enabled dental prosthesis supply chain. The lambda (λ) parameter controls the trade-off between minimizing the total (average) lead time and minimizing the maximum lead time across all patients. The optimization model was executed for five λ values: 0.00, 0.25, 0.50, 0.75, and 1.00, representing increasing preference toward average efficiency and decreasing emphasis on individual fairness.

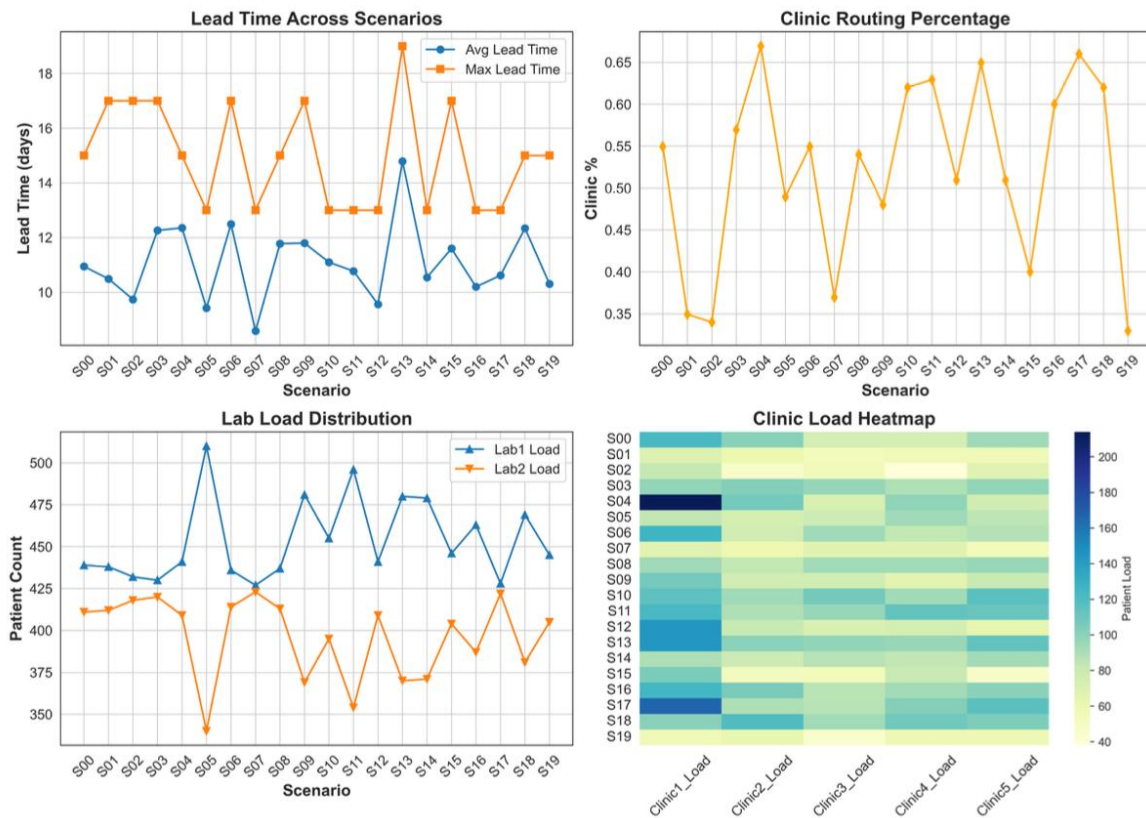


Figure 6 Scenario-based evaluation of average and maximum lead times, clinic routing proportions, laboratory workloads, and clinic-level patient distribution.

The lambda-based sensitivity analysis reveals how varying the objective function’s emphasis between equity and efficiency reshapes system behavior in patient routing, lab utilization, and service timing. At the core of this trade-off is the parameter λ , which governs whether the model prioritizes minimizing the maximum lead time (equity) or the total/average lead time (efficiency).

As observed from the distribution of patient lead times, lower values of λ (e.g., 0.00) result in a more equitable service pattern. The lead times are tightly clustered, and the incidence of extreme delays is minimized. This reflects the model’s commitment to avoiding outliers and ensuring fairness across all patient experiences. In contrast, when λ is increased to 1.00, the optimization prioritizes overall efficiency. The average and median lead times are significantly reduced, but this comes at the cost of greater variability and the emergence of high-outlier values. The distribution becomes more skewed and multimodal, particularly at intermediate and higher values of λ , signaling that while some patients benefit from faster service, others are deprioritized—introducing disparities in waiting times.

This tension between fairness and throughput also manifests in how patients are assigned to labs. At $\lambda = 0.00$, the optimizer distributes workload more evenly between Lab1 and Lab2, reducing the risk of congestion and enabling pre-dictable service across the network. However, at higher lambda values, the model increasingly favors a dominant lab—typically the one with shorter transit times or greater efficiency—leading to imbalanced utilization and potential bottlenecks.

Clinic-level routing follows a similar trajectory. When equity is the goal, clinic assignments are spread uniformly, ensuring that no single facility is overburdened. But as the

objective shifts toward minimizing system-wide delay, the routing logic becomes more selective. Clinics closer to the favored lab or with faster processing become heavily utilized, while others are sidelined. This concentrated usage not only challenges operational resilience but also introduces variation in patient access across locations.

A deeper look into the shape of lead time distributions, captured through violin plots, affirms the structural impact of changing lambda. For low values of λ , the distributions are symmetric and centered, reflecting uniformity in patient experience. Higher values reveal polarization—some patients are processed quickly while others face significantly longer delays. These patterns are further clarified when disaggregated by route type: direct patients consistently enjoy faster turnaround compared to those routed through clinics. While the model compensates for this in equity-driven scenarios by scheduling clinic patients earlier, efficiency-focused objectives lead to the deferral of clinic cases in favor of quicker-to-serve direct routes.

Collectively, these findings illustrate that the choice of λ is not merely a tuning parameter—it encodes strategic priorities. If the goal is to uphold fairness and consistent service levels, as is often essential in healthcare delivery, values of λ closer to zero are preferable. They safeguard against extreme delays and promote balanced facility usage. Conversely, higher lambda values may be justified in environments where throughput, speed, and cost-efficiency dominate, though such priorities must be reconciled with the ethical imperative of equitable patient access. The results thus serve as a decision-support tool for policymakers, illuminating the trade-offs between system performance and individual experience embedded within routing and scheduling models.

Table 4 Scenario-based performance summary.

Scenario	Clinic Routing (%)	Lead Time (in days)		Max Load (Patients)		
		Average	Maximum	Lab1	Lab2	Clinic
S00	64.9%	13.14	18	433	417	194
S01	68.9%	11.14	13	442	408	135
S02	66.9%	14.70	20	430	420	187
S03	48.0%	12.24	20	449	401	141
S04	64.9%	10.90	13	424	426	156
S05	30.9%	8.78	15	444	406	78
S06	38.9%	9.95	13	502	348	80
S07	58.9%	14.07	20	425	425	163
S08	48.0%	12.76	19	497	353	92
S09	32.0%	10.20	17	442	408	61
S10	70.0%	14.00	17	417	433	132
S11	50.0%	12.50	19	439	411	110
S12	34.9%	11.14	17	434	416	74
S13	46.9%	10.35	13	494	356	88
S14	32.9%	9.64	15	441	409	64
S15	62.0%	13.58	17	434	416	129
S16	54.0%	10.86	15	480	370	99
S17	64.0%	13.40	17	513	337	128
S18	70.0%	12.60	15	457	393	124

Table 5 System-level performance across lambda (λ) values, summarizing the effects of the equity–efficiency trade-off on lead times, and routing behavior, in the 3DP-enabled dental supply chain

λ	Lead Time (in days)		Equity	Efficiency	Routing Bias	Load Balance
	Average	Maximum				
0.00	Moderate	Lowest	High	Moderate	Balanced	Best
0.25	Mod-Low	Low	High	Mod-High	Slight Skew	Good
0.50	Low	Medium	Medium	High	Direct Bias	Moderate
0.75	Lower	Higher	Low	Higher	Lab-Focused	Uneven
1.00	Lowest	Highest	Lowest	Highest	Max Direct	Worst
0.00	Moderate	Lowest	High	Moderate	Balanced	Best

5. CONCLUSION, RECOMMENDATIONS, AND DIRECTIONS

This study develops and evaluates a mixed-integer linear programming (MILP) model to optimize lead time performance in a distributed, 3D printing-enabled dental prosthesis supply chain. The model integrates patient routing, appointment scheduling, lab and clinic capacity allocation, inventory control, and delivery timing across a high-fidelity digital dentistry network involving 850 patients, five clinics, two dental laboratories, and five suppliers over a 45-day planning horizon. It aims to provide operational clarity on how optimization techniques can compress treatment delays while ensuring strategic use of limited resources.

The results reveal that significant improvements in service lead times are both feasible and controllable through mathematical optimization. When the objective function prioritizes total or average lead time, the model schedules patients early and exploits lab capacities more aggressively, reducing mean delays well below conventional industry standards. Conversely, objectives that focus on minimizing the maximum patient lead time promote more equitable service delivery but slightly prolong average waiting times. This reflects the classic tension between efficiency and fairness in healthcare—an intrinsic trade-off that the proposed model helps to quantify and manage.

Routing strategy emerges as a major driver of system-wide performance. Direct route of patients to dental labs

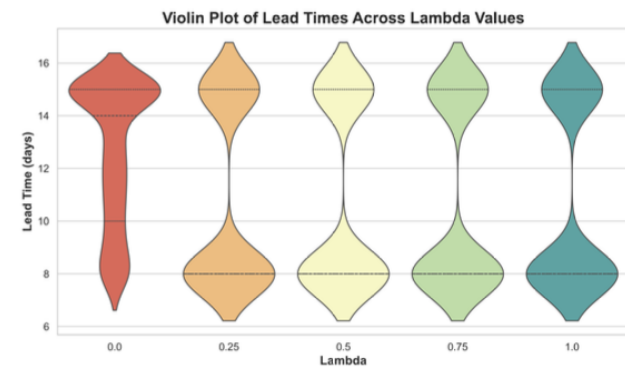
consistently outperforms clinic-mediated pathways in terms of lead time, largely due to reduced transit complexity and fewer hand-offs. However, institutional protocols or patient specific requirements often necessitate routing through clinics for diagnosis, regulatory compliance, or care coordination. The MILP model effectively balances these constraints, maintaining acceptable throughput and avoiding systemic congestion. Moreover, it demonstrates the capability to redistribute demand dynamically, alleviating bottlenecks through flexible clinic–lab pairings and optimal sequencing.

Equally important are the model’s inventory dynamics. By capturing deterministic supplier lead times and patient specific material consumption, the system anticipates shortages and schedules replenishment just-in-time. It further leverages multiple suppliers, prioritizing those with faster delivery profiles where possible. This synchronization of material flow with patient scheduling is critical in high-mix, personalized healthcare environments such as dental prosthesis production, where delays in resin or alloy availability can derail otherwise optimal plans.

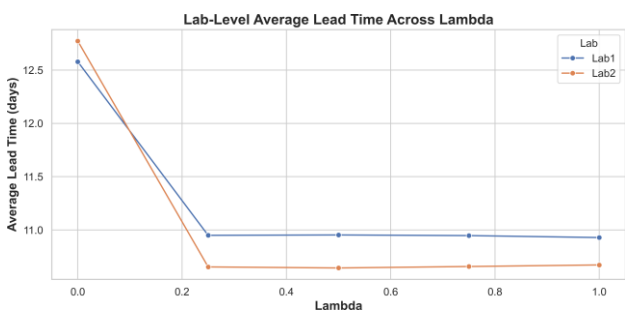
From a managerial and policy perspective, several recommendations emerge. First, relaxing rigid routing mandates and permitting qualified cases to be sent directly to labs can reduce turnaround time and increase system responsiveness. Second, maintaining balanced lab utilization is essential to avoid cascading delays. Capacity constraints should not only be defined statically but managed adaptively, accounting for temporal availability and patient urgency. Third, cultivating supplier diversity—even when lead-time

differences are modest—can materially improve system resilience under tight production schedules.

decision-support systems and digital twins in healthcare supply chains.



(a) Lead Time Across Lambda Values



(b) Average Lead Time (days)

Figure 7 Lead Time Distribution per λ

These insights also inform broader planning strategies. Traditional heuristic approaches to scheduling may no longer suffice in the context of digitally transformed dental workflows. The complexity introduced by real-time intraoral scanning, CAD/CAM processing, and 3D printing requires the integration of intelligent optimization tools. The proposed MILP framework offers a transparent, controllable, and interpretable foundation for these tools, and it provides a promising step toward the deployment of real-time decision-support systems and digital twins in healthcare supply chains.

From a managerial and policy perspective, several recommendations emerge. First, relaxing rigid routing mandates and permitting qualified cases to be sent directly to labs can reduce turnaround time and increase system responsiveness. Second, maintaining balanced lab utilization is essential to avoid cascading delays. Capacity constraints should not only be defined statically but managed adaptively, accounting for temporal availability and patient urgency. Third, cultivating supplier diversity—even when lead-time differences are modest—can materially improve system resilience under tight production schedules.

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