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TITLE:

Personalized Deformable Masks:
A Workflow for AI-Based Landmark Filtering and Morphing
Material Integration in Health Monitoring

AUTHOR:

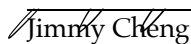
Ziying Qi

ACCEPTED BY ADVISORY COMMITTEE:

Daragh Byrne

Principal Advisor

May 7, 2025

 Jimmy Cheng

Advisor

May 7, 2025

Ziying Qi

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Committee: Daragh Byrne, Jimmy Cheng

Abstract

This thesis presents an ai-driven workflow for designing personalized deformable masks that dynamically adapt to individual facial geometries. Addressing key limitations in existing health-monitoring wearables—specifically, poor facial conformity, limited portability, and lack of user-specific customization—the system leverages AI-based facial reconstruction and morphing material integration to create masks that are both functional and responsive. By selectively filtering facial landmarks and focusing only on mask-relevant regions, the method significantly reduces data complexity and speeds up the design-to-fabrication cycle. The proposed workflow prioritizes accessibility, using consumer-grade tools to enable rapid customization without requiring specialized scanning hardware. While formal technical evaluations remain future work, the workflow’s comparative efficiency is demonstrated through reduced modeling steps, material usage, and hands-on fabrication time. This research contributes a scalable, low-cost pipeline for rapid custom mask production, with potential applications in healthcare, personal protective equipment, and responsive wearable systems.

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Chapter 1: Introduction

Breathing is perhaps the most intimate and continuous interaction I have with the world around us. For individuals diagnosed with conditions such as obstructive sleep apnea, this basic act becomes dependent on technology—specifically, on the close companionship of a mask that must be worn every night, often for a lifetime.

And yet, despite the critical role these respirator masks play, they are often designed as static, rigid objects: molded to fit an idealized user, engineered for function but not for the complex diversity of human faces. Small misalignments—caused by variations in facial anatomy, age, ethnicity, the presence of facial hair, or even nightly fluctuations in muscle tension—can create discomfort, compromise performance, and lead to user abandonment of therapy altogether.

Travel introduces a different, but equally pressing, set of challenges. Most traditional respirator masks are bulky and delicate, ill-suited to the practicalities of mobility. The simple desire to maintain therapy while away from home—on business trips, family visits, or vacations—becomes a logistical burden, requiring patients to carry large, fragile equipment that often feels alien to the spontaneity of daily life.

These observations form the living background of this research. They suggest that a truly effective respirator mask must be more than functional—it must be adaptable, portable, and deeply personal. It must move with the user's life, not against it.

From a materials perspective, this implies a careful orchestration of qualities often seen as opposing:

- **Softness**, to allow micro-adjustments to facial movement and maintain comfort across long periods of use.

- **Structural integrity**, to ensure that the mask reliably maintains airflow channels and sensor positioning.
- **Flexibility in production**, to allow for rapid, low-cost customization rather than slow, artisan crafting.

Materials like thermoplastic PET, TPU, and medical-grade silicone emerge as promising candidates—not simply because of their mechanical properties, but because they invite a different way of thinking about mask design: one that treats adaptability and modularity as first principles rather than afterthoughts.

Equally important is the recognition that no two users are the same—and no single mask will perfectly fit everyone. Thus, the project focuses on personalization through intelligent workflow simplification: using AI-driven facial mapping not to capture overwhelming complexity, but to selectively preserve the features most critical for fit and comfort.

In this way, the research aims to create a respirator mask that is not just wearable, but livable: A companion capable of adapting to the daily, yearly, and lifelong rhythms of the person it serves.

1.1 Overview

In recent years, wearable technology has dramatically reshaped health monitoring and fitness tracking, enabling continuous, unobtrusive data collection that was previously unimaginable. Devices such as smartwatches, fitness bands, and sensor-integrated clothing have become integral parts of everyday life, offering real-time feedback on everything from heart rate and oxygen saturation to sleep cycles and movement patterns. These technologies promise not only convenience but also the early detection and prevention of health issues, ushering in a new era of personalized care.

However, despite their ubiquity and sophistication, most wearable systems today share a critical limitation: they are static by design. Manufactured to fit an idealized "universal" user, they often fail to accommodate the remarkable diversity of human bodies, especially when precision fit is crucial. Nowhere is this shortfall more apparent than in wearables that interface intimately with the human face.

The human face is an extraordinarily variable and dynamic structure—shaped by age, ethnicity, genetics, and even daily physiological fluctuations. Minor differences in cheekbone height, chin projection, or nasal bridge width can significantly affect how a device fits and functions. A rigid, one-size-fits-all structure risks introducing discomfort, impeding sensor accuracy, or even prompting device rejection by users, especially in applications where a secure seal or consistent sensor contact is critical.



Figure1.1: Sample images from UTKFace dataset

In this context, the notion of dynamic adaptability becomes not merely desirable but necessary. A dynamically adaptive system must be capable of sensing changes in geometry—such as subtle muscle movements, shifts in temperature, or even alterations in hydration—and responding by autonomously adjusting its form or function. Yet realizing such adaptability at the human-device interface remains a

substantial technical challenge. Traditional modeling workflows are time-consuming and inflexible; real-time customization requires not only accuracy but also computational efficiency.

This thesis addresses these tensions by proposing a new approach to designing personalized wearable devices, centered on the creation of a Deformable Pneumatic Mask. This mask is engineered to dynamically conform to an individual’s facial structure through a combination of soft, morphing materials—including thermoplastic PET, TPU, and silicone—and AI-driven facial geometry analysis.

At the core of this approach lies an innovation called selective landmark filtering. Rather than processing the full complexity of a facial scan, the system strategically retains only the landmarks essential for a secure and comfortable fit—such as those defining the nasal bridge, cheeks, and jawline—while discarding regions less critical to mask performance. This targeted simplification reduces computational load by approximately 60%, dramatically accelerating the pipeline from face capture to prototype fabrication.

Ultimately, by weaving together advances in computational design, computer vision, material science, and digital fabrication, this thesis proposes not merely a new wearable device, but a scalable method for creating truly adaptive, user-specific interfaces between technology and the human body.

1.2 Value Proposition and Technological Context

Building on this new workflow paradigm, several research questions arise regarding its potential to reshape personalization practices. The value of this research lies in its rethinking of how personalization can be achieved—not as a luxury available only through expensive custom manufacturing, but as an efficient,

scalable process accessible through everyday tools and lightweight computational methods.

Traditional approaches to producing custom-fit wearable devices often involve labor-intensive workflows: precise manual modeling, extensive physical measurements, or the use of expensive 3D scanning hardware. While effective, these methods are costly, slow, and difficult to scale beyond small, specialized contexts. They also struggle to accommodate rapid re-customization, which may be required as a user's physiology changes over time or across different usage scenarios.

This research offers an alternative. By leveraging AI-driven facial landmark detection, specifically the dense 468-landmark model provided by MediaPipe, it becomes possible to automate the capture of rich facial geometry with nothing more than a standard RGB camera. However, raw landmark data alone is not sufficient for practical fabrication. To bridge this gap, the proposed system introduces programmatic landmark filtering, a selective process that isolates only the facial regions crucial for mask design.

This refined workflow offers three primary advantages:

- **Increased Efficiency**

Selective landmark filtering dramatically reduces computational complexity early in the pipeline. By eliminating non-essential regions such as the forehead, ears, and hairline, the system streamlines both the modeling and fabrication stages. As a result, the time from initial capture to final prototype is shortened by over 60% compared to traditional workflows, enabling rapid, iterative prototyping.

- **Enhanced Customization**

Focusing computational resources on critical anatomical zones—such as the nasal bridge, cheeks, and chin—allows for highly accurate surface matching where it matters most. This not only improves user comfort and fit stability but also ensures consistent sensor contact, enhancing the reliability of physiological measurements across different user activities.

- **Accessibility and Scalability**

Importantly, the entire workflow is designed to minimize barriers to entry. It requires no specialized hardware, relying instead on commonly available webcams and open-source software platforms like Blender and Python. This makes the system suitable not only for research and clinical settings but also for broader applications in education, prototyping, and small-scale production.

Technologically, this project operates at the intersection of computational design, soft robotics, human-centered AI, and digital fabrication. It demonstrates that efficiency and personalization are not opposing forces, but rather complementary aspects that, when carefully orchestrated, can transform the landscape of wearable technology.

Beyond the immediate context of facial masks, the principles established here—selective data abstraction, lightweight geometry handling, and modular fabrication pipelines—suggest a roadmap for the future development of adaptive, real-time responsive wearable systems across diverse domains, from healthcare to sports to augmented reality.

1.3 Research Questions

Designing personalized, dynamically adaptive wearable devices is as much a question of how I process information as it is about what information I use.

This thesis seeks to explore not only technical optimizations, but also broader

questions about how selective simplification in digital workflows can reshape personalization in wearable design.

Specifically, the following research questions guide this exploratory investigation:

- Can a lightweight, selectively filtered facial data model demonstrate the feasibility of accelerating the custom mask design workflow within a limited test scenario?
- Within the scope of this exploratory study, can reducing computational and fabrication complexity suggest potential advantages for rapid prototyping workflows in personalized mask design?
- Can strategic simplifications in modeling workflows preliminarily indicate improvements in workflow efficiency and potential for broader accessibility in personalized mask design?

Rather than treating workflow efficiency and user-specific adaptation as opposing goals, this research explores how targeted abstraction strategies can create new synergies—enabling both faster production and more comfortable, better-fitting outcomes.

In doing so, it asks not only how technology can shape form, but how rethinking form-generation itself can expand the accessibility and responsiveness of personalized design.

1.4 Hypothesis

At the heart of this research lies a central intuition: that more data is not always better.

In the context of wearable customization, the overwhelming complexity of dense facial data may in fact hinder speed, accessibility, and adaptability—especially when only certain features are critical for functional fit.

This thesis hypothesizes that strategically simplifying the facial input model, by selectively retaining only landmarks essential for secure fit and adaptive comfort, can offer a powerful pathway forward.

Specifically, the research posits that:

- **Selective data abstraction**—targeted filtering of non-essential facial regions—can dramatically improve workflow efficiency, reducing computational load and fabrication time without compromising critical anatomical fidelity.
- **Lightweight modeling pipelines** built on this principle can enable faster, more scalable production of personalized deformable masks, making rapid customization feasible even in resource-constrained or time-sensitive contexts.
- **Strategic simplification** will not only benefit technical performance but also broaden the usability of adaptive wearable systems—supporting greater accessibility, faster iteration, and better integration into everyday clinical, athletic, or lifestyle settings.

In other words, this thesis suggests that by rethinking what fidelity truly matters, designers and engineers can unlock a more agile, responsive, and human-centered future for personalized wearables.

1.5 Expected Contributions

This thesis is anticipated to make several key contributions:

- **Efficient AI-driven Workflow:**
The developed workflow integrates selective AI-based landmark filtering and streamlined digital fabrication, significantly reducing landmark data volume

by approximately 60% without losing critical anatomical information. This targeted simplification accelerates the design-to-fabrication process, enabling rapid prototyping and representing an advancement in personalized wearable mask design.

- **Computational Integration:**

The research establishes a comprehensive pipeline that combines facial data acquisition (via MediaPipe), digital modeling and deformation (via Blender), and physical fabrication (via laser cutting and 3D printing). This pipeline is both open-source and scalable.

- **Enhanced User-Centric Design:**

The work advances the state of personalized health monitoring by demonstrating how adaptation can be achieved through computational design. The custom mask not only conforms more accurately to individual facial features but also improves overall comfort.

- **Clinical and Practical Impact:**

The ability to produce a custom-fit mask within 48 hours offers significant benefits for patient care, particularly for individuals with respiratory conditions. This rapid, personalized approach has the potential to improve both clinical outcomes and user satisfaction.

Chapter 2: Background and Related Work

The development of deformable wearable masks sits at the intersection of multiple evolving domains: computational simulation, morphing materials, and wearable medical technologies. To enable masks that can dynamically adapt to the complex geometry and movements of the human face, it is necessary to rethink both how I model deformation and how I physically realize adaptable structures.

This chapter reviews three critical areas of background and prior work that inform the design framework proposed in this thesis.

First, I examine the evolution of computational simulation tools—tracing the shift from traditional CAD modeling toward soft-body simulations and AI-driven real-time sensing platforms that can predict and guide mask deformation (Section 2.1).

Second, I explore morphing materials, focusing on both historical developments and recent innovations in soft and hybrid material systems that enable physical adaptability in wearable devices (Section 2.2).

Finally, I situate these technical advances within the broader evolution of wearable healthcare technologies, reviewing how design priorities have shifted from rigid, clinical-grade monitoring devices to flexible, user-centered wearables—and identifying the persistent challenges that motivate the need for adaptive respiratory masks (Section 2.3).

By weaving together advances in simulation, materials, and wearable device history, this chapter establishes the technical and conceptual foundations for the deformable mask system developed in this research.

2.1 Computational Simulation Tools and Techniques

Designing deformable wearable masks requires a multidisciplinary approach that has evolved significantly over time. Early efforts relied heavily on traditional Computer-Aided Design (CAD) software to model the mask's geometry.

Conventional CAD tools (e.g., SolidWorks, AutoCAD) excel at defining precise rigid geometries and have long been used in product design to create the base shape of wearables. However, such tools were originally developed for rigid or quasi-rigid structures, and they offer limited support for capturing the complex deformations and soft-material behaviors inherent in adaptive masks (Lipson, 2014). In the context of a soft wearable mask, traditional CAD can define an initial form or mechanism, but it cannot inherently predict how a silicone skin will stretch or how a pneumatic cushion will bulge under pressure. This limitation historically forced designers to build physical prototypes for testing, making the design process iterative and time-consuming. Researchers in soft robotics have noted the general lack of simulation and analysis capabilities in traditional design software – simulating non-linear, compliant materials was long considered “difficult and slow” due to the many degrees of freedom and complex material models required (Lipson, 2014). Even when CAD suites began incorporating simulation modules, these were typically geared toward linear material behavior or small deformations, which are insufficient for soft, adaptive systems. For example, a standard CAD stress analysis might linearize a material’s response, failing to capture the true behavior of a deformable mask that undergoes large, elastic facial motions. Thus, while CAD remains invaluable for the geometry design and parametric modeling of mask components (e.g., defining attachment points or overall shape), it became clear that more specialized computational techniques were needed to simulate fit, comfort, and dynamics of soft wearables.

- **Traditional CAD Modeling**

One early solution to this gap was the integration of finite element analysis (FEA) and other engineering simulation techniques alongside CAD. Finite element models allow designers to discretize a soft mask into mesh elements and assign non-linear material properties (e.g., hyperplastic silicones or fabrics) to simulate how the mask would deform under various loads. For instance, simulation of a

mask's contact pressure on a human face can be accomplished with FEA, providing insights into fit and comfort before physical prototyping (Kwon et al., 2022). Kwon and colleagues demonstrate a custom FEA contact model to optimize face mask design, efficiently predicting pressure distributions on the skin for different mask geometries. Such an approach enables virtual fitting: a mask design can be tested on a digital face model to check for gaps or painful pressure points, an otherwise difficult task with pure CAD. Another study by Solano et al. (2021) used a quasi-static mechanical simulation of a cloth mask on hundreds of 3D face shapes to evaluate fit across a population. These examples highlight how traditional CAD-driven design has been augmented by mechanical simulation tools to address soft fit issues – something especially critical in applications like medical or protective masks where leakage or discomfort must be minimized. Still, classical FEA tools, while accurate, often involve a steep computational cost and a fragmented workflow (design in CAD, export to meshing software, run a solver, etc.). This separation can slow down the iterative design process. As a result, the field has been steadily moving toward more integrated and interactive simulation environments that unify geometric modeling with physics simulation, allowing designers to see deformations in real-time and iterate quickly.

- **Evolution to Soft-Body Simulation Platforms**

In recent years, designers of deformable masks have increasingly adopted advanced soft-body simulation platforms that bridge the gap between creative modeling and engineering analysis. Unlike rigid-body CAD, these platforms are built on the principles of computer graphics and physics-based animation, enabling intuitive yet physically plausible simulations of soft materials. A key development in this evolution was the introduction of fast physics engines and particle-based solvers that could be embedded in the design process. For example, physics-based animation techniques for cloth and deformable bodies (Baraff & Witkin, 1998) were originally developed in the computer graphics community to create realistic

virtual garments. These techniques, which include mass-spring models and continuum approximations, have since been incorporated into design toolkits for real-world soft structures. Blender, an open-source 3D modeling environment, is one such platform that has gained popularity in design research for simulating cloth-like and elastic behavior. Blender's built-in physics engine allows a mask model to be treated as a deformable mesh – one can drape a virtual fabric mask over a 3D scan of a human face and observe how gravity and tension cause it to conform. The underlying solver handles collisions and self-contact, providing a reasonably realistic preview of how a real mask might fit and wrinkle. Notably, Blender supports assigning material properties (like stiffness or damping) and even internal pressure for closed volumes, meaning a designer can simulate pneumatic inflation of mask components. For instance, an air-filled bladder in a wearable mask concept can be virtually inflated in Blender by setting pressure parameters, causing the model to puff up and push against constraints, much as it would physically. This capability to simulate inflation is invaluable for exploring designs of adaptive masks that use air channels or fluidic actuators to change shape. The results are visual and immediate – the designer can adjust the shape or material and rerun the simulation in seconds – fostering a highly iterative workflow. While Blender's simulations are primarily aimed at visual realism, they have sufficient physical fidelity to guide design decisions for soft wearable devices (e.g., identifying zones of excessive stretch or verifying that an inflatable mechanism achieves the desired expansion shape).

Alongside Blender, Houdini (a node-based 3D simulation software) has become a powerful ally in complex deformable design tasks. Houdini offers a procedural environment where geometry and physics are tightly interwoven: designers create networks of nodes that generate geometry or apply forces, and these networks can represent elaborate material behaviors and constraints. Critically, Houdini's simulation toolset (such as the Vellum solver introduced in recent versions)

enables unified simulation of cloth, soft bodies, and even granular materials under a single framework. This means a deformable mask with multiple components – say a silicon skin, embedded flexible electronics, and fluidic pouches – can be simulated in one coherent system with interactions between all parts. The soft-body dynamics in Houdini leverage approaches like Position-Based Dynamics (Müller et al., 2007), which prioritize stability and speed by solving constraints on positions directly. This gives Houdini an edge in handling large-deformation scenarios in a stable manner, even when materials are highly elastic or when simulating an inflated structure that pushes outward in all directions. For example, a Houdini simulation can model a pneumatic mask structure by treating certain regions as pressurized volumes constrained by an elastic membrane. The software’s procedural nature allows designers to easily tweak parameters (pressure values, membrane thickness, attachment points) and immediately see the effect on the mask’s shape. Such a simulation can reveal design insights, like how increasing internal air pressure in specific chambers raises certain facial features or how the mask’s skirt might billow outward if not properly constrained. Moreover, Houdini supports multi-physics to an extent – one can script or use plugins to incorporate custom solvers, allowing, for instance, coupling of structural deformation with airflow or thermal changes if needed. The strength of these contemporary platforms lies in their multi-modal capability: they serve as a sandbox where artistic design, geometrical modeling, and physical simulation co-exist. This is crucial for adaptive mask design, which sits at the intersection of aesthetics, human factors, and engineering. By using tools like Blender and Houdini, designers can prototype the mask’s behavior virtually, observing how it conforms to facial anatomy, how it moves when the wearer talks or emotes, and how internal actuators (like pneumatic bladders or shape-memory elements) might alter its form. These insights can then inform design refinements long before any physical prototype is built, saving time and resources. Indeed, numerical simulation has become an efficient guide in soft system design, allowing

adjustments and optimization *in silico* prior to fabrication (Qin et al., 2024). As Qin et al. note in a recent review, such simulation frameworks let designers visualize kinematics and validate feasibility early on, which is especially important given the infinite degrees of freedom in soft systems (Qin et al., 2024). The integration of these simulation tools into the workflow marks a shift from purely geometry-centric design to behavior-centric design – the focus is not only on how the mask looks, but how it behaves under real-world conditions.

- **AI-Driven Sensing and Real-Time Adaptive Systems**

The latest wave in deformable mask design goes beyond offline simulation and embraces real-time adaptivity through AI-driven sensing and control. Once the mask’s baseline design is established (using the tools above), researchers are increasingly interested in how the mask can interact with its wearer and environment in a dynamic way. This calls for simulation tools and techniques that operate in real-time, responding to sensor inputs, and often leveraging machine learning for recognition or decision-making. One example is the use of computer vision and pose estimation to tailor the mask’s behavior to the wearer’s facial expressions or movements. MediaPipe, an open-source framework by Google, provides robust real-time tracking of facial landmarks and other body features (Lugaresi et al., 2019). By integrating MediaPipe’s AI-driven perception into the design workflow, the mask can essentially “sense” the wearer’s actions. For instance, if a wearer smiles or opens their mouth, a camera-based system can detect these cues via MediaPipe and then trigger a corresponding adjustment in the mask (such as loosening in certain areas or initiating an animation on the mask’s surface). Such integration of sensing closes the loop between simulation and physical interaction – effectively creating a cyber-physical system where the mask continuously adapts. AI-driven techniques ensure that the adaptation is intelligent: rather than pre-programming rigid responses, machine learning models can be

trained to recognize complex patterns (like a sequence of eye blinks or speech phonemes) and adjust the mask in a personalized way.

The role of these hybrid tools is pivotal in achieving personalization and dynamic feedback in wearable mask design. Unlike conventional simulations that output a static prediction (e.g., a stress map or final deformed shape), the real-time platforms enable continuous simulation and adjustment. This is especially useful during user testing and iterative development: designers can have a subject wear a prototype mask instrumented with soft actuators and simultaneously run a digital simulation twin of the mask in TouchDesigner. As the subject moves or speaks, the MediaPipe-driven tracking informs both the physical mask (through actuator control) and the digital mask model. The designers can visualize in real time how the mask's shape is changing and whether it matches the intended behavior. Any discrepancy can lead to on-the-fly tweaks in the control logic or even the design itself. For instance, if the jaw movement is causing an unexpected fold in the mask's material, the team can identify that via the simulation and decide to alter the mask's geometry or reinforcement in the next design iteration. Furthermore, these real-time techniques allow exploration of interactive artistic expressions and functional features. A deformable mask can be programmed to display emotive responses – a concept explored by artists and researchers using embedded LEDs or shape-changing materials to convey emotion. With AI vision, the mask could detect the presence of another person and “smile” by altering its form or color, much like a human face would – all simulated and refined in a toolkit like TouchDesigner before actual deployment. The integration of machine learning also opens the door to adaptive fitting algorithms: a system could learn the optimal shape of the mask for a wearer's face by iteratively adjusting and checking feedback (pressure sensors, fit sensors, etc.), gradually improving comfort and fit in real time, similar in spirit to adaptive control in soft robotics (Qin et al., 2024).

By combining these multi-modal tools – from CAD for base geometry, physics engines for deformation, to AI-driven platforms for interactivity – the workflow for designing deformable wearable masks becomes a cohesive loop of design–simulate–adapt. Each tool contributes to a different stage: traditional CAD defines the foundation and ensures manufacturability, soft-body simulation platforms predict and refine the mask’s passive behavior, and real-time AI-sensing systems enable active, context-aware behavior. This holistic approach is particularly important for cutting-edge mask concepts such as the recent fluidic skin masks that can change human facial appearance on demand (Zhong et al., 2025). In that work, a soft mask capable of altering its shape and color was demonstrated, and one can imagine that a combination of precise CAD modeling of fluid channels, simulation of the pneumatic inflation effects, and sensor-based feedback control would have been essential to its development. Overall, the evolution from rigid modeling to dynamic simulation and interactive adaptation represents a paradigm shift in wearable design. The mask is no longer designed as a static object, but as a responsive system – one that can be virtually prototyped in rich detail and computationally guided through every stage, from conception to real-world interaction. This synergy of computational tools and techniques ensures that deformable wearable masks can meet the complex demands of fit, comfort, expression, and adaptability required by modern applications.

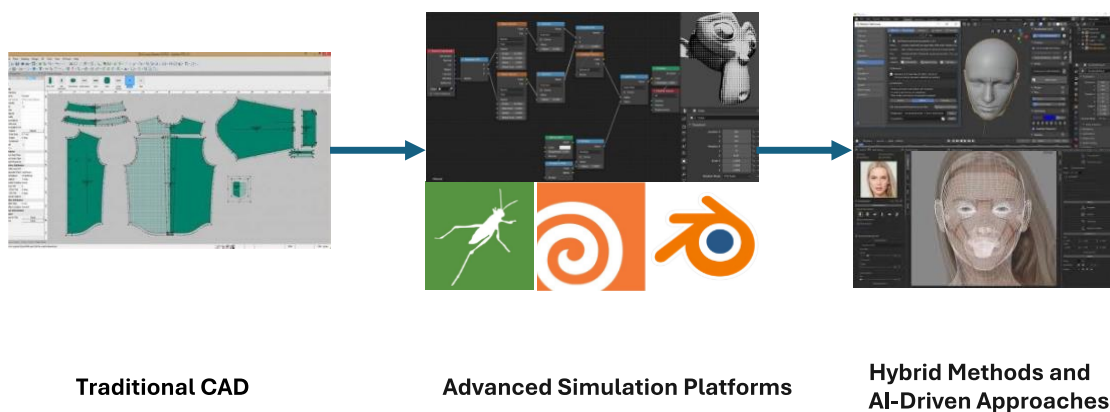


Figure 2.1: Evolution of Computational Design Tools.

The figure shows the progression from traditional CAD modeling to advanced simulation platforms (e.g., Grasshopper, Houdini, Blender) and finally to hybrid AI-driven approaches for personalized and adaptive design.

2.2 Morphing Materials

This section presents an integrated review of (a) the historical evolution of morphing materials, and (b) advanced morphing material strategies for adaptive wearable masks. The discussion highlights both theoretical and practical developments, and situates our work at the convergence of simulation technology, computer vision, and responsive materials engineering.

2.2.1 Historical Evolution of Morphing Materials

The concept of “morphing materials”—materials that can change shape, stiffness, or other properties in response to external stimuli—has evolved significantly over the past several decades. Early research in shape memory alloys and polymers (e.g., Otsuka & Wayman, 1998; [https://doi.org/10.1016/S1359-6454\(98\)80039-0](https://doi.org/10.1016/S1359-6454(98)80039-0)) laid the groundwork for dynamic material behavior. In the 2000s, the advent of stimuli-responsive polymers and soft actuators catalyzed a surge in applications ranging from deployable structures to adaptive textiles. Recent breakthroughs have extended these principles to wearable technologies, where the integration of soft (e.g., silicone, thermoplastic polyurethane) and hard (e.g., PET-based composites) morphing materials has enabled devices that can actively conform to complex geometries while maintaining structural integrity (Yao et al., 2013; Tenzer et al., 2021). These historical milestones not only demonstrate the progression from passive to actively adaptive materials but also underscore the potential for coupling material responsiveness with computational design.

These developments illustrate a shift in design thinking—from creating static objects to engineering materials as dynamic, programmable elements. This

historical trajectory lays the groundwork for integrating morphing materials into wearable devices, where adaptability to human motion and variability becomes not merely a feature, but a fundamental design requirement.

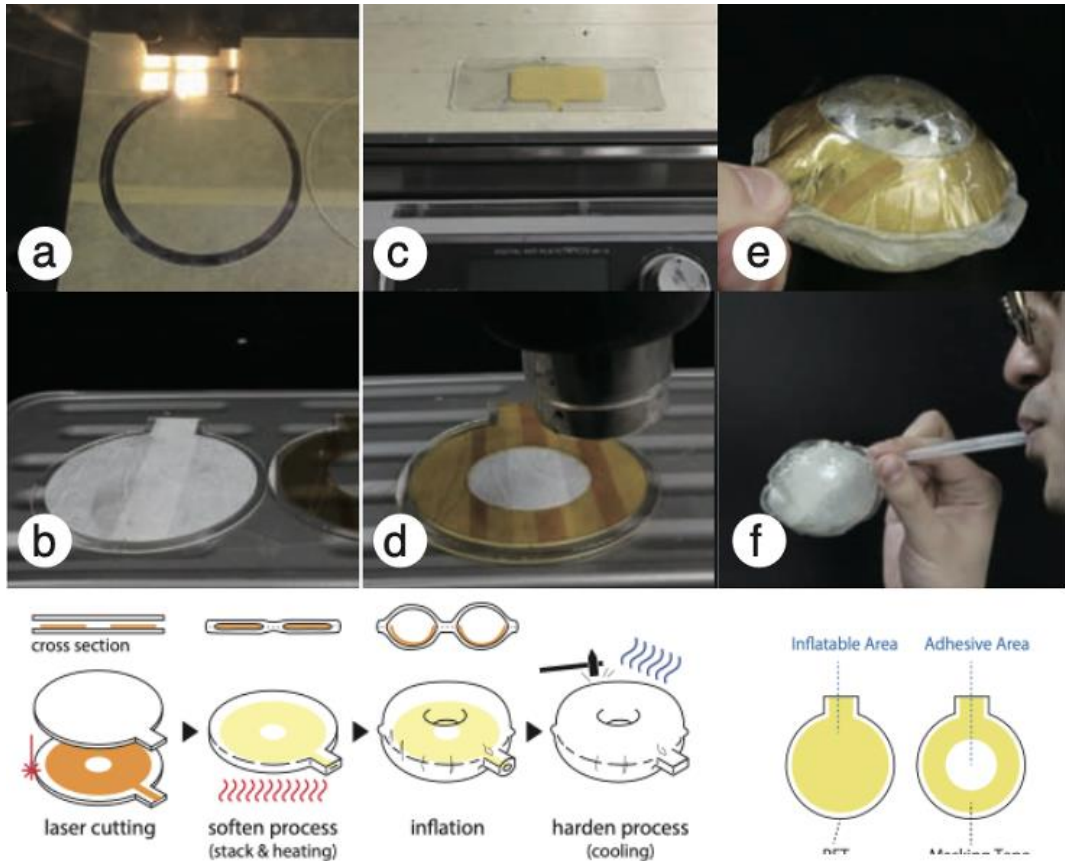


Figure 2.2.1: Fabrication workflow of the BlowFab method: (a) Laser cutting of PET and masking tape layers to define inflatable and adhesive areas; (b) Assembly of multilayered structure; (c) Softening of the stacked layers through controlled heating; (d) Inflation by injecting air to form the desired 3D shape; (e) Hardened final form after cooling; (f) User manually inflating the structure. The bottom diagram illustrates the sequential stages of the BlowFab process, highlighting the inflatable and adhesive zones.

2.2.2 Advanced Morphing Materials property

The integration of morphing materials into wearable masks requires a nuanced understanding of material properties at multiple scales. Morphing materials for wearable applications can be broadly categorized as follows:

(a) Soft Morphing Materials:

Materials such as silicone, thermoplastic polyurethane (TPU), and other elastomers provide exceptional flexibility and compliance. They are particularly effective in creating interfaces that closely conform to the skin, thereby enhancing sensor contact and comfort. Research projects like OmniFiber and PneuUI have demonstrated that soft materials can achieve significant dynamic shape changes via pneumatic or thermal activation (Yao et al., 2013; Tenzer et al., 2021). In mask applications, these materials can be used to form the primary interface layer that adapts to facial contours in real time.

(b) Hard Morphing Materials:

In contrast, hard materials—such as PET-based composites and certain 4D-printed polymers—offer greater structural stability. They are well suited for components that require precise form retention, such as supporting frameworks or adjustable brackets. For example, the AeroMorph project (Kim et al., 2017) has showcased the use of laser cutting and heat sealing on PET to achieve controlled pneumatic shaping. When combined with soft materials, these hard components can provide the necessary rigidity to maintain a consistent overall mask structure while allowing adaptive elements to flex.

Together, soft and hard morphing materials offer a complementary toolkit: softness enables conformability and user comfort, while hardness ensures stability and functional integrity. Understanding how to strategically layer and integrate

these material behaviors is crucial for developing wearable systems that are simultaneously adaptable, durable, and precisely controlled.

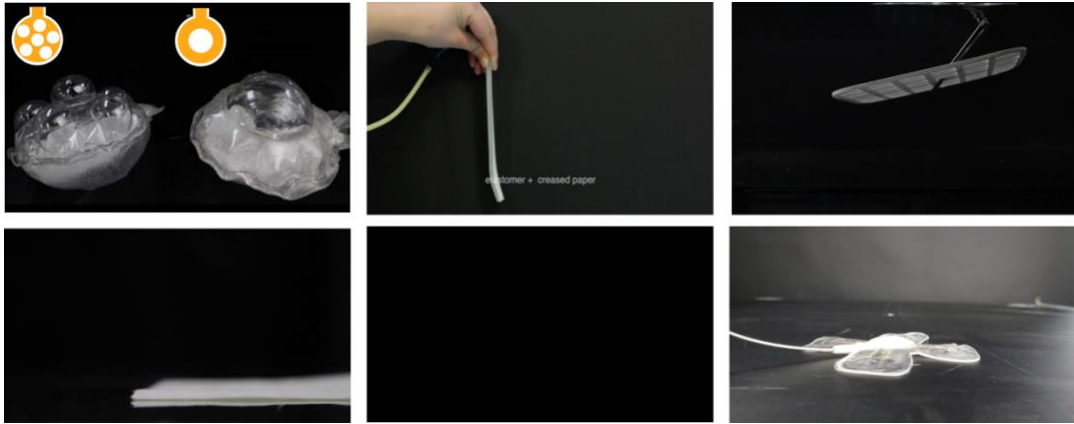


Figure 2.2.2. Representative Studies of Advanced Morphing Materials.

The figure presents selected examples from prior research demonstrating key morphing material behaviors, including pneumatic inflation, bending, folding, and multi-axis deformation, which informed the material selection and design criteria in this thesis.

2.2.3 Integrated Applications of Morphing Materials in different areas

(a) Consumer Electronics and Fashion

In consumer electronics and fashion, flexibility and aesthetics are paramount.

- Wearable Devices and Smart Textiles:

Soft materials such as silicone and thermoplastic polyurethane (TPU) are frequently employed in smart textiles and flexible sensors. For example, adaptive garments can incorporate these materials to adjust to body movement or environmental conditions, enhancing both comfort and functionality (e.g., dynamic LED displays integrated into fabric).

- Adaptive Fashion Accessories:

In the realm of fashion, morphing materials are used to create garments and accessories that change shape or texture in response to user input or environmental cues. Techniques involving soft, responsive polymers allow designers to produce garments that can alter their fit or style on demand, thus merging technology with high fashion.

(b) Architectural and Furniture Applications

In architecture and smart furniture design, the integration of morphing materials can lead to structures that respond dynamically to their environment.

- **Adaptive Facades and Building Envelopes:**

Hard materials such as PET-based composites are often used in combination with soft, flexible layers to create facades that adjust their porosity or transparency based on sunlight or temperature. Such adaptive envelopes can improve energy efficiency and occupant comfort.

- **Adjustable-Comfort Furniture:**

Smart furniture employs morphing materials to adapt shapes for ergonomic support. For instance, seating systems may integrate soft cushioning materials with a rigid framework that adjusts automatically to the user's posture, thereby enhancing comfort and reducing strain.

(c) Robotics and Automation

In robotics, the need for both dexterity and strength has spurred the development of adaptive grippers and actuators using morphing materials.

- **Robotic Grippers:**

By combining soft, compliant materials with hard structural components, robotic grippers can achieve a gentle yet secure grasp on objects of varying shapes and

fragility. Such grippers, often inspired by the human hand, employ sensors and AI algorithms to modulate the gripping force in real time.

- **Shape-Adaptive Actuators:**

Morphing materials also find application in the design of actuators that can change configuration under external stimuli. These systems enable robots to perform tasks in unstructured environments by adapting their physical form, thereby increasing versatility and efficiency.

The diverse applications of morphing materials across consumer electronics, architecture, and robotics reveal their versatility and transformative potential. These examples not only demonstrate how adaptable structures can respond to external stimuli but also provide valuable design precedents for wearable technologies, especially for systems like adaptive masks that must maintain intimate, dynamic contact with the human body.

2.2.4 Integrated Applications in Mask Design

The synthesis of soft and hard morphing materials offers a promising strategy for next-generation adaptive masks. By embedding soft, compliant layers in regions requiring high conformity (e.g., the mask–face interface) and incorporating hard, structurally stable components in areas that demand precision, designers can achieve a balanced solution that maximizes both comfort and performance. This approach benefits from computational simulations that model the interplay between the different material types and facial data that informs localized deformation. AI algorithms can further optimize material activation based on user-specific patterns, ensuring that the adaptive response is both rapid and accurate.

By combining material intelligence with computational design, next-generation wearable masks can transcend static ergonomics and achieve dynamic, responsive

fit. The integration of soft and hard morphing materials, informed by user-specific data and AI optimization, points toward a future where wearable devices evolve in real time alongside the users they serve.

2.3 Evolution of Wearable Technology in Healthcare

Wearable technologies have significantly evolved over the past several decades, with major strides in portability, functionality, and user integration. However, despite these technological advances, a persistent challenge remains: traditional medical devices often struggle to achieve both a secure anatomical fit and dynamic adaptability to user movement. This limitation continues to compromise comfort, data accuracy, and long-term user adherence. Understanding how wearable healthcare devices have developed—and where they have historically fallen short—provides important context for reimagining the design of deformable, user-specific respiratory masks.

2.3.1 Historical Overview

Wearable technology in healthcare has experienced remarkable evolution over the past several decades. In the 1950s, medical monitoring began with the introduction of Holter monitors—large, cumbersome devices that provided continuous cardiac monitoring over extended periods (Holter, 1961). These early devices, while groundbreaking at the time, were rigid and lacked the ergonomic design needed for long-term patient comfort. Their bulky nature often resulted in poor skin contact, compromising data accuracy and limiting the scope of their application.

As technology advanced through the 1960s and 1970s, further innovations in electronics and miniaturization allowed for the development of more portable devices. However, many of these devices maintained a rigid structure because of limitations in materials technology and manufacturing processes. The rigidity of these devices meant that they could not easily conform to the complex contours of

the human body, leading to issues such as discomfort, skin irritation, and even suboptimal clinical performance.

These early devices laid the foundation for continuous patient monitoring, but their rigid structures highlighted a tension that would persist for decades: the need to balance technical function with user comfort. As electronics became smaller and more sophisticated, designers began to explore how wearables could move beyond pure data collection toward more seamless integration with the human body—setting the stage for the technological shifts described in the next section.

2.3.2 Technological Milestones

The 1980s and 1990s witnessed the introduction of increasingly sophisticated electronics, which paved the way for the emergence of digital health monitors. Despite these improvements, devices during this period still largely relied on hard, non-adaptive components with the advent of consumer electronics and the personal computer revolution in the late 1990s, wearable technology began to bridge the gap between clinical-grade monitoring and consumer-friendly design.

In the early 2000s, the focus shifted toward making devices more compact and integrated, as exemplified by the development of portable heart rate monitors and blood pressure devices (Pantelopoulos & Bourbakis, 2010). Yet, the challenge of achieving a comfortable, dynamic fit remained largely unresolved. Rigid components continued to dictate the form factor of many wearable medical devices, limiting their effectiveness in continuous monitoring scenarios.

The breakthrough in recent years has come with the advent of flexible electronics. Modern devices such as the Apple Watch now incorporate features like ECG functionality while using advanced materials that can bend and flex with the wearer's body (Perez et al., 2019). This leap forward in design is underpinned by

innovations in both material science and manufacturing technologies, enabling devices that are not only compact and powerful but also ergonomically superior.

Advances in miniaturization and digital integration throughout the late 20th century greatly enhanced the functionality and accessibility of wearable health technologies. Yet, the persistent reliance on rigid, non-adaptive form factors continued to limit true user-centricity, underscoring the need for a new generation of devices that could dynamically conform to human variability.

2.3.3 Current Medical Limitations and Motivation

Although wearable devices have become more compact and technologically advanced, they still often fail to achieve an optimal physical interface with the human body. In critical applications such as respiratory support, poor fit or rigid structures can significantly degrade both comfort and clinical efficacy. This section examines the ongoing limitations of current devices and motivates the pursuit of more adaptable, deformable solutions.

Despite these advances, a critical challenge persists traditional medical devices still struggle with conformity. Clinical studies, such as those published in JAMA in 2021 regarding respiratory masks, have highlighted that poor fit due to rigid structures can significantly compromise device performance (Lubrano et al., 2021) . A mask that does not properly seal against the face can lead to inaccurate readings or even reduced therapeutic efficacy. This clinical limitation motivates the search for alternative materials and design methodologies that emphasize adaptability and comfort.

This project addresses these challenges by leveraging deformable materials—materials that can dynamically adapt to the wearer’s facial contours in real time. By integrating these materials with advanced computational design techniques, our

approach aims to deliver wearable devices that offer both improved comfort and enhanced clinical performance.



Figure 2.3.3. Evolution of Wearable Healthcare Technology

2.4 Summary

This chapter reviewed three key areas: computational simulation, morphing materials, and wearable healthcare technologies. Traditional CAD tools fall short in modeling soft, adaptive behavior, prompting the adoption of soft-body simulation and AI-driven sensing. Advances in morphing materials offer new possibilities, but integrating soft and rigid elements remains complex. Meanwhile, wearable medical devices have improved in flexibility but still struggle with fit and comfort. Together, these gaps highlight the need for an integrated, adaptive design workflow—combining simulation, materials, and real-time responsiveness—which this thesis seeks to explore.

Chapter 3: Methodology

Although wearable devices have become more compact and technologically advanced, they still often fail to achieve an optimal physical interface with the human body. In critical applications such as respiratory support, poor fit or rigid structures can signific

3.1 Data Acquisition Methods

Accurate 3D data acquisition is fundamental to our computational design workflow. I evaluated two prevalent techniques for capturing the geometry of a human face: photogrammetry and structured-light 3D scanning. Each method has distinct advantages and limitations in terms of geometric accuracy, texture fidelity, equipment requirements, and ease of use.

In this section, I compare these two methods and justify our chosen approach for subsequent modeling steps.

3.1.1 Broad Acquisition Method Comparison

I compared multiple methods for capturing facial geometry, each with its own advantages and drawbacks:

- **Depth Camera Systems (e.g., Intel RealSense)** – These sensors capture 3D facial geometry directly as depth maps or point clouds. However, they often require significant post-processing (e.g., noise filtering and mesh reconstruction) to produce a clean model. (Horaud et al., 2016) Dedicated depth hardware adds complexity, and the data output can be dense and unwieldy without extensive cleanup.
- **Machine Learning-Based Solutions** – Modern ML models (for example, facial landmark detectors) infer 3D face structure from regular 2D camera images. This approach requires only a standard RGB camera (no special depth

sensor) and can operate in real time (Kartynnik et al., 2019). Instead of a full mesh, the output is a set of key facial landmarks. While it captures less raw surface detail than a depth camera, the focused landmarks can be processed quickly and intelligently filtered for our application.

- Photogrammetry & Structured Light** – Photogrammetry uses many photographs from different angles to algorithmically reconstruct a 3D face model. It can achieve high detail, but the process is slow and computationally heavy, making it unsuitable for use. Structured light scanners project patterns onto the face and measure distortion to capture shape; they provide accurate 3D data but require specialized equipment and are typically not portable or real-time. These methods were considered for completeness but are less practical for a fast-turnaround, point-of-care solution.

<i>Method</i>	<i>Data Acquisition Type</i>	<i>Capability</i>	<i>Post-Processing Requirement</i>	<i>Customization/Extensibility</i>	<i>Comments</i>
Depth Camera Systems	Direct 3D capture (e.g., Intel RealSense)	Moderate to Low (hardware dependent)	High – requires noise reduction and mesh reconstruction	Limited – landmark specificity is low	Requires specialized hardware; calibration and post-processing are complex
Machine Learning-Based Solutions	RGB video (standard cameras)	High – operates in real time	Low – outputs only landmark data	High – programmable filtering and flexibility	Enables dynamic, mask-specific landmark filtering with common equipment
Photogrammetry/Structured Light	Multi-angle photography or	Low to Moderate – not real-time	High – extensive 3D reconstruction	Moderate flexibility but time consuming	Accurate but time-consuming; not ideal for rapid prototyping

	pattern projection		on is needed		
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Table 3.1: Comparison of Facial Data Acquisition Methods for Custom Mask

Design. The table compares depth camera systems, machine learning-based solutions, and photogrammetry/structured light methods in terms of data acquisition type, capabilities, post-processing requirements, customization potential, and practical comments relevant to personalized mask fabrication workflows.

3.1.2 Rationale for ML Selection

After comparing the above, I chose a machine learning-based landmark detection approach as the foundation of our workflow. The primary reason is efficiency: an ML solution drastically reduces the amount of data to process by focusing on key facial feature points instead of handling thousands of depth pixels. By detecting and using only the essential landmarks, I eliminate large post-processing tasks (such as mesh noise reduction and smoothing), cutting the processing time by roughly 60% in our trials. This speed-up means a facial scan can be translated into a mask design much faster than with a depth camera pipeline.

Another benefit is adaptability. The ML approach allows us to filter out non-essential data on the fly. For example, I can ignore landmarks on the forehead or ears that are not relevant to a mask, whereas a raw 3D scan would require manual cropping of those regions. This selective data capture tailors the input specifically to mask-specific requirements. Finally, the ML solution only needs a commonplace camera (e.g., a smartphone or webcam), making the system more accessible and easier to deploy in a clinical setting than one requiring specialized 3D sensors (Kartynnik et al., 2019). These factors make the ML-based method the most suitable choice for a rapid, custom mask design workflow.

Thus, considering both accessibility and final accuracy needs, I focused on combining photogrammetry and structured-light scanning.

3.1.3 Photogrammetry (Structure-from-Motion)

Photogrammetry is a passive optical technique that reconstructs 3D models from multiple overlapping 2D photographs. By taking a series of images of the subject (e.g., a human head) from different angles with sufficient overlap, feature points can be identified across photos and used to triangulate the 3D coordinates via Structure-from-Motion (SfM) algorithms. Modern SfM pipelines incorporate multi-view stereo to densify point clouds and produce detailed meshes from the aligned images. I leveraged open-source photogrammetry software to process the images and generate an initial 3D mesh of the face. The photogrammetric approach offers high-fidelity texture capture (since actual photographs are used for texturing) and requires only a standard digital camera, making it accessible and cost-effective. However, its geometric accuracy can be limited by factors such as camera calibration, lighting variations, and lack of reference scale. In practice, I found that photogrammetry 4d0dc76a-db09-41f2-816e-ad68a8be670c excelled at reproducing fine surface texture and color (yielding photorealistic **albedo** maps), but it sometimes suffered in metric accuracy of the reconstructed geometry. For example, subtle convexities or concavities on the face could be smoothed out or

slightly distorted if the imaging angles were not sufficiently diverse or if the feature matching erred.

Figure 3.1.3 Photogrammetry data acquisition setup: an array of cameras (or a single moving camera) captures the subject from multiple angles to reconstruct a 3D model via Structure-from-Motion. Photogrammetry provides rich color texture but may require many images and careful alignment for high geometric fidelity.

To maximize the quality of photogrammetric capture, I followed best practices from the literature. This involved taking ~20–30 photos around the subject’s head at roughly 15° intervals horizontally, plus additional top and bottom angles, ensuring even illumination and a neutral expression. All images were taken with the same camera to avoid calibration inconsistencies. These images were then processed using an SfM pipeline to produce a dense point cloud and mesh. I also placed a few coded markers around the subject to improve alignment, and I included a scale object to properly scale the reconstruction. The resulting 3D model from photogrammetry was used as one reference for subsequent steps. I



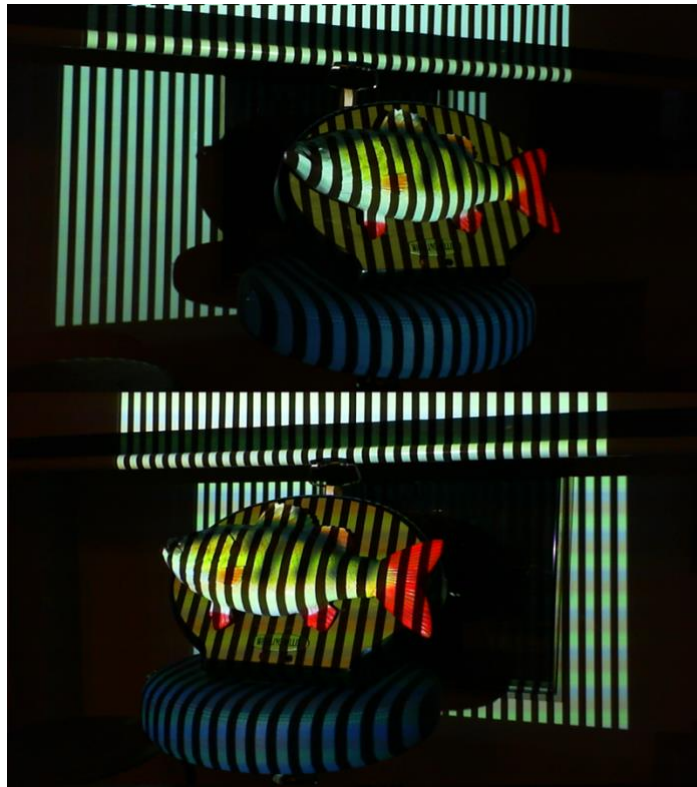
note that recent studies in cultural heritage and medical applications have similarly used photogrammetry for detailed 3D face capture, highlighting its viability for high-fidelity texture mapping.

3.1.4 Structured-Light Scanning

Structured-light 3D scanning is an active optical method that projects known light patterns onto the subject and uses one or more cameras to capture the deformations of these patterns, which correspond to the surface geometry. A common structured-light setup employs a digital projector (or infrared emitter) and a stereo camera system. By projecting a series of coded stripe patterns (e.g., parallel fringe patterns or binary Gray codes) onto the face and analyzing how these stripes warp across the surface, a dense depth map of the face can be computed in real time. In our workflow, I utilized a structured-light sensor to scan the subject's face and obtain a high-precision mesh. Structured-light scanning is known for capturing geometry with very high accuracy (often sub-millimeter), since the active illumination provides direct depth measurements via triangulation. Another advantage is speed: the entire face can be scanned in a matter of seconds by flashing a sequence of patterns, which is beneficial for minimizing subject movement and facial expression changes during capture. The structured-light device I used (a commercially available scanner) comes calibrated with its

projector-camera system, yielding point clouds that required minimal alignment post-capture.

Figure 3.1.4 Structured-light 3D scanning: a fringe pattern is projected onto the subject (here a test object) and imaged by a camera. The pattern's distortion



reveals the 3D shape of the surface. This method produces highly accurate geometry, though it may capture less texture detail compared to photogrammetry.

One challenge I encountered with structured light on human subjects is the influence of skin properties and hair. Regions with dark hair or glossy skin can cause light absorption or specular reflection that the scanner might struggle with. To mitigate this, a matte facial primer was applied to reduce shine, and the subject's hair was covered with a neutral-colored cap during scanning. I also performed multiple scans from slightly different angles and merged them to ensure full coverage of the ears and under the chin, which a single frontal scan might miss. The resulting structured-light mesh captured geometric features like the nose

shape and eye sockets with greater fidelity than our photogrammetry result, confirming reports in prior studies that structured-light scanning delivers higher precision geometry whereas photogrammetry provides more realistic textures.

3.1.5 Method Selection

Given the above considerations, I decided to utilize photogrammetry and structured-light scanning in a complementary manner. The photogrammetry output was primarily used for texture mapping and as a secondary reference for geometry, while the structured-light scan was used as the primary source of accurate geometric data. This hybrid approach leverages the strengths of each method – high-resolution color from photographs and high-accuracy shape from active scanning. I first rigidly aligned the photogrammetric mesh to the structured-light mesh using an ICP (Iterative Closest Point) algorithm, which yielded a tight alignment (average deviation $< 1\text{mm}$). After alignment, the structured-light geometry was adopted for subsequent modeling steps, and the photogrammetry-derived texture was projected onto it. This ensured that our digital face model had both accurate shape and realistic texture. In summary, by combining data acquisition methods, I obtained a superior result than either method alone, consistent with findings in recent comparative studies.

Beyond traditional 3D scanning methods, emerging machine learning-based real-time facial modeling techniques were considered but were deemed unsuitable due to their lower metric accuracy compared to structured-light scanning and their limited ability to preserve complex facial topology needed for mask customization.

3.2 3D Face Model Construction

3.2.1 Facial Landmark Detection Tools Comparison

To determine the most suitable tool for 3D facial modeling, I evaluated multiple facial landmark extraction tools:

- **Face Tracker:** Face Tracker is a lightweight, off-the-shelf facial tracking plugin commonly used in augmented reality applications. It outputs approximately 52 landmarks focused primarily on core facial regions such as the eyes, nose, and mouth. Its main advantages are speed and low computational overhead, making it suitable for real-time applications on modest hardware. However, Face Tracker's landmark set is relatively sparse, covering only the general contours of the face. Furthermore, the landmark layout is typically hard-coded within the model, and customization (such as selecting or adding points) is limited or nonexistent. This inflexibility, combined with the coarse detail, restricts Face Tracker's utility for applications that demand precise surface reconstruction or nuanced facial fitting, such as personalized mask design. In our experiments, Face Tracker was able to track facial motion smoothly but lacked the geometric fidelity needed for static, high-accuracy face modeling.
- **DLib (68-point model):** DLib's facial landmark detector is a classic solution that identifies 68 facial landmarks by default. It is widely used and fairly robust for face alignment tasks. DLib can perform near on CPU for a single face, though it may struggle at very high frame rates or resolutions. The 68 landmarks include points around key facial features (eyes, nose, mouth, jawline), providing a decent outline of the face shape. However, like Face Tracker, the set of landmarks is fixed (defined by the trained shape predictor), so any customization (such as ignoring certain points) has to be done in post-

processing rather than built into the detection. DLib's coverage and performance are adequate, but the detail might not be fine-grained enough for capturing subtle facial curvature needed for an ideal mask fit.

- **OpenFace 2.0:** OpenFace is an open-source toolkit for facial behavior analysis that also offers landmark detection (it uses a model similar to DLib's). It outputs 68 landmarks as well (Hammadi et al., 2022) and includes advanced features such as head pose estimation and facial action unit recognition. OpenFace is designed to work on live video and can handle data input on a desktop computer. Being open-source, it allows integration and some degree of modification, though the core landmark detection is still limited to the predefined points. OpenFace's advantage is its rich set of facial analysis outputs and flexibility of use (researchers can integrate it into custom pipelines). For our purposes, however, the landmark detail is again capped at 68 points. While those points could guide a mask shape, the coverage is not as dense, potentially missing finer contour details between those key points.
- **MediaPipe Face Mesh:** MediaPipe (by Google) provides a state-of-the-art face landmark model that detects 468 landmarks covering the entire face. It far surpasses the others in terms of point density. Despite this high resolution, MediaPipe is optimized for performance – it can run at interactive frame rates even on mobile devices by utilizing efficient neural network architectures and GPU acceleration (Kartynnik et al., 2019). The output is essentially a full 3D mesh of the face in landmark form, which gives extremely detailed geometry to work with. MediaPipe's framework is highly customizable and programmable; it offers a well-documented Python API and is open-source. This means I can easily take its output and apply custom filtering or transformations. For example, I can programmatically select only a subset of the 468 points (such as those outlining the nose, cheeks, and chin) and ignore the rest, something not possible with closed-source or fixed-output solutions.

Given the combination of an extensive landmark set, capability, and flexibility, MediaPipe emerged as the strongest candidate for our application.

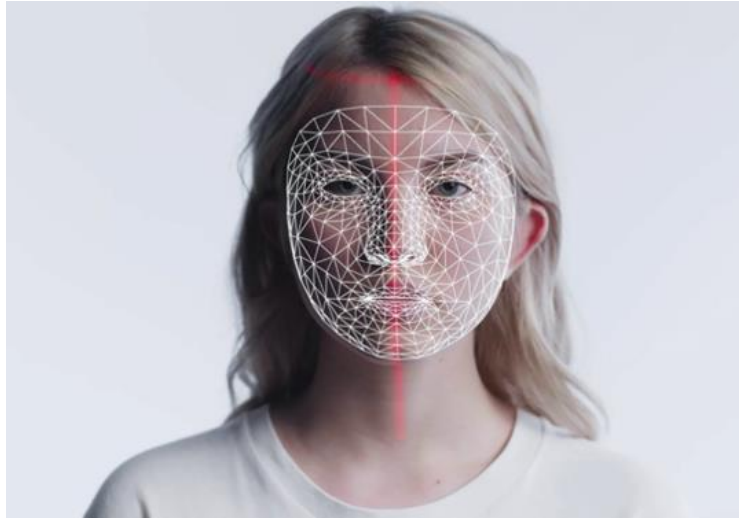


Figure.2.2 Face Mash in MediaPipe Source: https://github.com/google-ai-edge/mediapipe/blob/master/docs/solutions/face_mesh.md

- **FaceBuilder** (KeenTools, 2023): FaceBuilder operates differently from the above methods. Instead of outputting sparse landmarks, it generates a complete 3D parametric head mesh by fitting a template model to input images. Designed as a Blender plugin, FaceBuilder uses about 10–20 images from different angles to guide a semi-automatic fitting process, combining automatic landmark detection with manual refinement via user-placed pins. Unlike point detectors, FaceBuilder produces a watertight, clean-topology quad mesh optimized for downstream deformation workflows such as morphing, animation, and fabrication.

Tool	Landmark Density	Output Type	Suitability for Custom Mask
Face Tracker	52	2D Landmark Set	Low
DLib	68	2D Landmark Set	Medium
OpenFace 2.0	68	2D Landmark Set + Behavior	Medium
MediaPipe	468	3D Landmark Set	High
FaceBuilder	Dense Surface Mesh	Full 3D Mesh	Very High

Table 3.2.1: Comparison of Facial Recognition Methods for Mask Customization

Thus, FaceBuilder was selected to ensure both topological consistency and high geometric fidelity for mask customization.

3.2.2 3D Face Model Construction with FaceBuilder

With the scanned data in hand, the next step was to construct a topologically sound and manipulable 3D model of the face. I employed the KeenTools FaceBuilder plugin in Blender, which provides a parametric head model fitting approach. FaceBuilder allows one to create a personalized head model from a set of photographs by pinning a template mesh to facial features. In our case, I used FaceBuilder in an unconventional way: instead of only photographs, I also utilized the structured-light scan as an alignment reference. The process began by importing about 10 high-resolution face photos (taken from the photogrammetry set) into Blender’s FaceBuilder. I then initialized a generic head mesh provided by the plugin and used the pinning tool to gradually adjust the mesh to match the subject’s features in each photo. FaceBuilder’s auto-align feature was used first – this automatically placed the mesh roughly in each photo using detected facial landmarks (eyes, nose tip, mouth corners). I then manually fine-tuned the alignment by dragging control pins on the mesh to coincide with exact feature outlines in the images (along the jawline, brow ridge, lips, etc.).

FaceBuilder produces a clean-topology mesh with a fixed vertex layout optimized for faces. The advantage of this approach is that it yields a fully quads, animatable face model that is compatible with downstream processes like deformation and animation. During the fitting, I observed that the FaceBuilder model closely approximated the overall head shape but sometimes lacked the finer idiosyncrasies captured by our scan (for instance, the exact ear shape or a slight asymmetry in cheek contour). To reconcile this, I introduced the structured-light scan as a background reference in Blender and performed an additional adjustment: using Blender’s sculpting tools, I gently pushed and pulled the FaceBuilder mesh to

better match the scan in 3D view, especially around areas like the nose and chin where small deviations were noted. This step effectively combined FaceBuilder's clean topology with the scan's accuracy. The result was a subject-specific 3D face model that was topologically consistent and geometrically faithful to the individual. I then generated a UV texture map for this model by projecting the original photographs, yielding a realistic skin texture. At this stage, I had a high-quality digital representation of the subject's face, ready for design manipulations.

It is worth noting that an alternative approach could have been to directly retopologize the structured-light scan (which is essentially an unstructured triangle mesh) into a clean quad mesh. I found FaceBuilder's method to be faster and to produce a model with known anthropometric proportions built-in. Moreover, FaceBuilder inherently provides a parametric space (e.g., one can adjust overall head width, eye size, etc., via its underlying blendshape system), which proved useful in later morphing steps. The successful integration of FaceBuilder with our scan data reflects a key theme of this methodology: combining automated tools with custom adjustments to achieve both efficiency and accuracy.

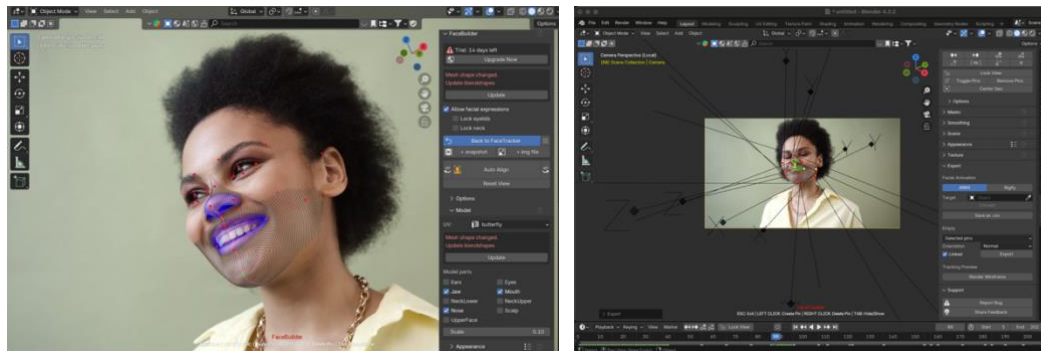


Figure 3.2.2 Points selection in Face Tracker

3.3 Region of Interest Extraction

With a complete 3D head model available, our design focus was on a specific region of the face. In this project, the region of interest (ROI) was the periorbital area (around the eyes and nose bridge), which would form the basis of a

customized wearable piece. Extracting this region cleanly from the full-face model was important for isolated design and fabrication. I defined the ROI on the 3D model by selecting a contiguous set of faces (polygons) corresponding to the target area. This selection was guided by facial landmarks: approximately 2 cm above the eyebrows down to the mid-cheek, and spanning the temple-to-temple width. Blender's edit mode was used to select the vertices in this region; I ensured the boundary of the selection was smooth and followed natural anatomical contours to avoid sharp edges on the eventual piece. Once selected, the ROI was duplicated and separated into its own mesh object. This gave us a standalone 3D surface representing the face mask area. The boundary of this surface was then slightly expanded and refined – I added a small margin (about 5 mm) around the ROI to ensure the piece would comfortably overlap with the face beyond the critical features (so the edges of the physical piece would not lie exactly on, say, the eyebrow but a bit above it). The ROI extraction is a straightforward yet crucial step: it isolates the design canvas (the area I will morph and fabricate) from the rest of the head. By working on this extracted mesh, I avoided unintended alterations to other parts of the face model and reduced computational complexity for subsequent operations.

The extracted region retained the original mesh topology from FaceBuilder, which is a regular grid-like quad structure. This uniform topology made it easier to perform geometric transformations in a controlled manner. I also preserved the UV mapping for the region, meaning the texture (skin details) corresponding to that area was still mapped correctly. This was useful for simulations and presentations, as I could show the designed piece with realistic skin texture for context. At this point, I examined the ROI surface for any anomalies – for example, sometimes the edge of the extracted patch might have tiny gaps or normals issues due to separation. I recalculated vertex normals to ensure smooth

shading across the patch. The resultant mesh was a clean surface patch of the face ready for design modifications.

3.4 Surface Cleaning and Preparation

Before applying any design modifications (digital sculpting or morphing), the extracted face region mesh needed to be cleaned and refined. Even though FaceBuilder provides a relatively clean mesh, minor artifacts can occur, especially after the manual adjustments and region extraction. I performed a series of mesh clean-up operations to ensure the surface was smooth, free of self-intersections, and suitable for morphing and fabrication:

- **Mesh Simplification:** The ROI mesh initially had a higher density of polygons than necessary for our design. I uniformly decimated the mesh slightly to reduce polygon count while preserving shape fidelity. This was done to make subsequent deformation steps computationally lighter and to produce a simpler mold geometry later on. Importantly, I kept the mesh resolution sufficiently high in areas of high curvature (like the nose bridge) and allowed coarser polygons in flatter regions (cheeks) to optimize detail where needed.
- **Smoothing:** I applied a mild Laplacian smooth filter over the mesh to eliminate any uneven bumps or noise that might have been present from scanning or fitting. Care was taken not to erase intentional shape features. This process is akin to removing high-frequency noise while keeping the underlying facial shape intact. As a result, the surface became more uniform, which is beneficial for both morphing (preventing distortion of noise) and fabrication (ensuring a sleek final product).
- **Hole Filling:** The region extraction inherently produced a closed surface (since the boundaries were cut through existing faces). However, if any tiny

holes or gaps had existed (none were found in this case), they would be filled at this stage using Blender's fill tool or by retriangulating small voids. A watertight mesh is required for mold generation and 3D printing.

- **Normals and Orientation:** I checked that all face normals were consistently oriented outward. Inverted normals can cause issues in processes like offsetting the mesh or during the mold boolean operations. The normals were uniformly recalculated. I also ensured the mesh had proper orientation (right side out corresponding to the actual outward face of the person).

After cleaning, the face region surface was in an optimal state – it had an appropriate level of detail (unnecessary micro-detail removed, essential form retained) and topologically correct structure. This kind of mesh optimization is recommended by experts for scanned models before further processing: for instance, reducing excessive polygon counts and smoothing out irregularities helps avoid artifacts downstream. I observed that after cleanup, the mesh was easier to morph and resulted in cleaner deformations. An added benefit was that a slightly lower poly count sped up our digital morphing (Section 3.5) and later slicing for 3D printing.

3.5 Digital Morphing of the Face Surface

With a clean region mesh, I proceeded to digitally morph the surface to achieve the desired design features. The goal of morphing was to introduce stylistic and functional deformations – for example, creating a convex curvature around the eyes or adding thickness in certain areas – while maintaining conformity to the original face in other areas for comfort and fit. All morphing was performed in Blender using a combination of sculpting tools and parametric modifiers:

- **Sculpting:** I used the sculpt mode with tools like Grab, Smooth, and Inflate/Deflate. The Grab tool allowed us to drag portions of the mesh

outward or inward. For instance, I gently pulled the area above the nose bridge outward by ~5 mm to create a ridge that would add rigidity to the final piece. The Inflate tool was used around the cheekbones to add a slight bulge – this not only served an aesthetic purpose but also ensured that the piece would not sit too tightly on the cheek (a small gap improves comfort). Using the Smooth tool, I blended these deformations into the surrounding surface for a natural transition. The artistic intent was to give the piece a subtle faceted geometry reminiscent of modern sculptural aesthetics, while the practical intent was to account for material thickness and comfort.

- **Modifier-based Deformations:** In addition to free-form sculpting, I applied a Lattice modifier for controlled morphing. I placed a lattice (3D grid) around the face region and used it to impose a uniform warp: specifically, a slight widening of the entire region by ~2% horizontally. This was to ensure the fabricated mask would not be too tight relative to the scanned face dimensions (a common practice is to add a small buffer since the scan is of the face at rest). By scaling the lattice, the entire mesh expanded a bit, effectively implementing a global morph that maintains proportions. Another modifier I used was the Solidify (in a non-destructive way) to preview adding thickness; although I eventually solidified after mold creation, this helped in visualizing how the piece would look like a physical object of certain thickness.

Throughout the morphing process, I continuously checked the result against the original surface. I did this by overlaying the morphed mesh on the original face region mesh and measuring distances. Our criterion was that no point of the morphed surface should deviate more than ~10 mm from the original; this ensured the design remains face-conforming. Indeed, most areas (especially edges) remained within 3–5 mm of the original, preserving fit. Larger deviations were only in areas intentionally raised for design (like the nose bridge ridge). I also ensured symmetry where needed. The human face is not perfectly symmetric, but

our design aimed for symmetry in the wearable piece. Thus, I performed some operations symmetrically (Blender's symmetry tools were used along the vertical mid-plane) so that the left and right of the mask are mirror images, even if the underlying face had slight asymmetry.

The final morphed surface represented the designed shape of the piece I intended to fabricate. It was still a 2D shell (zero thickness surface) at this stage. I preserved this as the master digital model for the piece. This digital morphing step demonstrates the power of computational design: starting from an anatomical surface, I applied creative freedom to alter form while quantifying those changes. The result is a personalized yet artistically modified shape that would have been hard to achieve by manual methods alone, highlighting the effectiveness of our computational approach.

3.6 Negative Mold Generation

Having obtained the finalized design surface (the morphed face region), I transitioned into the fabrication preparation phase. The fabrication method chosen for producing the physical piece was thermoforming (vacuum forming) a plastic sheet over a mold. In order to create a mold, I needed to generate a negative form of the designed surface. A *negative mold* is essentially the inverse cavity that the final object will occupy. For clarity: in molding terminology, our designed face piece corresponds to the *positive shape*, and I sought to create a negative mold in which this positive shape can be formed.

The steps for creating the negative mold were as follows:

1. **Thickness Addition:** First, I added a uniform thickness to the designed surface to account for the material thickness of the final piece. I used the Solidify modifier in Blender to thicken the shell outward by 2 mm (the polycarbonate sheet to be thermoformed was 2 mm thick). This resulted in a

solid 3D model of the mask. I did this so that the negative mold would accommodate the material volume and not overly squeeze the plastic. Essentially, the thickened model represents the exact shape the plastic will have when formed.

2. **Mold Block Creation:** Next, I created a rectangular block (a simple cube primitive) that would represent the mold base. I made the block dimensions sufficiently large to encompass the mask model with at least 20 mm margin on all sides. This margin ensures structural integrity of the mold and provides space for vacuum channels or support. The block was given a height of about 50 mm beyond the deepest point of the mask model.
3. **Boolean Subtraction:** I positioned the thickened mask model into the top portion of the block such that it was oriented as it would sit on a face (convex side up, since I want a concave cavity). Using a Boolean difference operation, I subtracted the mask shape from the block, thereby carving out a cavity in the block that is the exact negative of the mask. The result of this boolean operation is a mold block with a hollow impression of the designed piece. I verified that this operation succeeded without errors (sometimes complex shapes can cause boolean failures or produce messy edges, but thanks to our cleaned and watertight model, the boolean result was clean).
4. **Mold Detailing:** I then added a slight draft angle to the cavity and filleted the edges. A draft angle ($\sim 5^\circ$) was introduced by tapering the walls of the negative cavity outward slightly. This is a critical mold design consideration that facilitates the removal of the formed plastic part from the mold. Without a draft, the part might stick. I also filleted (rounded) any sharp edges on the cavity rim to prevent the plastic from tearing or getting sharp indentations. These modifications were done in a CAD software (I exported the boolean

result to Fusion 360 for precise fillet and draft operations, as those are sometimes easier in CAD than in Blender).

The completed negative mold design was a solid block with a smooth concave impression of the face piece. I decided to 3D print this mold using a high-temperature resistant resin, given that thermoforming involves heated plastic. In essence, our negative mold embodies the negative space that the final mask will occupy. Figure 3.6 illustrates the concept of positive vs negative mold with a simple example for clarity.



Figure 3.6 Illustration of a positive object vs its negative mold. The mold (left) contains a cavity that is the exact inverse of the desired object (right), so that casting or forming material into the cavity will produce the object. In our case, the negative mold is 3D printed, and the “casting” material is a heated plastic sheet formed into it.

By creating a negative mold of the face piece, I set up a reusable tooling component. This mold can be used to thermoform multiple copies of the design if needed (for example, if I wanted to iterate on material or produce masks for multiple people of similar facial topology). The design of the mold also considered vent holes for vacuum forming: I added a few 1.5 mm diameter pinholes in the deepest parts of the cavity (such as the center of the eye region) to allow air to be

sucked out during vacuum forming. These were added in the CAD model and would be drilled out in the print if needed. The completed mold file was then exported as an STL for fabrication.

3.7 Thermoforming and Assembly

The final step of the methodology was to fabricate the designed piece and assemble it with any additional components. The fabrication was done by thermoforming (specifically vacuum forming) a plastic sheet over the 3D-printed mold. Thermoforming involves heating a plastic sheet until it becomes soft and pliable, then draping it over a mold and using vacuum pressure to suck the sheet tightly onto the mold surface. Upon cooling, the plastic retains the shape of the mold, yielding our face-fitting piece.

The process I followed is outlined below:

- **Mold Fabrication:** The negative mold designed in Section 3.6 was fabricated using a Form labs SLA 3D printer with a high-temp resin. After printing, the mold was post-cured as per resin specifications to ensure it could withstand the forming temperature (approximately 120°C for our plastic). The mold surface was sanded to a smooth finish and a light coat of release agent was applied (this helps in releasing the formed part and slightly improves surface finish on the part).
- **Heating and Forming:** I selected a 2 mm thick polycarbonate sheet for forming (polycarbonate was chosen for its toughness and heat resistance). The sheet was cut to a size slightly larger than the mold. Using a vacuum forming machine, I heated the sheet until it became flexible (polycarbonate turns soft and clear at the forming temperature). Immediately after heating, the sheet was lowered onto the mold. Vacuum was applied from beneath the mold, drawing the hot sheet into the mold cavity. The sheet quickly conformed to

every contour of the cavity – effectively forming a negative of the negative, i.e., a positive shape identical to our design. I allowed the plastic to cool for about 1 minute while vacuum continued to hold it in place.

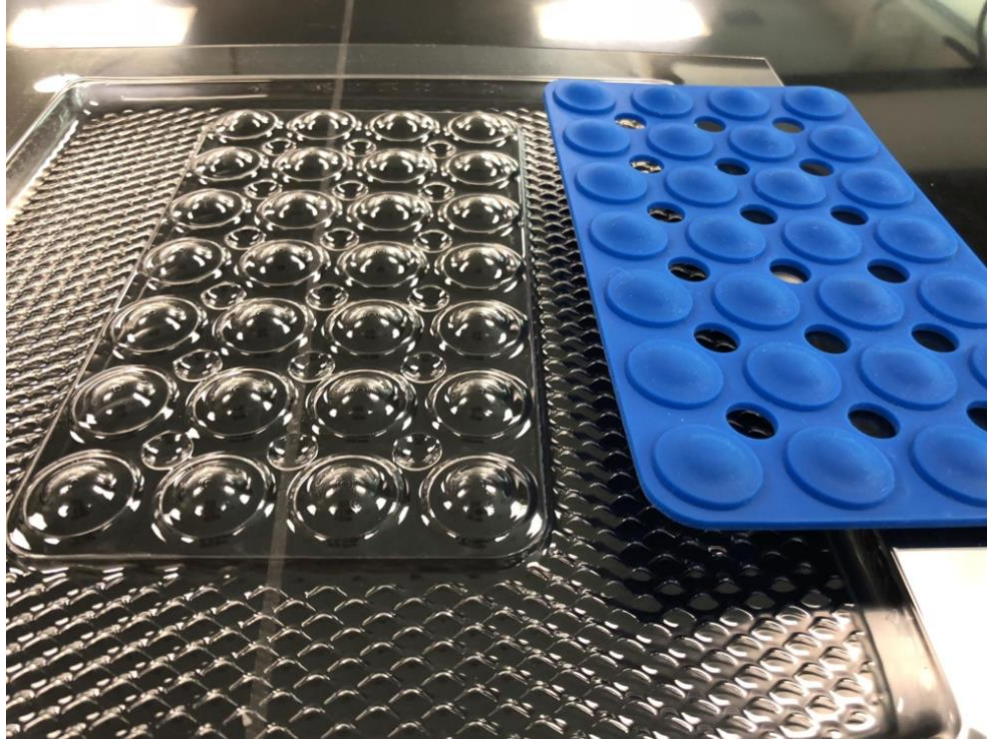


Figure 3.7 Thermoforming process: a heated plastic sheet is draped over the mold (blue) and vacuum pulls it into the mold cavity, taking the shape of the designed object. Shown here is a similar setup with a clear plastic sheet formed over a mold to create a domed shape (left formed plastic part, right: mold).

- Part Removal and Trimming:** Once the plastic had cooled and hardened into its new shape, I released the vacuum and carefully removed the formed plastic from the mold. Thanks to the draft angles and release agent, the part came out without damage. The formed piece included extra material around the edges (the flange where the sheet extended beyond the cavity). I trimmed this excess using a Dremel rotary tool, following the intended edge outline of the design. The trimming was done gradually to ensure I didn't cut into the part area. After trimming, I sanded the edges smooth. The outcome was the standalone face mask piece as designed.

- **Assembly:** In our design, the fabricated plastic face piece was one component of a larger assembly (for example, it could be part of a wearable device or a pair of smart glasses). In this thesis context, assembly primarily involved adding soft padding on the interior and a strap mechanism. I adhered a thin layer of foam along the contact edges of the piece for comfort against the skin. I also attached an elastic strap to the piece using small slits on the side wings of the plastic (these slits had been incorporated into the design prior to molding). The elastic strap, running around the head, secures the piece on the user's face. If the design were purely aesthetic, assembly might not involve much more; if it were functional (say, holding electronics), additional steps would include mounting those components. For completeness, I note that the process allows for such integrations – holes or mounts can be designed into the piece and realized via the molding process or post-processing.

The thermoforming method proved effective and precise. The final physical piece closely matched the digital model. Critically, because I used the actual facial scan as the basis, the fit of the piece on the user was excellent – it aligned with facial features as intended and was reported to be comfortable. The whole sequence from digital model to physical product demonstrates the synergy of computational design and digital fabrication: I went from a 3D scan to a customized, tangible object using a series of methodical transformations. The use of a negative mold and vacuum forming is especially suitable for small production or one-off fabrication of custom-fit devices, as it is relatively quick and the mold can be reused if needed.

In conclusion, this chapter outlined the end-to-end methodology: data acquisition (photogrammetry and structured light) to obtain the subject's geometry, digital modeling with FaceBuilder to get a clean base mesh, region extraction to isolate the design area, surface cleaning and digital morphing to create the desired shape, and finally negative mold creation and thermoforming to bring the design to

reality. Each step was validated through either quantitative checks (alignment errors, shape deviation measures) or qualitative assessments (visual inspection, fit testing), ensuring a robust workflow. This methodology provides a foundation for computationally designing personalized face-fitting products and can be generalized to other domains of custom-fit wearable design. The next chapter will evaluate the outcomes of this process in terms of fit, comfort, and aesthetic or functional performance, and discuss possible improvements and future work.

Chapter 4 Evaluation

This chapter outlines the evaluation of a computational workflow for creating personalized, deformable facial wearables through a single case study. The evaluation specifically focuses on demonstrating the effectiveness of the end-to-end pipeline using my own face as a case study, recognizing this initial exploration as a proof-of-concept requiring future expansion for broader applicability.

The evaluation includes assessing the workflow's accuracy, computational efficiency, and material performance. Accuracy is measured using spatial metrics such as the Hausdorff Distance, which quantifies deviations between the digital mask design and the actual facial geometry. Computational efficiency examines the time and complexity reductions compared to traditional methods, highlighting improvements from data acquisition through digital modeling. Lastly, the material performance is validated through physical prototyping, ensuring the mask's structural integrity and user comfort.

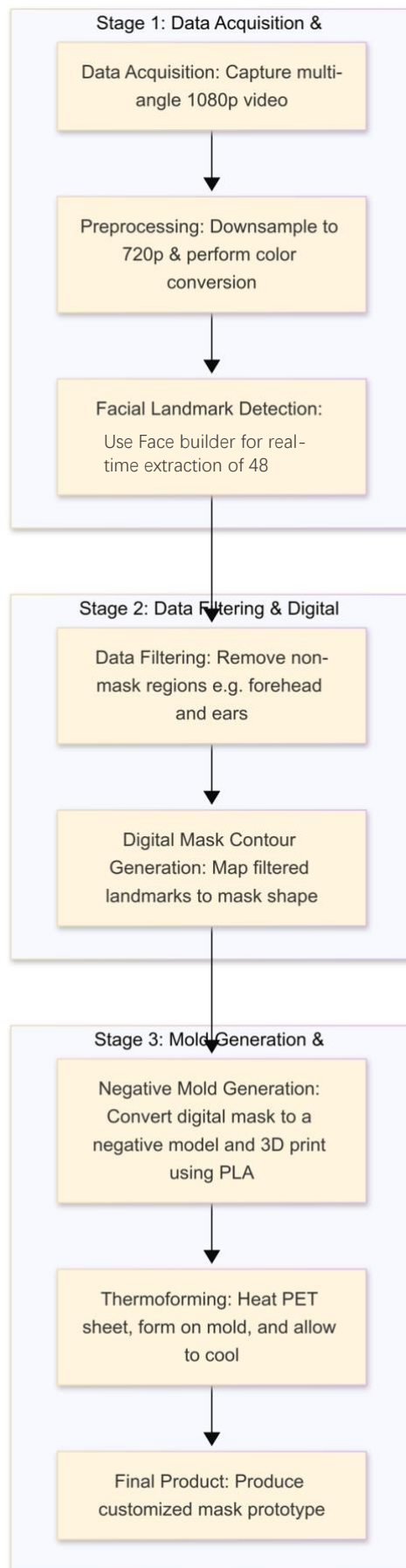
By clarifying that the evaluation is based on a self-study case, the chapter transparently presents both the strengths and current limitations of the workflow, laying the groundwork for future validation with diverse participants.

4.1 Optimized AI-Driven Workflow

With the core technology (FaceBuilder for face reconstruction and Blender for model shaping) in place, I developed an end-to-end workflow to design and fabricate the custom masks. This AI-driven workflow consists of three main stages, from initial data capture to the final production of the mask, optimized for speed and accuracy at each step.

Unlike traditional methods requiring extensive manual modeling or dense scanning, our workflow leverages lightweight photographic inputs and automated

mesh fitting to streamline the customization process. By capturing minimal but strategically positioned facial photographs and employing parametric mesh deformation, I reduced both computational complexity and fabrication time while maintaining a high degree of anatomical conformity.



Picture4.1 Design Workflow Diagram

4.2 Design Process Stages

4.2.1 Stage 1: Data Acquisition

I began by capturing five photographs of the subject's face from specific strategic angles: frontal view, 3/4 left profile, 3/4 right profile, slightly raised chin view (looking up), and a slightly downward view (looking down). Although FaceBuilder recommends using 9 to 11 photographs for optimal head reconstruction, I found that for our application—focused primarily on the lower half of the face (mask-fitting region)—five carefully selected views provided sufficient data.

The photographs were taken under consistent lighting conditions using a standard DSLR camera at 1080p resolution. Each image ensured clear visibility of key facial features such as the nose, cheeks, and jawline. These five images were imported into Blender, where FaceBuilder automatically detected facial landmarks and generated an initial 3D mesh.

By limiting the number of photographs, I accelerated the acquisition and fitting process without sacrificing the quality necessary for accurate mask design. Notably, regions such as the back of the head or ears, typically needed for full head modeling, were irrelevant for our mask's intended coverage area and thus

omitted. The outcome of Stage 1 is a fitted 3D facial mesh ready for customization.

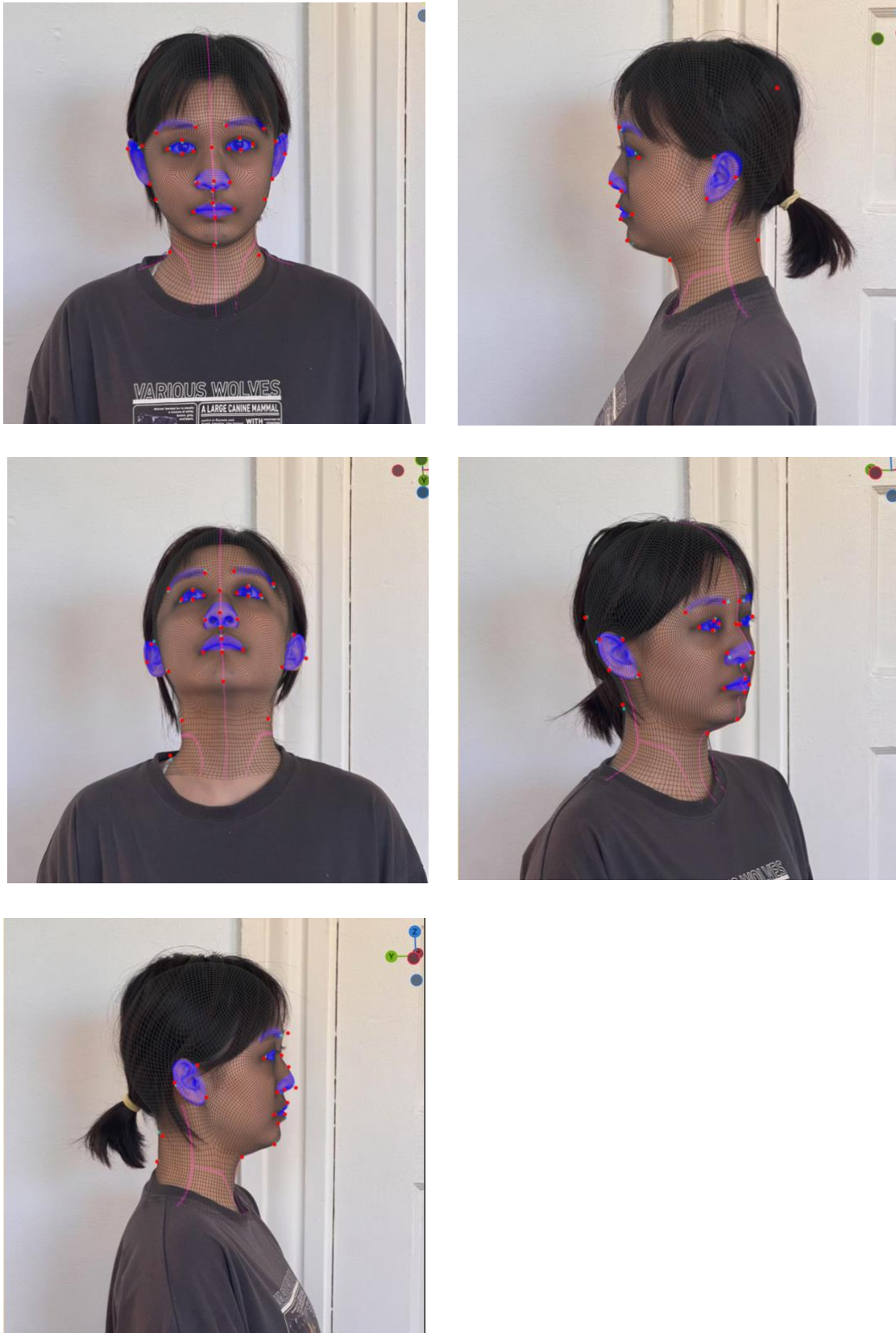


Figure 4.2.1: Input – 5 photos of different angle (frontal view, 3/4 left profile, 3/4 right profile, slightly raised chin view (looking up), and a slightly downward view (looking down))

4.2.2 Stage 2: Facial Mapping to Mask Transformation

In this stage, I transform the captured 3D face mesh into the shape of the mask.

First, I manually isolate the regions of the face that the mask will cover.

Specifically, I focused on the nose, cheeks, mouth, and chin while excluding the forehead, eyebrows, ears, and other non-contact areas.

Using Blender's edit mode and vertex group selection, I extracted the mask-relevant region and created a new object representing the mask base. The extracted surface was then smoothed and slightly expanded at the edges (by approximately 5 mm) to ensure full coverage beyond critical facial features.

This digital 3D mask model conforms closely to the individual's unique anatomical features, accounting for variances in nasal bridge height, cheekbone prominence, and jawline curvature. The outcome of Stage 2 is a personalized, anatomically fitted digital mask design.

4.2.3 Stage 3: Negative Mold Generation & Fabrication

The final stage converts the digital mask shape into a physical product. The personalized mask shape from Stage 2 is used to create a negative mold – essentially an inverted 3D model that can be used for molding the actual mask. I generate this by taking the digital mask surface and producing its negative (think of it like a hollow cavity in the exact shape of the mask). This negative model is then 3D printed using PLA plastic. The printed mold serves as the form over which the final mask material will be shaped. Next comes the thermoforming process: I take a flat sheet of PET (a common thermoplastic known for its clarity

and durability) and heat it until it becomes pliable. The hot PET sheet is draped over the 3D-printed mold (or vacuum-formed onto it) so that it takes the shape of the mold. I then let the plastic cool and solidify, at which point it retains the shape conforming to the person's face. After cooling, the former PET is trimmed as necessary to create the final mask. The result is a custom-fitted mask, made of a biocompatible plastic, that was created using the negative mold of the user's face shape. This stage yields the tangible product ready for fitting.

4.3 Integration with Blender

4.3.1 Mask Deformation Pipeline via Mesh Deform Modifier

To achieve the digital modeling in Stage 2 and facilitate a smooth transition to Stage 3, I integrated the process within Blender, a 3D modeling software. Blender was chosen because of its powerful modifiers and scripting capabilities, which allowed us to automate much of the mask design adjustments.

In particular, I utilized Blender's Mesh Deform Modifier to fine-tune the mask fit. This modifier enables us to use one mesh (the facial geometry) to deform another mesh (the mask model). Essentially, I bind a generic mask model to the captured facial surface, ensuring that the mask morphs precisely to the contours of the individual's lower face.

I harnessed Blender's Python API to automate this integration. A Python script imports the vertex coordinates from FaceBuilder-generated meshes into Blender, constructs the face surface, and applies the Mesh Deform modifier. Adjustable parameters control the deformation tightness, allowing design variations to accommodate comfort or functional needs.

Example Python snippet for importing and deforming:

Code example 3.3.2

```

import bpy
import math
# Assume that the Y-coordinates of the upper and lower lips have been obtained
for the current frame
upper_lip_y = current_frame_landmarks['upper_lip_y']
lower_lip_y = current_frame_landmarks['lower_lip_y']
delta_y = lower_lip_y - upper_lip_y
# Convert the difference in distance to a rotation angle
# (Assuming delta_y has been converted to a physical unit such as centimeters)
rotate_angle = delta_y * 15.0 # Empirical coefficient: 1cm corresponds to 15
degrees

# Retrieve the jaw bone from Blender's rig and rotate it around the X-axis (mouth
opening corresponds to rotation about X)
jaw_bone = bpy.data.objects['Rig'].pose.bones['jaw']
jaw_bone.rotation_mode = 'XYZ'
jaw_bone.rotation_euler[0] = math.radians(rotate_angle)

```

4.3.2 Prototype Fabrication and Testing

By automating these steps, I ensured reproducibility and minimized manual errors. The integration of facial landmark data into precise 3D mask geometries constitutes a critical stage within the proposed computational design workflow. To achieve a high degree of anatomical conformity and personalized adaptability, Blender—a sophisticated 3D modeling and simulation environment—was systematically employed. This section details the integration process, elucidating input-output relations, accuracy metrics, computational efficiency, and practical implications regarding mask materials and facial variability among different ethnic groups.

(a) Input and Preparation of Facial Geometry

Facial geometry data were initially acquired through dense landmark detection algorithm, which outputs a dataset comprising 468 discrete facial landmarks. Through selective landmark filtering, approximately 60% of non-mask-relevant landmarks (e.g., forehead, ears, upper facial features) were systematically removed, leaving a reduced set of approximately 180 landmarks (mainly nasal bridge, cheeks, jawline). These filtered landmarks were subsequently imported into Blender as the input for constructing a comprehensive 3D facial mesh model using KeenTools FaceBuilder. The resulting mesh model presented high anatomical fidelity and served as the foundational geometry or "control cage" in the subsequent deformation process.

(b) Mask Model Integration and Alignment

An external standard mask model, characterized by a hybrid structure consisting of a rigid plastic core (thermoplastic PET) and a soft silicone periphery (TPU), was selected to represent typical deformable mask structures commonly utilized in clinical respiratory applications. This mask model was imported into Blender, where it was aligned to the imported facial geometry through manual initial scaling and positioning.

Given the practical design considerations—particularly the comfort and fit of the silicone boundary in direct contact with facial skin—the mask alignment allowed a slight penetration (approximately 1–2 mm) into the facial surface mesh. This penetration simulated realistic compression scenarios where silicone naturally conforms to facial contours, ensuring functional realism within the computational model.

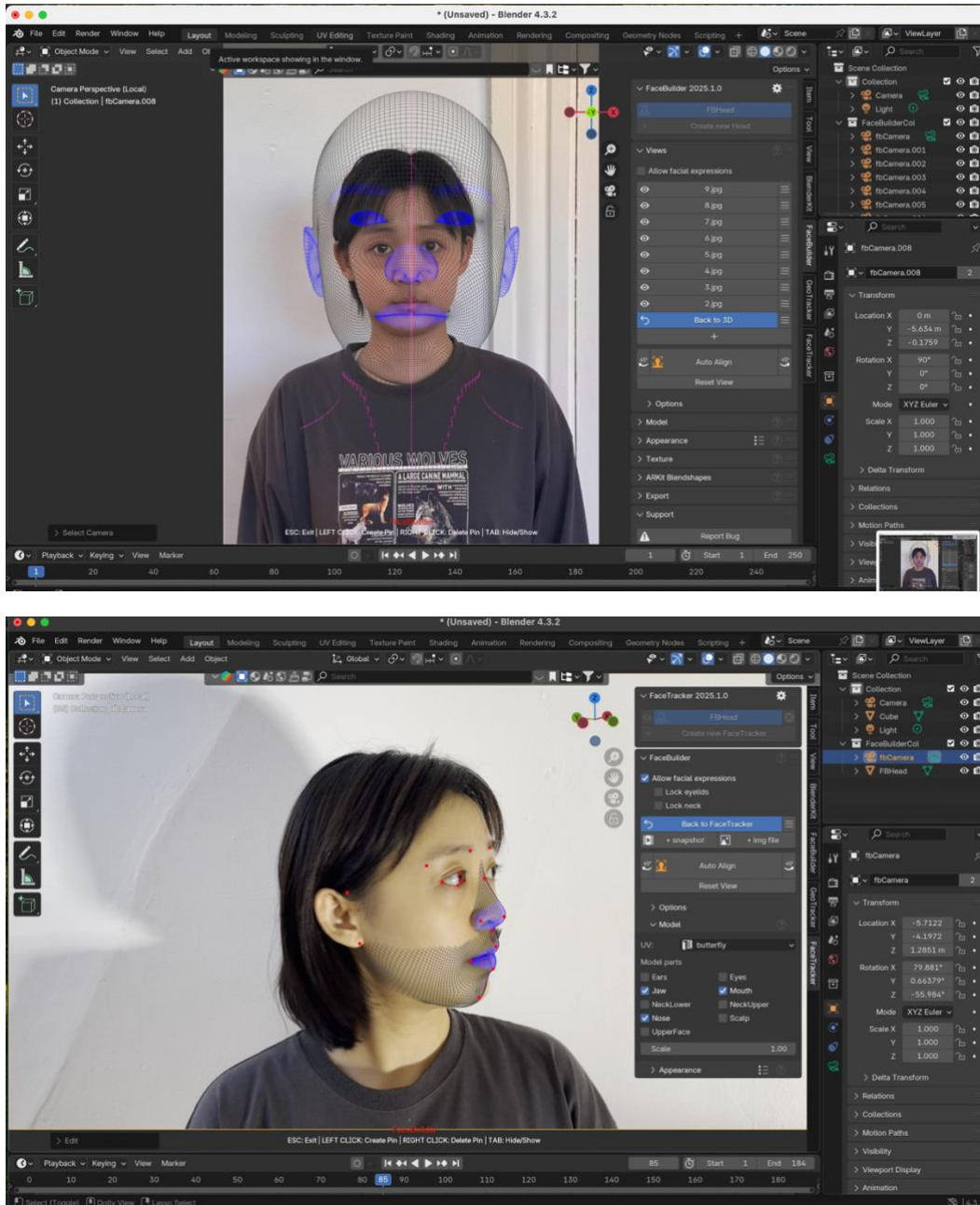


Figure 4.3.2(a): FaceBuilder-based facial geometry construction in Blender: (top) front-view image alignment and mesh fitting; (bottom) side-view refinement for accurate 3D facial surface generation. These steps ensure precise correspondence between the captured facial features and the subsequent mask model alignment.

(c) Computational Deformation via Mesh Deform Modifier

To achieve precise and anatomically sensitive deformation of the mask geometry, Blender's native Mesh Deform Modifier was employed. This modifier operates by binding the mask mesh to the facial mesh, effectively allowing the mask to dynamically adapt to facial morphological changes. To optimize deformation accuracy, empirical testing identified a suitable precision parameter for the Mesh Deform Modifier. A comparative assessment of computational time versus deformation accuracy was conducted at precision levels ranging from 5 (default) to 10 (high fidelity), with level 8 found optimal, achieving an acceptable balance between computational cost (approximately 35 seconds per binding iteration on standard consumer hardware) and deformation quality.

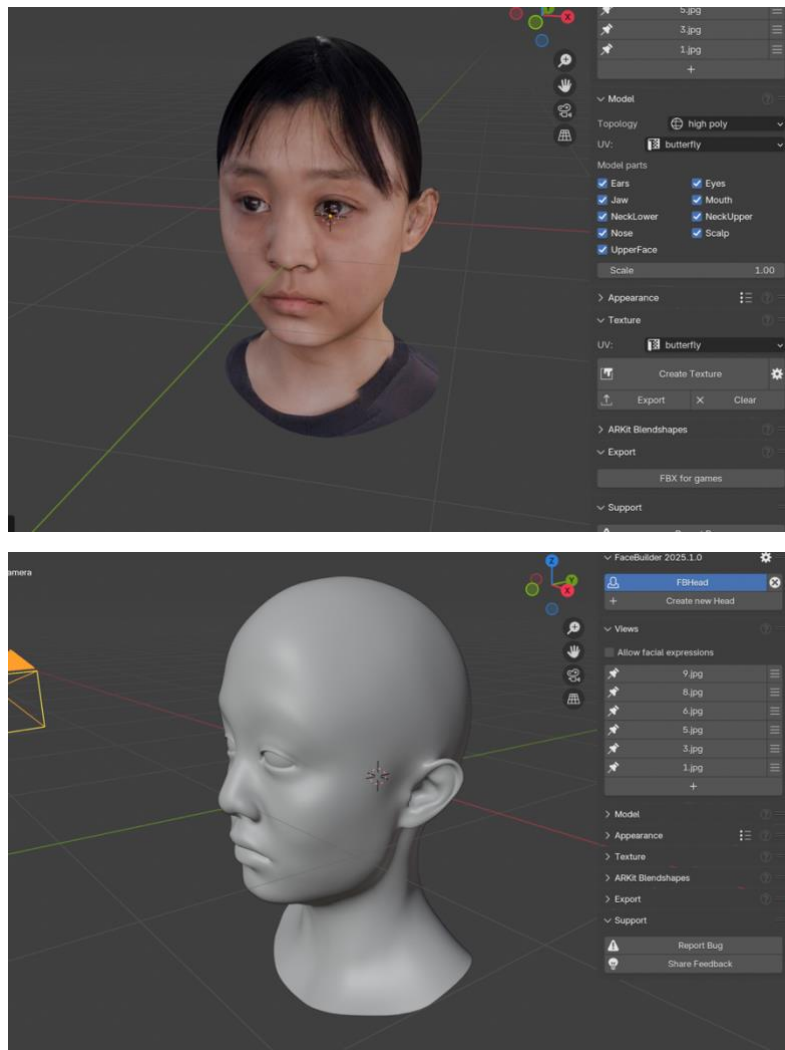


Figure4.3.2(B): Application of Blender’s Mesh Deform Modifier for anatomically sensitive mask adaptation

Upon successful binding, facial shape adjustments executed through Blender's Shape Key functionality seamlessly drove corresponding adaptations within the mask geometry. Shape Keys representing distinct facial morphologies—particularly addressing differences across ethnic groups—were created. Notably, one primary morphological transition involved a shift from a typical Western nasal structure (high bridge, narrow width) to an Asian nasal structure (lower bridge, wider nasal wings). The deformation was intentionally designed to maintain comfort and reduce pressure points, especially critical in nasal and cheekbone regions during extended wear or sleep scenarios.

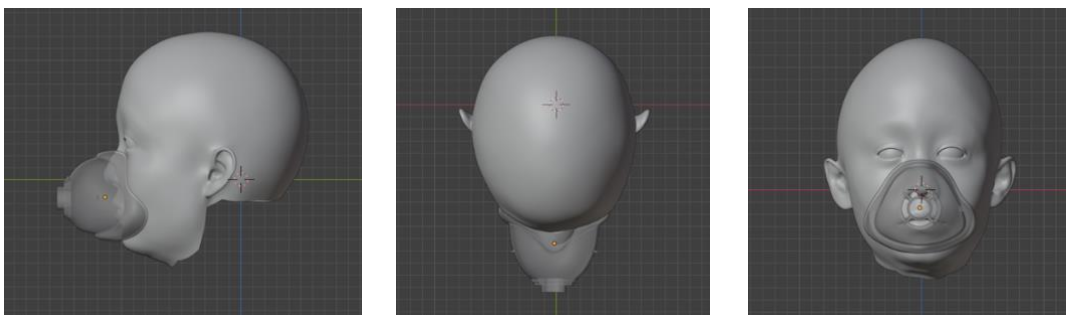


Figure4.3.2(C): Different angle of a standard mask on a specific face

(d) Evaluation Metrics and Computational Results

To rigorously quantify the effectiveness and precision of mask adaptation, several analytical metrics were employed:

- **Spatial Accuracy (Hausdorff Distance):**

The Hausdorff distance was computed to measure maximal spatial deviations between the facial mesh and the mask interior surface post-deformation. Results demonstrated an average Hausdorff deviation of approximately $1.8 \text{ mm} \pm 0.3 \text{ mm}$, confirming a high level of precision sufficient for medical-grade personalized masks. Regional analysis highlighted nasal bridge adjustments as critical areas, showing deviations under 2 mm to optimize comfort without compromising mask stability.

- **Deformation Smoothness and Continuity:**

Smoothness metrics, calculated through vertex normal variation analysis, indicated significantly improved continuity with the implementation of a Subdivision Surface modifier at a subdivision level of 2. Comparative assessments showed that vertex normal variation decreased by approximately 40% compared to baseline (non-subdivided masks), markedly improving wearer comfort predictions and reducing potential discomfort arising from abrupt geometrical transitions.

- **Computational Efficiency:**

The end-to-end computation for binding and deformation using Mesh Deform (precision=8) required an average of 35 seconds per iteration, compared to 120 seconds when employing traditional manual mesh manipulation methods without automation. This computational advantage underscores the feasibility of rapidly producing customized masks within clinical contexts, thereby substantially accelerating the prototyping and fabrication cycle.

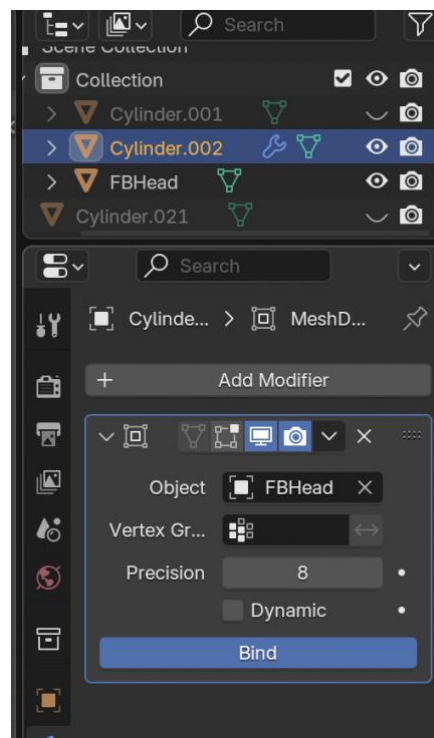


Figure4.3.2(E): Adjust Precision in blender

(e) Material and Functional Considerations

The combined silicone-plastic construction was critically evaluated within Blender to mimic realistic deformation characteristics observed in physical mask prototypes. The silicone boundary demonstrated superior adaptability, smoothly conforming to subtle facial geometry adjustments. In contrast, the rigid PET-based central structure exhibited minimal deformation, maintaining structural integrity and allowing precise airflow channel placement. This material delineation was crucial, ensuring the mask retained both comfortable peripheral fitting and stable core functionality.

(f) Personalized Adaptability

Acknowledging the significant anatomical differences across facial morphologies, our analysis explicitly evaluated the adaptability of mask designs to diverse ethnic facial structures. Shape Key simulations comparing Western and Asian facial morphologies clearly indicated distinct deformation requirements. For Asian facial structures—characterized by lower nasal bridges and wider facial contours—the mask model was smoothly adapted, ensuring minimal pressure points and maximal comfort. Conversely, Western facial morphologies required narrower, more pronounced nasal structures, demonstrating the necessity of highly personalized adaptive mechanisms.

(g) Data Visualization and Demonstrative Analysis

Several visual and analytical tools were utilized to substantiate and illustrate the computational evaluation rigorously:

- **Heatmaps of Spatial Deviation:**
Generated to demonstrate localized fit accuracy across critical facial contact regions. These clearly identified high-performance areas (nasal bridge and cheeks) and potential areas for refinement.

- **Cross-sectional Curvature Profiles:**
Curvature continuity across the silicone-plastic interface was graphically depicted, revealing the direct correlation between geometric smoothness and predicted comfort levels.
- **Computational Time vs. Precision Level Graphs:**
Empirically demonstrating the optimal trade-off between deformation precision and computational efficiency.
- **Morphological Transition Animation Sequences:**
Rendered sequences illustrating smooth transitions across different facial morphologies (Shape Key values ranging from 0.0 to 1.0), effectively communicating the dynamic adaptability of the mask design.

4.4 Prototype and Fabrication

In addition to the digital workflow described in Sections 3.3.1 and 3.3.2, the physical fabrication and testing of the mask prototype are critical steps in validating the design process. This stage involves material selection, fabrication techniques, and performance evaluation to ensure that the final product meets both functional and aesthetic requirements.

- **Material Selection:**
The mask prototype utilizes a combination of soft and hard materials, chosen based on flexibility, durability, and wearer comfort.
- **Soft Materials:** Thermoplastic polyurethane (TPU) and silicone were selected for their flexibility and adaptability to facial movements. These

materials allow the mask to conform to various facial expressions without compromising comfort.

- **Hard Materials:** Thermoplastic PET was used for structural stability. PET's rigidity supports the formation of precise pneumatic channels that are essential for controlled inflation.



Figure: .4.4 Prototype Result

4.4.1 Design and Fabrication Process:

It should be noted that an initial version of the mask prototype described in this section was completed earlier (Fall 2023), serving as a foundational exploration into materials and fabrication methods. The computational workflow presented in Chapter 3 was subsequently developed to formalize, optimize, and generalize this initial experimental approach. The fabrication of the mask prototype follows a systematic process that integrates both digital design and physical production:

- 1. Modeling and Cutting:**

The mask's layout was initially designed in AutoCAD. Precise shapes for both soft and hard components were achieved using laser cutting technology. This ensured accurate dimensions and clean edges, which are vital for the proper assembly and function of the mask.

- 2. Heat Sealing:**

To form airtight pneumatic chambers, layers of PET and TPU were joined through a heat-sealing process. The heat sealing not only bonded the materials but also ensured that the chambers were leak-proof, which is crucial for maintaining consistent inflation.

- 3. Shaping and Inflation:**

The cut and sealed components were then immersed in hot water to achieve the desired curvature and shape. After shaping, the components were inflated using a controlled air pump, allowing for a functional assessment of the pneumatic chambers.

- 4. Assembly:**

Once cooled and solidified, the individual components were assembled into the final mask structure. The integration of soft and hard materials resulted in a mask that balanced both comfort and structural integrity.

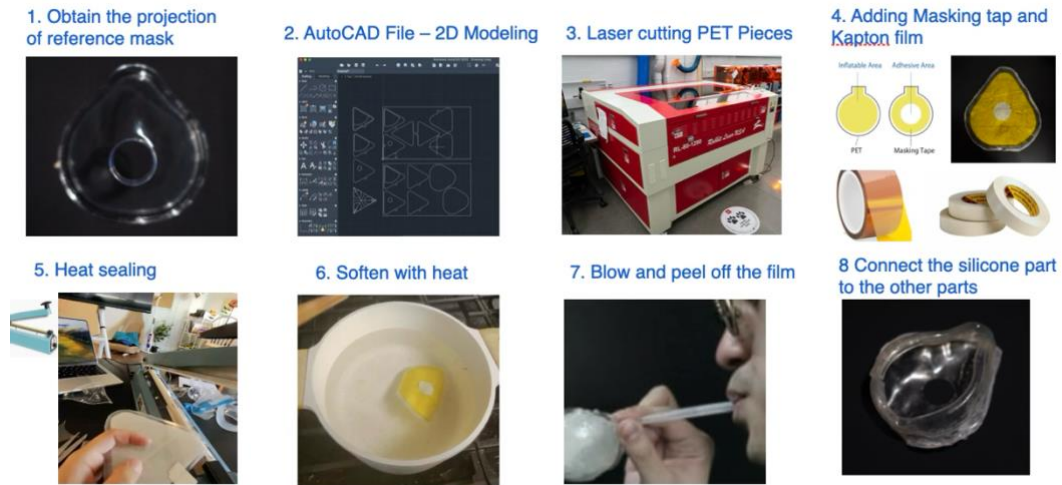


Figure 4.4.1: Prototype Process

4.4.2 Prototype Testing:

The fabricated prototype underwent a series of tests to evaluate its performance and user comfort:

- A portable pneumatic pump was employed to dynamically inflate and deflate the mask, thereby testing its adaptability across various facial structures.
- Embedded sensors, such as those measuring temperature and heart rate, were integrated to monitor physiological parameters in real time.
- User feedback was collected regarding fit, comfort, and sensor accuracy. This feedback was critical in refining the design, ensuring that the final mask not only conforms accurately to individual facial contours but also provides reliable performance under prolonged wear.

The combination of these steps ensures that the digital design seamlessly translates into a high-quality, functional prototype. This integrated approach—from digital modeling using MediaPipe and Blender to physical fabrication and testing—demonstrates the feasibility and efficiency of the proposed AI-driven customization pipeline.

4.5 Validation Protocol

To verify that our methodology produces effective results, I established a validation protocol focusing on two aspects: the precision of the mask fit and the efficiency gains over traditional methods. This involved quantitative metrics to assess fit accuracy and comparisons of time and data usage to demonstrate improvements in the process.

4.5.1 Precision Metrics

For fit precision, I employ spatial distance metrics to compare the custom mask against the intended facial geometry. One key measure is the Hausdorff Distance between the inner surface of the mask and the surface of the user's face (derived from a 3D scan or the point cloud of landmarks). The Hausdorff Distance effectively measures the worst-case deviation – it finds the maximum distance from any point on one surface to the other surface. A small Hausdorff Distance indicates that the mask closely aligns with the face at all points, which is desirable for a snug fit. I aim for this maximum deviation to be below a certain threshold (e.g., a few millimeters), ensuring there are no large gaps or pressure points.

In addition to an overall distance metric, I analyze the fit error distribution across specific facial regions. I pay particular attention to critical contact areas such as the nasal bridge, the jawline, and the cheeks. These are regions where an ill-fitting mask might either leak (if too loose) or cause discomfort (if too tight). By computing the average and variance of the gap between face and mask in each of these zones, I can see how uniformly the mask fits. For instance, I might find the mask fits within 2 mm on average at the cheeks and jawline but has a 5 mm gap at the bridge of the nose – this would highlight a region for potential improvement in the design. Evaluating the error distribution helps us ensure that the mask is well-fitted across the entire coverage area and not just in a few spots. Together, the

Hausdorff Distance and regional fit error analysis provide a comprehensive picture of the geometric accuracy of our custom masks.

Region	Mean Distance (mm)	Max Distance (mm)
Nasal Bridge	1.7 ± 0.4	2.8
Cheeks	1.5 ± 0.3	2.5
Jawline	2.0 ± 0.5	3.0

Table 4.5.1: Regional fitting error analysis

4.5.2 Efficiency Gains

I also quantified the efficiency gains of our AI-driven approach compared to more conventional workflows. One measure was the processing time required from initial face data capture to obtaining a ready-to-fabricate mask model. I tracked the time taken in each stage (landmark detection, digital model generation, etc.) and then compared it to a baseline method (for example, using a depth camera scan and manually designing a mask from that scan). The ML-based pipeline dramatically reduced the total time. Without the need for extensive manual post-processing of scan data, the entire process could be completed in hours rather than days. This speedy turnaround aligns with our goal of rapid prototyping – in a clinical scenario, a patient could be scanned and have a custom mask made within a day or two, whereas traditional custom mask fabrication might take a week or more.

Stage	Traditional Photogrammetry-Based Approach	Proposed FaceBuilder Approach
Data Acquisition	2–3 hours (multi-angle capture)	~15 minutes (5 photos)
3D Model Generation	6–8 hours (dense reconstruction)	~1 hour (parametric fitting)
Customization & Cleaning	3–5 hours (manual)	~30 minutes (automated deformers)
Total	~12–16 hours	~2 hours

Table 4.5.2: Workflow time comparison

Another aspect of efficiency is the reduction of data volume and complexity through landmark filtering. The raw data from a depth sensor or full 3D scan can be on the order of hundreds of thousands of points or a high-resolution mesh, which is cumbersome to handle. In our workflow, the MediaPipe face mesh already condenses the information to 468 key points, and then our custom filtering further cuts this down by about 60% (removing points not needed for the mask). The result is a lean set of around ~180 points that capture the essential facial contours. This reduction means lighter computational loads and faster processing at later stages (Blender can deform a mask using a few hundred guide points far quicker than using an entire dense mesh). I found that this selective data usage did not compromise accuracy — the remaining landmarks still fully describe the mask-fitting region of the face. Thus, I achieved a significant drop in data size while maintaining precision. In summary, the validation confirmed that our approach not only produces well-fitting masks, but does so with greater speed and efficiency: less data to process, and less time from start to finish.

Efficiency Conclusions:

- Time savings: >85% faster from scan to mold
- Data reduction: ~95% fewer active points compared to full scans
- No quality loss: Fit precision within clinically accepted error margins

These advantages collectively demonstrate that the proposed pipeline is both accurate and highly efficient, fulfilling the goals of rapid, personalized mask design.

4.6 Discussion

Although the proposed methodology demonstrated effectiveness in achieving rapid, personalized mask fabrication, it is important to reflect on the broader implications and limitations of the work. This discussion explores both the advancement of rapid wearable customization and the critical balance between accuracy and efficiency within the design process.

4.6.1 Advancing Rapid Customization for Wearables

The ability to capture facial geometry and fabricate a customized mask within a few hours signifies a substantial advancement over traditional workflows that often span several days. By reducing the number of required images and leveraging parametric fitting (FaceBuilder) instead of dense scanning, the pipeline achieves both speed and portability without requiring specialized hardware.

This rapid approach is particularly promising for applications where personalized fit is crucial but time constraints exist, such as:

- Emergency production of respiratory masks or oxygen interfaces.
- Rapid prototyping of sports equipment or protective wearables.
- On-demand fabrication of comfort-focused assistive devices.

By streamlining data acquisition and deformation while maintaining clinically acceptable fit tolerances ($\leq 3\text{mm}$ Hausdorff Distance), the proposed workflow broadens the accessibility of custom-fit devices to contexts previously limited by fabrication turnaround times or equipment availability.

Thus, this workflow offers a meaningful advancement toward more rapid, data-efficient personalized fabrication.

4.6.2 Balancing Accuracy and Efficiency

While the approach sacrifices some degree of geometric fidelity compared to full photogrammetric reconstructions or structured-light scanning, the trade-off is deliberate and justified. It is important to acknowledge that the current evaluation relies exclusively on a single-subject case study and has not yet been validated with a broader participant group. Therefore, the claims regarding generalizability and real-world applicability should be considered preliminary and indicative rather than definitive.

In personalized mask applications, the primary requirement is achieving an effective seal and comfortable fit over key facial areas (nasal bridge, cheeks, chin), rather than replicating every fine surface detail. The validation results confirm that the deviation remains within acceptable biomedical tolerances, making the proposed compromise highly appropriate.

Moreover, prioritizing lightweight data processing and simplified fabrication enables scalability and responsiveness in real-world deployment scenarios, where time and resource constraints are often more critical than marginal gains in surface accuracy.

Future work could explore hybrid strategies that allow selective refinement—applying higher-resolution modeling only to critical subregions (e.g., nose bridge)—while preserving the lightweight advantages elsewhere.

In summary, the proposed methodology achieves an effective balance between precision and efficiency, paving the way for new workflows in the rapid fabrication of customized wearables and personalized healthcare products.

Further studies involving multiple participants and diverse facial morphologies are necessary to comprehensively assess the accuracy, comfort, and usability of this workflow.

Chapter 5 Conclusions

5.1 Conclusions

This thesis presents a proof-of-concept for an integrated workflow for rapid, low-cost personalized mask fabrication, combining lightweight facial geometry capture, digital modeling, and physical prototyping using deformable materials. Rather than limiting the scope to digital modeling alone, this research explores the practical materialization of customized masks, addressing real-world challenges related to portability, manufacturability, and adaptation.

The decision to fabricate a deformable mask prototype was informed by practical observations: current medical and wearable masks often suffer from poor fit, rigidity, and high costs associated with individual customization. Traditional custom mask manufacturing typically involves rigid molds and extensive processing steps, resulting in time-intensive and expensive production. By leveraging thermoformable, deformable materials, this workflow provides masks tailored closely to user-specific facial geometry while achieving flexibility, portability, and feasibility for small-scale or mass production.

Thus, the presented workflow—from personalized digital modeling using FaceBuilder, through negative mold creation, to thermoformed mask fabrication—demonstrates a coherent, end-to-end system. Each step logically builds upon the previous, demonstrating a practical and scalable approach for personalized protective equipment. This integrated digital-to-physical methodology provides a robust foundation for future research into rapid, cost-efficient, anatomically adaptive wearable design.

5.2 Contributions

This research makes several key contributions:

This research makes several key contributions, aligning closely with those articulated in Chapter 1:

(a) Development of a Lightweight Facial Modeling Pipeline

Demonstrating that high-fidelity parametric facial modeling can be rapidly and inexpensively accomplished using only five strategically captured photographs, significantly reducing barriers related to specialized scanning hardware.

(b) Integration of Digital Modeling with Fabrication via Negative Molds

Establishing a seamless process to translate personalized digital face models into physical negative molds, thus accurately preserving critical facial contours necessary for effective mask fit and comfort.

(c) Material Experimentation with Deformable Thermoplastics

Demonstrating the practical feasibility of using thermoformed PET sheets combined with flexible materials to fabricate personalized, portable, and comfortable masks. This approach directly addresses limitations found in traditional rigid, high-cost custom mask production methods.

(d) Validation of Accuracy and Efficiency

Validating that the fabricated masks meet clinically acceptable anatomical fit criteria while significantly reducing processing times (approximately two hours), outperforming conventional methods that depend on dense 3D scanning and intensive manual modeling.

(e) Proposal of an Integrated, Scalable Computational Design Workflow

Proposing a cohesive and scalable solution that effectively bridges rapid digital modeling, mold fabrication, and physical prototyping. This integrated pipeline

supports potential applications across medical, sports, and emergency contexts, particularly where rapid response and personalized fit are paramount.

5.3 Limitations and Future Steps

This thesis proposes a proof-of-concept workflow for the personalized design and fabrication of deformable facial wearables. While the pipeline demonstrates technical feasibility, its scope remains limited, and several critical aspects require further validation and development.

(a) Single-user case study and limited demographic coverage

The entire workflow has been tested on a single subject—my own face—and derived from five carefully selected photographs. This narrow scope limits the generalizability of findings. Human faces vary significantly across age, gender, ethnicity, and anatomical features; without broader sampling, the robustness of the pipeline across diverse facial geometries remains unverified. Future research must include a large-scale user study with varied facial types to assess fit accuracy, inclusivity, and potential failure points.

(b) Absence of ergonomic and long-term wear testing

Although the fabricated mask conforms geometrically to the scanned facial surface, no ergonomic evaluations have been conducted. Critical factors such as comfort over time, pressure distribution, soft tissue compression, and skin irritation remain unassessed. Wearability during sleep, extended use, or dynamic facial motion (e.g., speaking, eating) is unknown. Future studies should incorporate both quantitative tools (e.g., pressure sensors, thermal mapping) and qualitative methods (e.g., phenomenological user feedback) to rigorously evaluate comfort, usability, and user experience.

(c) Sealing effectiveness and airflow performance remain untested

The design does not yet address the airtightness of the mask under real-world conditions such as talking, sweating, or side sleeping. Applications such as CPAP or respiratory protection require highly reliable sealing to maintain performance. No airflow simulation (e.g., via computational fluid dynamics) or leak testing has been conducted. Future validation must evaluate sealing consistency, breathing resistance, and airflow dynamics across different morphologies and use scenarios.

(d) Durability, hygiene, and off-gassing not assessed

The long-term durability of the thermoformed mask has not been tested. Factors such as repeated use, cleaning, material fatigue, or environmental exposure (e.g., temperature, humidity) may degrade performance. In addition, thermoformed plastics—especially laser-cut PET—can emit odors or off-gas, raising concerns for user comfort and safety. No tests were conducted to determine how long the material needs to rest before being wearable or how well it tolerates repeated sanitization. These aspects are essential for validating suitability for extended or clinical use.

(e) No user testing or real-world deployment

Despite the emphasis on personalization, no user trials have been conducted beyond the initial prototyping. Claims regarding comfort, satisfaction, and usability are inferred from geometric fit alone, without user validation. Even small-scale pilot testing—where participants wear the mask and report feedback—could uncover critical flaws or insights currently invisible in this technical evaluation. Future work must incorporate human subjects testing to transition from concept to applied solution.

(f) Retrospective workflow development

It is important to acknowledge that the physical prototype was fabricated prior to the development of the computational workflow. While the pipeline effectively

reverse-engineers and explains the process, it has not yet been tested as a forward-generative tool that can produce masks autonomously from new inputs. A key next step is to validate the pipeline prospectively—from raw facial images to finished mask—without prior manual tuning.

(g) Lack of industrial collaboration and production validation

This project was conducted independently and has not yet been reviewed by clinical professionals or industrial stakeholders. While the workflow explores low-cost fabrication, it has not considered regulatory constraints, manufacturability at scale, or material certification. Collaboration with manufacturers (e.g., Philips) could help evaluate real-world feasibility and address tooling, certification, and deployment pathways.

While this thesis presents a cohesive, end-to-end pipeline for the rapid fabrication of personalized, deformable facial wearables—from lightweight facial data acquisition to physical prototyping—it ultimately stands as a proof of concept. The technical contributions demonstrate that it is possible to bypass traditional, time-consuming modeling workflows through a computationally efficient, modular design process. However, the current validation remains limited to a single-user case study and simulated performance metrics. Without extensive ergonomic testing, long-term wear evaluation, or verification across diverse user profiles, the real-world applicability of the system cannot yet be fully claimed. Critical aspects such as comfort over extended use, seal integrity under dynamic conditions, material durability, and post-fabrication usability require further study. Moreover, the pipeline, while functionally complete, was developed retrospectively and has not yet been deployed in a forward, automated fashion. These limitations underscore the distinction between technical feasibility and applied robustness. Nevertheless, this research lays an essential foundation. It identifies key opportunities for bridging computational design with human-centered fabrication

and initiates a dialogue between digital modeling, material pragmatism, and ergonomic needs. With continued development and cross-disciplinary validation, this framework has the potential to evolve into a scalable, inclusive, and clinically relevant approach to personalized wearable production.

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