ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

DATA-DRIVEN DESIGN FRAMEWORK FOR AI-AIDED INTERACTIVE ARCHITECTURAL PANELS

M.Sc. THESIS

Ömer Kasım KAROUT

Department of Informatics
Architectural Design Computing Programme

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<u>ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ</u>

YAPAY ZEKÂ DESTEKLİ ETKİLEŞİMLİ MİMARİ PANELLER İÇİN VERİ ODAKLI TASARIM ÇERÇEVESİ

YÜKSEK LİSANS TEZİ

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KASIM 2025

Ömer Kasim KAROUT, a M.Sc. student of İTU Graduate School student ID 523241019, successfully defended the thesis/dissertation entitled "DATA-DRIVEN DESIGN FRAMEWORK FOR AI-AIDED INTERACTIVE ARCHITECTURAL PANELS", which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my 16-year-old self,

FOREWORD

I am deeply grateful to my advisor, Assoc. Prof. Dr. Ayşegül Akçay Kavakoğlu, whose guidance has shaped not only the research in this thesis but also the past decade of my architectural education. Her vision and generosity as a mentor have left an indelible mark on how I think, question, and design. I would also like to extend my heartfelt thanks to Prof. Dr. Mine Özkar Kabakçıoğlu and Prof. Dr. Leman Figen Gül for their invaluable guidance and support throughout my academic journey. Their insights and encouragement have been instrumental in shaping my path.

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Istanbul Technical University has been more than an academic institution. It has been a place of growth, challenge, and inspiration. I am grateful to be part of a community of brilliant professors, research assistants, and students, each of whom has contributed, in ways big and small, to the formation of this research.

A special thanks to my brother, whose interest in architecture introduced me to the field. Watching his journey was my first exposure to this discipline, and it played a key role in guiding my own direction. His presence and support have been an important part of my academic and personal growth.

To my family, thank you for raising me to value knowledge and for giving me the freedom to invest in my ideas. Your unwavering love and patience have been the quiet engine behind everything I do. And to my cat, Ouzi, thank you for your silent companionship, curled up beside me through countless nights of writing and work.

The work presented in this thesis is not an endpoint. It is a beginning. Every prototype, every experiment, every line of code or material trial is a foundation upon which I will continue to build. This project is part of something larger, an evolving exploration of how architecture can interact, reflect, and respond. My ambition is to see data-driven panels integrated into real spaces, to watch people engage with them not as technology, but as living parts of architecture.

December 2025

Ömer Kasım KAROUT
(Architect)

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ABBREVIATIONS

AI	: Artificial Intelligence
CNN	: Convolutional Neural Network
DDD	: Data-driven Design
DDP	: Data-driven Prediction
DeePC	: Data-enabled Predictive Control
DNNs	: Deep neural networks
GANs	: Generative Adversarial Networks
HBI	: Human-building Interaction
HMI	: Human-machine Interaction
HOG	: Histogram of Oriented Gradients
IPO	: Input–processing–output
IR	: Interactive Architecture
ML	: Machine Learning
MPC	: Model Predictive Control
RA	: Responsive Architecture
SSD	: Single Shot MultiBox Detector
SIFT	: Scale-Invariant Feature Transform
YOLO	: You Only Look Once

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DATA-DRIVEN DESIGN FRAMEWORK FOR AI-AIDED INTERACTIVE ARCHITECTURAL PANELS

SUMMARY

This thesis explores a workflow to develop an AI-aided, data-driven design framework aimed to achieve interactive panels on walls to improve user engagement. The study aims to achieve wall tiling tessellations to become interactive paneling systems, capable of responding physically to human presence. Using image and motion capture; these panels translate body movement into coordinated kinetic gestures, bridging a form of spatial communication between users and environments.

Within the domains of computational design, artificial intelligence and interactive architecture, this research proposes a medium in which AI is housed in physical spaces. While researches of AI whithin the domain of architecture have typically been working on tools to help generate forms or optimize designs behind digital interfaces, this thesis explores its potential as a more physical layer embedded within architecture itself, allowing walls to sense, process and react to human activity in real-time.

The thesis uses design-led research method to explore the interaction potentials within the defined design process and prototyping. This exploration bases upon four stages: (1) Case-study prototyping to explore the interaction system and needs, (2) Integration of AI to the interactive system (3) Simulation and re-creation of the system to generate different designs and experiment visual potentials, (4) design and fabrication of data-driven panels, which combines all knowledge gathered in the study.

Moreover, The first stage focuses on the development of a data-driven panels' prototype using 36 display units inspired by Rozin's Weave Mirror. Using depth cameras and Arduino based controls enabled the prototype to interact and reflect the user's movement. The aim of the first stage is to investigate the necessary components and workflows needed for this project and how motion and perception can be represented using physical materials. Supporting the research with Gestalt psychology provides a conceptual base for how forms emerge through arrangement and proximity.

In the second stage, artificial intelligence (AI) is introduced to aid the system's interactivity. Through Machine learning models, the panel is trained to recognize gestures, body positions, and voice inputs, each will trigger different responses and actions. These include expressive visual outputs or directional movement, transforming the panel into an interactive interface that evolves its behavior based on what it learns from the users interacting with it.

The third stage centers on simulation and system creation. Digital tools are utilized to experiment with design variations, such as the number, shape and placement of display units.

The fourth stage informs the construction and design of a second, more advanced prototype that enhances structural integrity, sensory responsiveness, and real-time feedback. Beyond the technical framework, the research in this thesis also reflects on questions of perception and engagement. The system operates between finding the balance between abstraction and recognition, prompting viewers to interpret meaning through motion. Design strategies rooted in Gestalt psychology to ensure that the interface remains perceptually understandable.

YAPAY ZEKÂ DESTEKLİ ETKİLEŞİMLİ MİMARİ PANELLER İÇİN VERİ ODAKLI TASARIM ÇERÇEVESİÖZET

ÖZET

Mimari çevreler tarihsel olarak teknolojik dönüşümlerle yakın bir ilişki içinde evrilmiştir; ancak yapay zekânın (YZ) mimarlık alanındaki entegrasyonu büyük ölçüde soyut ve dolaylı bir düzeyde kalmıştır. Güncel mimari pratikte YZ, çoğunlukla biçim üretimi, optimizasyon, görselleştirme veya performans analizi gibi süreçlerde bir tasarım aracı olarak kullanılmakta; fiziksel mekânın kendisine doğrudan entegre edilmek yerine dijital arayüzlerin arkasında konumlanmaktadır. Bu durumun bir sonucu olarak mimari duvarlar, hâlen ağırlıklı olarak durağan sınırlar ya da pasif bilgi taşıyıcıları olarak varlığını sürdürmektedir. Bu tez, söz konusu yaklaşımı sorgulayarak, yapay zekânın doğrudan mimari elemanların içine yerleştirildiği, YZ destekli ve veri odaklı bir tasarım çerçevesi önermektedir. Bu çerçeve kapsamında duvar kaplama ve döşeme sistemlerinin, insan varlığını algılayabilen, yorumlayabilen ve fiziksel olarak tepki verebilen etkileşimli panel sistemlerine dönüşmesi hedeflenmektedir. Araştırma, bu tür duvar sistemlerinin insan–yapı etkileşimine aktif olarak katılan, algısal olarak okunabilir ve kinetik arayüzler hâline nasıl gelebileceğini incelemektedir Hesaplamalı tasarım, yapay zekâ, etkileşimli mimarlık, medya mimarlığı ve görsel algı alanlarının kesişiminde konumlanan bu çalışma, hesaplamalı zekânın ekranlar ve dijital gösterimler aracılığıyla dışsallaştırılması yerine, fiziksel mimari sistemlerin içine nasıl yerleştirilebileceğini araştırmaktadır. Mimarlık alanındaki YZ araştırmalarının büyük bir kısmı, tasarımcıyı destekleyen dijital araçlar geliştirmeye odaklanırken, bu tez YZ'yi mimarinin fiziksel bir katmanı olarak ele almakta; duvarların insan etkinliğini gerçek zamanlı olarak algılayabilen, işleyebilen ve buna yanıt verebilen sistemler hâline gelmesini amaçlamaktadır. Yapay zekâ bu bağlamda otonom bir yaratıcı özne olarak değil, algısal girdiler, mekânsal davranışlar ve insan algısı arasında aracılık eden destekleyici bir katman olarak konumlandırılmaktadır. Fiziksel prototipleme, makine öğrenmesi, hareket ve görüntü yakalama teknikleri, dijital simülasyon ve algı kuramlarını bir araya getiren araştırma, duvarların temsili görüntüler yerine eşgüdümlü kinetik jestler aracılığıyla iletişim kurmasını sağlayan bir iş akışı önermektedir. Araştırma, tanımlanan tasarım süreci ve prototipleme aşamaları içerisinde etkileşim potansiyellerini incelemek amacıyla tasarım odaklı bir araştırma metodolojisi benimsemektedir. Bu metodolojik yaklaşım, birbirini izleyen ve birbiriyle ilişkili dört ana aşama üzerinden yapılandırılmıştır: (1) etkileşim sistemlerinin, davranış mantıklarının ve teknik gereksinimlerin araştırıldığı vaka çalışması temelli prototipleme süreci; (2) doğrudan yansıtma davranışlarının ötesine geçmek amacıyla yapay zekânın etkileşimli sisteme entegre edilmesi; (3) farklı tasarım varyasyonlarının üretilmesi, görsel ve mekânsal potansiyellerin test edilmesi ve algısal performansın değerlendirilmesi için simülasyon ve sistemin yeniden oluşturulması; (4) araştırma boyunca elde edilen bilgilerin bir araya getirilerek veri odaklı panel sistemlerinin tasarımı ve üretimi. Bu dört aşama, kavramsal sorgulama ile deneysel üretimi ve fiziksel gerçekleştirmeyi birbirine bağlayan bütüncül bir iş akışı oluşturmaktadır.

Araştırmanın çıkış noktası, mimari mekânlarda etkileşimli dijital medyanın giderek artan varlığıdır. Ekranlar ve projeksiyon sistemleri yaygınlaşmış olsa da, bu araçlar çoğu zaman mimarinin malzeme ve mekânsal mantığından kopuk bir görsel dil üretmekte; bedensel katılımdan ziyade izlemeye dayalı bir etkileşim biçimini ön plana çıkarmaktadır. Bu tez ise etkileşimi fiziksel hareket ve malzeme artikülasyonu üzerinden ele alarak, kullanıcı ile mimari arasında bedensel bir ilişki kurmayı amaçlamaktadır. Görüntü ve hareket yakalama verileri kullanılarak, önerilen paneller insan hareketini eşgüdümlü mekanik tepkilere dönüştürmekte ve kullanıcı ile çevresi arasında mekânsal bir iletişim biçimi oluşturmaktadır. Paneller, geleneksel anlamda görüntü sergilemek yerine veriyi harekete dönüştürerek yorumlama, hareket ve mekânsal farkındalığı teşvik eden bir deneyim sunmaktadır.

Araştırmanın merkezinde algı kavramı yer almaktadır. Etkileşimli mimari sistemler, davranışları algısal bir düzene sahip olmadığında görsel olarak kaotik ya da bilişsel açıdan erişilemez hâle gelebilmektedir. Bu soruna yanıt olarak çalışma, Gestalt psikolojisini hem analitik hem de üretken bir çerçeve olarak ele almaktadır. Gestalt ilkeleri, dağınık elemanlardan tutarlı görsel bütünlerin nasıl oluştuğunu açıklamak ve önerilen panel sisteminin tasarım mantığını yönlendirmek amacıyla kullanılmaktadır. Bu ilkeler, özellikle Daniel Rozin'in Weave Mirror adlı kinetik çalışmasının analizinde uygulanmakta; soyutlama, senkronizasyon, yakınlık ve görsel süreklilik gibi tasarım kararlarına yön vermektedir. Bu bağlamda hareket, başlı başına bir animasyon unsuru olarak değil, tanınabilirliği ve mekânsal okunabilirliği destekleyen bir kompozisyon aracı olarak ele alınmaktadır.

Birinci tasarım aşaması, Rozin'in Weave Mirror çalışmasından esinlenen veri odaklı bir panel prototipinin geliştirilmesine odaklanmaktadır. Prototip, 36 adet motorize görüntü biriminden oluşan bir iç mekân duvar yüzeyi olarak kurgulanmıştır. Derinlik algılayıcı kameralar ve Arduino tabanlı kontrol sistemleri aracılığıyla kullanıcının varlığı ve hareketi algılanmakta; elde edilen görüntü verileri gri ton değerlerine dönüştürülerek servo motor hareketlerine yeniden eşlenmektedir. Bu süreç sonucunda kullanıcının silueti, düşük çözünürlüklü ancak fiziksel bir yansıma olarak ortaya çıkmaktadır. Bu aşamanın amacı birebir bir temsil üretmek değil, hareket, soyutlama ve algının eşgüdümlü fiziksel bileşenler aracılığıyla nasıl ifade edilebileceğini araştırmaktır.

Bu ilk prototip, çözünürlük, soyutlama, hareket hızı, senkronizasyon ve tanınabilirlik arasındaki ilişkileri açığa çıkaran keşifsel bir araç olarak işlev görmektedir. Yinelemeli testler, mekanik kısıtların algısal etkilerini ortaya koyarken; kalibrasyon, sistem gecikmesi, malzeme sınırları ve üretim koşulları gibi pratik sorunları da görünür kılmaktadır. Böylece araştırma, etkileşimli mimari sistemlerin fiziksel üretim gerçeklikleriyle doğrudan ilişkilendirilmektedir.

İkinci aşamada, yapay zekâ sistemin etkileşim kapasitesini genişletmek amacıyla sürece dâhil edilmektedir. Erişilebilir makine öğrenmesi araçları ve görsel geliştirme platformları kullanılarak panel; jestleri, beden pozisyonlarını, nesneleri ve sesli girdileri tanıyacak şekilde eğitilmektedir. Tanımlanan her bir girdi, yönlü hareketler veya ifade edici kinetik desenler gibi önceden belirlenmiş mimari tepkileri tetiklemektedir. Yapay zekâ bu bağlamda opak veya otonom bir yapı olarak değil, öğrenilen girdileri tasarımcı tarafından belirlenen davranışlara eşleyen kontrollü bir tetikleyici mekanizma olarak kullanılmaktadır. Bu sayede panel, kullanıcı etkileşimine bağlı olarak davranışını uyarlayan koşullu bir arayüze dönüşmektedir.

Üçüncü aşama, simülasyon ve sistemin yeniden oluşturulmasına odaklanmaktadır. Dijital araçlar aracılığıyla birim sayısı, geometri, aralıklar, malzeme özellikleri ve hareket davranışları gibi parametreler değiştirilerek farklı tasarım varyasyonları üretilmekte; bu varyasyonların görsel netlik, hareket sürekliliği ve kullanıcı etkileşimi üzerindeki etkileri değerlendirilmek üzere önceden render alınan ve gerçek zamanlı simülasyonlar gerçekleştirilmektedir. Bu süreç, üretim öncesinde yapısal ve mekânsal tasarım kararlarının yönlendirilmesini sağlamaktadır.

Dördüncü ve son aşama, araştırma boyunca elde edilen tüm bilgilerin bir araya getirilerek daha gelişmiş ikinci bir prototipin tasarımına ve üretimine aktarılmasını kapsamaktadır. Bu prototip, yapısal bütünlüğü, duyusal tepkiselliği ve gerçek zamanlı geri bildirimi geliştirmekte; döküm elemanlar ve üç boyutlu baskı bileşenleri gibi farklı malzeme stratejilerini içermektedir. Bu aşama, önerilen çerçevenin tek bir üretim yöntemi, ölçek veya estetikle sınırlı olmadığını ortaya koymaktadır.

Araştırma boyunca yinelenen temel bir tema, soyutlama ile tanınabilirlik arasındaki dengedir. Aşırı gerçekçilik sistemi mekanik bir ekrana indirgerken, aşırı soyutlama etkileşimi belirsizleştirebilmektedir. Bu iki uç arasında konumlanan paneller, kullanıcıyı görsel tüketimden ziyade bedensel hareket ve yorumlama yoluyla etkileşime davet etmektedir. Gestalt psikolojisine dayalı tasarım stratejileri, arayüzün algısal olarak okunabilir kalmasını sağlarken aktif katılımı teşvik etmektedir.

Bu tezin temel katkısı, yapay zekâ destekli etkileşimi fiziksel olarak uygulanabilir mimari panellere entegre eden, çoğaltılabilir ve veri odaklı bir tasarım çerçevesi ortaya koymasıdır. Algı kuramı, makine öğrenmesi, simülasyon ve malzeme prototiplemesini tasarım odaklı bir metodoloji içinde bir araya getiren çalışma, mimarlıkta akıllı davranışların tasarımcı kontrolünü ve mekânsal netliği koruyarak nasıl yerleştirilebileceğini göstermektedir. Nihai bir ürün sunmaktan ziyade, bu araştırma etkileşimli paneller, uyarlanabilir iç mekânlar ve bedensel insan–yapı etkileşimi üzerine yapılacak gelecekteki çalışmalar için metodolojik bir zemin oluşturmaktadır.

Sonuç olarak bu tez, mimarlığın teknolojiyi yalnızca barındıran bir çerçeve olmak zorunda olmadığını; aksine zekânın mekânsallaştırıldığı, maddeselleştirildiği ve deneyimlendiği bir alan hâline gelebileceğini savunmaktadır. Duvarların algılayabilen, yorumlayabilen ve tepki verebilen sistemlere dönüşmesiyle mimarlık, durağan bir arka plan olmaktan çıkarak insan deneyiminin aktif bir katılımcısı hâline gelmekte; dinleyen, uyumlanan ve hareket aracılığıyla iletişim kuran bir mimarlık anlayışı önermektedir.

1. INTRODUCTION

The fast-paced development of artificial intelligence (AI) is having a substantial and accelerating impact on spatial design. Applications powered by AI in architecture, particularly those involving interactive architecture and human-machine interaction, are gaining attention in this context. While numerous studies have focused on the adaptation of these technologies within the digital realm (Sarirete, Balfagih, Brahimi, 2022), a natural growing interest in their integration into spatial contexts through hybrid mediums, aiming to explore the complex interaction between humans, machines, and spaces (Sharafi Rohani and Akçay Kavakoglu, 2023). Hybrid mediums cover a wide range of technologies that merge both digital and physical environments. In this regard, interactive, kinetic spaces, along with responsive and dynamic environments, are particularly noteworthy, as AI and data-driven processes enrich human experiences. The evolution of architecture has consistently aligned with the availability of technological resources (Maia & Meyboom, 2015). Thus, the integration of AI into architectural design can have a slow pace, but will eventually turn spaces to be more adaptive and feasible to usher in a new era of technological harmony and transforming architectural aesthetics (Bryson, 2021). With the rise of AI and its integration with people's routine, from solving complex equations to suggesting personal preferences, and with the popularity of powering smart devices with AI to broaden their capabilities, it will only be a matter of time where architecture will be powered by AI to find more intelligent solutions in architectural spaces to enhance comfort and interaction, and to form customized experiences to participants.

1.1 Purpose of Thesis

In contemporary architectural research, the integration of data-driven systems and interactive technologies has redefined the relationship between human behavior and spatial experience. While artificial intelligence (AI) has made significant contributions to generative and analytical design processes, its role as an assisting tool in the intersection between physical, perceptual and interactive dimensions of architecture remains relativily underexplored. The purpose of this thesis is to develop an AI-aided data-driven design framework that facilitates the development of interactive panels on walls, transforming static surfaces into dynamic interfaces that respond to human motion and actions.

Within the domain of Human–Building Interaction (HBI), this research seeks to bridge computational design methodologies with user interactivity, framing AI not as an autonomous generator but as a supportive agent for interpreting sensor-based data and informing responsive behavior. This study establishes a design-to-fabrication workflow that links digital inputs with mechanical performance in physical prototypes. Moreover, this thesis contributes to the field of interactive architectural systems, proposing a framework through which can evolve into perceptually active environmental spaces that mediate human–building interaction, encouraging engagement and enhancing spatial awareness through data-informed designs.

Numerous studies in Human–Building Interaction demonstrate that interactive systems significantly improve user engagement, perception, and spatial experience in measurable ways. For example, interactive displays in public environments have been shown to increase dwell time by up to 50% (Falk, 1982) and raise user satisfaction and perceived usefulness at statistically significant levels (Kluckner et al., 2013). Other research found that interactive architectural elements, such as responsive floors, substantially reduce anxiety in hospital waiting areas compared to passive screens (Yoo et al., 2019). Heuken's (2020) PhD dissertation further supports these findings by showing that interactive museum installations consistently produce higher engagement scores, longer dwell times, and more sustained visitor attention compared to non-interactive exhibits. These quantitative findings show a clear pattern: physical environments that can sense and respond to people create better psychological, behavioral, and experiential outcomes. Building on this evidence, the purpose of this thesis is not only to design interactive panels, but to create a replicable framework through which such systems can be developed and adapted in future architectural contexts.

The research and experimentation is set to be within architectural spaces. These boundaries are important to set because designing kinetic panels in outdoor spaces create a completely different set of challenges that need to be addressed such as weather, rain, humidity and temperatures, which will result in a rapid changes in the surrounding environment hosting the panels. Thus, need to be taken into consideration.

1.2 Research Questions

Building upon the mentioned purpose, the research advances the discussion toward how artificial intelligence and data-driven design processes can be embedded within the material and spatial layers of architecture to create an interaction between humans and their surroundings. While previous applications of AI in design have largely focused on digital modeling or optimization, this study shifts attention toward the integration of AI as an assisting mechanism within the built environment itself, enabling architectural elements to interpret and respond to human activity. Within this framework, Human–Building Interaction (HBI) provides the conceptual grounding for the development of architectural wall tiles as active components that engage occupants through motion, perception, and feedback.

The focus is to inherent capacity to host diverse patterns of movement, social interaction, and collective experience conditions that make them ideal for examining responsive architectural systems. Such spaces, including museums, educational facilities, and transit hubs, allow for observable variations in user behavior, providing a rich context for testing how motion-responsive wall systems can create engagement.

Accordingly, this study addresses the following research question: How can an AI-aided, data-driven design framework transform wall tiles into interfaces to enhance human–building interaction?

1.3 Research Gap

Although architecture has increasingly incorporated digital design tools and sensor-based technologies, the integration of intelligent behavior within the architectural surface itself remains limited. Many existing studies on responsive systems focus on kinetic mechanisms, environmental adaptation, or media façades, often prioritizing performance efficiency or visual spectacle over embodied interaction and perceptual engagement. Similarly, research in Human–Building Interaction (HBI) tends to emphasize data collection and behavioral analysis rather than exploring how architectural materials and geometries can become active participants in spatial communication. Wall systems are still predominantly treated as static boundaries or carriers of information, not as agents of interaction capable of mediating between human motion and spatial feedback.

This absence of materially grounded, data-informed, and perceptually oriented frameworks underscores the need for approaches that unite computational design, AI-assisted sensing, and fabrication logic to activate the architectural envelope as an interface. Addressing this gap, the present study proposes a design framework that redefines wall assemblies as interactive systems embedded with behavioral intelligence, contributing to the evolution of environments that engage occupants through dynamic, data-driven communication.

1.4 Research Relevance

Although the interactive design and data-driven surfaces have been explored since the early 2000s, much of this previous work has remained either purely speculative, confined to digital art installations, or technically inaccessible to practitioners without advanced coding skills. Thus, this research covers the development of a practical framework that focuses on integrating AI-aided interactivity into a physically fabricated, architecturally deployable panel system designed for walls. The research in this thesis attempts to develop a replicable, modular workflow that combines gesture-based machine learning, real-time simulation and material prototyping. Tools like Google Teachable Machine and TouchDesigner have been deliberately chosen in order to democratize the use of AI within the design process and make the creation of interactive systems more accessible to architects and designers. Furthermore, the inclusion of physical material considerations, such as concrete, plaster, and 3D-printed components, pushes the research beyond digital simulations to reach a built reality. The relevance of the research accordingly does not lie in the novelty of interactivity but in its applicability with modern tools, material integration and methodological accessibility within architectural practice.

1.5 Methodology

A design-led research is used in this study. The literature review will revolve around three main research domains: computational design, integration of AI in architecture, and interactive architecture. The case study will include an analysis of Daniel Rozin's Mechanical Mirrors, examined in relation to the seven principles of Gestalt psychology. This thesis involves two different prototypes and experimentation across multiple domains, such as creative coding, data management and remapping, machine learning, and simulation. The stages undertaken in this research are as follows: (1) Data-driven Panels' First Prototype, (2) AI Integration with Data-driven Panels & Simulation, and (3) Data-driven Panels' Second Prototype.

The first prototype focuses on achieving basic hardware functionalities, such as the use of image-capturing sensors, 3D printing, and CNC cutting. In terms of software, it involves image capturing and processing within a programming environment, remapping image data to control servo motor rotation, and managing servo motor control within the Arduino environment. The outcome of this stage is a prototype inspired by Daniel Rozin's *Weave Mirror* (2007), which comprises 768 laminated C-ring pixel units total. In comparison, the prototype developed in this study consists of 36 pixel units. The aim of this stage is to identify the key elements present in Rozin's work.

The knowledge obtained through constructing the first prototype is used to guide the development of a more advanced project that integrates AI and architecture. However, the method adopted to build the prototype is grounded solely in hypotheses and does not necessarily represent the artist's original process. In other words, while the visual qualities of the piece are examined and adapted for reproduction in terms of form and kinetic behavior, the mechanical and computational design processes of the prototype, as well as the modes of interaction, are redefined by the authors and collaborators of this project (Karout, Akçay Kavakoğlu, & Ayech, 2024).

The aim of the second stage of the research is to integrate smart, interactive features into the data-driven panels that respond to user interaction through the application of machine learning techniques. These techniques are implemented using Google's Teachable Machine model, in which body gestures, image recognition, and speech recognition are trained to trigger specific responses. Moreover, the next stage involves simulation experiments, in which various designs of data-driven panels are tested to assess their visual functionality and image reflection capabilities before the construction of the second prototype. The third and final stage of the research is to build a prototype that would combine everything learned in previous experimentations in terms of hardware and software.

The structured approach outlined in Figure (1.1) demonstrates how computational design methods, informed by psychological theory and enabled through iterative prototyping, can be synthesized into a comprehensive architectural framework. This thesis not only presents a working prototype but also proposes a replicable framework for integrating responsive systems into walls. Future research may build upon this framework to expand functionality, explore multisensory interactions, or develop scalable panel systems for larger architectural applications.

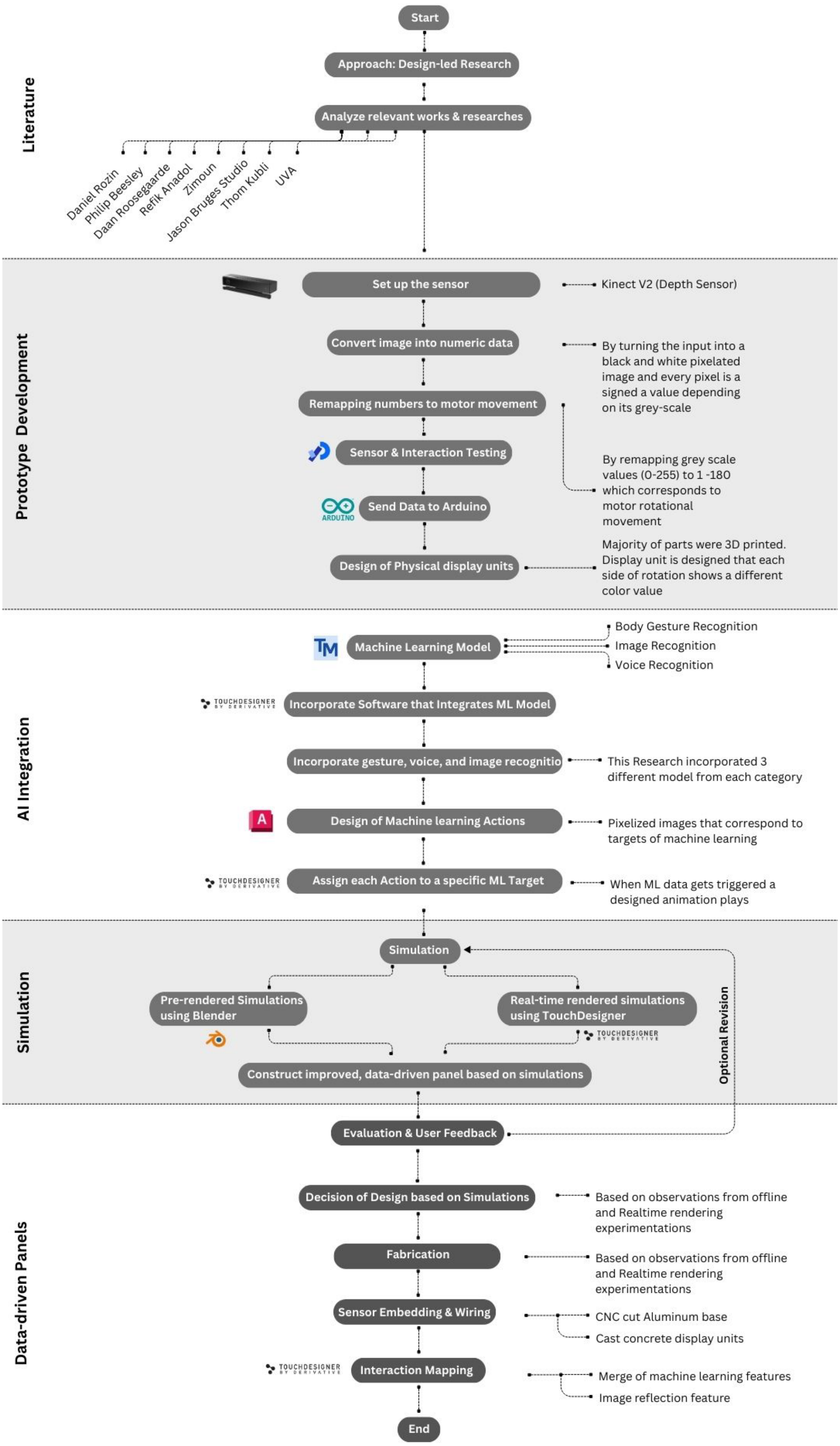

Figure 1.1: Framework of designing and building of data-driven panels

2. LITERATURE REVIEW

The literature review is organized according to four primary research areas; image perception, integration of AI in architecture, media architecture and the difference between interactive architecture and responsive architecture. These domains overlap conceptually with the design of a data-driven panels'. Borrowing from the fields of psychology, computational design and architectural theory, this chapter seeks to explore the fundamentals of how a relationship between responsive and intelligent systems might be meaningfully integrated into architectural environments. Figure (1.2) shows a map of domains included in the research as well as neighboring domains.

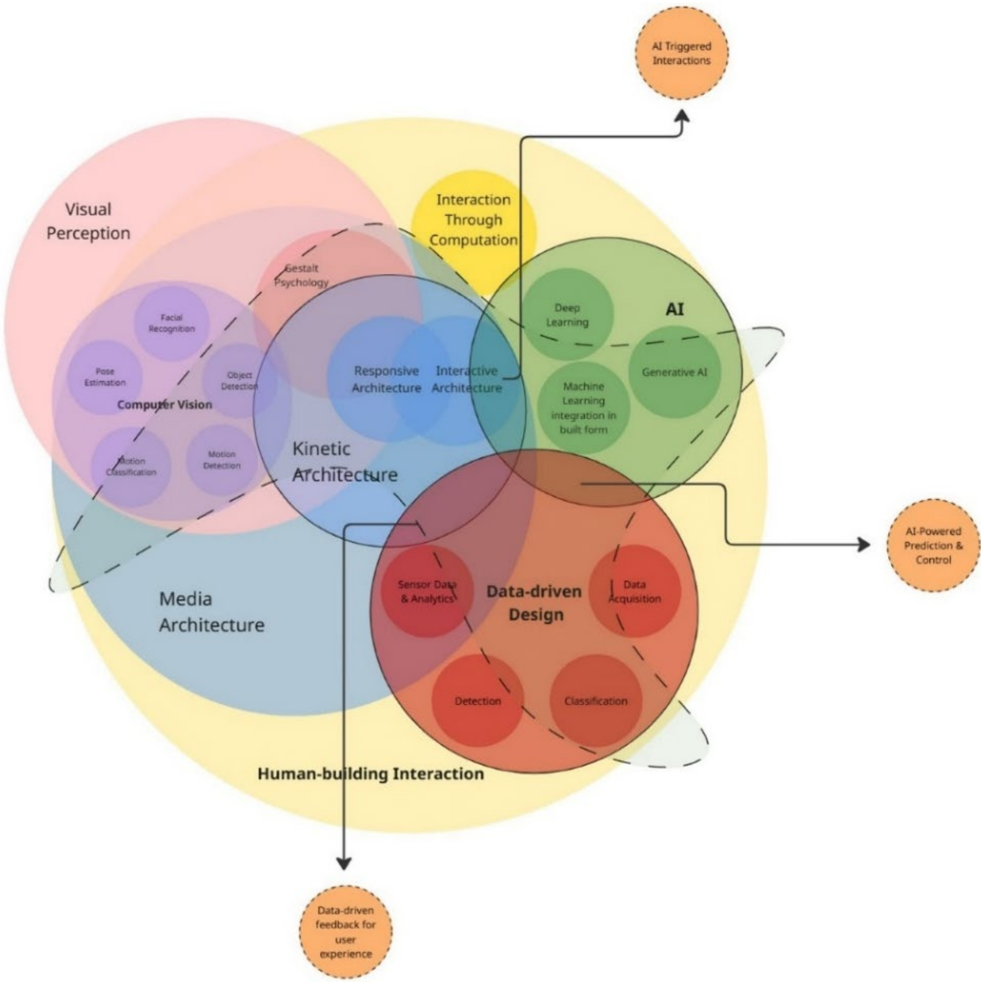

Figure 1.2: Showing thesis's main and sub-research domains and thesis focus.

2.1 Integration of AI in Architecture

AI started to integrate with architecture in a meaningful and traceable way in the period between the late 1980s and early 1990s. It initially started through expert systems and simple rule-based design automation. Its major acceleration came after the year 2010, due to the rise of machine learning (ML), neural networks, and the increasing availability of computational power and architectural data information (Khean et al. 2018).

2.1.1 Historical background of AI in architecture

Architecture is often regarded as one of the slowest professions to adopt new technologies such as artificial intelligence (AI) (Khean, Fabbri, & Haeusler, 2018), despite its slow adoption, meaningful steps in integrating AI for architecture took place in the 1980s. However, literature on AI and architecture started to gradually gain prominence in the early 2000s (Nasir & Alkhalidi, 2023) and became a notable area of research in the late 2010s. This slow integration speaks to the difficulties of applying AI to a creative, highly contextual discipline such as architecture, in which traditional processes dominate, and at the forefront of many conversations in the industry. However, researchers and architects are adopting AI as a tool to be integrated with new technologies and processes in the architecture field.

The application of AI in the field of architecture and design is changing the shape of construction, as it provides us with a whole new world of algorithm-based combinations that lead us to more abstract and conceptual forms and allows the generation of an infinite number of ideas based on mathematically structured parameters. Throughout the history of using AI in architecture, four main phases can be distinguished: modularity, computational design, parametric design, and AI. Modularity brought a new level of standardization and interchangeability to design, allowing for greater flexibility and adaptability. This approach was further developed by parametric design to implement variables that yield different design solutions based on parameters. Finally, AI has extended these concepts by incorporating advanced machine learning algorithms to create optimized and innovative designs (Hegazy & Saleh, 2023).

A foundational concept for architectural evolution is modularity which is associated with the modernist movement. Prefabricated units were introduced as flexible building blocks, and figures like Le Corbusier refined these ideas with systems such as the Modulor, which set the groundwork for more advanced computational frameworks. A significant milestone in computational design occurred when Frank Gehry's firm utilized the computer-aided design (CAD) software CATIA to design the Guggenheim Bilbao Museum shown in Figure (2.1) , showing how digital tools could be applied to managing complex, curved surfaces and paving the way for more advanced AI-based tools (Hegazy & Saleh, 2023).

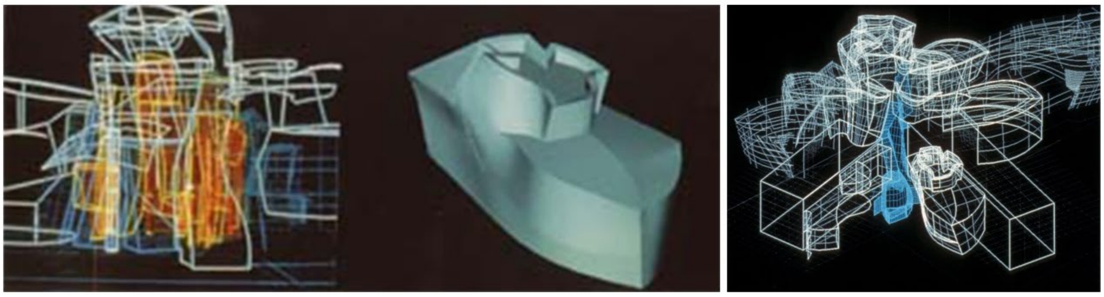

Figure 2.1: CATIA 3D modelling software by Gehry foundation – Adapted from Runddy Ramilo & Mohamed Rashid Embi. (2014).

In the early days of AI research, it was defined in 1956 Dartmouth Summer Research Project, setting the discipline in motion based on the use of human cognitive processes as the basis for intelligent human logic. This was a major moment in history, establishing AI as an official area of research. In the 1970s, Nicholas Negroponte's Architectural Machine examined human-machine interaction, employing software that transformed the layout of rooms based on inputs provided by users and existing light conditions. His work was a precursor to integrating human intuition to machine-based design logic. At the same time, Cedric Price's Generator project (1976) proposed a similar concept of self-adapting, autonomous, partition-type buildings, based on user actions and reactions, showcasing the capacity for AI to drive the adaptability of architecture projects (Chaillou, 2022).

Machine learning in the early 21st century also revolutionized the field. This is in contrast to older approaches such as shape grammars, shown in Figure (2.2), which generate designs according to rules that were defined beforehand, whereas deep learning techniques allow AI systems to discover patterns from data without the need for rules to be programmed beforehand. With the evolution of deep neural networks

(DNNs), they are increasingly being extended to span as diverse as spatial design, despite the increased challenge in doing so. Another promising approach is generative adversarial networks (GANs), which train on existing datasets and create unseen yet plausible architectural forms and new design variations that transcend classical design processes (As, Pal, & Basu, 2018).

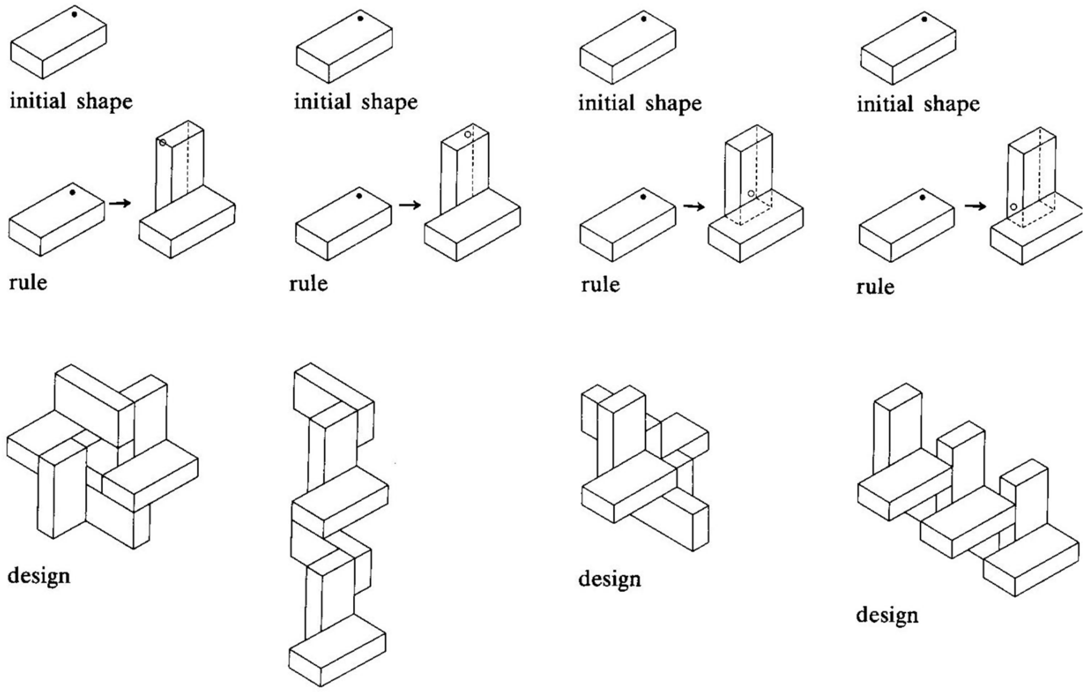

Figure 2.2: Shows organization of shape grammar – Adapted from Maya Gao. (2020).

In the last decade deep learning has ushered in major progress in the role of AI in architecture. From generating nesting beyond human preconception, to a paradigm shift in how we generate form, all the way to the radical transformation of how we and machines work together. Today, we recognize AI as the fourth great turning point in the history of architectural technology, alongside modularity, CAD, and parametricism. Here, we will see how AI can drive innovative approaches with new tools that enhance creativity and adaptability, establishing architecture as a discipline that leads technological advances (Chaillou, 2022).

2.1.2 AI-driven design processes

Innovative designer architects in the computational architecture domain have indicated that contemporary architecture practices will be increasingly shaped by artificial intelligence (AI) and machine learning (ML) as anticipated in future design ideas that are far more advanced in shaping architectural concepts (Tamke, Nicholas, & Zwierzycki, 2018). This stance also presents a challenge to architects and designers to rethink how architecture can develop in association with AI in novel ways. Yet to be able to devise an effective combination between AI systems and a human designer, it requires expertise in the management of data preparation, refinement, and the arrangement of results (Akcay Kavakoglu, Almaç, Eser, & Alaçam, 2022). These processes require the handling of large amounts of data: environmental or user data of different scale as well as subjectively synthesised and often contradicting design inputs.

Inevitably instead of being seen as a peripheral instrument, AI is a radical communication bridge between the design environment, the architect and the final user. Such a paradigm helps to mitigate the glut of itemized information that the designer has to make sense of from a relatively constricting perspective and allows for a more flexible and organic flow of design (Andreou et al., 2023). As such, AI is capable of shifting architectural practice from linear, static processes to processes that are fluid, adaptive, and continually volatile.

Generative AI technologies that produce content ranging from text and images to music videos and 3D models, are maturing fast and restructuring architectural pipelines. Generative networks such as Generative Adversarial Networks (GANs) and variational autoencoder (VAEs) have been predominantly utilized for image and content generation within the criteria of architecture. Lately, however, emerging Denoising Diffusion Probabilistic Models (DDPMs) and Laboratory Data Management System (LDMs) outperformed earlier techniques for more relevant and varied image generation abilities, showing a gradual change toward a better and AI-oriented method for improving design quality (Li et al., 2024). The architectural design process moves from the abstract to the concrete: first design concept, then 3D form, next floor plan, structural system, facade composition, and section. Generative AI models can be used during each of the above stages to enhance workflow and creativity (Li, Zhang, Du, Zhang, & Xie, 2024). Similar to how DALL-E and Stable Diffusion use vision models, deep learning-based methods for different types of vision tasks including image classification, object detection, and creative image generation tasks have become popular as shown in Figure (2.3).

Figure 2.3: Architectural renders generated by Midjourney (Source: Author)

They allow architects to rapidly create conceptual imagery and improve visual communication. The recent coupling of generative AI tools like ChatGPT with design softwares such as Dynamo and Grasshopper enables the generation of 3D architectural models that are parametric as per the requirements and data enriched (Ko, Ajibefuna, & Yan, 2023). With this approach, repetitive design tasks are automated, models are iteratively refined in real time, and the designer's agency to orchestrate complex, architectural elements is amplified. Moreover, tools such as Veras offer immediate visual feedback in the design phase, helping architects to explore different design alternatives and fine-tune their creations dynamically (Ko et al., 2023). The incremental feedback enhances the efficiency of the design pipeline, allowing for rapid iteration and exploration of ideas.

2.1.3 Systems powered by AI

Energy management utilizes incoming measurements together with multiple linear regression, artificial neural networks, or vector regression to create responsive environments. The idea of "iBuilding", for example, denotes a digital infrastructure that integrates the digital and physical elements of a building to permit AI to monitor, modulate, and virtualize the building's systems. This platform is structured based on the building's desired function and performance goals, aiming to deliver a modular and interoperable system, wherein autonomous physical buildings (PB) could be linked within a commensal digital environment (Serrano, 2021).

One class of the predictive models used in energy management are data-driven models that take an integrated network of systems and collects real-time monitored data including temperature, humidity, weather parameters, and real-time energy consumption patterns (Candanedo, Feldheim, & Deramaix, 2017). These systems can optimize energy use while showcasing how AI-driven design can be used to create buildings that are not only more intelligent but responsive to their environment as well. Building control based on AI started in the 1990s, where the first intelligent controllers were optimized using evolutionary algorithms. These rudimentary systems made independent decisions about HVAC based on the preferences of occupants. Despite its simplicity, more advanced implementations exist such as direct neural network controllers that apply back-propagation algorithms to train HVAC systems to adapt to user preference while maintaining optimal comfort levels (Merabet et al., 2021). Moreover, besides neural networks, another well-known method, Fuzzy Logic Control (FLC) has been popularized in the field of smart systems in buildings, in the attempt to reflect human decision making process and formulate the logic of dynamic comfort control rules. The ability of using both qualitative and quantitative observations to identify the rules governing a specific environment is then fine-tuned with pilot testing, making FLC based systems flexible to incorporate non-linear indicators of significance. Also, with the help of ANFIS, energy savings of 21.81% to 44.36% and comfort increasement of up to 85.77% have been reached (Merabet et al., 2021).

Although, AI powered control systems have their advantages, they are not always perfect as they are directly correlated to the quality of data attached to the system, which is usually hard to gather in the building energy domain. The complexity of the algorithms employed may also pose barriers to implementation (Merabet et al., 2021). Overcoming these obstacles will require rigorous data collection methods, more efficient AI algorithms, and cross disciplinary efforts, so that adaptive systems powered by AI can fully reach their potential of assisting and empowering humanity.

2.2 Data-driven Design

Data-Driven Design (DDD) represents a fundamental shift from intuition-based practices toward evidence-informed decision-making within the design process. As Quiñones-Gómez, Mor, and Chacón (2025) note, the growing integration of computational analysis, artificial intelligence, and large-scale data has transformed how designers conceptualize and execute projects in the digital era. DDD merges creative intuition with analytical precision, allowing design to operate simultaneously as an expressive and scientific discipline. By embedding data analysis within iterative workflows, designers can test, predict, and refine outcomes based on measurable feedback rather than subjective interpretation.

Johnson, Hurst, and Safayeni (2023) expand this perspective by defining DDD as the integration of data collection, analysis, and interpretation throughout all stages of the design process. In this view, both quantitative and qualitative information guide— and at times automate—design decisions. Designers increasingly use predictive analytics, machine learning, and artificial intelligence to interpret "use-phase" data, customer feedback, and behavioral patterns. Yet, as these authors emphasize, there is no single, universally accepted definition of DDD. Some scholars distinguish between data-informed, data-inspired, and data-driven approaches, underscoring different degrees of human involvement. The most balanced understanding positions DDD as a collaborative framework in which data enhances human creativity and reasoning rather than replaces them.

Briard, Jean, Aoussat, and Véron (2023) further describe DDD as a response to the growing digitalization of products and the influence of Industry 4.0. In physical product and architectural design, DDD relies on both captured data—obtained through sensors during use—and external data, such as online reviews or social media input. This combination allows designers to evaluate real-world performance and user behavior, translating empirical evidence into improvements in functionality, efficiency, and experience. While its adoption in physical design remains emergent, DDD has redefined the designer's role as both creator and analyst, requiring fluency in interpreting complex datasets and collaborating across disciplines.

DDD reframes the process as adaptive and continuously learning, where data serves as an active medium linking human intuition, technological intelligence, and empirical validation. Through this synthesis, design evolves into an evidence-based and responsive practice capable of addressing dynamic human and environmental needs (Quiñones-Gómez et al., 2025; Johnson et al., 2023; Briard et al., 2023).

2.2.1 Data acquisition and processing

Data acquisition refers to the process of collecting, conditioning, and digitizing information from physical systems to enable analysis and decision-making. As Todd (2014) explains, a typical data acquisition system (DAQ) is composed of several key modules: the sensor, which detects and converts physical phenomena into measurable electrical signals; the signal conditioning unit, which amplifies, filters, and digitizes these signals; the output module, which displays or stores data; and, in some cases, a control module that feeds real-time feedback into the system. The precision of data collection depends heavily on sampling theory, particularly the Nyquist criterion, which ensures that signals are captured at a frequency sufficient to prevent aliasing and distortion. Once sampled, analog signals are quantized and encoded into digital form, typically through analog-to-digital conversion, where bit depth determines resolution and accuracy. The integration of these components allows for accurate, real-time monitoring and analysis, transforming raw sensor input into actionable digital data (Todd, 2014).

In the broader context of data-driven design, data acquisition and processing form the foundation of any analytical or computational workflow. As Biswas et al. (2022) explain, these two stages are the first and most critical components of a data science pipeline, determining the quality, usability, and reliability of the insights generated. The acquisition phase involves collecting data from a variety of heterogeneous sources, such as sensors, user interactions, simulation outputs, or online datasets. Effective acquisition requires an understanding of *data provenance*—that is, where the data comes from, how it was generated, and under what conditions—to ensure consistency and validity throughout the process.

Following acquisition, the processing stage prepares raw data for analysis through cleaning, transformation, and validation. This stage often includes handling missing or noisy values, standardizing data formats, and aggregating information into structured forms suitable for computational modeling. According to Biswas et al. (2022), this process is not purely technical; it requires careful design thinking to balance automation with human judgment, ensuring that data is both contextually meaningful and computationally efficient. The authors emphasize that acquisition and processing should not be seen as linear or isolated steps, but as interconnected processes within a feedback-driven ecosystem that supports continuous learning and refinement.

When integrated into a design or architectural workflow, these practices enable designers to translate complex real-world phenomena into structured, interpretable information. This allows for adaptive systems that can respond dynamically to user behavior, environmental conditions, or performance data—ultimately transforming data acquisition and processing into creative and analytical extensions of the design process (Biswas et al., 2022).

Data acquisition serves as the foundation of intelligent and networked systems, enabling real-time monitoring, automation, and predictive control. Integrating data acquisition technologies allows for remote management of installations through sensor networks and node devices that continuously collect and transmit information. This process improves efficiency by detecting faults, monitoring performance, and supporting predictive maintenance (Petilla, 2025).

In renewable energy systems, especially solar photovoltaic (PV) applications, data acquisition is crucial for tracking power generation, environmental conditions, and storage performance. Sensors convert physical parameters into measurable signals, which are processed through communication networks and analyzed in cloud or edge systems. The resulting feedback optimizes operation, reduces maintenance costs, and enhances system reliability (Petilla, 2025).

Ultimately, data acquisition and processing create a continuous feedback loop in which information is gathered, analyzed, and used to inform decisions. This transforms static monitoring systems into adaptive, learning environments capable of responding intelligently to real-time conditions (Petilla, 2025).

2.2.2 Prediction

In the context of data-driven design, *prediction* serves as a core mechanism that enables buildings and systems to forecast and respond intelligently to dynamic environmental and operational conditions. It involves the use of artificial intelligence and machine learning models to anticipate future states—such as energy demand, occupancy, and climatic fluctuations—based on real-time and historical data (Rajaram & Swathika, 2025). Predictive modeling transforms buildings from passive structures into adaptive systems capable of optimizing performance, minimizing waste, and enhancing occupant comfort.

Within smart building systems, predictive algorithms process large streams of sensor data, including temperature, humidity, lighting, and CO_2 concentration, to generate actionable insights. Ensemble learning methods such as Random Forest, XGBoost, and AdaBoost have proven particularly effective, achieving accuracies above 99% in forecasting occupancy and energy demand. By accurately distinguishing between occupied and unoccupied states, these models prevent unnecessary energy use and support measurable reductions in both operational costs and carbon emissions. Complementary feature selection techniques, such as ANOVA and Principal Component Analysis (PCA), further refine predictive accuracy by identifying the most influential input parameters, improving both computational efficiency and interpretability (Rajaram & Swathika, 2025).

Building upon this foundation, adaptive data-driven frameworks such as *Data-enabled Predictive Control* (DeePC) integrate prediction within control architectures that evolve through continuous learning. These systems update their parameters automatically using real-time building management data, ensuring stable and accurate forecasts even under variable conditions like changing weather or occupancy patterns (Shi et al., 2025). In a 52-day case study conducted at EPFL's Polydome building, an adaptive predictive model achieved a 24.7% reduction in operating costs compared to traditional control strategies, demonstrating its capacity for robust and energy-efficient operation. Prediction, in this sense, becomes a continuous learning process embedded within intelligent building systems—enabling proactive energy management and optimized comfort levels through self-adaptive control (Shi et al., 2025).

Similarly, in data-driven control applications, predictive models such as artificial neural networks, Gaussian process regression, and linear regression serve as forecasting engines for *model predictive control* (MPC) frameworks. These models anticipate system behavior and inform control actions over a defined time horizon, allowing systems to act preemptively rather than reactively (Stoffel, Berktold, & Müller, 2024). While neural networks achieve high predictive accuracy, simpler regression models often provide greater robustness and easier calibration for real-world applications. By incorporating learning-based forecasting into control workflows, buildings can reduce energy consumption, maintain thermal stability, and achieve measurable performance gains.

Ultimately, prediction bridges data and design by transforming raw information into foresight. It allows systems to evolve from static monitoring to adaptive reasoning, forming the analytical backbone of data-driven architecture and enabling environments that continuously learn, forecast, and optimize their own behavior (Rajaram & Swathika, 2025; Shi et al., 2025; Stoffel et al., 2024).

2.2.3 Classification

In data-driven and intelligent design systems, *classification* functions as a critical interpretive process that converts raw sensory data into structured categories capable of driving responsive behavior. It determines what an input represents—such as a gesture, environmental change, or behavioral pattern—before predictive or control actions are executed. This process forms the bridge between perception and action, allowing computational systems to understand and respond intelligently to contextual cues. Convolutional neural networks (CNNs) have emerged as dominant architectures for classification tasks because of their ability to automatically extract hierarchical features from complex data without requiring manual feature engineering, shown in Figure (2.4) (Sen, Mishra, & Dash, 2022).

Sen, Mishra, and Dash (2022) proposed an ensemble-based CNN framework that enhances the reliability and adaptability of classification. Their approach begins with preprocessing operations such as background subtraction, contour extraction, segmentation, and resizing, before passing the refined data through three distinct CNN architectures—GoogLeNet, VGGNet, and AlexNet. The averaged outputs of these networks form an ensemble classifier that reduces overfitting and improves generalization by balancing the biases of individual models. This system achieved accuracy rates of up to 99.8% on multimodal gesture datasets such as the hand classification model shown in Figure (2.5), underscoring the robustness of ensemble deep learning for real-time recognition in complex or unpredictable environments.

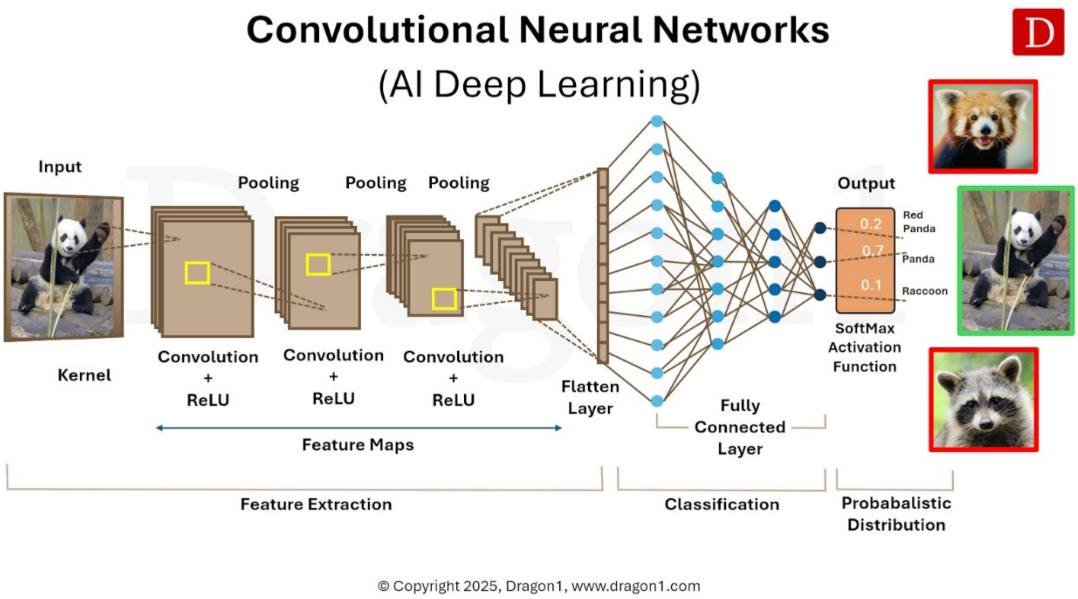

Figure 2.4: Convolutional Neural Networks – Adapted from Dragon1.

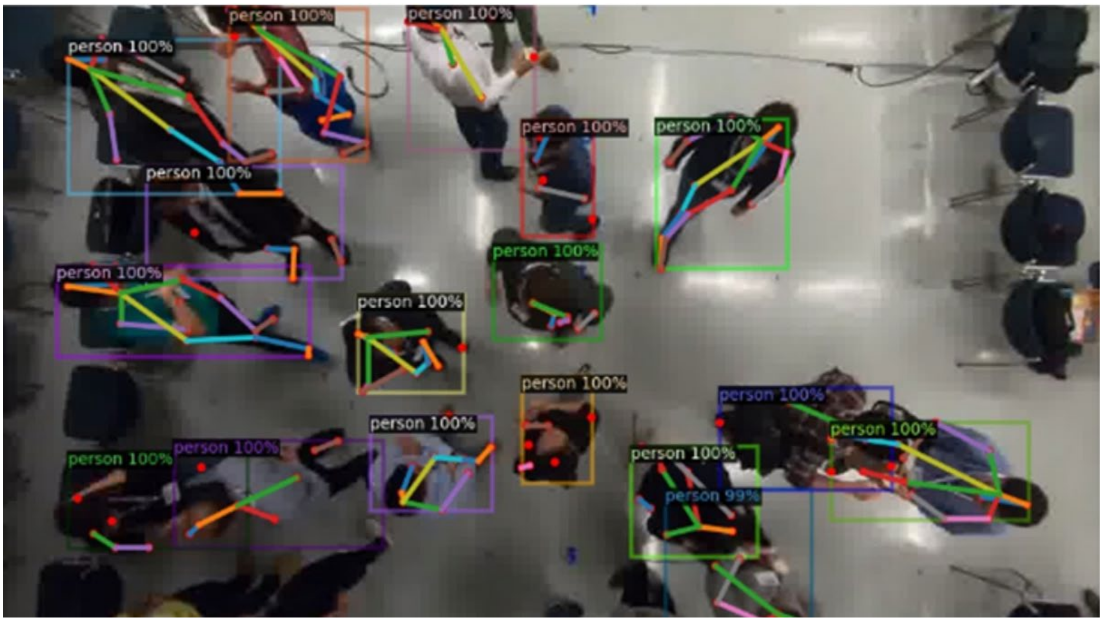

Figure 2.5: Adapted from "Hand gestures classification in crowded environments" by A. Grigore, 2024 (Delft University of Technology).

Köpüklü, Gunduz, Kose, and Rigoll (2019) further developed a hierarchical deep-learning architecture that integrates detection and classification into a real-time framework shown in Figure (2.6). The model employs two CNNs: a lightweight detector that identifies gesture presence and a deeper classifier that recognizes specific gestures. This structure ensures computational efficiency by activating the heavier classifier only when a gesture is detected. Using a 3D CNN to capture both spatial and temporal features of motion, the system achieved accuracy levels of 94.03% and

83.82% on benchmark datasets. Weighted averaging and temporal filtering techniques were applied to ensure that each gesture was recognized only once, eliminating redundant activations. This approach illustrates how classification can function dynamically, enabling systems to make confident, early predictions while maintaining real-time responsiveness (Köpüklü et al., 2019).

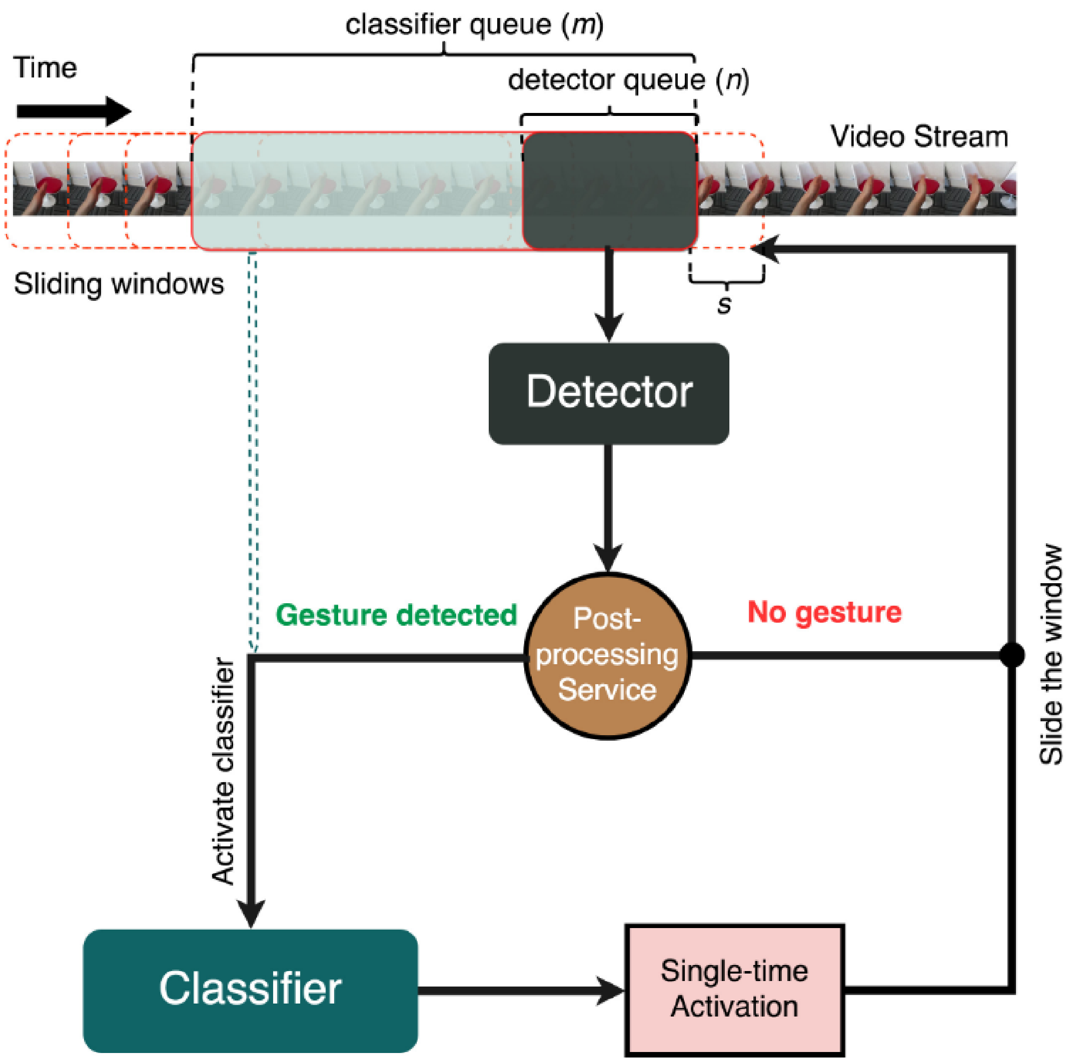

Figure 2.6: Adapted from "Real-time hand gesture detection and classification using convolutional neural networks" by Köpüklü et al., 2019

Beyond traditional CNN approaches, classification also extends to hybrid and sensor-based systems that emphasize energy efficiency and hardware adaptability. Almania, Alhouli, and Sahoo (2024) demonstrated this through a photovoltaic sensor-based framework designed to classify dynamic hover gestures while simultaneously harvesting ambient light energy. A dataset of 3,696 samples from 48 participants was preprocessed through smoothing, normalization, and resampling to mitigate noise caused by variations in motion and lighting. Among several machine learning algorithms evaluated—K-Nearest Neighbors (KNN), Gradient Boosting (GB), Logistic Regression (LR), Decision Tree (DT), and Random Forest (RF)—the Random Forest model achieved superior performance with 97.17% accuracy, 97.25% precision, and 97.11% F1-score. The ensemble structure allowed for strong generalization, effectively distinguishing between visually similar gestures while maintaining low energy consumption.

More recently, transformer-based classification models have shown strong potential in decoding complex human behavior in dynamic and crowded environments. Grigore (2024) applied visual transformer architectures, specifically a fine-tuned VideoMAE model, to classify gestures captured from top-view recordings in multi-person interactions. By segmenting gestures into phases—preparation, hold, stroke, and recovery—the model achieved 95% accuracy in phase classification and 93% accuracy in identifying complete gesture units. Despite challenges with data imbalance, the inclusion of bounding-box annotation and temporal segmentation improved model stability and reduced phase confusion. These advancements illustrate how classification continues to evolve toward greater spatial and temporal sensitivity, enabling nuanced recognition of human movement within complex environments.

Ultimately, classification transforms data-driven systems from passive sensors into active interpreters capable of understanding human intent and environmental context. Whether achieved through CNN ensembles, hierarchical detectors, ensemble forests, or transformer-based models, classification provides the computational foundation for intelligent, adaptive, and responsive environments—bridging perception, data interpretation, and interactive architectural performance (Sen et al., 2022; Köpüklü et al., 2019; Almania et al., 2024; Grigore, 2024).

2.2.4 Detection

In data-driven and intelligent systems, detection represents the foundational process of recognizing and localizing objects or events within an environment. It integrates classification with spatial localization, identifying what an object is and where it exists within a frame or dataset. Detection serves as the perceptual foundation for computer vision, forming the first step toward systems that can perceive, analyze, and respond to their surroundings. This process is essential not only in surveillance and robotics but also in responsive architectural applications where the recognition of movement, gestures, or environmental change enables adaptive spatial behavior (Neha, Bhati, Shukla, & Amiruzzaman, 2024; Wahab et al., 2022).

Early detection techniques relied on handcrafted feature extraction methods such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and edge-based operators. These techniques offered robustness to variations in scale, rotation, and lighting but were limited in their ability to interpret high-level semantic patterns. Classical models like the Viola–Jones detector and the Deformable Part Model introduced real-time detection and part-based representation, yet they often struggled in cluttered or multi-object scenes due to computational inefficiency and limited generalization (Neha et al., 2024; Edozie, Shuaibu, John, & Sadiq, 2025).

The emergence of deep learning marked a transformative shift in detection research. Convolutional neural networks (CNNs) enabled systems to automatically extract hierarchical features directly from image data, replacing manual feature engineering with learned representations. Early deep models such as R-CNN achieved remarkable accuracy but required extensive computational resources. This limitation was addressed by subsequent versions—Fast R-CNN and Faster R-CNN—which introduced region-of-interest pooling and Region Proposal Networks (RPNs) for end-to-end training. These two-stage detectors offered high precision but were less suited for real-time applications (Neha et al., 2024; Edozie et al., 2025).

To improve computational efficiency, one-stage detectors such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector) reframed detection as a single regression task, performing bounding box prediction and classification in a unified process. These models provided near real-time inference, often exceeding 30 frames per second, while maintaining competitive accuracy. Wahab et al. (2022) demonstrated the effectiveness of SSD for real-time detection, achieving 97% accuracy across benchmark datasets including MS COCO and PASCAL VOC. Their SSD-based pipeline integrated feature extraction, background subtraction, and motion tracking modules to enable both static and dynamic object recognition.

Further advancements in neural network design have balanced accuracy and computational efficiency. Yao, Sun, Wong, and Lv (2021) introduced an improved version of YOLOv4 optimized for detecting fine-grained structural features such as concrete surface cracks. Their architecture incorporated SwishBlock bottlenecks and depthwise separable convolutions, reducing model parameters from 64 million to 8 million while maintaining a mean average precision (mAP) of 94.09%. The inclusion of focal loss functions and enhanced feature aggregation modules increased model robustness, allowing accurate real-time detection even under varied lighting and texture conditions. These improvements highlight how detection has evolved from manual inspection toward intelligent, automated recognition capable of adapting to large-scale, dynamic environments.

Contemporary research continues to push detection toward greater flexibility and scalability. Transformer-based models such as DETR (DEtection TRansformer) have unified detection and recognition under attention-driven frameworks, eliminating the need for region proposals and achieving state-of-the-art performance across multiple datasets. Complementary methods such as Feature Pyramid Networks (FPNs), Neural Architecture Search (NAS), and pre-trained backbones like ResNet and EfficientNet have further enhanced adaptability across object scales and domains (Edozie et al., 2025).

Ultimately, detection functions as both a perceptual and cognitive layer within intelligent systems. It transforms raw spatial data into structured, actionable information that enables systems to perceive and interpret their environment in real time. Within architecture, these advancements allow spaces to detect presence, motion, and behavior—serving as the foundation for interactive and adaptive built environments. As lightweight and transformer-based detection models continue to mature, they promise to bridge computation and spatial experience, redefining how data-driven design systems perceive and respond to human activity (Neha et al., 2024; Wahab et al., 2022; Yao et al., 2021; Edozie et al., 2025).

2.3 Overview on Media Architecture

Technological developments, coupled with the rise of media and visual arts, have significantly influenced the trajectory of contemporary architecture, particularly under the conditions of globalization and the dominance of capitalism. Building facades have increasingly adopted media-integrated surfaces, providing society—especially the users of public spaces—with new channels of interaction through advanced technologies (Taşkıranlar, 2016). The changing trends in technology have thus reshaped the design and role of architectural skins, transforming them from static enclosures into dynamic communicative interfaces.

Central to this transformation is the influence of computer media on architectural space. As Murray (2003) identifies, computer technologies are defined by four key characteristics: procedure, participation, encyclopedic capacity, and spatiality. Each of these has directly shaped new media architecture. Procedurality has fostered performative and generative design approaches, where forms emerge through sets of instructions and algorithms (Kolarevic, 2005). Participation, paired with procedurality, has become foundational in the creation of interactive and responsive architectural environments. The encyclopedic nature of computers, with their ability to process and store vast amounts of data, has enabled architecture to engage with contextually expanded and networked information spaces, often visualized as immersive environments. Meanwhile, spatiality highlights the computer's representational capacity to create symbolic and virtual places, where users can form mental maps of fictional or data-driven territories (Murray, 2003).

Interactive installations and new media art have further enriched this field, stimulating human senses beyond the visual and enhancing the experiential dimensions of space (Urbanowicz & Nyka, 2012). In this sense, media architecture not only redefines architectural space but also links closely with urban computing, introducing a fourth dimension—interactivity—into the urban fabric (Haeusler, 2009).

Historically, this trajectory can be traced back to the early 20th century, when theaters and casinos began integrating illuminated text and neon tubes during the 1930s as part of the commercialization of urban environments. With the rise of capitalism and the consumer society, the demand for communication-driven architecture expanded globally, leading to what Huhtamo (2004) describes as "advertising architecture." Today, these evolving media elements continue to serve as critical tools for communication in the digital city, merging technological innovation with cultural expression.

2.3.1 Static media architecture

The rise of capitalism played a decisive role in shaping a consumer-oriented society, embedding advertising features such as neon lights, billboards, scrolling marquees, and large-scale screens into the fabric of architecture. These elements created a new capitalist language of spectacle, where signs and symbols transformed building facades into communicative surfaces (Moza, 2012).

Figure 2.7: Las Vegas Strip in 1970, (The National Archives Catalog, 2014)

Static media architecture can therefore be understood as an architectural mode where meaning is conveyed through fixed imagery and symbols rather than through kinetic or adaptive systems. Robert Venturi, Denise Scott Brown, and Steven Izenour's Learning from Las Vegas remains one of the most influential texts in defining this condition. Their analysis of the Las Vegas Strip showed how buildings function less as spatial enclosures and more as symbolic icons shown in Figure (2.7), dominated by oversized signage. As they famously argued, in such landscapes "symbol in space [comes] before form in space" (Venturi, Scott Brown, & Izenour, 1977, p. 8).

The Las Vegas Strip stands as the archetype of this phenomenon. Motorists encounter illuminated billboards and monumental casino facades long before they interact with the physical buildings, shown in Figure (2.8). At times, the sign itself becomes the architecture—for example, the Motel Monticello's massive Chippendale highboy sign, visible from afar, which effectively substitutes for the building's presence. This reliance on static media has deep architectural precedents, from the symbolic ornament of Gothic cathedrals to the decorative excesses of Renaissance and nineteenth-century eclecticism. Yet unlike those traditions, the Strip's iconography responded to the cultural logic of postwar America: vast open landscapes, automobile mobility, and the demands of a growing consumer economy (Venturi et al., 1977, pp. 6–9).

Figure 2.8: Modern Las Vegas Strip, (The National Archives Catalog, 2014)

In sharp contrast to modernist ideals of purity and functional form, static media architecture unabashedly embraces persuasion and spectacle. Venturi and his colleagues describe this approach as "the architecture of persuasion," where neon, signage, and decorated facades work collectively to attract attention and communicate identity (Venturi et al., 1977, p. 9). Far from being dismissed as superficial, static media architecture represents a powerful communicative strategy—one that relies on permanence, recognizability, and symbolic imagery to anchor meaning in the built environment. In doing so, it demonstrates how architecture participates in cultural and economic life through its capacity to embody and project messages that remain fixed yet enduring.

2.3.2 Digital media Architecture

Digitally dynamic media architecture builds on the integration of immersive technologies, interactivity, and real-time responsiveness to create environments that transcend static representation. Contemporary examples such as teamLab's large-scale installations shown in Figures (2.9 & 2.10) illustrate how architecture can function as a continuously adaptive digital ecosystem. In these works, architectural space becomes less about fixed form and more about shared experience, where visitors engage with environments that evolve through their presence and interaction (Lawhead, 2023).

Figure 2.9: teamLab, Forest of Flowers and People: Lost, Immersed and Reborn, 2017/2021

What distinguishes such environments is their emphasis on continuity. Rather than presenting discrete, isolated media experiences, teamLab constructs fluid, interconnected digital worlds where art, architecture, and technology merge seamlessly. This continuity allows participants to experience space as a dynamic field of relations that shift with movement, perception, and interaction. It creates the sense of inhabiting an environment that is always “in process,” constantly shaped by both computational systems and human engagement (Lawhead, 2023).

Lawhead (2023) emphasizes that these projects resist the logic of spectacle often associated with media façades and instead cultivate collective spatial experiences. The installations rely on real-time sensing and generative digital processes to respond to participants’ actions, producing environments that change unpredictably. This approach reframes architecture as a medium for ecological interaction, where the boundaries between the digital and the physical are blurred, and where space is redefined through continuous feedback loops between human presence and digital systems.

One of the newest projects of media architecture is the Las Vegas Sphere shown in Figures (2.11 & 2.12), or MSG Sphere, which is the world's largest spherical structure, rising 366 feet and accommodating up to 18,000 spectators. More than a venue, it represents a new model of visually dynamic architecture, where space itself becomes a medium of performance. Its defining feature is a 160,000-square-foot 16K interior LED screen, supported by advanced audio, haptic, and sensory systems that create fully immersive environments (Nisa, 2023).

Figure 2.10: teamLab, Forest of Flowers and People: Lost, Immersed and Reborn (Summer), 2017/2021, Asian

Figure 2.11: Las Vegas Sphere used in F1 Race event – Adapted from Charles Curtis (2023).

Externally, the “Exosphere” transforms the building into the largest LED display in the world. During the Formula 1 Las Vegas Grand Prix, for example, it broadcasted live race data and animations, turning the façade into a dynamic communication interface (Nisa, 2023; Feldman, 2023). This integration of technology and architecture expands Las Vegas beyond its casino identity, positioning the Sphere as both cultural landmark and economic catalyst (The Star, 2023).

In this way, the Sphere illustrates how visually dynamic architecture merges structure, screen, and spectacle, making visual media not an accessory but the defining element of architectural experience (Weprin, Giardina, & Weprin, 2023).

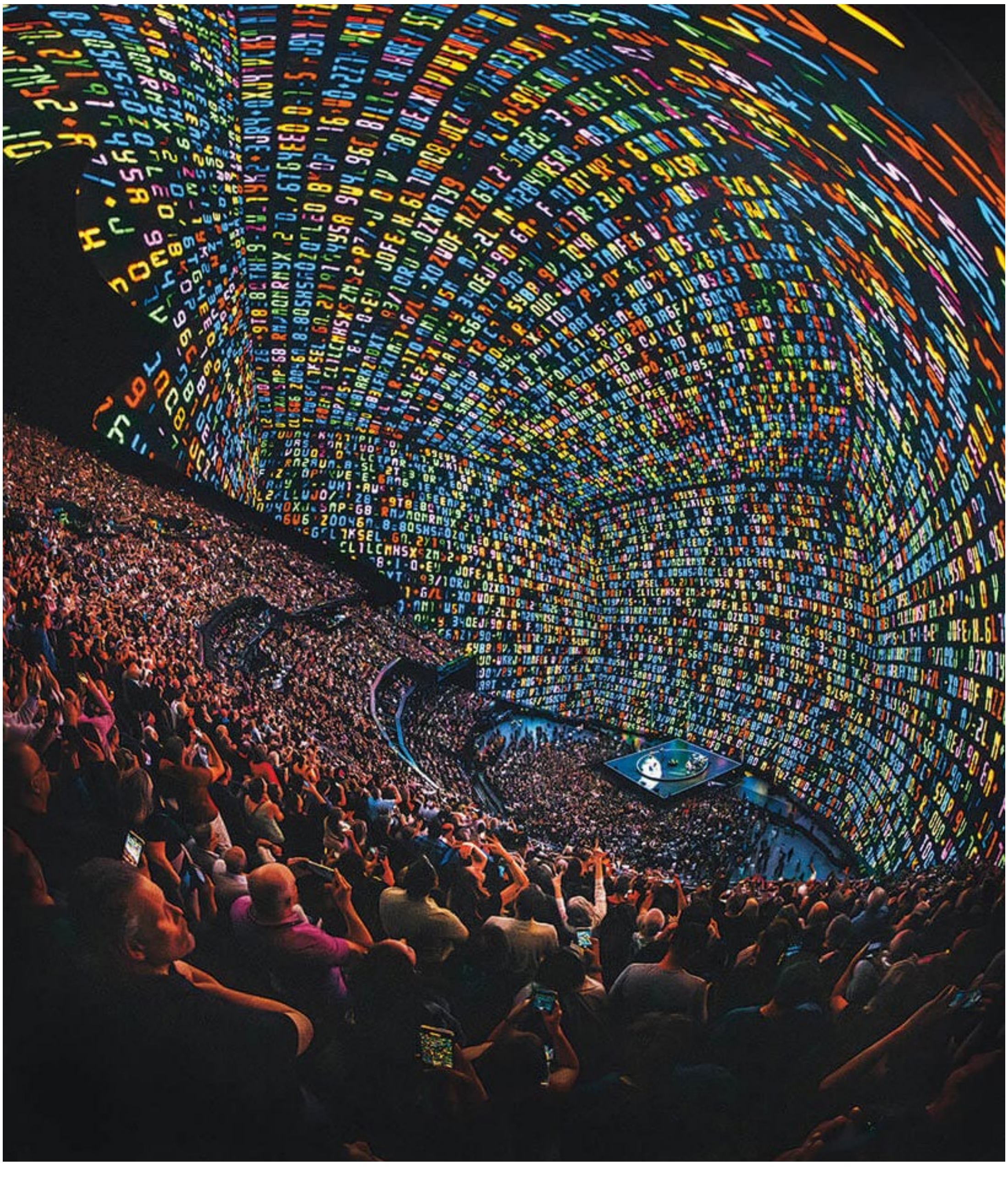

Figure 2.12: The interior display of Sphere – Adapted from Jen Chaney (2023).

As such, digitally dynamic media architecture points toward a new paradigm in architectural practice. It demonstrates how computational systems can expand the role of architecture beyond static form and into the realm of temporal, adaptive, and immersive experience. By prioritizing continuity, interactivity, and shared spatiality, projects like teamLab's establish a framework for understanding architecture as a living digital organism (Lawhead, 2023).

2.3.3 Kinetic media architecture

Mechanically dynamic media architecture refers to systems in which movement, transformation, and responsiveness are embedded into the very fabric of the building through mechanical means. Unlike static media architecture, which communicates through fixed signs and ornament, mechanically dynamic systems rely on actuators, motors, or pneumatic devices to physically shift surfaces and structures in real time. These transformations often respond to environmental conditions, user interaction, or computational inputs, turning façades into performative interfaces rather than passive enclosures. By integrating sensors and control systems with mechanical components, such architectures translate data—whether algorithms, environmental stimuli, or human presence—into visible, tangible motion. In doing so, they redefine buildings as temporal and adaptive systems, emphasizing process and experience as much as form.

One of the earliest and most influential examples of this approach is the Aegis Hyposurface shown in Figures (2.13. 2.14 & 2.15), conceived by dECOi architects and unveiled in 2001. Described as an "architecture with a central nervous system," the installation demonstrated how a building skin could reconfigure itself in real time in response to stimuli (Goulthorpe, Burry, & Dunlop, 2001). The project combined a metallic faceted surface with 576 pneumatic pistons and rubber connectors, producing wave-like motions and three-dimensional deformations. A sophisticated control system delivered data to the pistons every few milliseconds, enabling the surface to translate mathematical algorithms, manual input, or even live video capture into immediate physical movement (Goulthorpe et al., 2001).

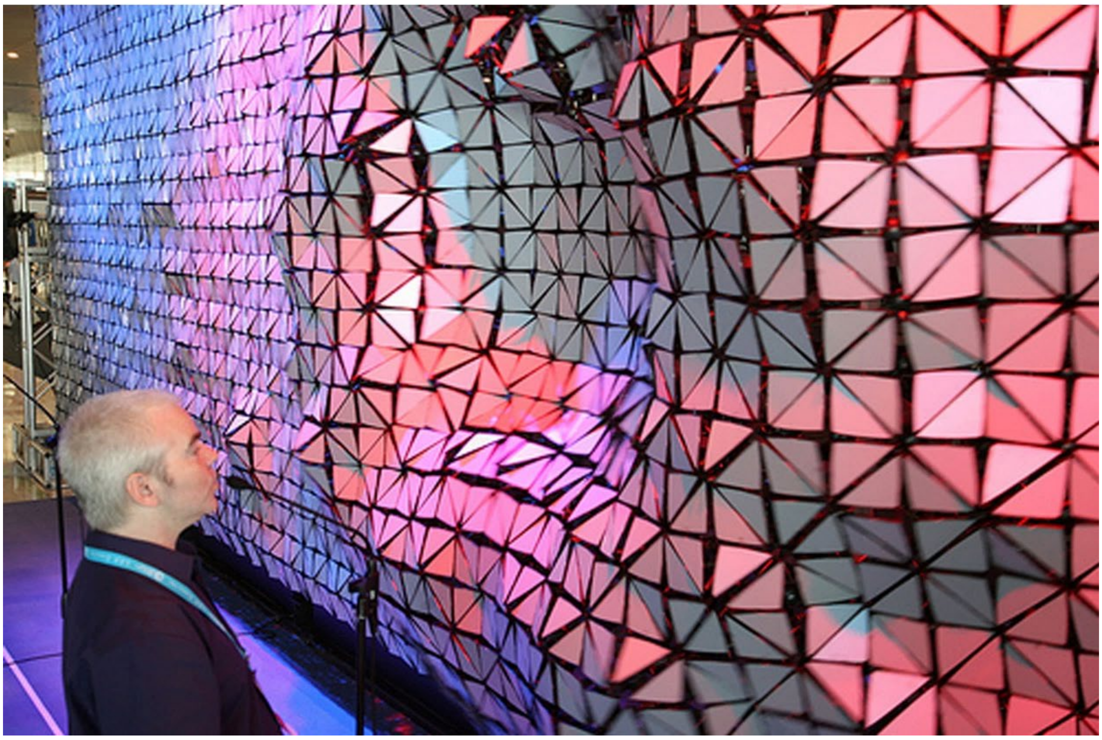

Figure 2.13: Aegis Hyposurface Installation – Adapted from Michael Mascioni (2013).

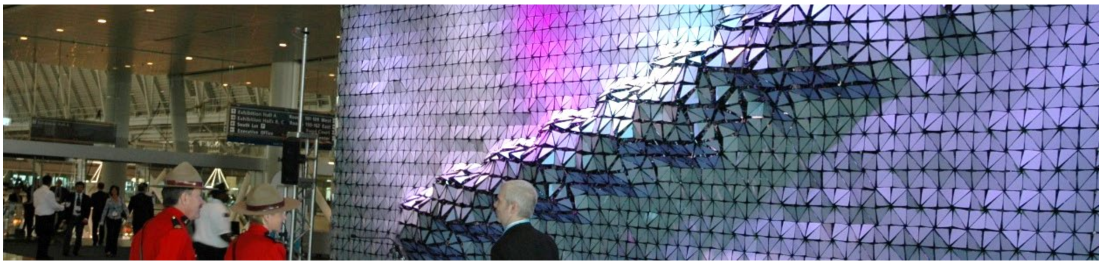

Figure 2.14: Aegis Hyposurface Installation – Adapted from Michael Mascioni (2013).

What made the Hyposurface distinctive was its conceptual departure from static geometry toward a performative surface. Instead of embodying a fixed form, it materialized a shift from autoplastic (closed and determinate) to alloplastic (reciprocal and indeterminate) space, positioning the façade as an active interface between subject, environment, and digital system (Küçükbaşlar, 2006). In Deleuzian terms, it "actualized the virtual" by converting computational simulations into unpredictable, emergent realities. Its movements were non-linear, fluid, and temporal, reframing architectural experience as responsive and adaptive rather than static and predetermined (Küçükbaşlar, 2006).

Ultimately, the Aegis Hyposurface was more than a technological experiment; it signaled a cultural and disciplinary shift. Emerging from collaboration across architecture, engineering, mathematics, and material science, the project revealed how digital media could transform the architectural surface into a communicative and adaptive medium. By doing so, it laid the groundwork for mechanically dynamic media architecture as a field where buildings are not simply containers of activity, but active participants that engage, respond, and interact with their surroundings (Goulthorpe et al., 2001; Küçükbaşlar, 2006).

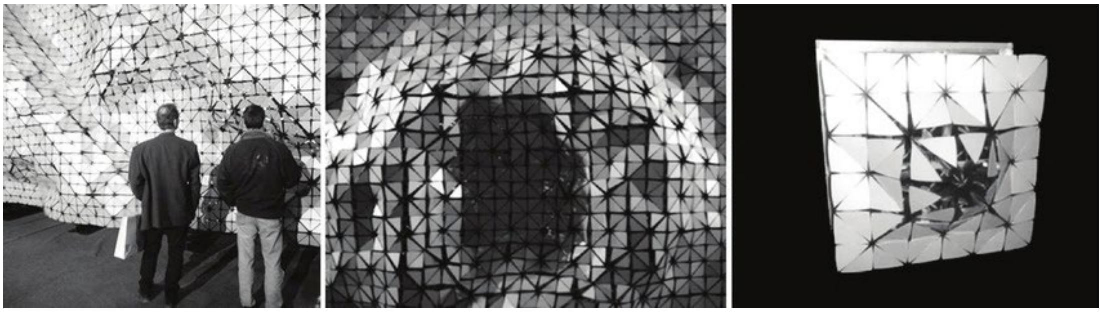

Figure 2.15: Aegis Hyposurface (Goulthorpe 2001).

2.4 Kinetic Architecture

The distinction between responsive architecture (RA), interactive architecture (IA) and adaptive architecture remains contested, with definitions frequently overlapping and applied inconsistently across the literature. As Maia and Meyboom (2015) note, justifications for each term are dispersed across multiple perspectives rather than consolidated into a coherent theoretical framework. Despite these tendencies, the boundary remains blurred. Many kinetic façades and installations operate as simple responsive systems, while a smaller subset achieve full-fledged interactivity or adaptability. In their comparative review of 77 publications and 41 projects, Maia and Meyboom (2015) find that RA tends to prioritize environmental responsiveness, whereas IA places greater weight on human engagement even though both share similar technological foundations.

2.4.1 Interactive architecture

IA is more closely linked to participatory engagement and spatial performance. Fox and Kemp (2009) argue that IA moves beyond environmental adaptation by staging a two-way dialogue between users and the built environment, allowing space to evolve with individual, social, and environmental demands; in practice, this often entails sensory, gestural, or behavioral input that produces more immersive and dynamic experiences (Maia & Meyboom, 2015).

Elmokadem, Ekram, Waseef, and Nashaat (2018) define interactive architecture as an evolving paradigm that merges human participation with computational systems, transforming the built environment into an interface for dialogue between people and technology. Unlike conventional static spaces, interactive architecture enables users to influence and shape their surroundings through direct engagement. The authors describe it as an interactive interface between humans and computers, in which architectural components such as walls, floors, or façades act as mediators that both sense and respond to human activity (Elmokadem et al., 2018).

At its core, interactive architecture operates through a continuous feedback loop based on the input–processing–output (IPO) model. In this process, sensors capture data from environmental or human stimuli (input), computational systems analyze and interpret this data (processing), and actuators trigger corresponding physical or visual responses (output). This dynamic exchange enables architecture to react intelligently and in real time to user behavior and environmental change (Elmokadem et al., 2018).

The study further categorizes interactive spaces into three interrelated layers: sensible spaces, which perceive external stimuli; thinker spaces, which process and make decisions based on the gathered data; and responsive spaces, which execute actions or transformations in response. Together, these layers allow architecture to transcend static functionality and become performative, adaptive, and participatory (Elmokadem et al., 2018).

Ultimately, interactive architecture redefines the relationship between humans and their built environments. It moves beyond mechanical or visual reaction to establish continuous communication between users and systems. In this sense, interactivity becomes both technological and experiential, an active dialogue through which architecture learns from and evolves with its inhabitants (Elmokadem et al., 2018).

A compelling example of interactive architecture can be found in Design for Life, a project developed by Studio INI in collaboration with Dassault Systèmes, shown in Figures (2.16 & 2.17). Designed by Nassia Inglessis, the installation reimagines architecture as an active medium of engagement rather than a static container. The work explores how digital technologies and human presence can coexist within an adaptive spatial environment, transforming architectural form into a living interface that senses and responds to its occupants (Lindsay, C, 2020).

Figure 2.16: “Urban Imprint” by Studio INI – Adapted from Lindsay, C. (2020).

Figure 2.17: “Urban Imprint” by Studio INI – Adapted from Lindsay, C. (2020).

Through the integration of motion sensors, kinetic elements, and real-time data processing, Design for Life enables users to physically influence their surroundings. As people move through the space, their gestures and proximity trigger subtle material transformations and visual shifts across the structure’s surfaces. This interaction establishes a feedback loop between human input and environmental response, allowing the architecture to communicate dynamically with its users. Rather than treating technology as an external layer, the project embeds computation directly into material behavior, merging physical craftsmanship with digital intelligence (Lindsay, C, 2020).

2.4.2 Responsive architecture

RA is commonly aligned with sustainability and user-centered adaptation in which a building reacts to environmental conditions—light, temperature, or energy demand—often with limited or no direct user input. Bullivant (2006) frames such responsive environments as mediating devices that enable new forms of social and artistic expression, suggesting that RA systems are environmentally or performatively oriented, leveraging kinetic technologies to optimize building performance while supporting experiential qualities (Maia & Meyboom, 2015).

The Kunsthaus Graz shown in Figure (2.18 & 2.19) demonstrates how interactivity can be embedded within a responsive architectural framework through its BIX media façade. Designed by realities: united, the 930 circular fluorescent light rings act as pixels, integrating a programmable, low-resolution display into the building's biomorphic skin. Here, the building becomes a communicative surface rather than a mere carrier of technology: it "responds" dynamically to artistic programming and curatorial intent while mediating between institution and city. At night the building's physical form recedes as shifting light patterns animate the envelope, reinforcing the perception of a responsive skin. By enabling artists and curators to author content via custom software, BIX functions simultaneously as a cultural display surface and a responsive architectural element that redefines how architecture engages environment and publics (Bullivant, 2005).

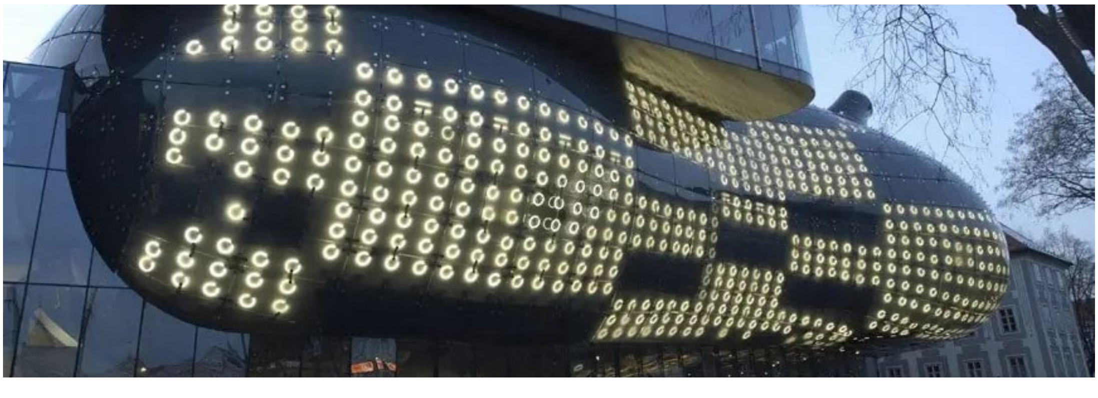

Figure 2.18: Kunsthaus Graz by Peter Cook – Adapted from Riccardo Bianchini. (2014).

Figure 2.19: Kunsthaus Graz by Peter Cook – Adapted from Riccardo Bianchini. (2014).

Hylozoic Ground shown in Figures (2.20 & 2.21) extends responsiveness beyond mechanics into synthetic ecologies. Exhibited in the Canadian Pavilion at the 2010 Venice Architecture Biennale, the suspended textile matrix combined digital fabrication, embedded sensing, and protocell chemistry to form a porous, adaptive milieu. Proximity and touch sensors triggered breathing waves, caressing motions, and rippling movements across kinetic pores and frond-like whiskers, fostering empathic, mutual exchange between visitors and the installation. Concurrently, protocells and chemical membranes supported carbon capture and self-organizing material growth, what Beesley and Armstrong describe as “synthetic succession” that evolves over time (Beesley & Armstrong, 2011). In this way, Hylozoic Ground situates RA as a metabolic system that can also host interactive qualities, positioning the built environment as an active participant in ecological and human interaction.

Figure 2.20: Hylozoic Ground by Philip Beesley – Adapted from Rose Etherington. (2010).

Figure 2.21: Hylozoic Ground by Philip Beesley – Adapted from Rose Etherington. (2010).

A historical arc underscores this conceptual spectrum. Early exemplars like the Institut du Monde Arabe (1987) shown in Figure (2.22), reinterpreted the Mashrabiya as mechanical diaphragms to regulate daylight and heat—visionary but maintenance-intensive, with many features falling into disrepair over time. The subsequent digital wave brought projects such as Barcelona’s Media-TIC (2009), where Arduino-driven sensing modulated ETFE cushions to adjust opacity in response to sunlight—effective but largely reactive and rule-based. More recent work, including Abu Dhabi’s Al Bahar Towers (2012), integrates cultural geometry with predictive algorithms and machine learning to anticipate conditions and optimize performance across 1,000+ mashrabiya-like units (Cocho-Bermejo, 2025). Together, these trajectories show a shift from mechanical ingenuity to digital automation and, increasingly, to intelligent, AI-driven systems. Responsiveness today is tied not only to short-term reaction but to predictive behaviors that evolve with use and context—bringing RA and IA into closer dialogue around energy efficiency, occupant comfort, communicative expression, and long-term environmental balance (Cocho-Bermejo, 2025).

Figure 2.22: Institut du Monde Arabe by Jean Novel – Adapted from Philippe Paupert. (2017).

2.4.3 Adaptive architecture

Adaptive architecture builds upon the principles of responsiveness but extends them by incorporating time as a defining dimension of change. Elmokadem, Ekram, Waseef, and Nashaat (2018) describe adaptive spaces as environments that flexibly adjust to the evolving demands of human activity whether habitation, education, medicine, or industry. This adaptability ranges from reconfigurable interiors to structural systems capable of transformation and programmatic shifts. Unlike purely responsive designs, which react instantly to stimuli, adaptive architecture evolves gradually, responding to patterns and conditions that unfold over time.

According to Elmokadem et al. (2018), adaptation operates at multiple scales from movable partitions and reprogrammable furniture to morphing structural envelopes that respond to climatic forces or user occupation. These systems integrate mechanical, material, and computational adaptability to ensure spatial flexibility, environmental performance, and user comfort. Time thus becomes an essential factor, allowing the architecture to learn and recalibrate its behavior in response to recurring environmental or social changes.

In essence, adaptive architecture represents a progression beyond responsive systems. While responsiveness implies immediate reaction, adaptability implies *learning and evolution* the ability of a system to anticipate, transform, and redefine its function continuously. It embodies the concept of buildings as living organisms, capable of negotiating between user needs, environmental forces, and temporal variability through embedded intelligence and flexible design logic (Elmokadem et al., 2018).

2.5 Visual Perception

The images we perceive on smart-phones and TV screens are usually constructed out of LCD pixel units shown in Figure (2.23). Liquid Crystal Display (LCD) technology uses liquid crystals to electronically control light to display pictures or images.

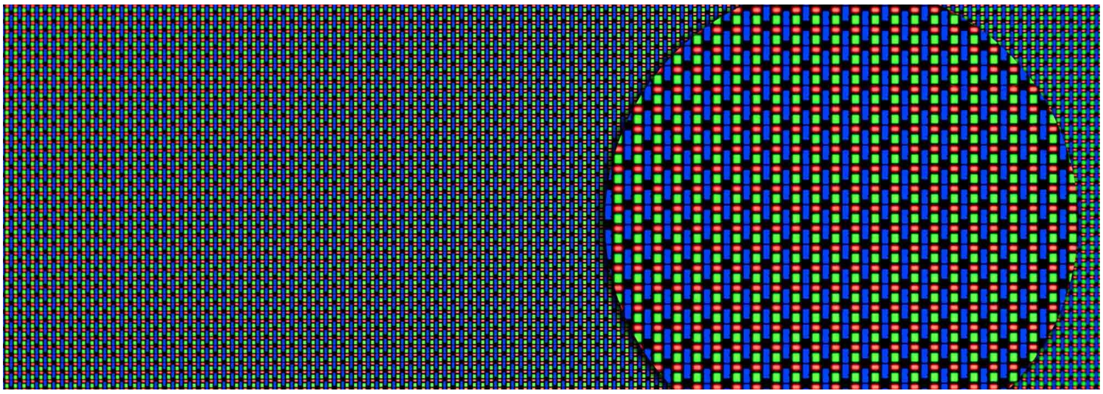

Figure 2.23: LCD Pixels – Adapted from AG Displays. (2020).

But although this is the most common way for seeing images; because all reality such as color, shape or movement is accurately reflected, many other media can also be used to perceive images. In fact, any collection of objects, when arranged in a particular order and with defined attributes, can generate an image (Wertheimer, 1945), as noted by Max Wertheimer, the researcher who played a role in establishing Gestalt psychology. The term Gestalt in German is used to describe the act of assembling or organizing something into a whole in contemporary language. When translated directly into English, there is no exact equivalent for it. It is commonly understood as shape, form, figure, configuration, or appearance in psychological discourse (Encyclopaedia Britannica Editors, 2025). Gestalt psychology, describing mind and brain, explains the processes through which humans perceive elements as organized patterns and unified wholes, rather than as the sum of parts, as shown in Figure 2.24 (Karout, Akçay Kavakoğlu, & Ayech, 2024).

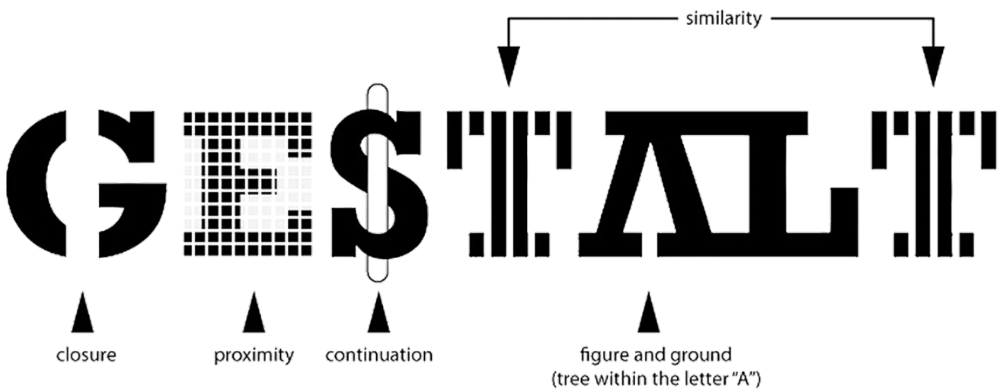

Figure 2.24: Principles of Gestalt psychology – Adapted from Aimee. (2020).

Gestalt psychology contains seven principles: proximity, similarity, continuity, closure, symmetry, common fate and figure/ground (Rock & Palmer, 1990). This theory was developed in the early 20th century in Germany, notably represented by three thinkers: Max Wertheimer, Kurt Koffka, and Wolfgang Köhler (Karout, Akçay Kavakoğlu, & Ayech, 2024). Gestalt Principles had been used widely in the design of software user interface to help with the subconscious aspect of the human species to group together the details, interpreting each element in light of the cluster, thereby making up the software environment without anything being said (Lidwell, Holden & Butler, 2010). He claimed that perception is a cognitive process that demands reasoning, problem-solving, and abstract thinking. The process is not the reception of stimuli; it is the exploration and interpretation of the environment such as in Figure (2.25) (Arnheim, 1969). It describes how people see every element in any environment. It should be noted that this can be implemented with respect to audial, tactile and visual environments (MacNamara, 2016). They can produce more insightful interfaces that help improve the human-machine interaction by using the perception principles of Gestalt psychology.

Figure 2.25: Rubin’s glass showing different perceptions – Adapted from Michael Dain. (2014).

2.5.1 Movement and transformation in perceived forms

Visual perception is a process of cognition, researchers refer to this process as “visual thinking” connected with movement, transform of shape and brightness; Movement and transformation of forms are not simply random transitions, but meaningful transitions within an ordered visual field. When perception is observed via motion, it consists of predictive component since the mind predicts the kinematics and end result of the motion. Abstract visual representations enable the brain to model such dynamic and complex phenomena, says Arnheim, reinforcing the role imagery plays in our understanding of transformations in spatial structures. According to Arnheim, we do not simply see a motion of the objects; we synthesize a series of images in our mind into a fluid motion. In other fields, such as cinema and animation, the brain combines still pictures into a continuous flow such as Figure (2.26).

Visual perception will want balance and symmetry even in changing forms. As an object changes its position or form, viewers subconsciously look for new visual clues. And that is, the brain converts complex visual stimuli into simple patterns and that is a skill that is absolutely necessary to understand transformations, as it prevents sensory overload. Time is an important component in interpretation of transformation–in which how quickly and how long something changed will shape the way viewers interpret it. Rapid transformations can feel chaotic or disorienting; slower shifts can read as fluid or graceful. Understanding requires prediction, meaning that observers can anticipate future states of a moving object depending on its movement direction, velocity, and form. the more realistic they are, the less the audience should be expected to work to fill in the gaps and build meaning and so they can actually lead them into an experience less engaged with imagination and staring into the piece in an amaze (MacNamara, 2016). In book “Visual Thinking,” Rudolf Arnheim argues that human beings are predisposed by our bodies to have an intuitive awareness of dynamic forms (Arnheim, 1969). Actually, humans’ minds are more sensitive about movable objects. It attempts to comprehend the visuals inputs by categorizing the visual cues into organized forms relying on theories of Gestalt psychology which originated from a school of thought founded by Max Wertheimer, Wolfgang Köhler, and Kurt Koffka, in the early 20th century (MacNamara, 2016).

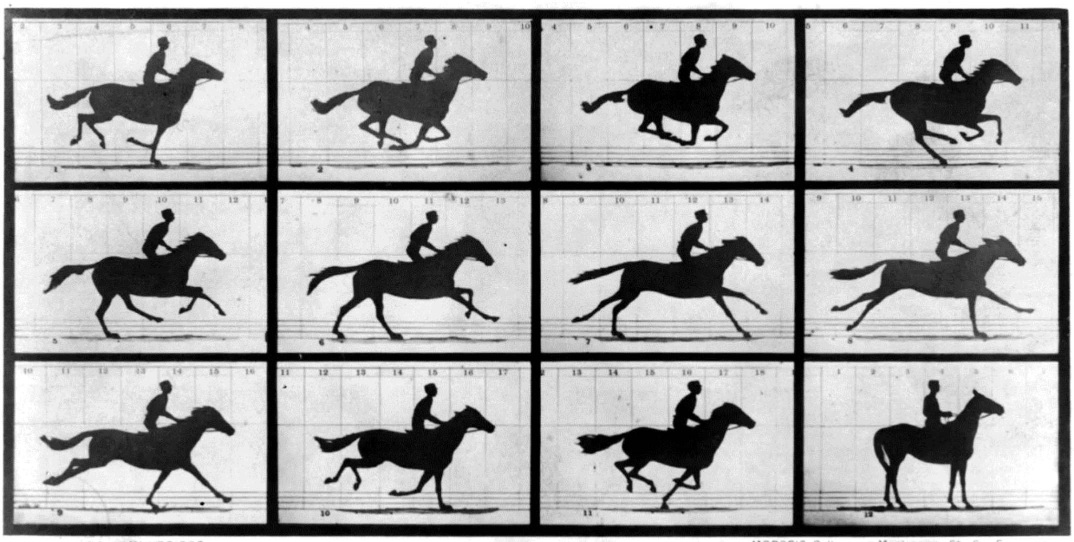

Figure 2.26: Eadweard Muybridge's galloping horse – Adapted from Gregory Singer. (2002).

2.5.2 Interaction and user engagement in visual experiences

Interaction and user engagement in visual experiences is generally governed by a combination of users’ personal histories, knowledge, skills, and emotions, along with system characteristics such as interface design and information architecture. Engagement covers affective, cognitive and behavioral dimensions, meaning it is a holistic concept and not a simple metric (O’Brien & Cairns, 2016). Visual features, sounds, motion, and touch are commonly used to attract users, but they also physically interact with the interface features by watching, clicking, swiping, or hovering such as Figure (2.27).

Figure 2.27: Immersive visual experience – Adapted from TeamLab. (2022).

Interactive media often does not have it such a structure that allows engagement to remain constant throughout an experience, people often drop out and come back in later, The flow theory was developed by Mihaly Csikszentmihalyi and refers to a state in which the user becomes completely absorbed in performing an activity until he/she loses track of time and distractions and reaches a profound feeling of enjoyment and satisfaction (Csikszentmihalyi, 1990). Conversely, Sundar identifies three drivers that attract us to interactive designs: customization, multimodality and contingency. Furthermore, customization is the power to make changes or control user's own communication setting according to their choice. For example, people can use the web tools provided by portal websites to personalize the appearance of the home page or synchronize the website with people's mobile devices or other applications. Multimodality is the extent to which the interface supports multiple types of input modes of communication, such as speech, touch, gaze and gesture. Lastly, contingency is the amount of the given message that is dependent on its reception of the prior message and the one before that (Sundar, 2007).

2.5.3 Multisensory cognition of architectural spaces

Human engagement with architectural spaces is inherently multisensorial. Architects such as Juhani Pallasmaa have argued that we do not perceive spaces through our eyes alone; instead, we perceive them through our ears, our skin, our nose, and our tongue (Pallasmaa, 1996). Until the last two decades, architecture practice has been heavily commitment-based, giving detail to the “eye of the beholder”. As the brain allocates disproportionate resources for processing information visually (Spence, 2020), it becomes perhaps unsurprisingly that the visual modality was found to consistently dominate the other modalities. The sense of vision is the most prevalent guiding the characterized architectural space, however, deja-vu creates visual discipline with other sensory cues including sound and touch, which can impact what is visible in relation to architecture. Visual cognition is also with influence of perceptual illusions. That being so, architecture may thus be moulded by it. As trapezoidal balconies can have different slopes depending on the observer viewpoint (Bruno & Pavani, 2018). Visual memory has a large part to play in navigation of spaces and recalling things in them. Visually distinctive elements, like changes in color, patterns, or material, are mentioned by Spence as aiding in the creation of mental maps of spaces, allowing for easier navigation and recollection. Such architectural cues improve visual cognition, as they provide specific reference points. Perceived depth, structure and spatial quality can also be enhanced or flattened through the appropriateness of architectural lighting design, Spence notes. For instance, lighting with high intensity pointed towards the back of a space can give the impression of extended depth. Spaces with visually cluttered designs can lead to cognitive overload, reducing comfort and engagement. As Spence puts it, the architectural spaces in which users navigate need to find a balance between visual complexity and visual simplicity: in order to support cognitive clarity but not distract or overwhelm the users. By leveraging multisensory design techniques, architects can offer a richer cognitive and emotional experience, as sight and sound and touch intertwine, turning mere buildings into inviting, immersive environments.

2.5.4 Interactive media through physical pixels

Since late twenties century, Media artist, designers and researchers have been trying to innovate approaches to physically interact with the digital world, some sort of a physical portal that encourages other senses such as the tactile perception to interact with digital content. Pioneered researchers in this field were Hiroshi Ishii and Daniel Leithinger, who started their research on tangible pixels in early 90s. Their works represent a fusion of physical and digital pixels, enabling direct, tangible interaction with digital data in a 3D space.Tangible Pixels are physical and mechanical elements that can dynamically change position, shape, or configuration to embody digital information in a tactile, physical form. One of their important collaborative projects they did is InForm done in 2013 shown in Figure (2.28) & (2.29), which is a dynamic shape display that enables physical interaction with digital information by transforming a flat surface into a 3D shape that can move and respond to inputs in real time.

Figure 2.28: inFORM by Daniel Leithinger – Adapted from Daniel Leithinger. (2013).

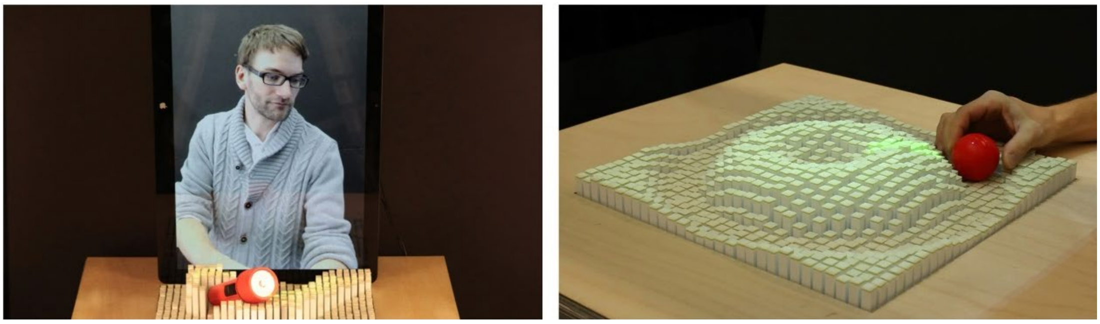

Figure 2.29: inFORM by Daniel Leithinger – Adapted from Daniel Leithinger. (2013).

The integration of perception in human machine interaction (HMI) and interactive media was a pivotal point of research in the 1990s and early 2000s. Daniel Rozin is an artist, educator, and researcher, best known for creating interactive installations and kinetic sculptures that explore the relationships between viewers, technology, and perception in Figure (2.8).

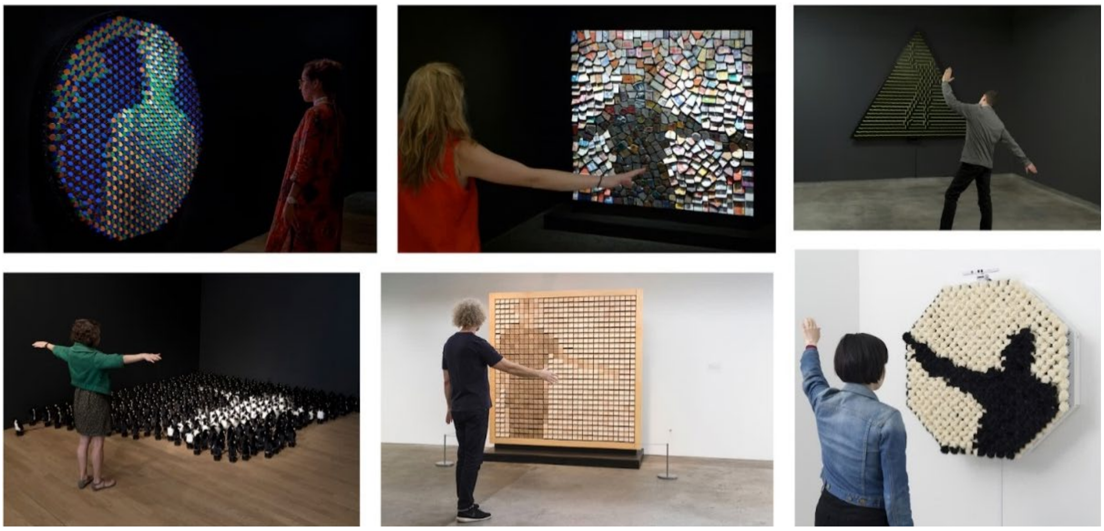

Figure 2.30: A collection mechanical mirror installations by Daniel Rozin. – Adapted from Matt Hussey. (2007).

Rozin's work consisted of the exploration of image perception through art installations that contained depth sensors and cameras to capture visual information, to be later transformed into numerical data to control mechanical components such as servo and stepper motors that have designed pixel unit pieces attached to them. Rozin's pixel units are usually made out of unusual forms and materials to reflect images of the subject standing infront of his installations. Rozin used wood, metal, Pom-poms, plastic and recycled materials to form his pieces, shown in Figure (2.30). His installations usually use light and shadow to form images by moving, rotating and protruding. The number of pixels contained in Rozin's installations typically vary from 500 to 1000 pixel units which would naturally result in a highly pixelated images if compared with modern screens. Several artists, including Daniel Rozin, have used Gestalt psychology principles as a guideline in understanding how to take advantage of any array of objects to create images using atypical methods.

Figure (2.31) gathers all of the research covered in the literature review chapter and aligns them in a timeline, dividing innovations on the left and inventions and theories on the right. The diagram covers three different eras which are modularity, CAD, parametric design and artificial intelligence, the timeline starts from 1920 till it reaches the present.

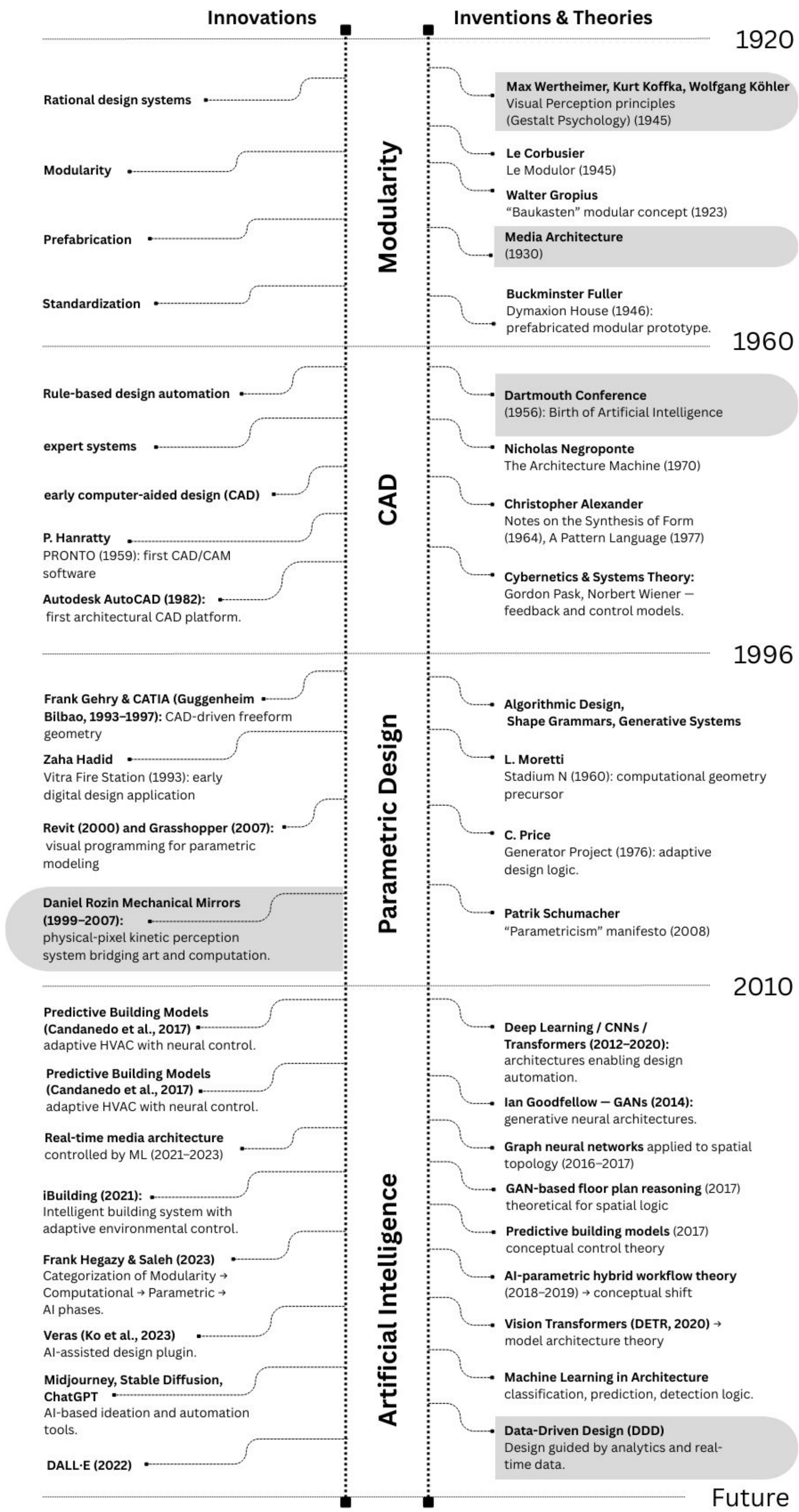

Figure 2.31: Literature review timeline Adapted from Chaillou (2019), with additions and modifications by the author

3. CASE STUDY: DANIEL ROZIN IN THE SCOPE OF GESTALT

This study showcases each principle of the seven principles of Gestalt psychology featured in Daniel Rozin's installation "Weave Mirror" (2007) shown in Figure (3.5), to interpret further how viewers can perceive their live image on a structure made out of physical materials such as wood, steel or fabric.

3.1 Introductory Experiment

This study starts with a simple introductory experiment, aiming to understand the basics of image perception, which will be a core concept of research in this thesis, to interpret further how viewers can perceive an image made out of an array of same objects. Futhermore, in order to achieve turning architectural elements to visual displays, it is important to understand what forms a display that our brain can perceive image from when looked at, this is heavily related to the principles of image perception, and one of the most important perception principles is Gestalt pshycology. Abstraction is simplifying or distorting recognizable forms to emphasize certain visual or conceptual elements, and even though abstraction can be about distorting visual information, we get to understand the visual content by trying to fill in the puzzle of missing information. Abstraction has been used as a powerful tool by artists to promote personal interpretation of images. Abstraction can be formed in different ways and shapes, such as the Cubisim movement created by Pablo Picasso which consists of emphasizing geometric forms and the deconstruction of objects into fragmented, abstracted shapes shown in Figure (3.1) One of the first steps done in this case study is to use computational tools to abstract an image in different levels to produce variations and assign them on an abstraction scale to understand how much can the human mind comprehend abstraction.

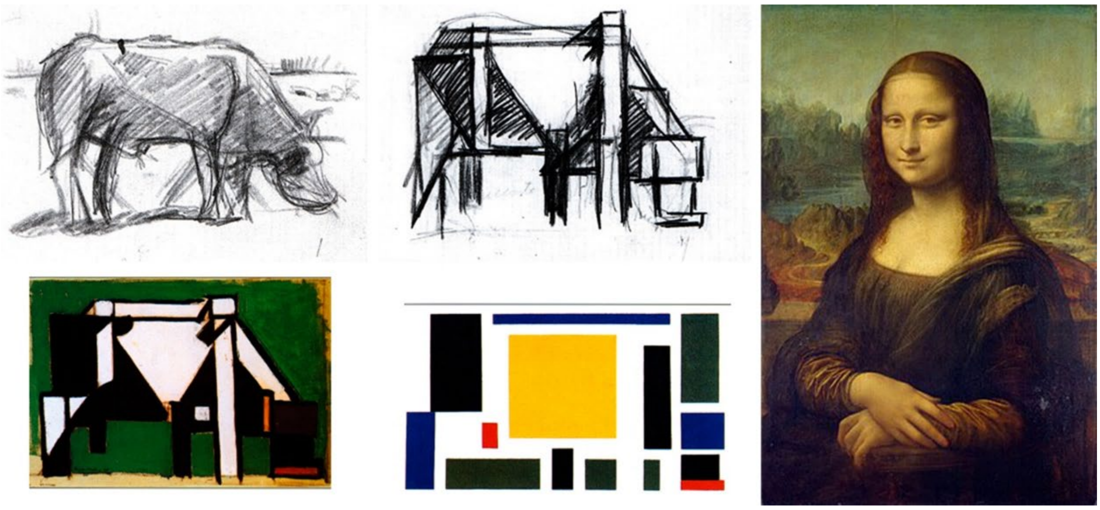

Figure 3.1: On left is the cow by Pablo Picasso in 1917, on right is Mona Lisa by Leonardo da Vinci painted between 1503 and 1519.

The painting of Mona Lisa in Figure (3.1) was chosen to be the medium experemintend on in grasshopper for rhinocerosn using the code shown in Figure (3.2). The painting will be reconstructed out of black circles, which can atterate in scale and density using curvature graph shown in Figure (3.3).

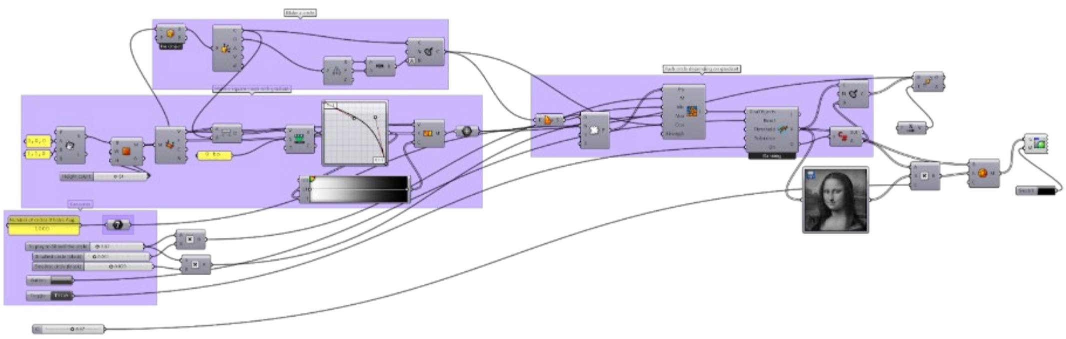

Figure 3.2: Grasshopper nodes used to generate abstraction images of Mona Lisa Painting.

The outcome of the grasshopper processing was 18 different reconstructions of the Mona Lisa Painting. Each outcome has a different numerical value in its parameters inside grasshopper shown in Figure (3.3).

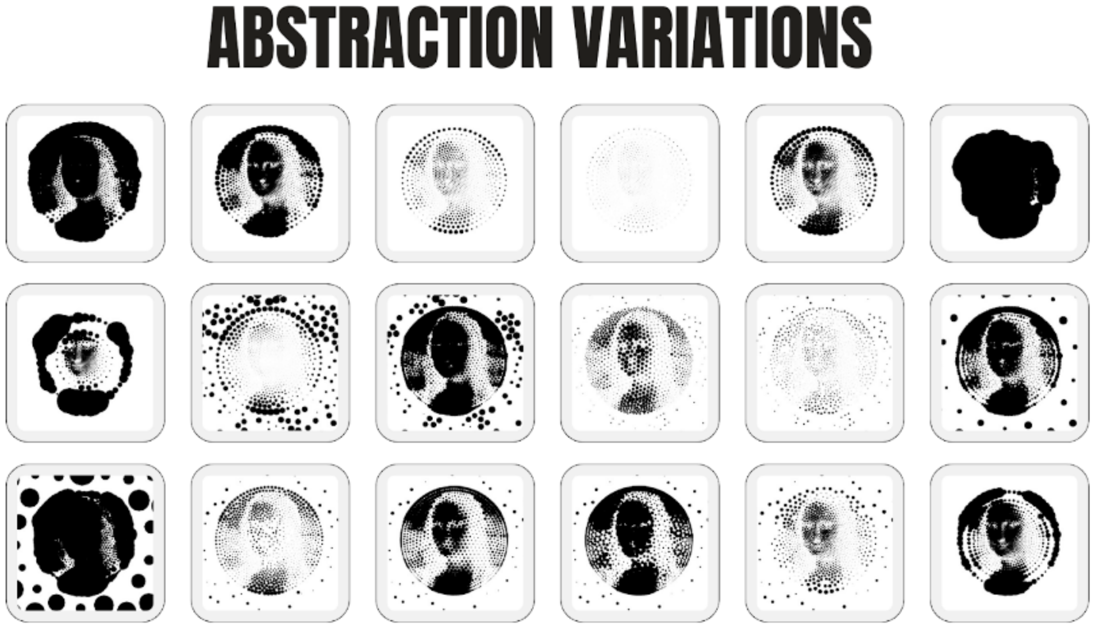

Figure 3.3: Results of Mona Lisa abstraction images created on Grasshopper.

It was recognizable that when circles get attached to each other or get too far from each other, the image gets unclear and when the change in scale of circles gets too radical, the relationship between the components of the image gets unclear. The outcome of images was put in an order from most to least clear perceptual according to personal analysis shown in Figure (3.4).

Figure 3.4: List of abstraction level in term of perception of Mona Lisa painting.

The outcome of this experiment proved that even though an image can be made with the same designed pixel unit, sometime it can be perceivable and something it can be not, This prove that it does not matter from what kind of object the image is constructed of, but rather how these objects were put into use to collaborate together and form an image. This concept is highly used in Daniel Rozin's work and other researchers and artists to achieve live images from different kind of objects and materials in the physical world

Several artists, including Daniel Rozin, have applied Gestalt psychology principles to construct images through distinctive techniques. Rozin is especially known for his "mechanical mirror" works, where materials such as wood, metal, and fabric are integrated with digital and mechanical systems to produce real-time viewer reflections. Gestalt psychology defines seven principles of perceptual organization frequently employed in visual design: Proximity, Similarity, Symmetry, Continuity, Closure, Common Movement, and Figure/Ground (MacNamara, 2017). This study presents each of the seven Gestalt principles as observed in Rozin's installation "Weave Mirror" (2007), which consists of 768 woven fabric panels shown in Figure (3.5), in order to interpret how viewers perceive and recognize their reflected image (Karout, Akçay Kavakoğlu, & Ayech, 2024). The identified principles and their contextual relationship to the "Weave Mirror" work are outlined as follows:

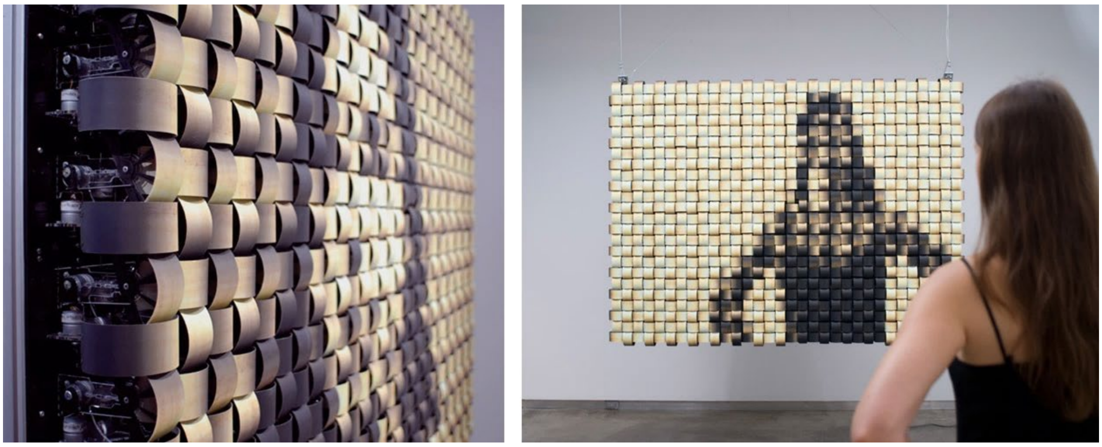

Figure 3.5: Weaver mirror by Daniel Rozin – Adapted from Matt Hussey. (2007).

3.2 Spatial Grouping via Proximity

Proximity is widely regarded as one of the most powerful cues for perceiving relatedness within a visual composition, often overriding other competing visual information (Lidwell, Holden, & Butler, 2010). When elements are arranged in close spatial relation, viewers tend to interpret them as belonging to the same group. This principle is especially relevant in user interface design, where the arrangement of components can suggest functional or conceptual relationships. For example, overlapping or touching elements are generally perceived as closely related, while components that are merely near each other without physical connection are interpreted as separate but associated (Lidwell et al., 2010). The principle of proximity is among the most effective Gestalt principles for enhancing usability, as it enables users to discern which elements are functionally significant and facilitates clearer, more intuitive layouts (Han, Humphreys, & Chen, 1999). According to this principle, objects situated near one another are mentally grouped as a cohesive unit. This concept is exemplified in Daniel Rozin's Weave Mirror, where individual units are tightly positioned on a single base, creating a unified visual field. As shown in (Figure 3.6). when the panels tilt or move to generate light and shadow, the viewer's perceptual system naturally groups adjacent units together. This spatial grouping allows for the emergence of legible patterns that mirror the shape and tone of the reflected subject.

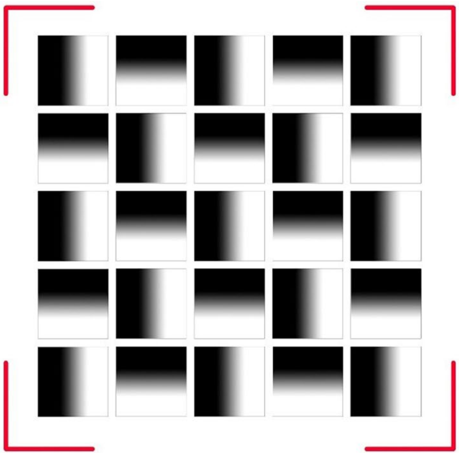

Figure 3.6: Weave mirror in comparison to proximity principle by Gestalt psychology.

3.3 Visual Resonance through Similarity

The principle of similarity suggests that elements sharing visual characteristics are perceived as part of the same group or unit. Such elements whether similar in size, shape, color, or texture are cognitively associated with one another and processed as a coherent set (Fisher & Smith-Gratto, 1999). This perceptual tendency enables viewers to recognize and interpret major forms or patterns more efficiently. In visual communication and interface design, the use of similarity enhances clarity and usability by simplifying complex compositions and highlighting relationships among components. According to Lidwell, Holden, and Butler (2010), attributes such as size and color are particularly effective in establishing perceived connectedness, while variations in shape and texture are more commonly used to introduce visual contrast. The application of this principle is evident in Daniel Rozin's Weave Mirror, an installation composed of numerous identical pixel units formed by C-ring shapes, each exhibiting consistent tonal gradients (Freyer et al., 2011). In this context, the similarity of form and tonal quality enables viewers to perceive grouped repetitions of the pixel units. These recurring visual groupings support the emergence of a larger, coherent image, reinforcing the function of similarity in constructing perceptual order shown in Figure (3.7)

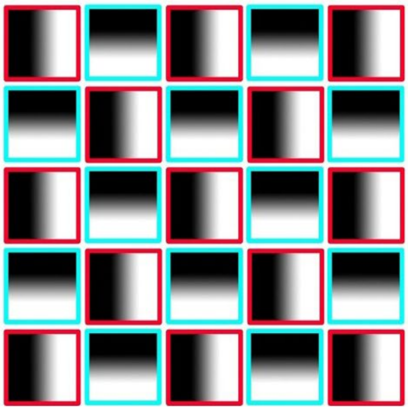

Figure 3.7: Weave mirror in comparison to similarity principle by Gestalt psychology.

3.4 Visual Balance through Symmetry

Symmetry has long been appreciated for its capacity to facilitate transitions and transformations within a system, offering a sense of visual order and structural continuity. Hambridge (2012) notes that symmetry embodies a modulating process that is central to many forms of artistic expression. Visually, symmetrical arrangements tend to be more memorable and aesthetically pleasing, as humans are generally more inclined to retain images that exhibit beauty, harmony, and balance over those perceived as disordered or unattractive (Lidwell, Holden, & Butler, 2010). In user interface design, the absence of symmetry whether through reflection, rotation, or translational balance can lead to a perceptual sense that something is missing or misaligned. This imbalance may result in user confusion or disengagement, ultimately reducing the effectiveness and usability of the interface (Chang, Nesbitt, & Wilkins, 2007). Although symmetry is not a defining characteristic of all of Daniel Rozin's installations, it nonetheless plays a critical role in how viewers perceive structure and coherence. In Weave Mirror, symmetrical qualities are evident in the gridded layout of identical units, contributing to a sense of visual regularity. Conversely, Rozin's Trash Mirror, constructed from pieces of recycled metal (Figure 3.8), deliberately departs from symmetrical composition. This contrast demonstrates that while symmetry can enhance visual comprehension and aesthetic appeal, it is not strictly necessary for successful image recognition.

Figure 3.8: Weave mirror in comparison to symmetry principle by Gestalt psychology.

3.5 Image Completion via Closure

The principle of closure enables designers to reduce visual complexity by minimizing the number of elements needed to convey information, while simultaneously enhancing the aesthetic appeal of the composition. This principle leverages the viewer's unconscious tendency to mentally complete incomplete forms, thus promoting cognitive engagement with the design (Lidwell, Holden, & Butler, 2010). Rather than perceiving a collection of fragmented or disorganized components, the viewer instinctively interprets them as parts of a larger, cohesive structure or pattern. Closure allows the mind to infer and reconstruct the whole from partial visual information, completing the gaps to form a unified image. In Daniel Rozin's Weave Mirror, this principle is clearly illustrated through the use of a binary color system that differentiates foreground from background (Figure 3.9). The resulting output is a pixelated silhouette of the subject standing before the mirror. Although the image lacks fine detail, the human perceptual system quickly identifies the overall form and subsequently begins to predict and mentally fill in the missing visual information. This dynamic interaction between perception and imagination underscores the effectiveness of closure in facilitating meaningful image recognition through minimal visual input.

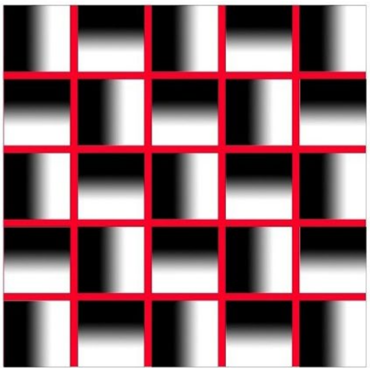

Figure 3.9: Weave mirror in comparison to closure principle by Gestalt psychology.

3.6 Visual Guidance in Continuity

According to the principle of continuity, elements aligned along a straight path or a smooth curve are perceived as part of a unified group and interpreted as being more closely related than elements that are not aligned (Lidwell, Holden, & Butler, 2010). When segments of a visual path are interrupted or partially obscured, the human perceptual system often continues the implied trajectory mentally, anticipating the reappearance of the line in a consistent direction. This cognitive tendency facilitates the perception of seamless, uninterrupted forms, even when visual information is incomplete. In Daniel Rozin's Weave Mirror, this principle is strategically employed through the alternating orientation of each mechanical unit. As illustrated in Figure 3.10, the units are rotated 90 degrees relative to their adjacent counterparts, creating a rhythmic and continuous visual pattern. This deliberate arrangement enables viewers to interpret the installation as a cohesive surface, allowing the brain to perceive the overall image as an integrated whole, despite the angular variations within the individual components.

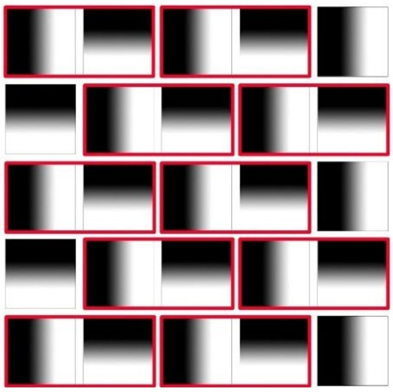

Figure 3.10: Weave mirror in comparison to continuity principle by Gestalt psychology.

3.7 Synchronized Movements via Common Fate

The principle of common fate explains how elements that move in the same direction are perceived as part of a unified group, while those that remain static or move differently are interpreted as unrelated (Lidwell, Holden, & Butler, 2010). This principle emphasizes the perceptual grouping that occurs through motion, allowing the viewer to identify patterns and relationships dynamically. In Daniel Rozin's Weave Mirror, the application of this principle is evident in the coordinated movement of the installation's mechanical components. Each unit rotates either horizontally or vertically, creating two distinct axes of motion. These synchronized rotational directions contribute to the overall perception of the image, as the viewer associates similarly moving elements as belonging to a common visual structure. The movement is governed by 90-degree rotations of the C-ring units, which gradually alter the orientation of their reflective surfaces. This controlled shift produces variations in light and shadow across the surface, forming a continuous gradient that conveys depth and dimensionality in the reflected image.

3.8 Foregrounding the Viewer through Figure/Ground

Changes in the figure/ground relationship play a significant role in providing visual feedback, helping to distinguish foreground from background (Graham, 2008). The Figure/Ground principle highlights that, when presented with multiple interpretations of a design, individuals tend to perceive first the version that is simplest or most familiar to them (Lidwell, Holden, & Butler, 2010). This is particularly powerful because users can detect changes in the figure/ground relationship, effectively creating a feedback loop within the environment. A practical example in software or web development is the "hover" effect, where the cursor or visual indicators change to signal that a user is interacting with a specific element (Graham, 2008). In the context of design, the Figure/Ground principle enables viewers to separate an object from its background. In Daniel Rozin's *Weave Mirror*, this principle is demonstrated through the use of two primary colors which are black and gold with gradients applied; here, gold functions as the background while black serves as the foreground shown in Figure (3.11).

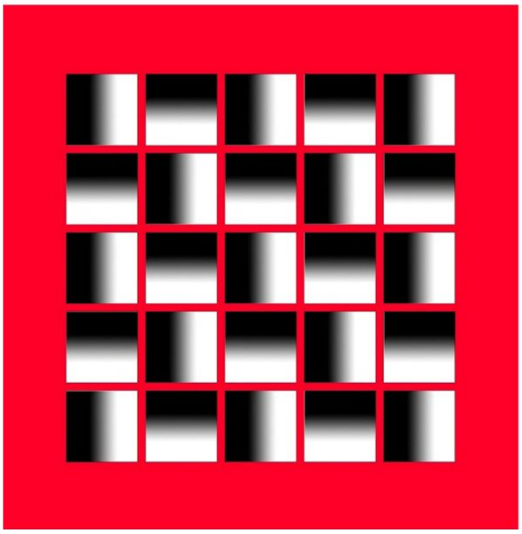

Figure 3.11: Weave mirror in comparison to figure/ground principle by Gestalt psychology.

3.9 Outcome of Case Study

This study provided insights regarding the theoretical logic of which physical kinetic installations create cohesive visual experiences by displaying visual information from physical objects. Rozin's designs embody the principles of Gestalt psychology, including proximity, similarity, closure and continuity. Rozin combines separate units that, when viewed as a whole, they get recognized as a single image. Table (3.1) shows the features of Weave Mirror in comparison to Gestalt psychology principles. The findings demonstrate that the type or design of an individual element in a visual system is not the primary factor that form the image, but the organization and order of the elements within the guidelines of Gestalt psychology are the key factors for forming an image. This research establishes a foundational understanding of how an array of objects can effectively display an image when arranged according to specific design guidelines.

Table 3.1: Table showing the features of Weave Mirror by Daniel Rozin in comparison to Gestalt principles

Gestalt Principle	Brief Definition	How It Appears in Weave Mirror	Presence
Proximity	Close elements form groups.	Tight grid makes tiles read as unified shapes.	Yes
Similarity	Similar items group together.	Identical wooden tiles behave uniformly.	Yes
Symmetry	Balanced forms feel coherent.	Symmetrical grid, though image output varies.	Partial
Closure	Mind completes incomplete forms.	Viewer fills gaps in low-resolution patterns.	Yes
Continuity	Eye follows smooth patterns.	Gradual tonal shifts create continuous flow.	Yes
Common Fate	Elements moving together feel united.	Tiles rotate in coordinated response to movement.	Yes
Figure–Ground	Distinguishing object vs. background.	Light–dark contrast isolates viewer silhouette.	Yes
Emergence	Whole perceived before parts.	Full image appears before noticing strips.	Yes
Multistability	Multiple interpretations possible.	Seen as both a mirror and a machine.	Yes
Invariance	Recognition despite distortions.	Form remains readable despite tile rotation.	Yes

Furthermore, this demonstrates that perceiving an image created from an arrangement of objects does not require the presence of all Gestalt principles. To explore this, six additional installations by Daniel Rozin shown in fiiure (3.12) were analyzed in relation to Gestalt psychology (Table 3.2). The findings revealed that the principles of similarity, proximity, and common fate consistently appeared across his works, suggesting their central role in visual comprehension. In contrast, symmetry, continuity, and closure were less critical, as Rozin's installations remained visually understandable even when these principles were absent.

Table 3.2: Table showing the features of deffirent installations of Daniel Rozin in comparison to Gestalt principles

Mirror Design	Similarity	Proximity	Symmetry	Continuity	Closure	Common Fate	Figure–Ground
Weave Mirror	Strong	Strong	Strong	Strong	Strong	Strong	Strong
Wooden Mirror	Strong	Strong	Strong	Strong	Strong	Strong	Strong
PomPom Mirror	Moderate	Moderate	Weak	Weak	Weak	Moderate	Moderate
Penguin Mirror	Moderate	Weak	Absent	Absent	Absent	Weak	Weak
Trash / Rust Mirrors	Absent	Absent	Absent	Absent	Absent	Absent	Absent
Split-Flap Mirror	Strong	Strong	Strong	Strong	Moderate	Weak	Strong
Shiny Balls Mirror	Moderate	Weak	Weak	Weak	Absent	Weak	Absent

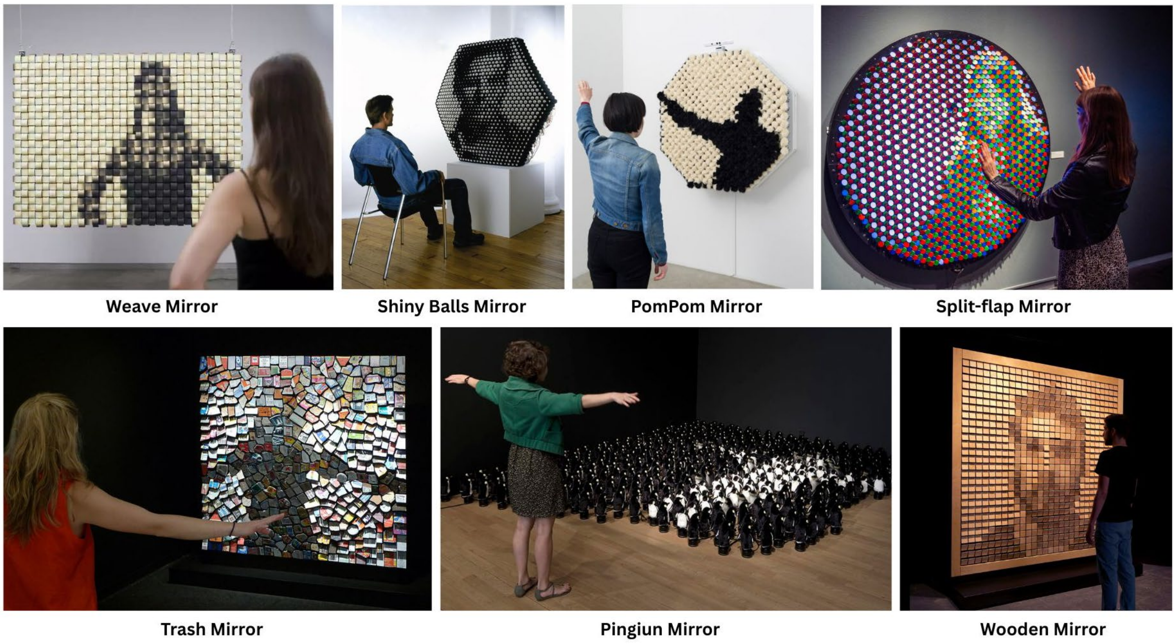

Figure 3.12: Installations by Daniel Rozin mentioned in table (3.2).

4. DATA-DRIVEN PANELS' PROTOTYPE

The development of the physical prototypes in this thesis involved collaborative efforts during fabrication and testing phases. Mechanical assembly, prototyping iterations, and on-site testing were supported through collaborative[1] work.

4.1 Data Capturing & Processing

The core element in this project is the subject interacting with the installation, since the main functionality is to reflect the images and interact with movement. Thus, The first data that need to be fed into the system is visual data. After that, it needs to be processed into numerical data that will be later transferred into servo motor movement information which will be responsonble for moving every physical pixel unit inside of the installation.

4.1.1 Image Capture

The initial phase of this study involves acquiring visual input from a participant positioned in front of the prototype, enabling the formation of a dataset necessary to activate the image capture process. The prototype is composed of 36 elements, each functioning as a pixel translated onto data-driven panels, resulting in a pixelated output. Consequently, an abstract representation of the participant positioned before the installation is to be displayed (Karout, Akçay Kavakoğlu, & Ayech, 2024). An intuitive choice of a device to capture image would be a normal camera. However, it is important to keep in mind that the output image in data-driven panels will be a 36

[1] The fabrication and testing of the physical prototypes presented in this thesis were supported through collaborative efforts during the mechanical assembly and iterative prototyping phases. Abdulhamid Kahlous contributed to aspects of mechanical assembly, fabrication support, and on-site testing. Conceptual discussions and critical feedback concerning system behavior, interaction logic, and prototype refinement were informed through exchanges with Fatima Ayech and Salim Salim.

pixel unit image. Thus, it is important to find the optimal solution to result in the most clear and understandable result possible. for an example, if a person stood in front of the installation and if his whole body was represented in only 36 pixel unit colored black and white, the outcome will be a pixilized silhouette of that person which will represent the foreground, and the surroundings of his subject's body will represent the background. An improvement of such a workflow will be to isolate the foreground and background from each other, and each element of them will be represented in a different color to emphazie the visibility of the outcome. Thus, a depth sensor is employed. Depth sensors are instruments used to calculate the distance between the sensor and surrounding objects within a predefined range, ensuring that no visual data is recorded from elements located behind the subject. The depth sensor utilized in this study is the Microsoft Kinect V2, shown in Figure (4.1). Foreground and background regions are distinguished by generating a three-dimensional (3D) representation of the environment through depth data acquisition. The prototype units are hemicylindrical in form and display a color gradient transitioning from white to black. White indicates negative visual values associated with the background, while black represents positive visual values corresponding to the foreground. The white-to-black gradient reflects varying distances, allowing a distance threshold to be defined, for example between 50 cm and 200 cm, whereby the depth sensor captures only values within this range, isolating the main subject while elements behind are rendered blank, as shown in Figure (4.1). The subject positioned within the sensor range appears as a pixelated silhouette on the data-driven panel (Karout, Akçay Kavakoğlu, & Ayech, 2024).

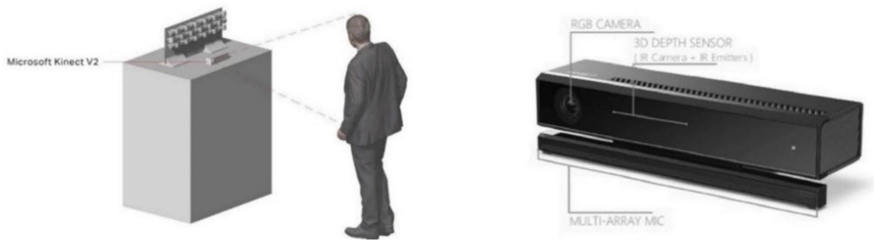

Figure 4.1: Showing Microsoft Kinect V2 and its location in the data-driven panels' prototype.

4.1.2 Image Processing

Microsoft Kinect is connected to an open source integrated development environment (Processing) as the second stage of the process for creating data-driven panels. Once the depth data is captured by Kinect, the same data is then fed into Processing. A custom code converts the live-recorded data into black and white values that make up pixels of the final image. The number of pixels in the code matches the number of units in the prototype. Each pixel in the code output corresponds to a specific value based on its grayscale number, which ranges from 0 to 255, with 0 representing black and 255 representing white, shown in Figure (4.2). Tthe closest objects to the sensor are depicted as black, while the furthest objects appear as white, ensuring that the depth information is accurately represented in the final visual output.

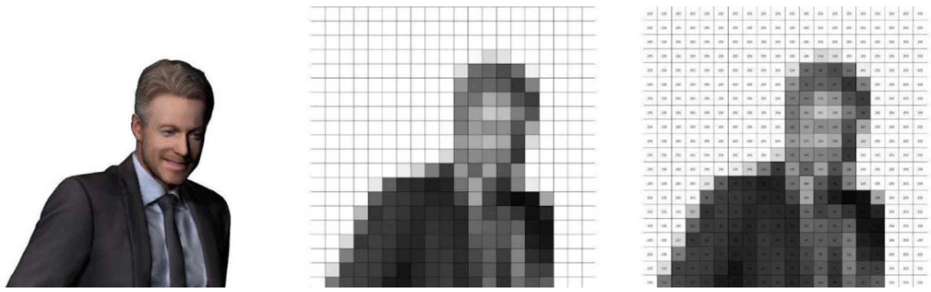

Figure 4.2: Showing image capture, image pixelization and greyscale value numbers.

4.1.3 Image Data Remapping and Motor Controlling

The grayscale values assigned to each pixel are transmitted in real time to Arduino, where they are processed to control the system. Since the prototype contains 36 pixels, Processing sends Arduino a sequence of 36 values per frame, which are remapped to drive the servo motors positioned behind each pixel unit. Because servo motors rotate only up to 180 degrees, grayscale values ranging from 0 to 255 are converted to a 0–180 range, defining the rotational angles of the motors, as shown in Figure (4.3) (Karout, Akçay Kavakoğlu, & Ayech, 2024).

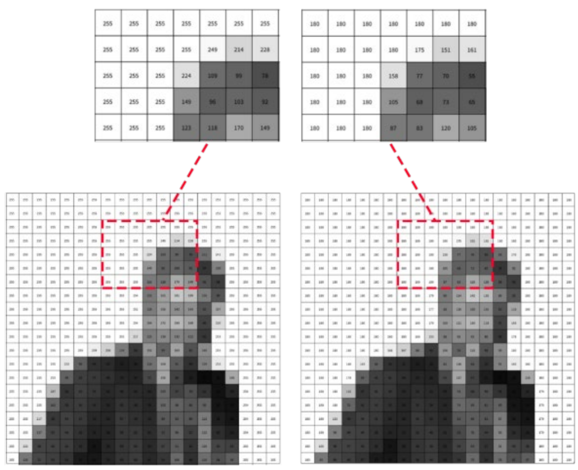

Figure 4.3: Showing, greyscale values' remapping to motor rotation values.

4.2 Designing & Fabricating

The design and implementation of data-driven panels within the field of interactive architecture present several inherent challenges. First, the technical complexity and financial cost of integrating physical mechanical systems and sensing devices can become significantly high, especially when applied at larger scales. In addition, the project's reliance on precise mechanical and electronic elements, such as 3D-printed components and servo motors shown in Figure (4.4), introduces concerns related to durability and long-term maintenance, restricting its applicability primarily to indoor environments due to limited resistance to outdoor conditions. Over extended use, these components may deteriorate or demand regular servicing, affecting system reliability and operational lifespan. Furthermore, although the panels translate depth data into visual outputs, the limited number of pixel units constrains resolution. This results in low-resolution imagery, which may be unsuitable for applications requiring greater accuracy. Finally, implementing such interactive systems in real contexts may face hesitation due to their novelty and the requirement for specialized technical expertise. This underscores the importance of testing physical prototypes beyond digital simulations, as material realization represents one of the project's most significant challenges (Karout, Akçay Kavakoğlu, & Ayech, 2024).

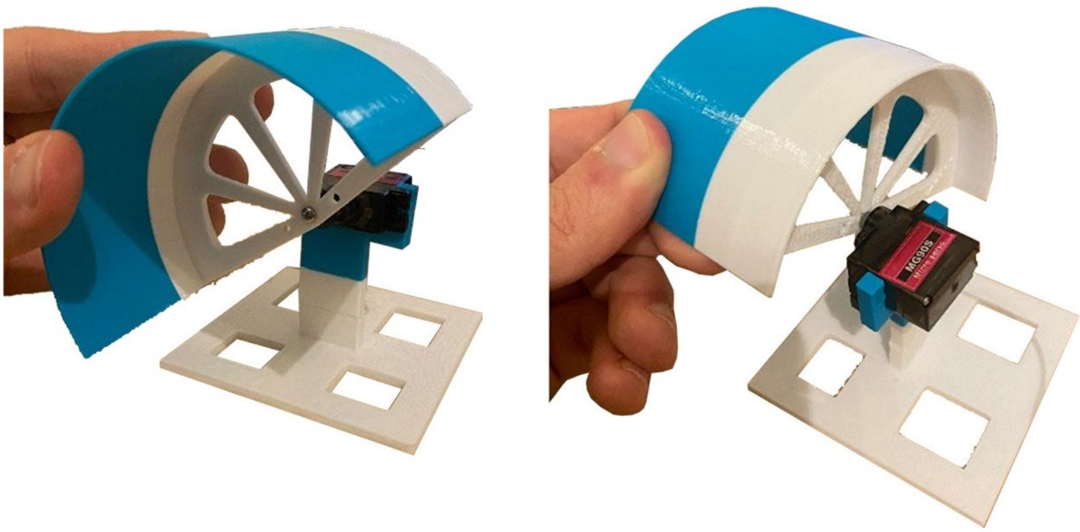

Figure 4.4: Initial design experimentation of data-driven panels' display units.

The C-ring display units in the data-driven panel are constructed from 3D-printed components, and aligned in a way that each pixel unit is rotated 90 degrees from the one next and ubove it. Looking at the design from a front elevation perspective in

Figure (4.6); the panels are visualy integrating so that their movements represent woven fabric which is intented by Daniel Rozin. 3D printing is used to address mechanical constraints commonly associated with custom designs while keeping the prototype lightweight. The prototype base consists of a 2 mm CNC-cut aluminum sheet, shown in Figure (4.5), with custom openings to secure pixel units and route motor wiring to the driver boards at the rear. The supporting feet are also 3D printed. Each pixel unit includes a grayscale gradient printed on paper and attached to a 3D-printed component. On the back of the prototype, an Arduino board and three PCA9685 driver boards are mounted to distribute control signals to the servo motors (Karout, Akçay Kavakoğlu, & Ayech, 2024).

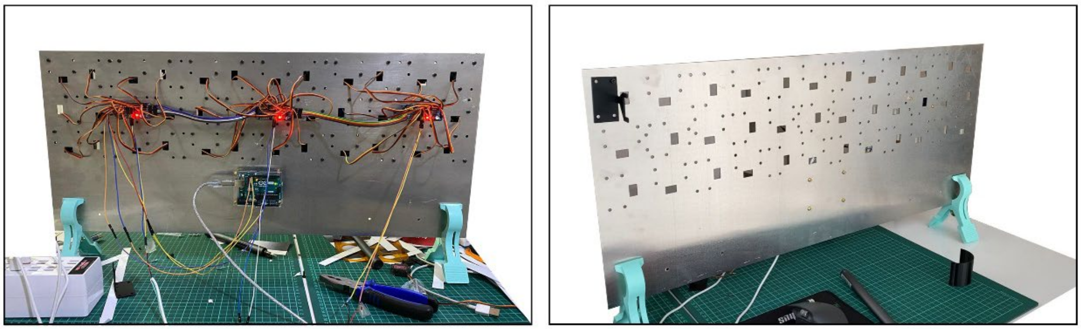

Figure 4.5: Shows aluminium base of data-driven panels' prototype.

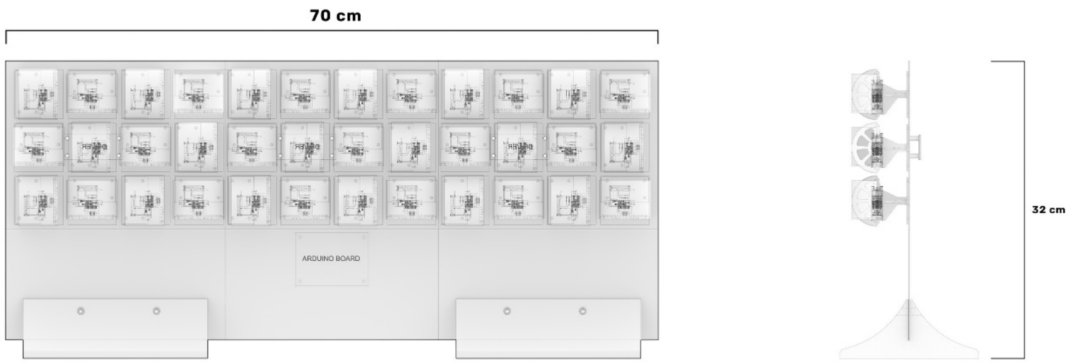

Figure 4.6: Orthographic views of prototype.

4.3 Features of Prototype

The first prototype of data-driven panels was successfully developed and demonstrated effective performance across its stages from image capturing, processing, data remapping, and prototype building. Utilizing Microsoft Kinect V2 depth sensor, Processing coding environment, and Arduino-controlled servo motors, the prototype accurately captured and translated depth data into mechanical rotations, forming a coherent, and pixelated silhouette of the subject. The 3D-printed display units, supports, and aluminum base ensured a lightweight yet stable structure. The panels successfully translate sensed movement and respond to environmental stimuli such as sound or passing users, demonstrating their potential as dynamic, data-driven architectural interfaces. This project provides a foundation for future research integrating artificial intelligence into architectural elements to enhance human–building interaction and user experience (Karout, Akçay Kavakoğlu, & Ayech, 2024).The flowchart in Figure (4.7) showcases all the tools and workflows used in the prototype, along with table (4.1) design process & data collection methods mentioning their performances and suggesting their future improvements. Moreover, table (4.2) showcases the materials and components used in the prototype as well as their evaluation.

Table 4.1: Table shows design process & data collection methods of first prototype

Method	IDE	OOP/ VP	Device Used	Performance	Potential Improvements / Comments for AI Integration
Image Capturing	Processing	OOP	PC + Microsoft Kinect V2	High	Kinect proved effective and relatively inexpensive for image capturing.
Image Processing	Processing	OOP	PC	Mid	Simple and straightforward but not optimal for AI; TouchDesigner planned for future use.
Data Remapping	Arduino	OOP	PC	High	Arduino effective for controlling servo motors.
Motor Controlling	Arduino	OOP	Servo Motors + Arduino + PCA9685 Driver	Low	Easy to implement, but servo motors are not high-performance; alternatives needed.
Depth Capturing	Processing	OOP	Microsoft Kinect V2	High	Suitable for final implementation.
Motion Capturing	Processing	OOP	Microsoft Kinect V2	High	Suitable for final implementation.
Voice Recognition	Processing	OOP	PC Built-in Microphone	Mid	Higher-quality mic and noise filters would improve input clarity and overall performance.

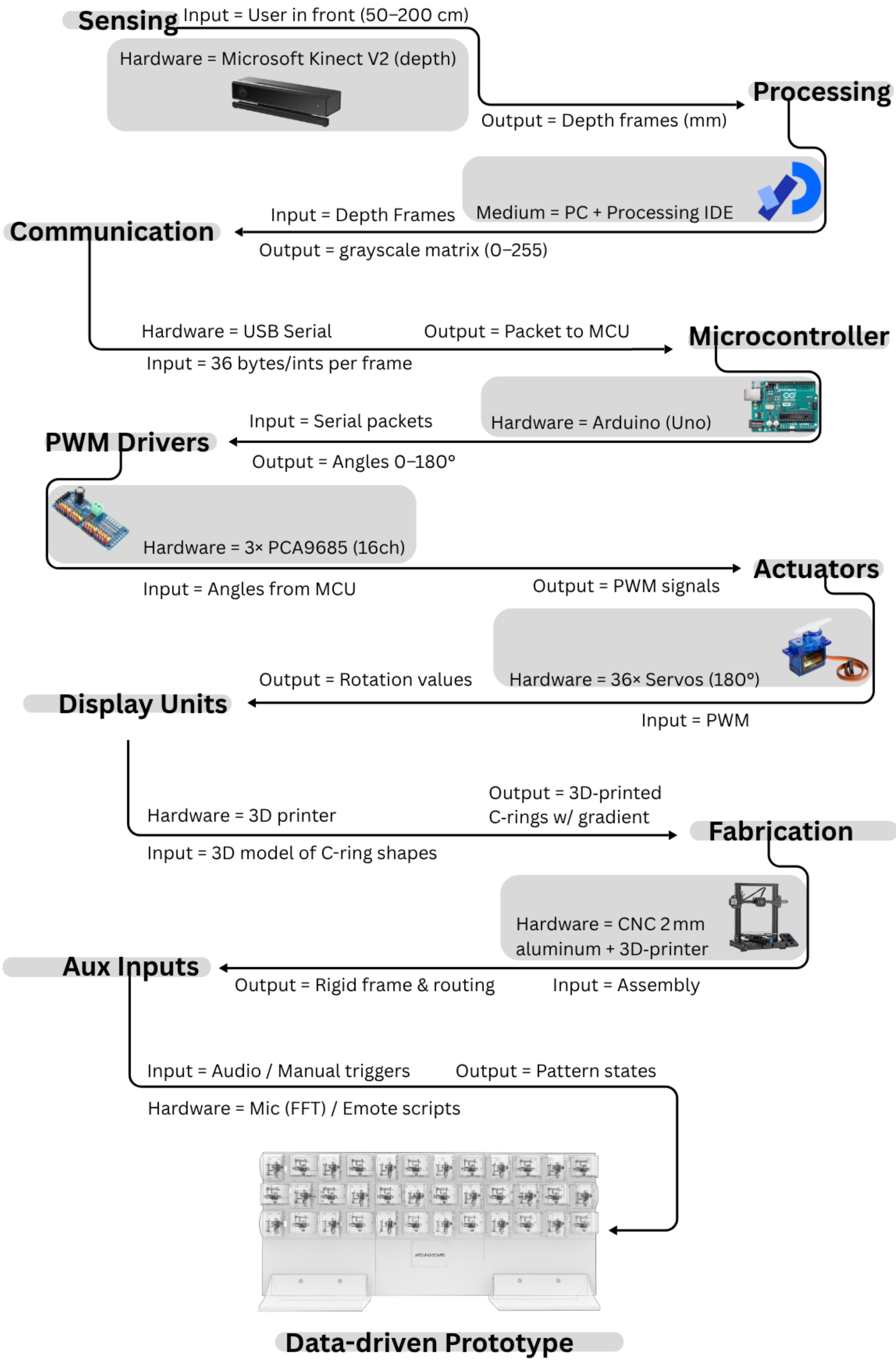

Figure 4.7: Prototype workflow diagram.

Table 4.2: Table shows materials / components evaluation first prototype

Type	Usage	Characteristics	Cost Efficiency	Performance	Potential Improvements / Comments for AI Integration
3D Printed Filament	Pixel Units + Footing	Highly customizable, lightweight	Mid	Mid	Materials like wood, ceramics, or concrete could create better cohesion with building finishes.
Aluminium Sheets	Base	Strong and lightweight	Mid	High	Performed efficiently; recommended for final use.
Servo Motors	Movement Generation	Affordable and easy to program	Mid	Low	Prone to breakdown; stepper motors planned as more durable and cost-effective alternative.

4.3.1 Image Reflection

Utilizing Microsoft Kinect v2, Image reflection feature was achieved by dividing the input image into 36 pixel units that each had values between black and white. Even though 36 pixels are not enough to display an understandable image. However, it has the ability to display a clear representation of the subject's movement. Figure (4.9) shows a close-up of the first prototype's units and Figure (4.10) shows a movement capture of the prototype.

Figure 4.9: Close up on prototype dispolay units.

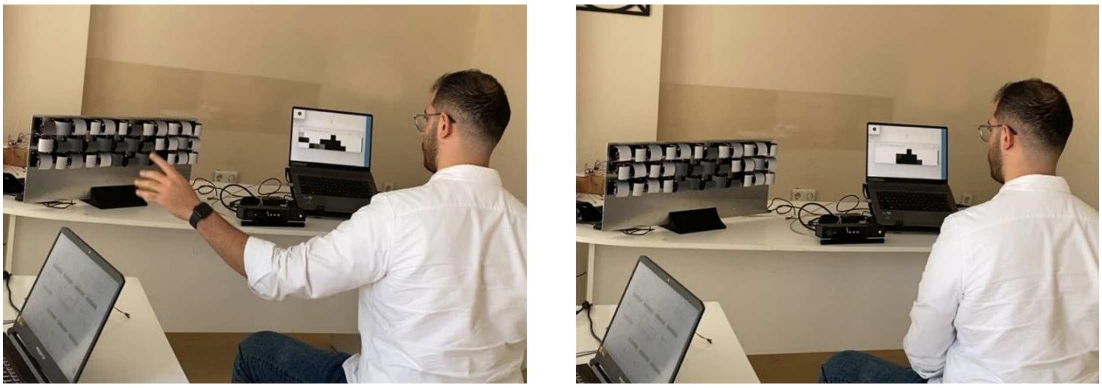

Figure 4.10: Image reflection feature of prototype.

4.3.2 Interaction with Sound

The prototype has the ability to capture live sound inputs and analyse them as sound waves, shown in Figure (4.11), which they can be represented as movement in the prototype by moving back and forth. The soundwaves are remapped where shortest waves are mapped as 0 values and longest waves are mapped as 1 value, then these values are remmaped to be numbers from 0 to 180 which represent the degrees the servo motors will be rotating in. Finally, all the values are imported in a list that is updating once every second to have final outcome of a visual representation of music or sound.

Figure 4.11: Interaction with sound feature of prototype.

4.3.3 Display Of Emotes

Emote design was among the first features appliedin the prototype as it provided an ability to test the functionality of individual motors as well as the overall responsiveness, speed, and movement of the display system. One of the initial programmed emotes involved is mouse cursor movement to panel activation, for instance, activating all units on the right side of the display when the cursor moves toward the right on the computer screen. Another emote featured a wave motion, in which the display units were sequentially activated from left to right or vice versa. These foundational behaviors proved especially useful for troubleshooting and filling operational gaps during periods when more complex functions were not yet operational.

5. AI INTEGRATION WITH DATA-DRIVEN PANELS & SIMULATION

5.1 AI Integration

The following study aims to integrate basic machine learning techniques to power the system of data-driven panels with basic artificial intelligence functionality in attempt to enhance human-machine interaction and achieve a true integration between AI and architecture where architectural elements can be more interactive and aware of its surroundings.

5.1.1 Integration of Visual Development Platform

In the development of data-driven panels, TouchDesigner is selected as the primary tool to initiate the workflow due to its advanced capabilities that enhance the creative and technical aspects of the project. Additionally, it integrates seamlessly with various hardware components, including Microsoft Kinect, which is responsible for capturing depth images in the data-driven panels. Moreover, TouchDesigner excels in handling without heavy computing power. The initial setup of the TouchDesigner environment involved migrating features previously implemented in Processing. This process begins by utilizing the depth sensor of Microsoft Kinect as the primary input unit. The captured live image is then processed into a channel that pixelates the input into 529 pixels in black and white, each assigned a value between 0 and 1 in which white is 0 and black is 1. These pixel values are updated with each frame by Kinect and are compiled into a list of numerical values and transmitted to Processing via the Open Sound Control (OSC) protocol, which is a network that helps transferring data in real-time between two channels from different software or computers. Once the data reaches Processing, the list of numbers are remapped to be from 0 to 90, which represents the rotation movement of the stepper motors that will be generated once the data-driven panels are in action. After that, Processing sends the remapped data to

Arduino programming software, which distributes every number in the list with its corresponding motor.

5.1.2 Utilizing Machine Learning to Setup Targets

By employing machine learning techniques through Google's web-based tool, Teachable Machine, and integrating it with TouchDesigner using the Teachable Machine plugin, three primary recognition features are achieved: (1) Image recognition, which identifies various objects in front of the camera, such as a vase, mouse, or shelf (2) Body gesture recognition, which uses camera input to map an illustration of a human stick figure, analyzing main body parts in a simplified manner. The AI is trained to recognize gestures like raising both hands, waving one hand, and crossing hands. (3) Speech recognition, which captures the user's voice through a microphone, identifying distinct words or short phrases, such as "apple" "action" and "water bottle". The AI is also trained to filter out background noise, focusing on relevant commands. The machine learning algorithms capture images and voice to use them to learn target recognition and generate percentage-based confidence scores for each target contained within separate channels in TouchDesigner. Each channel's output is connected to a video file that activates corresponding animations when the confidence score meets the determined thresholds. Integrating these features enhances the capabilities and enables dynamic and intuitive responses in the data-driven panels, overall improving their functionality and interactivity.

5.1.3 Designing Actions for ML Targets

The series of animations were drawn manually frame by frame in AutoCAD as shown in Figure (5.1). These animations comprised 529 pixels arranged in a 23x23 grid, corresponding to the pixel units in the planned installation. The first set of animations is designed for the image recognition feature, representing objects such as a mouse, a vase, and a shelf with the animation illustrating the object's movement from left to right. The second set focuses on body gesture recognition, featuring emotes that represent specific body movements, including one waving hand, two hands raised, and crossed arms, each with distinct animation sequences. The third set was dedicated to the speech recognition feature, where written words of the spoken phrases were animated, with each letter or phrase moving from left to right. Following the completion of the workflow in TouchDesigner, the same list that is used to represent the gray numerical value of each pixel is transferred in real-time. Utilizing geometry nodes in Blender, an array of shapes - such as spheres, cubes, or any object that can serve as a medium to reflect an image - is generated. The channel of each unit within this array is individually connected to Blender using the Open Sound Control (OSC) feature, which facilitates direct data transfer from TouchDesigner. Each number in the transferred data gets assigned to a different unit within the array, determining its rotation angle, scale factor, or movement necessary to compose an image. Subsequently, each frame of the unit's movement is rendered, resulting in the production of an animation corresponding to the final data-driven panel's design (Figure 5.8).

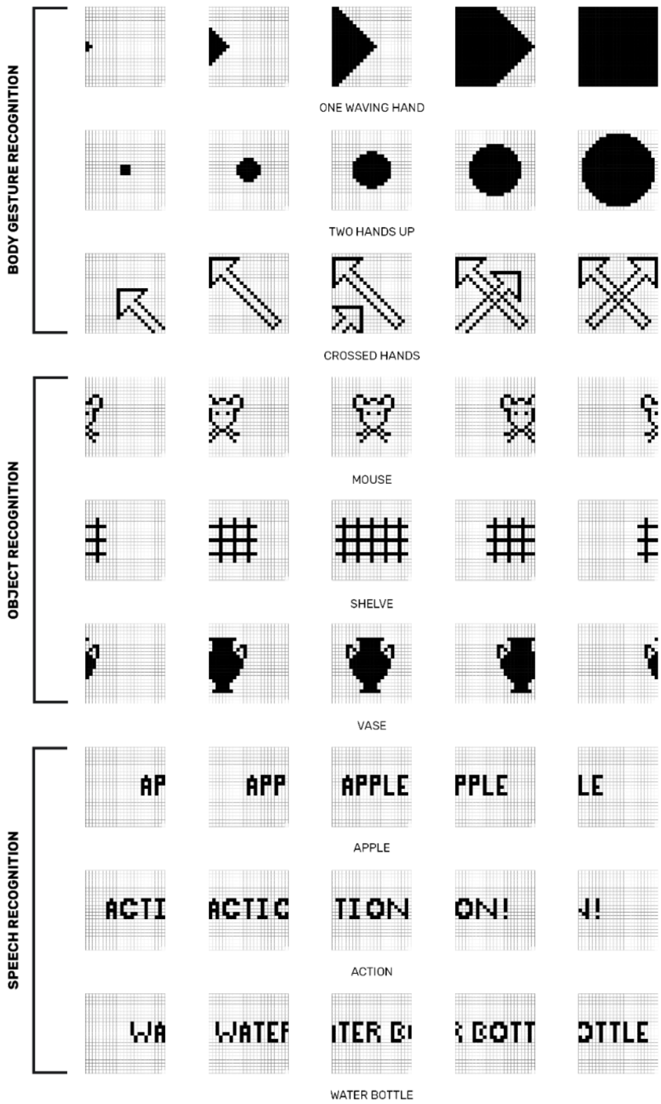

Figure 5.1: Designs of animations of machine learning triggered actions.

5.2 Simulation of Design Variations

Experementing with a project that contains multidisciplinary applications such as mechanical engineering, electrical engineering, industrial engineering and architectural design, will result in expected complications and a big room for error. For this reason, it is important to start the first stages of research in design inside the digital medium to prevent uneccessary cost and time wasting. The simulations in this research branches into two types: (1) pre-rendered simulations (2) real-time simulations. To tackle different needs and goals for the project. The main aim for the simulation is to test and validate different pixel unit designs to be able to comprehent their ability to reflect images and actions.

5.2.1 Pre-rendered Simulations

Pre-rendered simulations offer realistic result that represent real life in term of lighting, materials and reflections. Understanding the visual behavior and functional potential of data-driven panels needed a development of workflow to produce a series of simulations that can be conducted before building any physical prototyping. These simulations aim to test how different panel designs respond to different image inputs and user interactions such as image reflections in real time and display of emotes. By experimenting with geometric layouts and different grids of design, pixel unit densities and motion parameters, the simulations offer a low-risk environment for exploring design alternatives and refining aesthetic and mechanical outcomes. A 3D modelling tool such as Blender is utilized to replicate motion-based interactions and visualize how real-time data could drive the kinetic behavior and motion of individual units. This virtual experimentation enabled the identification of optimal patterns, component arrangements and response logic, which informed the design of the following physical prototypes. In addition, simulation served as a critical step in bridging conceptual ideas with practical implementation by enabling iterative testing of form, responsiveness, and user experience under diverse conditions and settings.

Figure 5.2: Simulations of image reflection feature.

One of the first simulations created focused on visualizing image reflection feature using a pre-recorded video of a person waving. This animation used the same display unit design developed in the first physical prototype, shown in Figure (5.2). In addition, a second simulation placed the same data-driven panel design inside a public building, featuring context elements such as a chair and surrounding vegetation. This scenario aimed to examine the system's spatial behavior in a realistic environment. The animation depicted a man walking past the data-driven panels, with his movement dynamically mirrored on the surface of the installation, shown in Figure (5.3).

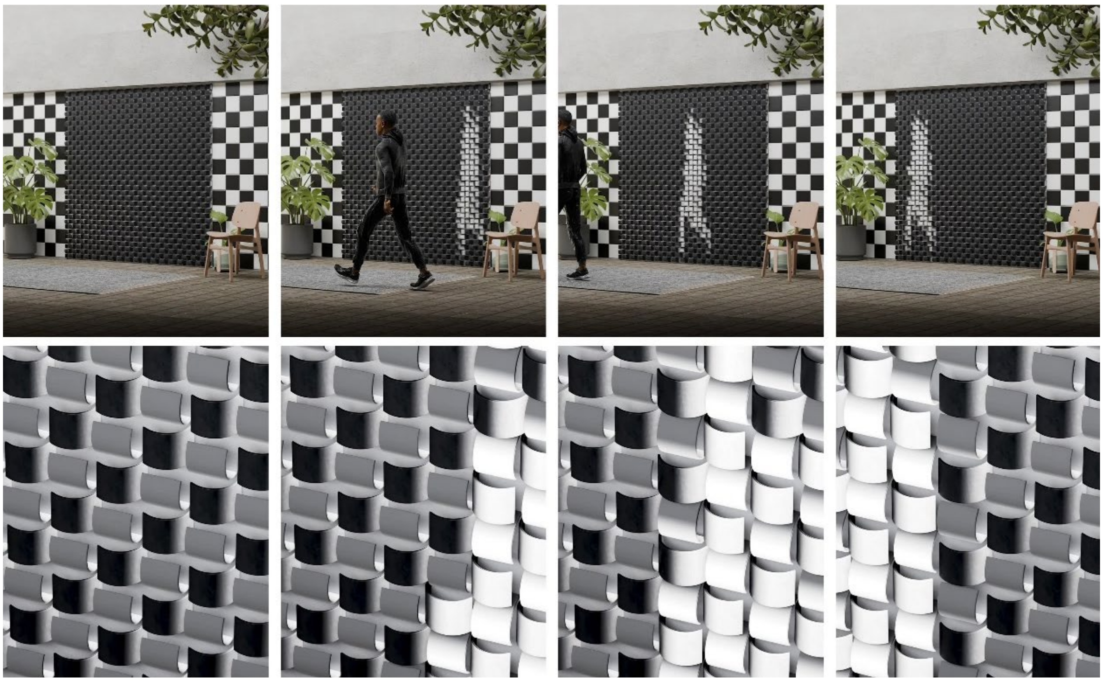

Figure 5.3: Simulation of first data-driven panels' design.

The simulation phase is considered to be a valuable opportunity to explore and expand design possibilities beyond the boundaries of physical prototyping. In the third simulation, an experimental approach was taken to conceptually merge gaming consoles with architectural elements. Rather than using a traditional television screen in a room, the architecture itself becomes the display medium. This idea draws inspiration from the aesthetics of early 8-bit video games, which, due to their highly pixelated visual output, provided a fitting reference for testing the potential of low-resolution, data-driven panel systems as an interactive surface, shown in Figure (5.4).

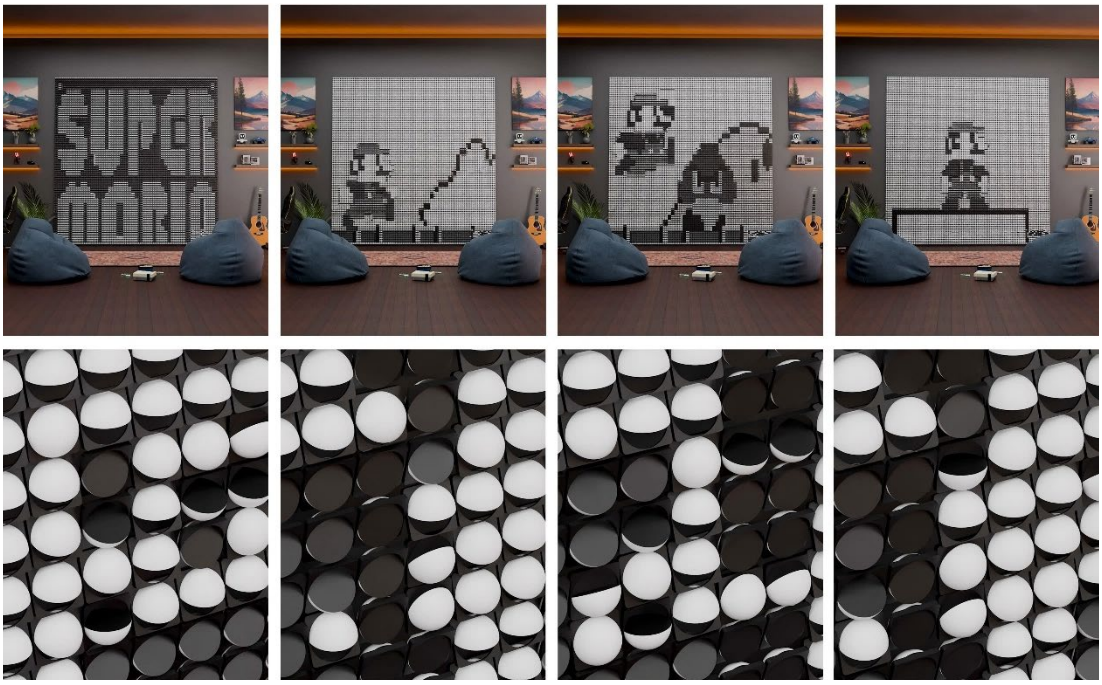

Figure 5.4: Simulation of second data-driven panels' design.

The forth simulation is located inside a spirtual space, which can be a temple, church or mosque, where a wooden data-driven panel is located under a skylight which can control the penetartion of light that gets inside the space shown in Figure (5.5). This example showcases the potential of this technology in playing a role in passive design techniques to control tempratures and illumination in a space.

The final simulation created is located in a space covered in concrete finish material shown in Figure (5.6). The design of display unit consists of a hexagon shaped units that is devided into 4 irregular pentagonal units snd the overral grid is called Cairo pattern. The concept of this simulation is to try and experiment with irrigular X and Y grid system to have a more compact outcome of units. This design was chosen to be carried out to become a physical prototype.

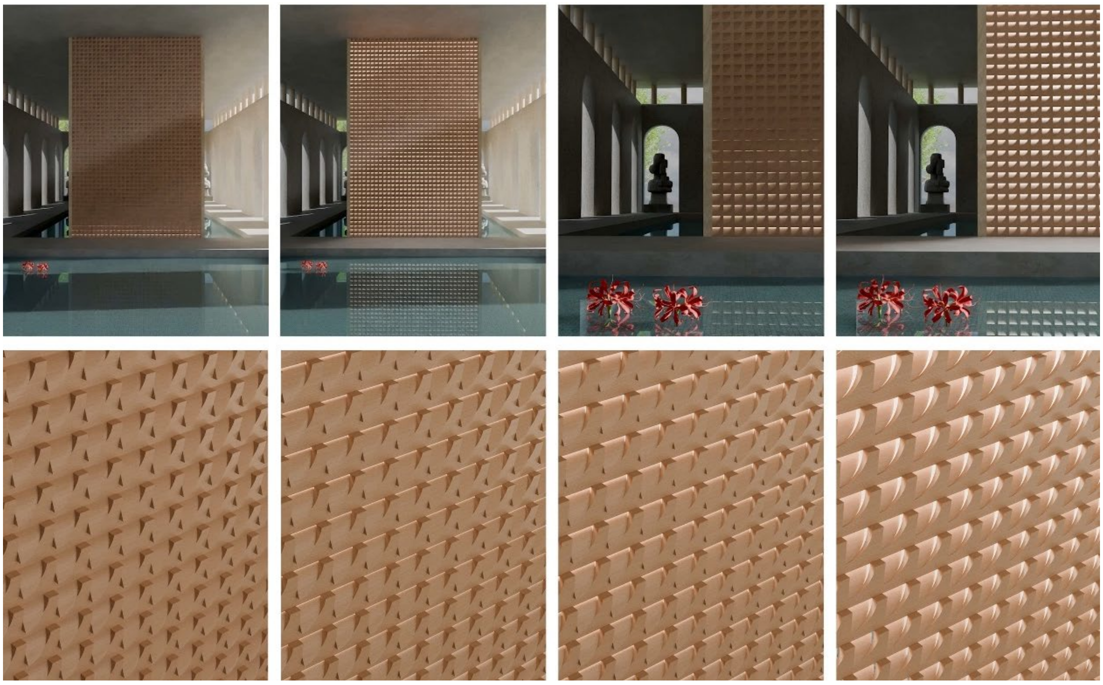

Figure 5.5: Simulation of third data-driven panels' design.

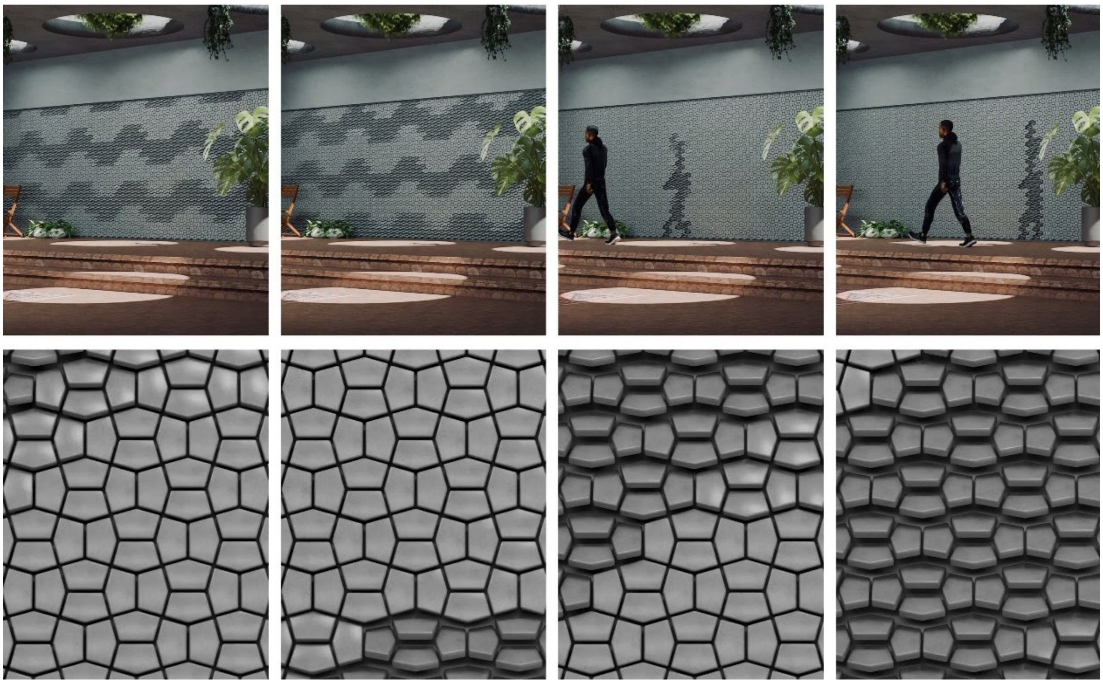

Figure 5.6: Simulation of forth data-driven panels' design.

All of the pre-rendered simulations were done inside a 3D modeling software (Blender). Doing simualtions inside its invironment has benefits in flexibility and handling of complicaions in designs. It also provides realistic presentation of sun, light and shadow which is important in this project because some designs used shade and shadow to reflect images.

5.2.2 Real-time rendered Simulations

Even though real-time simulations are considered to have low level of realisim in term of shade, shadow and materials rendered, they offer a different range of benefits such as the performance of display with real time images. The real-time simulations are done inside Touchdesigner which is a node-based visual programming language for real-time interactive multimedia content shown in Figure (5.7). Experimenting in such an environment gives access to experience inputs from AI websites and softwares that contain machine learning techniques to determine targets such as body gestures, object recognition and voice recognition to be set as target that trigger certain actions and emotes that can be displayed in the simulation of data-driven panels. Real-time simulations also help for real time editing of display features such as rotation angles and moving speed and scalability without the need to wait for rendering process to see the final result.

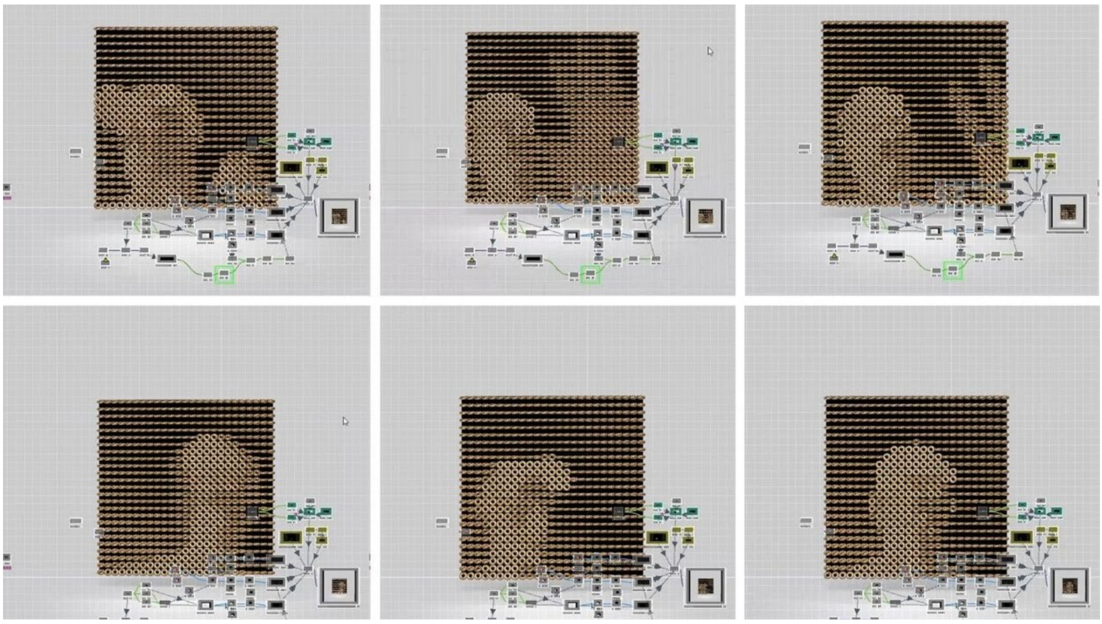

Figure 5.7: Real-time simulation in Touchdesigner.

5.2.3 Simulations of Machine Learning Triggered Actions

Since machine learning is utilized inside data-driven panels, responding actions must be designed to be later mapped to get displayed whenever an action is triggered, simulations played a big role with experimenting with these triggered actions whether it was the action of displaying “HELLO!” when it is spoken, or creating arrow emotes that would move with the same direction of people moving infront of it, shown in

Figure (5.9). Figure (5.8) shows the complete framework of simulation phase, branching into two different methods, offline rendering and real-time rendering workflows. Moreover, Table (5.1) shows a comparison of the two workflows.

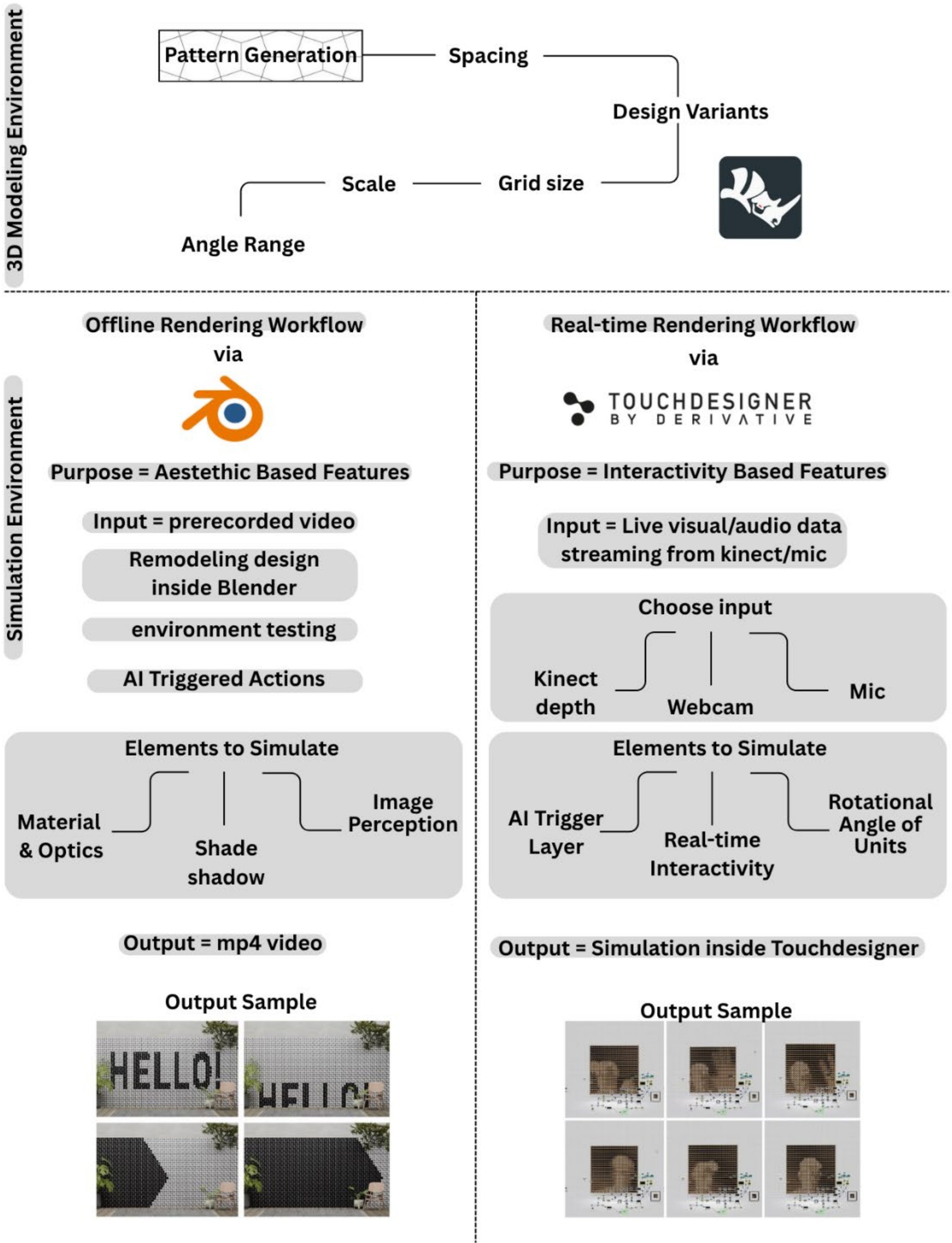

Figure 5.8: Simulation workflow diagram.

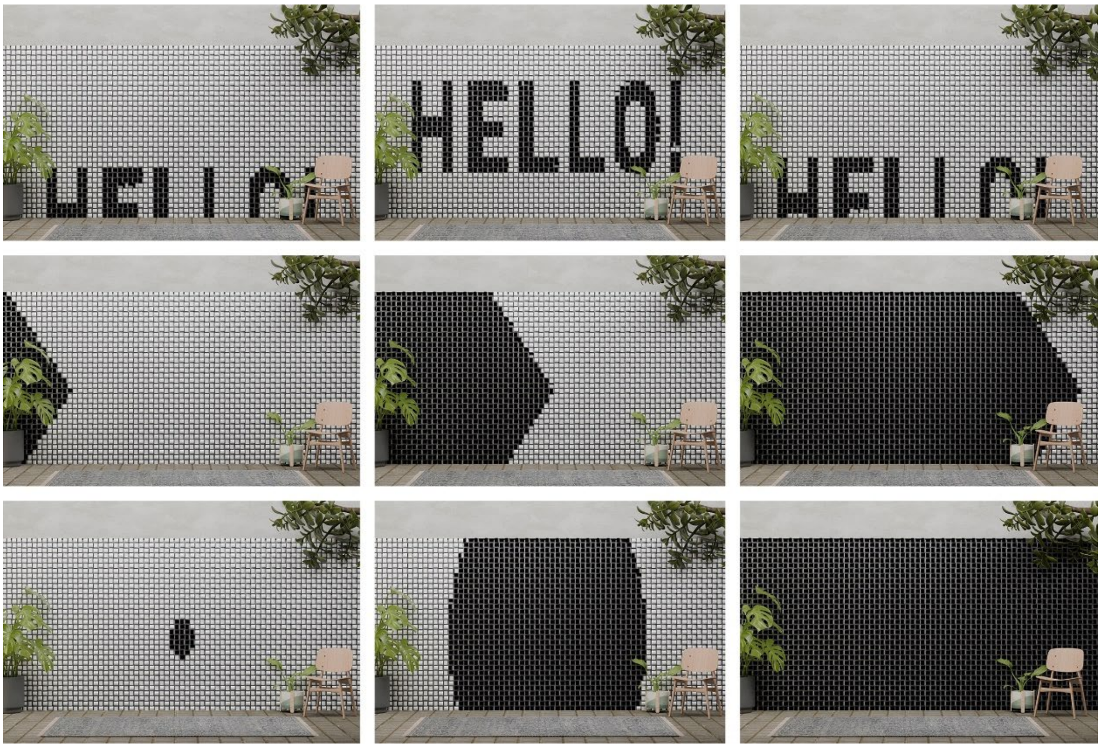

Figure 5.9: Simulation of triggered actions of machine learning feature.

Table 5.1: Comparison of Simulation Approaches for Data-Driven Panels

Aspect	Pre-rendered Simulation	Real-time Simulation	ML-Triggered Simulation
Primary Purpose	Visualize motion/design before building	Test interactive responses with live input	Evaluate intelligent, trained responses to specific user behaviors
Tool(s) Used	Blender	TouchDesigner	Teachable Machine + TouchDesigner/Arduino
Interactivity	None (fully offline)	High (camera/audio input)	Conditional (triggered by recognition events)
Timing	Static sequence, pre-recorded	Live, real-time feedback	Real-time but dependent on ML classification timing
Hardware Required	None (software only)	Camera, microphone	Camera/mic + trained ML model
Design Impact	Aesthetic and spatial optimization	Usability and system latency tuning	Behavioral fine-tuning and trigger-action mapping
Flexibility	Limited (fixed scenarios only)	High (responds to varied user input)	Medium (based on trained gestures or voice inputs)

6. DATA-DRIVEN PANELS’ DESIGN & FABRICATION

A second prototype was developed in order to gather up all the improvements learned from previous studies and experiments. The second prototype is developed to tackle the main concerns that occurred in the first prototype, which are problems related to performance, durabilities and relatedness to architecture.

6.1 Design and Improvements

The design of the second prototype focused on pushing the project into becoming an architectural element in term of shape and materials rather than the interactive art installation the first prototype had. The new prototype uses patterns and materials that can be found commonly in architectural finishes.

6.1.1 Display units

The firsty prototype was made out of 3d printed filaments which was easy to be damaged due to weather conditions and user engagement. The second prototype focuses on introducing new materials that are used more in architectural applications such as concrete and steel. The design of the data-driven panel in the second prototype is within an hexagonal grid and each hexagonal unit is devided into 4 irregular pentagonal unit shape; This pattern is refered to as Cairo pattern (Figure 6.1). Cairo pattern is a pentagonal tiling system composed of congruent convex pentagons that completely cover the plane without gaps or overlaps. It emerges from the intersection of two orthogonal hexagonal grids, where each pentagon is formed by shortening alternating edges of the hexagons, shown in Figure (6.2). This geometric configuration results in four distinct pentagon orientations—up, down, right, and left—each defined by the position of its 120° angle. Historically observed in the paving of Cairo’s streets, the pattern represents the dual of a semi-regular grid and exhibits applications that extend into crystallography and materials science. Its geometric framework allows for the calculation of weighted distances and minimal paths between adjacent polygons, establishing a mathematical basis for both spatial analysis and architectural design considerations (Turgay, Nagy, Kovács, & Vizvári, 2023).

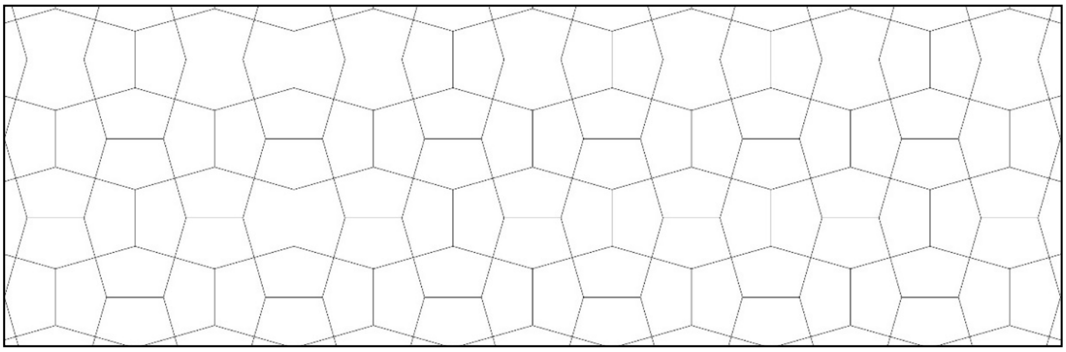

Figure 6.1: Shows Cairo pattern.

Figure 6.2: “Grand Cairo” pentagon field tile – Adapted from Lea Nigel Studios. (2020).

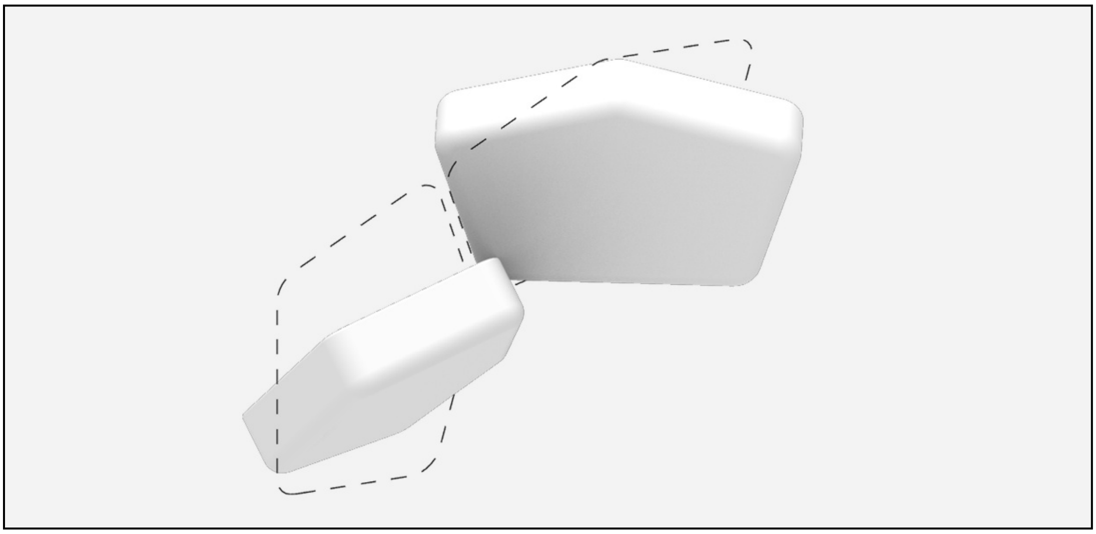

Figure 6.3: Shows second prototype's display units' rotations.

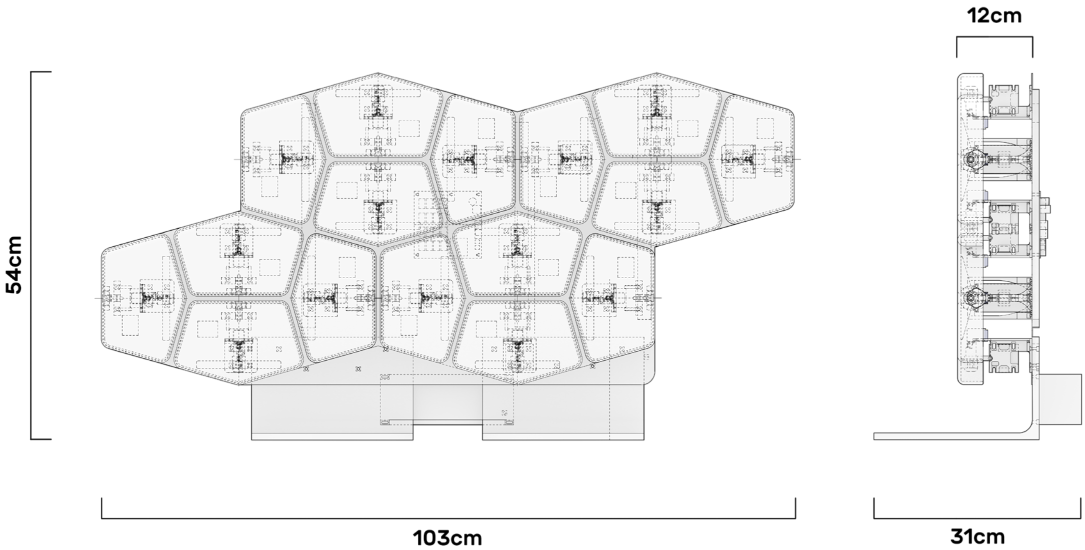

Figure 6.4: Shows front and side elevations of the second prototype.

The decision of drifting away from traditional grid system was taken to result in a more compact design which refers to architectural tiling systems such as Herringbone, escher and offseted tiles patterns. The movement of units in this prototype consists of two movements, vertical and horizental (Figure 6.2). A major improvement in the second prototype is display units. The display units are cast out of a mixture of plaster and concrete. The first steps to craete the display units are as follow. First a 3d printed model is created to have silicon cast inside of it, the form of the model is a positive form of the display unit inside a thin border to have the silicon cast inside of it, shown in Figure (6.3).

Figure 6.5: 3D printed model to have silicon poured in it.

After casting the silicon and letting it dry out, the mold is ready to used. The second step is to prepare the material which will be cast insid the mold, which is a mixture of 200g of plaster and 200g of concrete mixture and 120 ml of water, shown in Figure (6.6).

Figure 6.6: Mixture of concrete and plaster.

After mixing the mixture well, it is slowly poured into the silicon mold while placing the silicon mold on a casting vibrator to release air bubbles, shown in Figure (6.7).

Figure 6.7: Pouring mixture into silicon mold.

The mixture is set to dry for around 15 minutes before it is ready to be released, shown in Figure (6.8).

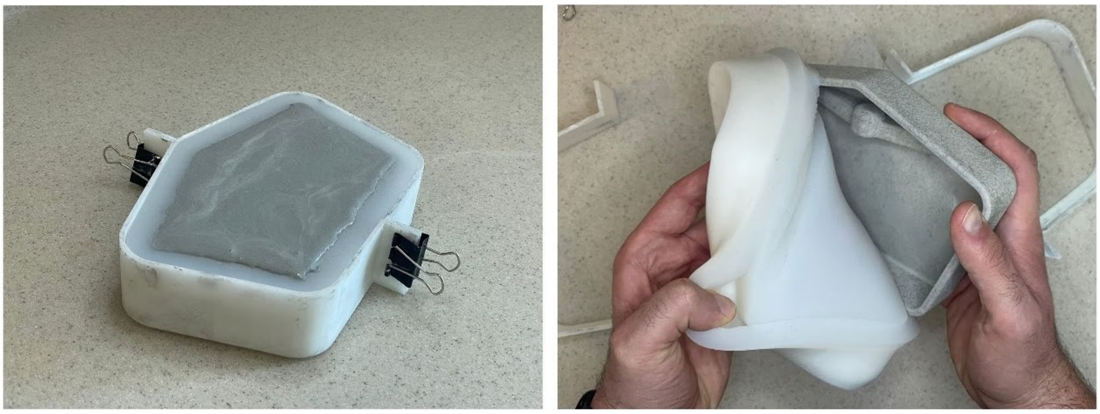

Figure 6.8: Releasing silicon mold.

The final outcome of the unit is an irrigular pentagonal shape, which has a smooth front surface and from the back it has two surface intrusions from top and bottom to have 3D printed holder attach to it, which will lock it in place (Figure 6.9).

Figure 6.9: Finished display unit of second prototype.

6.1.2 Structure

The structure of the prototype has a number of different improvements. The main improvement is the material used in 3d printing which is PETG, which has more strength durability and heat resistance compared to the material used in the first prototype which was PLA.

The 3D printed parts for each display unit consisted of 3 parts. The first part shown in Figure (6.10) holds the stepper motor and the driver board which controls the stepper motor, which will be responsible for moving the display units. The second part shown in Figure (6.10) is a cylindrical piece attached to the head of the stepper motor and has an extruded part with a little magnet attached to it, the magnet plays a roll in triggering the driver board to identify home position. The third piece shown in Figure (6.10) plays a role in looking the display unit in place using a bearing zz809 fitting inside the display unit and help in having a smooth rotation when the prototype is working.

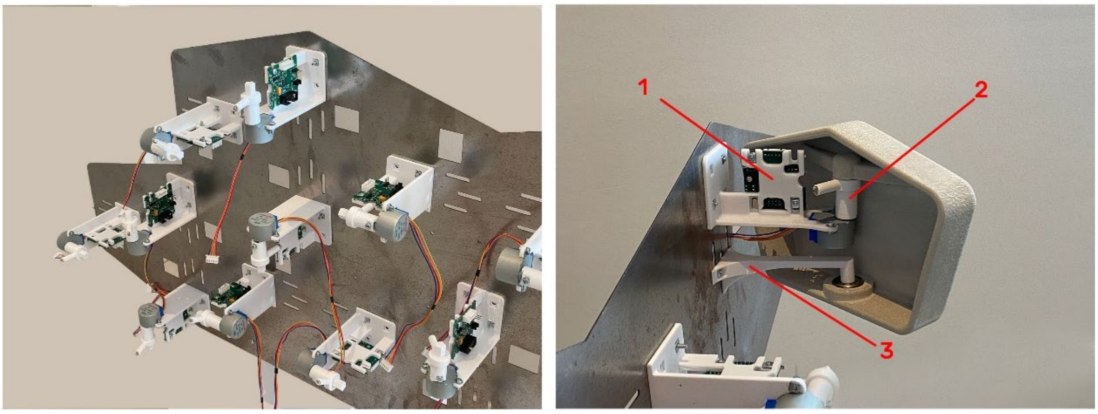

Figure 6.10: Shows inner components of each display unit.

The main base that is holding the prototype is made out of 1mm steel sheet. The base is cut by CNC machine to produce a number of holes which are used to fix the pieces in using screws and to let wires go though to reach the main controlling board in the back, shown in Figure (6.11).

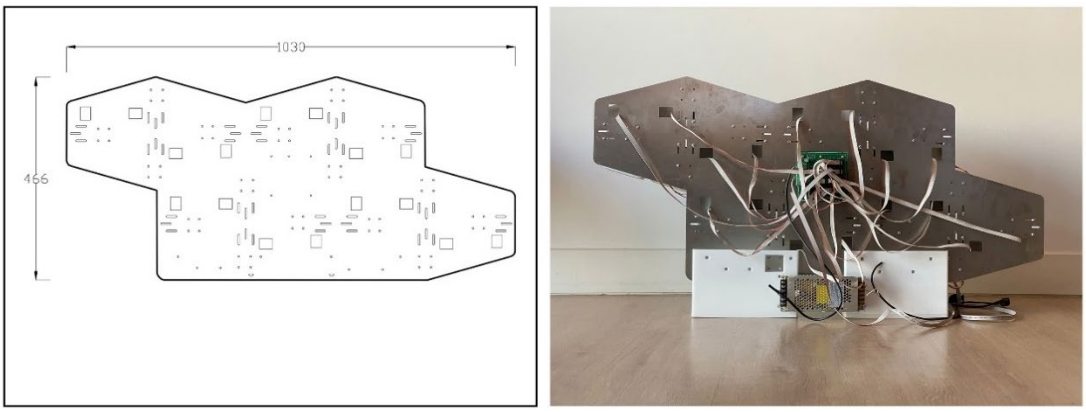

Figure 6.11: Shows steel base of second prototype.

Figure 6.12: Finished prototype with inactive units.

Figure 6.13: Finished prototype with active units.

6.2 Features

The features of the second prototype shown in Figures (6.12, 6.13 & 6.14) consists of all the features developed in this study which are responding to peoples' movement, voice recognition shown in Figure (6.18), body gesture recognition shown in Figure

(6.16) and object recognition shown in Figure (6.17). Which means that it will be able to do certain actions when certain words are spoken, it will also be able to identify certain body gestures such as raising hands and waving. In addition it will be able to recognize objects and respond to them. Most of the features that will be hosted inside this prototype are based on machine learning.

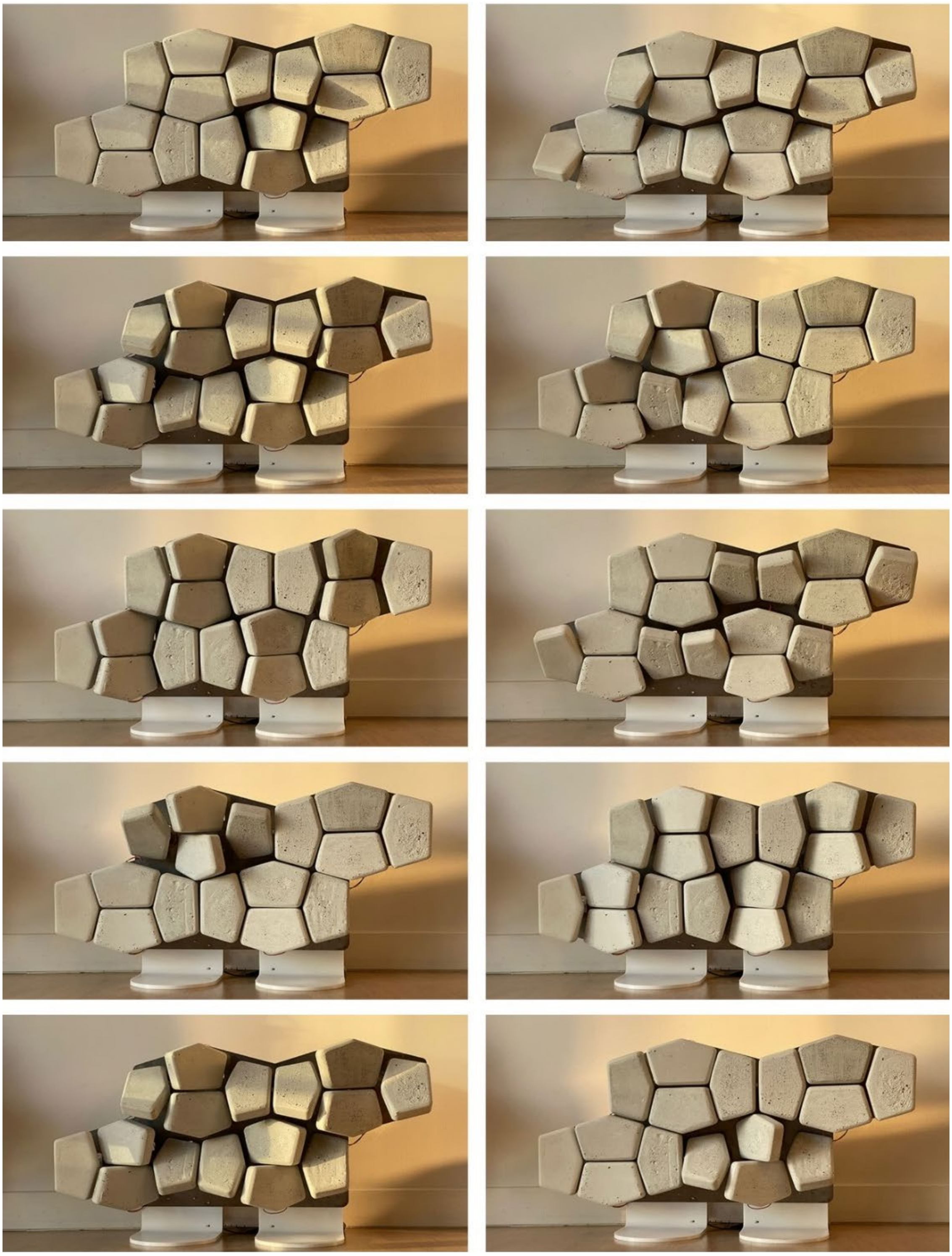

Figure 6.14: Shows different movements of the second prototype.

Table 7.1: Summary of the research-led design workflow and outcome

Research Phase	Methodology / Tools	Related Works / Theories	Outcome / Contribution
Theoretical Framing	Literature review (computational design, HBI, Gestalt psychology)	Gestalt Principles, HBI Theory, Bryson (2021), Costa Maia & Meyboom (2015)	Established conceptual framework for responsive architectural surfaces
Case Study Analysis	Visual and interaction analysis of kinetic mirrors	Daniel Rozin's *Weave Mirror*, Gestalt visual perception	Mapped visual principles to kinetic systems; inspired pixel-movement design logic
Prototype Development	Arduino, servo control, 3D-printed pixel units	Inspired by Rozin's *Weave Mirror*	Demonstrated basic motion and form reflection; validated Gestalt perception in physical form
AI Integration	Google Teachable Machine, TouchDesigner	Human–Machine Interaction (HMI), ML gesture recognition	Enabled intelligent triggers; introduced gesture-based interactivity
Simulation & Evaluation	Blender (pre-rendered), TouchDesigner (real-time, ML-triggered)	Visualization techniques, adaptive feedback loops	Refined user interaction design; pre-evaluated performance before fabrication
Data-driven Panels Design & Fabrication	Parametric design (Grasshopper), mold casting, motor integration	Material-based prototyping practices, responsive systems	Full-scale responsive panel integrating machine learning, user input, and kinetic behavior
Architectural Reflection	In-situ testing, perceptual feedback analysis	HBI theory, interactive architecture	Positioned panels as interactive architectural elements; enabled perceptual and spatial engagement
Thesis Contribution	Research-led iterative design process	Research-through-prototype methodology	Proposed a replicable AI-aided, data-driven design framework for responsive architectural panels
Thesis Contribution	Research-led iterative design process	Research-through-prototype methodology	Proposed a replicable AI-aided, data-driven design framework for responsive architectural panels

Table (7.1) summarizes the full design workflow, associated tools, theoretical references, and outcomes that collectively shaped the research contribution.

Table 7.2: Comparison between Daniel Rozin's installations and data-driven panels

Mirror Design	Similarity	Proximity	Symmetry	Continuity	Closure	Common Fate	Figure–Ground
Weave Mirror	Strong	Strong	Strong	Strong	Strong	Strong	Strong
Wooden Mirror	Strong	Strong	Strong	Strong	Strong	Strong	Strong
PomPom Mirror	Moderate	Moderate	Weak	Weak	Weak	Moderate	Moderate
Penguin Mirror	Moderate	Weak	Absent	Absent	Absent	Weak	Weak
Trash / Rust Mirrors	Absent	Absent	Absent	Absent	Absent	Absent	Absent
Split-Flap Mirror	Strong	Strong	Strong	Strong	Moderate	Weak	Strong
Shiny Balls Mirror	Moderate	Weak	Weak	Weak	Absent	Weak	Absent
Data-driven Panels	Moderate	Strong	Moderate	Strong	Moderate	Moderate	Strong

To further incorporate the perceptual understanding in data-driven panels, in table (7.2) Daniel Rozin's installations and data-driven panels created in this thesis are compared in terms of the Gestalt psychology based on the degree of physical design, material arrangement, and mechanical order. Applying the same standards applied to Rozin's work to the thesis prototype makes the comparison clear on how various structural decisions reinforce or weaken certain Gestalt principles like proximity, similarity, continuity or common fate. Placing the data-driven panels with the mirrors by Rozin is an objective way to study how the design logics such as modularity, grid organization, mechanical synchronization, and expression of material influence the perceptual coherence in the absence of the reflected imagery.

6.3 Reflection on Architecture

The second attempt to create a data-driven panel is achieving a closer vision to be an architectural element rather than an installation and this is done by making the prototype more durable with using architectural materials such as concrete. The final outcome of the project is a 16 display units, 8 of of wich rotate on a horizontal axis and the other 8 rotate on a vertical axis (Figure 6.13). The prototype is standing on two feet attached to the steel back base. Different type of material were experimented to test different variations, such as terrazzo tiles, wood PLA, transparent PLA and white plaster. These material exploring open more potentials to have this project integrated with real architectural applications, such as facades, public spaces, or adaptive environments.

Apart from creating concrete displays, other kinds of materials were tested, such a terrazzo tiles, which is made from plaster mixed with colored plaster particles. Moreover, wood PLA is also used to look like a typical wooden finish that can be seen in architectural projects. The third material used is transparent PLA, in effort to mimic translucent architectural material such semi-opaque glass. The last alternative tested is white plaster, mimicing plaster wall finish, the four alternative materials are shown in Figure (6.15).

Figure 6.15: Material variations of display units.

Figure 6.16: Body gesture recognition feature in prototype.

Figure 6.17: Object recognition in prototype.

Figure 6.18: Voice recognition in prototype.

7. CONCLUSION

In order to sum up the contributions of this thesis, it is vital to consider the steps-by-steps and research-based approach that helped the creation of the AI-assisted, data-informed panels. The conceptual framing and precedent analysis up to the prototyping, simulation, and fabrication stages developed on each other with the hybrid approach combining computational design, machine learning, and experiment of materials. Utilizing Microsoft Kinect V2 depth sensor, touchdesigner as the visual coding and creative environment, and controlled by stepper motors, the prototype accurately captured and translated depth data into mechanical rotations, forming a coherent, pixelated silhouette of the subject standing in front of it. The concrete cast display units and footing as well as the steel base ensured mechanical stability and lightweight construction. The concrete-cast display units and supports, together with the steel base, provided mechanical stability while maintaining a lightweight construction. The panels successfully translate detected movement and respond to environmental inputs, such as passing users, sound, or music, demonstrating their dynamic and interactive performance and their potential as data-driven architectural features informed by real-time information. This project successfully integrated artificial intelligence within architectural elements, enabling dynamic and responsive environments that enhance human–building interaction (HBI) as part of the overall user experience (Karout, Akçay Kavakoğlu, & Ayech, 2024).

Both the simulation of data-driven panels and the integration of AI have further broadened the scope of this research in terms of human-machine interaction, particularly within architectural contexts. The developed simulation, consisting of big number of pixel units which imagines what this project can look like in its full potential, successfully demonstrates the capacity for dynamic and responsive interaction. TouchDesigner, Blender, Processing and Arduino are used for visual development and data handling. This custom setup processes depth sensor inputs and converts them into movements through Blender, achieving real-time feedback from environmental stimuli such as movement and sound. It was further improved with the functionality of the integration of machine learning through the Teachable Machine model of Google, which made it possible to recognize objects, body movements, and speech. The identification triggered particular pixel animations thereby demonstrating the potential of the system to have a variety of interactions. A real-time workflow of simulation with the help of Blender allowed trying a range of design solutions, which needed to be efficiently tested before the actual construction of denser installations. This advancement in interactive architecture provides a guideline on the future possibilities of AI-enriched architectural systems where a possibility of making smarter, more responsive, and more interactive architecture are possible.

The relationship between humans and machines is becoming increasingly close, to the point where artificial intelligence is now perceived as a personal companion. The primary aim of developing data-driven mechanical panels is to introduce an additional layer of interaction between humans and machines within architectural space. The potential lies in rethinking the role of the wall, transforming it into a responsive and reciprocal surface rather than a purely isolating architectural component. Future advancements of this project may significantly influence the field of interactive design. For instance, upcoming applications could improve occupant comfort by regulating environmental factors such as temperature and ventilation through the opening and closing of voids that allow light and air penetration. Furthermore, kinetic acoustic panels may be developed in later stages and integrated into environments such as concert halls and auditoriums to enhance auditory experiences for both audiences and performers. This experimental research investigates human–building interaction by embedding artificial intelligence within architectural elements, thereby elevating the quality and standards of spatial interaction (Karout, Akçay Kavakoğlu, & Ayech, 2024).

Building upon the concept of Human–Building Interaction (HBI), it is essential to further examine the implications and possible applications of these emerging technologies. As technology becomes more deeply embedded within society, interactive architectural systems increasingly influence the way environments are formed and experienced. The ambition is approaching a stage where buildings operate as dynamic systems capable of responding and adapting to human needs and interactions. With ongoing progress in mechanical engineering and artificial intelligence, this vision is increasingly attainable. In a future where mechanical panels are no longer confined to static representations but are seamlessly woven into everyday spatial contexts, novel architectural experiences may emerge, reshaping how architecture is perceived and understood (Karout, Akçay Kavakoğlu, & Ayech, 2024). These interactive surfaces could add to the user experience when coming in touch with the built environment, blurring the lines between architecture and machines.

Moreover, the possible uses of this technology go beyond purely aesthetic installations. Data-driven panels may be applied across multiple sectors, including retail, advertising, healthcare, and education. For example, shopping environments could be tailored to present relevant products based on customer preferences and purchasing history. Another application involves interactive learning through the presentation of dynamic visual data within immersive educational settings. Integrating artificial intelligence into mechanical panels introduces a wide range of data-driven adaptive possibilities. Through collecting and processing user data, these systems can predict and respond to user requirements in real time, enabling personalized experiences that improve efficiency and convenience. In smart home contexts, Internet of Things (IoT) technologies could be combined with data-driven panels to regulate room temperature and lighting according to user preferences and daily habits, thereby optimizing energy consumption and occupant comfort (Karout, Akçay Kavakoğlu, & Ayech, 2024).

In conclusion, this study examines the creation of data-driven mechanical panels and their capacity to enable new forms of interaction within architecture. By integrating infocentric systems directly into the built environment, existing constraints and boundaries are extended further. This research engages in rethinking the possibilities of AI and interactive architecture while enabling new applications across this interdisciplinary domain.

The design and implementation of data-driven panels within interactive architecture involve several inherent constraints. First, the technical complexity and financial burden associated with integrating artificial intelligence and sensing technologies such as Kinect can become excessively high, especially when scaled to larger applications. Furthermore, the prototype’s dependence on precise mechanical and electronic elements, including 3D-printed components and servo motors, introduces challenges related to durability and ongoing maintenance, limiting its applicability primarily to indoor environments due to low resistance to outdoor conditions. Over extended periods, these components may degrade or demand frequent servicing, thereby affecting overall system reliability and operational lifespan (Karout, Akçay Kavakoğlu, & Ayech, 2024).

Moreover, while the panels effectively translate depth data into visual out-turn, the number of pixel units inherently limits the resolution. This can result in low resolution images, which may not be suitable for applications requiring high precision. Lastly, practically, adopting such interactive systems in real-world environments may encounter resistance due to their novelty and the need for specialized knowledge to operate and maintain them. This highlights the need for ongoing research and development to address these limitations and improve the feasibility of integrating AI-driven interactive panels into everyday architectural applications.

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