ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

THE DESIGN SPACE OF THE BASIC DESIGN STUDIO: AN ANALYSIS AND ASSESSMENT WITH SYNTHETIC SOLUTIONS

M.Sc. THESIS

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Department of Informatics

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

TEMEL TASARIM STÜDYOSUNUN TASARIM UZAYI: SENTETİK ÇÖZÜMLERLE BİR ÖLÇME VE DEĞERLENDİRME

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Selen ÇİÇEK, a M.Sc. student of İTU Graduate School student ID 523201013, successfully defended the thesis/dissertation entitled "THE DESIGN SPACE OF THE BASIC DESIGN STUDIO: AN ANALYSIS AND ASSESSMENT WITH SYNTHETIC SOLUTIONS", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family,

FOREWORD

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June 2023

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TABLE OF CONTENTS

Page

ABBREVIATIONS

AI	: Artificial Intelligence
ANN	: Artificial Neural Network
ARCH 101	: Basic Design Studio I
CNN	: Convolutional Neural Networks
DDPM	: Denoising Diffusion Probabilistic Model
DE	: Design Experts
DM	: Diffusion Model
DNN	: Deep Neural Network
DSS	: Design Solution Space
FFD 101	: Arts and Design Studio I
GAN	: Generative Adversarial Networks
IUE	: Izmir University of Economics
METU	: Middle East Tecnhical University
NLP	: Natural Language Processing
PS	: Problem Space
RNN	: Recurrent Neural Networks
VAE	: Variational Autoencoders

LIST OF TABLES

Page

LIST OF FIGURES

Page

THE DESIGN SPACE OF THE BASIC DESIGN STUDIO: AN ANALYSIS AND ASSESSMENT WITH SYNTHETIC SOLUTIONS

SUMMARY

The basic design studio is considered as the core of the design education in terms of teaching novice designer how to reason for design. Despite its crucial role, the first-year design students often recorded to have difficulties to understand the abstract concepts and principles conveyed in the studio by the design problems. These problems present challenges for students due to implicit definitions and abstract concepts given in the assignment briefs. Because the students have neither previous experience in dealing with abstract design problems that require elaborating multiple and interrelated aspects of the problem at once, nor developed a reasoning mechanism to generate design solutions. Thus, this research aimed to search for a method to help students better understand the abstract concepts and principles conveyed the in the basic design studio and explore the impact of the design problems on the generated solutions by a text-to-image artificial intelligence (AI) model.

It is hypothesized that the concept of the design space can offer a medium for the students to reconstruct the design problems to generate solutions since the concept inherits problem and solution spaces bonded with the design process. By reviewing the literature the concept reframed in the scope of the study as: assignment briefs constituting the problem space with inherent ill and well definitions; solution space contains the design process outputs. To explore the impact of the problem space on the solution space, a series of synthetic design solution spaces were generated using a text-to-image diffusion model.

The selection of the AI model was critical for the study. The text-to-image diffusion models are assumed in this study as suitable for assignment-based design education that emphasized learning-by-doing type through solution assessment and development during a generative process. Hence, the synthetic design solution spaces are created as alternative assessments to elucidate the problem definitions in a sample set of assignment briefs and to consider the impact of the brief and the feedback process on design solution space generation.

The methodology encompasses a retrospective perspective in terms of using two sets of problem spaces of two different design schools to generate a series of synthetic design solution spaces. In total three solution spaces were generated for each problem space analyzed in the study. These solution spaces had substantial differences in terms of including a feedback mechanism.

In the first step, the analyzed two sets of assignment briefs were translated into text prompts by preserving their semantic organization. These prompts were used to generate the first and second synthetic solution spaces that correspond to the two problem spaces of different institutions. The first solution spaces were subjected to an evaluation process by design experts, alluding to a feedback/critique session in a conventional design studio, whereas the second solution spaces were kept as a control

group for the further assessment process. Secondly, text-prompts were revised based on the feedback and the third synthetic solution space was generated using the diffusion model.

Lastly, the performances of the generated synthetic solution spaces, including the control groups, were evaluated in semi-structured design expert interviews. The expert interviews indicated a retrospective discussion in terms of comparing the visual impacts of the explicitness of the problem spaces on the synthetic design solution instances. Overall findings indicated that the performances of the generated solutions tend to increase when the brief defines the problems explicitly. Besides, the feedback process enhances the overall performance of the design solution spaces, as they introduce the implicit agenda of the briefs defined with the ill-defined design problems. Although the assessment results indicated several limitations of the model for representing well-defined design problems, experts evaluated the performance of the model as promising to elucidate the ill-defined problems for the students. Thus, with expert guidance, synthetic solution spaces can be used to expose students to a large number of solutions as they interpret the given design problem, the principles, and key concepts, and develop critical perspectives on their process and productions. Moreover, the potential implementation strategies of the AI tool in the first-year design studio were discussed in terms of enlarging the design space of the novice designer, to enable them to develop a reasoning mechanism.

TEMEL TASARIM STÜDYOSUNUN TASARIM UZAYI: SENTETİK ÇÖZÜMLERLE BİR ÖLÇME VE DEĞERLENDİRME

ÖZET

Temel tasarım stüdyosu, tasarım problemlerini çözme noktasında birinci sınıf öğrencilerine tasarım için akıl yürütme sürecini kavratma hedefi ile tüm tasarım disiplinleri için temel yapıtaşı sayılır. Temel tasarım stüdyosunda verilen ödev yönergelerindeki tasarım problemleri sıklıkla problemin farklı boyutlarını bütünleşik bir biçimde yönetmeyi gerektirir. Birinci sınıf öğrencileri bu tür problemleri çözmek için henüz bir akıl yürütme becerisi kazanmamış olduklarından, çoğu zaman stüdyonun temel kazanımları olan tasarım kavramlarını ve prensiplerini içselleştirmekte zorlanmaktalardır. Bu bağlamda tez muğlak tasarım problemlerinin sürece olan etkilerini üretilen çözüm uzayları üzerinden incelenmesini önceleyerek ve öğrencilere bu tür tasarım problemlerini kavrama ve çözüm üretme süreçlerinde yardımcı olabilecek bir yöntemin geliştirilmesini hedeflemektedir.

Tasarım uzayı kavramı, içerisinde barındırdığı problem ve çözüm uzayları ile öğrencilerin tasarım problemlerini temsil ederek yeniden yorumlaması ve böylelikle çözüm uzayı üretmesi için uygun bir ortam olarak değerlendirilmiştir. Farklı hesaplamalı tasarım alanlarının literatürlerindeki tasarım uzayı kavramı taranarak, kavrama temel tasarım eğitim bağlamında yeni bir çerçeve çizilmiştir. Tasarım metodolojisi literatüründe tasarım problemleri, iyi tanımlı ve eksik tanımlı problemler olarak ayrışmaktadır. İyi tanımlı tasarım problemleri, problemin amacını ve çözüm için takip edilmesi gereken adımları açık bir biçimde tariflerken, eksik tanımlı problemler soyut kavram ve olgular içeren, çözüm yolunun tek olmadığı durumları işaret eder. Tez kapsamında, tasarım uzayı kavramı için çizilen çerçevede, stüdyoda öğrencilere verilen ödev yönergeleri problem uzayını oluştururken, bu problemlere yanıt vermesi hedeflenen tasarım süreci çıktıları ise çözüm uzayını oluşturmaktadır.

Yöntem, problem uzayının etkilerini ölçmek amacıyla bir seri sentetik çözüm uzaylarının bir yapay zekâ modeli ile üretilmesini amaçlar. Temel tasarım stüdyosu, pedagojik olarak ödev tabanlı yaparak öğrenme modeline sahip olduğu için, metinden görsele dönüşüm sağlayan doğal dil işleme tabanlı difüzyon modeli, problem uzaylarının veri olarak kullanılarak çözüm uzaylarının üretilmesi için uygun bir araç olarak seçilmiştir.

Farklı tanımlı tasarım problemlerinin etkilerini retrospektif bir bakış açısı ile ölçmek için yöntem, iki tasarım okulundan elde edilen problem uzaylarını veri olarak kullanır. İncelenen ilk problem uzayı 2003-2007 yılları arası Orta Doğu Teknik Üniversitesi, ARCH 101 kodlu "Temel Tasarım Stüdyosu I" ödev yönergelerinden bir seçkiyi kapsarken, ikinci problem uzayı İzmir Ekonomi Üniversitesi FFD 101 kodlu "Sanat ve Tasarım Stüdyosu I" kapsamında verilen ödev yönergelerinin bir seçkisini içermektedir. İlk olarak bu iki problem uzayının içinde barındırdıkları problemler, iyi ve eksik tanımlı tasarım problemleri olarak analiz edilmiştir. Ödev yönergelerinde, tasarım elemanlarının veya ortamının materyal özelliklerini açıkça tanımlayan ifadeler

iyi tanımlanmış tasarım problemi olarak nitelendirilmiştir. Öte yandan, birinci sınıf öğrencisinin anlamasının güç olduğu, muğlak ifadeler ile temel tasarım kavramlarını ve prensiplerinin altını çizen ifadeler eksik tanımlı tasarım problemleri olarak değerlendirilmiştir.

Bu iki problem uzayı içerisinde yer alan problemlere yanıt veren çözüm uzayları kendi içlerinde barındırdıkları üretim metotları kapsamında da farklılıklar göstermektedir. Her iki problem uzayı için ayrı ayrı üretilen birincil çözüm uzayları, ödev yönergelerinin semantik yapısı korunarak metin komutlarına çevrilmesi ile elde edilmiştir. İkincil çözüm uzayları ise üretim metotlarına eklemlenen geri-bildirim katmanları ile birincil örneklerden ayrışmaktadır. İki farklı tip çözüm uzaylarının üretim metotlarındaki farklılıkların, problem tanımının çözümler üzerindeki etkisine ışık tutması beklenmiştir.

İkincil çözüm uzaylarının üretiminde, tasarım stüdyosundaki eğitmenlerin geri bildirimlerine/kritiklerine atıfta bulunan, ödev yönergeleri ile tasarım uzmanı kritiklerini de içeren metin komutları kullanılmıştır. Bu kapsamda ilk çözüm uzaylarının elemanları üç kişilik bir tasarım uzmanı ekibi ile değerlendirilmiş, elde edilen geri bildirimler ödev yönergelerindeki muğlak problem tanımlarını aydınlatmak üzere anahtar kelimeler olarak metin komutlarına entegre edilmiştir.

Farklı problem uzaylarının ve komutların kullanımıyla elde edilen sentetik çözüm kümelerinin, tasarım problemlerini yanıtlama performansı üç tasarım uzmanı ile gerçekleştirilen birebir, yarı-yapılandırılmış görüşmeler ile ölçülmüştür. Bu görüşmeler, tasarım uzmanlarının hem nicel ölçümlerini hem de nitel değerlendirmelerini edinebilmek adına iki kısımdan oluşacak şekilde kurgulanmıştır.

Nicel değerlendirme safhasının ilk sorusunda, tasarım uzmanlarına üretilen sentetik çözümlerin üretiminde kullanılan ödev yönergeleri okutulmuş ve uzmanların bu tanımların açıklık seviyelerini sıralı ölçekte (1=zayıf, 2= zayıf-ortalama, 3=ortalama, 4=iyi, 5= çok iyi) puanlamaları istenmiştir. Tasarım uzmanlara yönetilen ikinci soru ile, uzmanlardan üretilen çözüm uzayı elemanlarının yönergedeki iyi tanımlı problemlere cevap verme performanslarını puanlamaları beklenmiştir. Üçüncü soruda ise üretilen çözüm elemanının genel kalitesinin (kompozisyonun) ölçülmesi hedeflenmiştir.

Değerlendirme aşamasının nitel kısmında ise sentetik çözüm uzayı üretim yönteminin temel tasarım stüdyosuna potansiyel eklemlenme stratejilerinin, pedagojik açıdan değerlendirilmesi hedeflenmiştir. Tasarım uzmanlarına yöneltilen üç soru ile kendi temel tasarım stüdyosundaki eğitici izlenimlerini göz önünde bulundurarak, organik ve sentetik çözüm üretme süreçlerindeki farklılıkların kıyaslanması ve potansiyel eklemlenmenin pedagojik çıktılarını aydınlatmak amaçlanmıştır.

Elde edilen nicel veriler, araştırma sorusuna yanıt vermek üzere hem girdi verisi olarak kullanılan iki tip problem uzayı bakımından, hem de birincil ve ikinci çözüm uzaylarının tanımlanan farklı problemlere yanıt verme performansları bakımından karşılaştırmalı olarak değerlendirilmiştir. Elde edilen sonuçlar üretilen tüm sentetik çözüm uzaylarının kompozisyon kalitelerinin, iyi-tanımlanmış problemlere cevap verme performanslarından daha yüksek olduğunu göstermektedir. Bu durum kullanılan yapay zekâ modelinin mevcut durumdaki limitasyonlarından kaynaklanmış olma ihtimali farklı başlıklar altında değerlendirilmiştir. Bu limitasyonlara dayalı olarak elde edilen sonuçlar, üretilen tüm çözüm uzaylarının performanslarının ortalamanın altında kaldığını gösterse de iyi tanımlanmış ödev yönergeleri ile üretilen çözümlerin, muğlak tanımlı problemler ile üretilen örneklere kıyasla daha yüksek performans gösterdiği saptanmıştır. Benzer şekilde, eklemlenen geri-bildirim katmanının yapay zekâ modelinin probleme doğru yanıt veren çözümler üretme performansına belirgin bir katkı sağladığı açıktır.

Modelin güncel durumdaki performansı iyi tanımlı problemler olarak ifade edilen eleman özelliklerini temsil etme konusunda ortalamanın altında kalsa dahi, nitel değerlendirme sürecinde tüm uzmanlar, modelin eksik tanımlı problemler ışığında çözüm üretme potansiyelini ümit verici olarak nitelendirmişlerdir.

Bu kapsamda önerilen yöntemin temel tasarım stüdyosu pratiğine iki farklı araç olarak sunulabileceği tartışılmıştır. İlk olarak stüdyonun erken evrelerinde ödev yönergeleri öğrencilere verildiği ilk anda yapay zekâ modeli ile üretilen çözümlerin, stüdyo eğiticilerinin kontrollü seçimi ile panel tartışmalarının tasarım uzayını genişletme potansiyeli sunulmuştur. Genişletilen bu tasarım uzayı öğrencilere eksik tanımlı problemlerin gereksinimlerini üretilen birçok çözüm üzerinden örnekleyip, aynı zamanda problemin farklı bakış açıları ile ele alınmış çözümlerini sergileyerek, stüdyonun temel eğitim pedagojisinde yer alan "gör-hamle yap-gör" pratiğini pekiştirebilir. Böylelikle birinci sınıf öğrencileri verilen tasarım problemlerine kendi organik çözümlerini geliştirmeden önce problemlerin gereksinimlerini daha iyi kavramış olarak daha tutarlı ve kaliteli üretimler gerçekleştirebilirler.

İkinci bir strateji olarak, yöntemin stüdyo eğiticileri tarafından verilen yönergelerdeki problem tanımlarını test etmek için bir araç olarak kullanılabileceği tartışılmıştır. Aynı zamanda yöntemin limitasyonları olarak da tanımlanan modelin sabit öğrenme eğrisinin ve bağlamsal bilgi birikimi eksikliğinin, birinci sınıf öğrencisinin stüdyonun erken aşamasındaki hali ile benzeştiği varsayılabilir. Bu kapsamda stüdyonun başlangıç aşamasında verilmesi planlanan ödev yönergelerinin önerilen yöntemin kullanılması ile elde edilecek çözümlerinin analiz edilmesi ile problem tanımlarının muğlaklık derecelerinin öğrencinin kavrama seviyesine göre uyarlanması söz konusu olabilir.

1. INTRODUCTION

Basic design, as an educational model is considered as foundational for all design disciplines in the first year of design studios (Besgen et al., 2015; Kocadere, 2012). The studio is commonly referred to as the foundational studio, preliminary design studio, or basic design studio (Çakmaklı et al., 2022). However, regardless of its name, its critical role remains the same: teaching novice designers the concept of design reasoning implicitly (Akin, 1984). Despite its critical role in teaching students how to think for design, students have difficulty fully comprehending the significance of the studio, due to its primary characteristic of preparing a ground for the students for their first encounter with design problems (Dorst et al., 2005). The students who have previously been exposed only to well-defined or tamed problems during their former education that are generally structured with one goal and one-valid-answer are often devastated by the first challenge opposed to the ill-defined design problems (Saranlı,1998; Dorst, 2003).

Since novice designers have no previous experience, they learn the concepts and key principles of design by delivering solutions through a 'learning by doing' paradigm supported by studio instructors' critiques (Dewey, 1916; Schön, 1985; Özkar, 2007). However, in this process, students often struggle in the beginning stages while dealing with abstract design problems to develop a design reasoning mechanism to generate a solution.

Hence, this thesis reconsiders the gap in understanding and elucidating the various definitions of design problems and seeks a method to help students better understand the ill-defined design problems to convey key concepts and principles in the Basic Design Studio. It is hypothesized that offering a synthetic design solution space generation mechanism using AI-aided tools may help elucidate the ambiguous problem definitions that are not clearly stated in given assignment briefs. Assuming that the concept of design space offers a promising medium for the students to represent these problems and highlight the potential solutions, alluding to the see-move-see pattern of the reflective practice conveyed in the studio.

To evaluate the impact of various definitions in the problem spaces on the design solutions, the proposed methodology draws a comparative framework by retrospectively analyzing the assignment brief data of two renowned design intuitions that constitutes the two-problem spaces of the study. To analyze and assess the visual impacts of these problem spaces on the generated solutions, it is intended to generate a series of synthetic design solution spaces.

In the field of generative design, numerous research studies aim to create design solution spaces using various computational algorithms as teaching aids for early stages of design education (Chase, 2003). Rule-based systems like shape grammars are effective in generating complex forms and patterns from a simple set of rules defined by explicit constraints, making them suitable for educational design studio setups (Knight, 1999; Economou, 2000). However, the application of these rule-based systems in basic design studios is limited when the design brief does not provide explicit rules or objectives. Additionally, these systems often confine designers to a single visual domain. Consequently, first-year design students face the challenge of translating written design problems into a visual medium through their own interpretation in the basic design studio.

In this context, the potential implementation of AI-aided tools can be considered as promising for novice designers. Machine learning models (ML) generate novel solution instances by analyzing and synthesizing the hidden patterns of the provided data in multiple-domains, that do not require a certain structure of rules or algorithms. Unlike the prior generative design algorithms, it might be possible to generate solution instances that answer the design problems that are not defined explicitly. Thus, for the generation of synthetic solution spaces through variously defined design problems stated in the assignment briefs, an AI model was employed.

The selection of the AI model was critical for the study as the primary objective was to identify the impacts of problem statements defined in design briefs on the generated solutions. Therefore, a generic text-to-image diffusion model was selected to conduct the research, to generate solution instances directly from the written design briefs without a need of visual transition. The architecture of the natural language processing (NLP)-based text-to-image diffusion model was deemed suitable for the generation process of solution instances, aligning with the assignment-based, learning-by-doing educational model of the basic design studio.

The synthetic design solution spaces generated by the diffusion model that correspond to the two problem spaces also vary based on their generation procedures in terms of being generated through the direct translation of the assignment brief into text-prompts or revised-text prompts by the implemented feedback mechanism. To generate the initial solution spaces, the briefs are translated into text-prompts by preserving the semantic organization. These initial solution spaces are subjected to an evaluation process by the design experts to retrieve feedback, similar to the critique session in the studio. The feedback obtained in these sessions is used to revise the text-prompts, which are used to generate the secondary solution spaces.

By comparing the two types of solution spaces of two problem spaces, it is expected to highlight the difference between processes in order to test out the potentials and limitations of the implementation of the method as a tool in the studio. The initial design solution spaces generated by the solo guidance of the assignment briefs are expected to show the visual impacts of the brief statements in a constrained context. Whereas the secondary solution spaces generated through revised prompts are expected to also show the visual impacts of the ill-defined design problems conveyed implicitly in the briefs, that are highlighted during the feedback sessions.

1.1 Structure of the Study

As the initial aim of the thesis puts the initial emphasis on the novice designers' process of obtaining reasoning mechanisms in basic design studio by the guidance of the design problems, the theoretical foundations of the deeply rooted concepts in the design pedagogy were reviewed in Chapter 2. Starting from reviewing the definition way of the design problems in the literature of design methodology, the representation and representation issues of these problems were discussed to reframe the concept of design space in the context of the basic design studio. To draw a concise framework for the design space as a potential medium for the students, definitions and connotations of the term including its subspaces were reviewed systematically in a wide range of computational design field literature.

Secondly, as the proposed methodology requires the generation of the design solution spaces synthetically to explore the impact of the problem space, Chapter 3 presents a literature review on generative deep learning models, to identify the current gap of implementation of the AI models in the design education and to explain the selection criteria of the suitable model.

Chapter 4 outlines the methodology of the study, which was divided into three main sections: the retrospective analysis of the problem spaces, the generation of synthetic design solution spaces, and the assessment procedure of the design solution spaces through the design expert interviews. In section 4.1 the assignment brief data that constitute the two problem spaces of the study were retrospectively analyzed. Data collected from the first-year design studios of Middle East Technical University (METU) and the Izmir University of Economics (IUE) were briefly introduced and compared in terms of the inherent differences in problem identifications. Secondly, the generation processes of the synthetic design solution spaces were explained. The translation protocol used to translate the assignment briefs into text-prompts for generating the initial design solution spaces was described in detail. Following that, the implementation of the feedback mechanism for the generation of the secondary solution spaces was demonstrated by the sessions held with the design experts. Thirdly, the evaluation process of the generated design solution spaces was explained in terms of the semi-structured design expert interviews for qualitative and quantitative assessments.

Chapter 5 of the thesis presents the results of both quantitative and qualitative assessments obtained through the semi-structured interview sessions conducted with design experts. The quantitative analysis focused on two comparative aspects perspectives: the impact of two different problem spaces on the performance of generated solutions spaces and the impact of the implemented feedback mechanisms. On the other hand, the qualitative assessment explored the experts' insights gained through open-ended questions regarding the potential implementation strategies of the model as a tool in the basic design studio, with a focus on the pedagogical impacts. Starting from section 5.3, the overall performance results of the generated solution spaces by the guidance of ill-defined and well-defined design problems were discussed, while considering the limitations of the model. Potential implementation strategies of the text-to-image AI tool in the basic design studio were also ex also explored to help novice designers better understand ill-defined design problems.

2. REFRAMING THE DESIGN SPACE OF THE BASIC DESIGN STUDIO

The first year of architectural design education, particularly the basic design studio, is widely regarded as the most challenging phase of the entire curriculum (Ghom, George, 2020; Boucharenc,2006). This is due to a variety of factors that arise in various contexts of design education. For instance, students may struggle to adapt to the new working environment of studios, which is typically very different from the traditional classrooms they may have been accustomed to in their earlier education phases (Aytaç-Dural, 2002). Additionally, students may find it difficult to navigate unfamiliar interactions with design instructors during panel critics and juries.

However, the main reason and the underlying cause of previously mentioned situations can be related to the design reasoning concept, which novice designers have not been acquainted with, yet. Van Dooren et al. exemplifies this situation by quoting Schön (1985), in which he illustrates this impasse character of the foundational design studio as a challenge for the students, as follows:

> (Student) is expected to plunge into the studio, trying from the very outset to do what he does not yet know how to do, in order to get the sort of experience that will help him learn what designing means. (van Dooren et al., 2014)

Since novice students have no previous design experience to develop a reasoning mechanism through questions that they have never been exposed to before, guiding them is important in the foundational design studio. Thus, we refer to the concept of design reasoning as a key instrument of basic design education, for making novice designers enable to understand the main logic of what to do and how to do design in the process.

Keeping in mind that design is a continuous action that proceeds on both visual and cognitive levels, it is possible to say that reasoning takes place at all stages of this process in different levels and mediums (Demirbaş & Demirkan, 2003). The following sections of the thesis intend to identify these intricate processes of design in the basic design studio by analyzing the inherent stages of it to highlight the role of design reasoning in the context of the foundational design studio.

Firstly, starting with the definition way of the design problems, the learning strategies and the deeply rooted concepts of the basic design studio were explored in the seminal publications to gain a comprehensive understanding. Additionally, an extensive review of the definitions of the design space concept was conducted in the computational design literature; to establish a concise framework for addressing the reconstruction and representation challenges of the design problems on that conceptual medium.

2.1 First Encounter with the Design Problems

The initial struggle for the students in the basic design studio begins with the first encounter with the definition way of the design problems, and their solution processes. In general, novice designers who enter the basic design studio for the first time have encountered well-defined or tamed problems throughout their previous education. These problems are generally structured with one goal that requires single, absolute truth or one-way valid answers. Since they are mostly brought up to derive instant solutions to those kinds of problems by applying the pre-established methods and formulas in primary and secondary education, the students are not used to make interrogation about the nature of the given problem; or developing a methodology to tackle with it (Saranlı, 1998).

However, it should be noted that the design problem definitions do not generally permit the derivation of solutions through pre-defined, straightforward, and simple methodologies. In most cases, each unique design problem requires reconstruction of it through the interpretation of the student in order to fully reveal itself in terms of what it seeks. As a result, the first encounter with the ill-defined or wicked nature of design problems can have a devastating impact on novice students (Casakin, 2004; Dorst, 2005), as they are not trained to provide answers in contexts where even the given problem is not explicitly structured.

Therefore, the students in the basic design studio, generally neither have a clear insight about how to approach it to solve the problem nor can see what the actual problem is about the given task, that requires an action to be taken. Therefore, defining an explicit conceptual framework about the nature of the given problems might be useful to introduce the student to the inherent ambiguities of the design process, which includes the reconstruction of the problem (van Dooren, 2020).

The first understanding takes the design problems as primary examples of the ill-defined or ill-structured ones; in terms of their initial, goal, and intermediate states are being specified incompletely (Reed, 2015; Simon, 1975). The generated solutions of ill-structured problems have no direct relations with the precedent solution cases, which means that the algorithms that would be applied to solve the problems are totally unidentified and unexplored (Casakin, 2002; Goldschmidt, Weil,1998). In that case, each solution attempt towards the design problem produces potential alternatives that have not been explored yet, which can be directly related to design creativity.

Also, Simon's perspective sees design as a challenge of instrumental problem-solving activity, ill-structured definitions of the design problems do not pose an obstacle to getting solved, as long as their solution process can get systematized like-wise the well-structured ones (Simon, 1975). From his point of view, design problems as the primary examples of ill-defined problems can be solved "in the sense of a number of sequential well-structured problems" (Lloyd, Scott, 1994).

The definition of the design problems bounded with wickedness, takes the problem as open to reconstruction in different ways at any time during the process of solving it. Since they are formulated loosely, there is no single goal of an objective to be reached, but only the viewpoint of a designer in constrained contexts can be determined in order to solve it (Coyne, 2005; Rittel,Webber, 1973).

At this point of the discussion, it is also important to underline that these design problem definitions are not the only challenge in the basic design studio. The ambiguity level of the design problem and also the process is bounded by the context and subject. Simon (1957) discusses this issue with the term bounded rationality, the decision-making process of a human to rationalize an idea is limited by their knowledge and cognitive capacity. Therefore, the prior knowledge contextual knowledge, and the comprehension ability of a subject might change the definition of the problem statement during the design process.

In the basic design frame work, this difference in the perception of design problems can be observed between the studio instructors and the students. Since basic design instructors are more experienced in the design process than the novice designers, they can find the implicit, ill-defined design problem statements as explicit as well-defined problems.

2.1.1 Reconstruction and representation of the design problems

The definitions of the design as an ill-structured or wicked problem indicate different characteristics, although the initial conflict which underlies both can be considered the same: The design problem gets formulated after certain intents are performed or actions are taken by the designer since the further steps cannot be seen in the first place due to the ambiguous nature of the problem. It never reveals itself clearly in terms of its goal and intermediate stages without any solution attempts performed, which changes the characteristics of the design object and medium (Newell & Simon, 1972). As well as those changes an occur in material properties to be distinguished by the five senses on the design medium, it can also simply alter the perception of the designer to grasp new characteristics of the existing material. For instance, Stiny (2016) discusses those changes and their implications on the process in the context of shape grammar. He denotes the importance of the change, which can acquire different implications than merely the visual ones, as well as the perceptional ones by the introduction of the useless rules.

The integration of the perceptual changes in the process can be seen as an entry of another level of ambiguity that underlies that design problems need to be reconstructed both perceptually and visually to get represented. The design problems can get defined as ambiguous and uncertain, which could be interpreted as the main characteristics that make the design process "creative at least innovative" (Goldschmidt and Weil, 1998). Those ambiguities inherent in problems mostly have tried to get omitted in the process of the solution delivery in a variety of scientific fields including mathematics, engineering, etc. However, in the design-related realms, they are considered to be the creative resources for emerging applications, that designers should neither ignore nor repress (Gaver et al., 2003). Although it is also considered that the designer's role is to control them during the process to answer the given design problem in an orderly manner (Cross, 1993). Therefore, the main aim of the designer might be named as producing coherent and internally consistent design outputs which would avoid coincidentally at all, by developing new methodologies to control them.

In accordance with that, Simon’s attitude towards the design as a problem-solving activity proposes a solution mechanism for the ill-defined design problems. His suggestion is to represent the complexity of an ill-defined design problem in “smaller, more manageable sub-problems that can potentially be well-defined” (Akin, 2001; Simon, 2019). At this point, in Simon’s terminology the “representation” might be considered as the key point to the delivery of solutions to the ill-defined problems.

His initial statement advocates that, if each stage of the interrelated process of design can get explicitly represented on a medium to be seen from, it would be feasible to develop new solutions accordingly. However, the limited cognitive abilities of humans to represent the intermediate stages of the process on the visual medium prevents the derivation of the potential alternative answers, since the upcoming stages after certain moves had taken cannot get foreseen easily. Simon (2019) illustrates this situation with the well-known analogy of an ant trying to find his path to his home :

> Whoever made the path, and in whatever space, why is it not straight; why does it not aim directly from its starting point to its goal?... He has a general sense of where home lies, but he cannot foresee all the obstacles between them. He must adapt his course repeatedly to the difficulties he encounters and often detours uncrossable barriers. His horizons are very close so that he deals with each obstacle as he comes to it; he probes for ways around or over it, without much thought for future obstacles. It is easy to trap him into deep detours. (Simon, 2019, pp.51)

The altered path of the ant due to obstacles and environmental changes can be viewed as a two-fold problem. While the obstacles initially defined and those that occur during the journey due to changes in the environment are the primary reasons for the ant's altered route, they are not the only contributing factors. The ant's limited cognitive capacity to anticipate future disruptions caused by the environment also plays a significant role in the ant's altered course.

To derive an analogy from Simon's ant into the design education framework, we can refer to the novice designers as the ants trying to solve the given design problems in the basic design studio. The cognitive abilities of the students as the ants of this case are limited in foreseeing the upcoming stages of the process, as they have no previous design experience to be able to know how to proceed. The assignment briefs as the design problems of the basic design studio can be seen as the defined task environment, that causes disruptions on the fly, which alter the perception of the designer and the expected solution delivery process. Therefore, students might fall into deep detours during the process, as they have no chance to learn how to design besides experiencing it by making.

This experience of learning by the trial-and-error mechanisms indicates a significant type of reasoning that has been explained by the learning-by-doing paradigm (Schön, 1987). He defines the general educating setting of the design studio as a reflective practicum, in which the student learns design by doing it with the help of coaching provided by the design studio instructor:

> Studios are typically organized around manageable projects of design, individually or collectively undertaken, more or less closely patterned on projects drawn from actual practice. They have evolved their own rituals such as matter demonstrations design reviews desk critics and design juries all attached to the core process of learning by doing. (Schön, 1987, p.12)

The reflective conversation between the student and the design object gets strengthened in the light of the dialogue and critics of the coach, as well as the student becomes more proficient in design reasoning during the reflection-in-action. At this point of the discussion, the definition of design as a reflective practice or act of making might be first seen as contradictory with the perspective of design as a problem-solving, in terms of the attitudes towards the design problem-solution process. Since Simon tries to decipher the design problem and its solution process explicitly in a manner of rationalization, whereas Schön elaborates on it as an act of making which corresponds to grasping the essence of the design problem implicitly. Schön expresses his critics about neglecting the essential parts of the problem, the inherent ambiguities and uncertainties, by underestimating designing into a "process of optimization":

> (Herbert Simon's) view ignores the most important functions of designing in situations of uncertainty, uniqueness, and conflict where instrumental problem solving- and certainly optimization- occupy a secondary place if they have a place at all. In contrast, I see designing as a kind of making. (Schön, 1987,p.41)

Although the initial attitudes of two seminal design researchers towards the design process have sharp differences, looking from the design education context both perspectives of design problem might be considered as converging at the same point: The design problems need to get clarified implicitly or explicitly during the process, to enable the novice designer to represent and reconstruct them on the design medium to see and move from. However, the medium of this convergence can be considered still unidentified, in order to utilize it as a tool in design education for teaching novice design students how to reason for design.

At that point, the concept of Design Space might be offered as a promising medium for representing the reflective action of design that takes place during the design studio with the contributions of the individuals as students and design instructors.

The definitions of the design space concept vary wildly in a wide range of computation-related literature. In terms of approaching the concept only as a display case of the generated design solution alternatives, or interrogating the term as a design tool in the generative application processes(Goldschmidt, 2015). Although the computational structures of the concept have been discussed widely regarding its construction and exploration issues, a number of the research is fewer that focus on the abilities provided for the designer using the design space(Woodbury & Burrow, 2006). Yet in the basic design education framework, the design space term barely finds itself a place; besides the role of it mere as a solution space, in few applications held in courses that focuses on computer-aided design.

However, the initial hypothesis of this research is that it might be valuable for teaching novice designers reasoning, by approaching it from the definition that takes design space as a combination of problem and solution spaces and the design process as a binder of those sub-spaces (Krishnamurti, 2006).

It might be possible to name two initial benefits for the design students by reframing the concept in the basic design studio, as follows: The problem sub-space forming out of the design problems given in the form of assignment briefs in the studio, and the design process outputs of those assignment briefs composing the solution sub-space.

First, that kind of explicit reframing might enable the students to understand the essence of the ambiguous nature of the design problems, which maintains to deliver unique solution methods in the process that enables to generate a myriad of design alternatives to a single design problem. Thus, the student understands that there is neither one way of reconstruction of the design problem, nor a single solution strategy to generate more than one design product. Therefore, the concept might conquer a new function as an explicit design reasoning in the design process, besides its existing characteristic of being the display-case of alternative design solutions.

2.2 Design Space

As the zeitgeist of design research suggests, the cognitive limits of the human designer using computational tools and methods have been extended in terms of increased memory capacity and process speed (Kelly & Gero, 2021). Thus, it is possible to generate a myriad of alternative solutions to given design challenges with pre-defined algorithmic processes controlled with specified parameters in constrained contexts. The generated alternative design solutions compromise a “vast” set (Dennet C. Daniel, 1995), which generally tends to connote with the concept of design space.

However, in the current state of the art in various computation-related literature, the conceptual limit of the term is generally misconceived, and still unclear, whether it represents solely the solution space. Yet also, it is not clear whether the alternatives represented in that space answer the needs of the design problem, or whether they are only combinatorial outputs of the algorithmic design processes. Therefore, the limitations posed by the design space concept require a critical overview as well as its potential for enlightening the design problems, as well as implying it into basic design education as a design reasoning tool.

2.2.1 Definitions of the design space

Design space often carries imprecise metaphors and unspoken assumptions, that take several different forms in the design research field (Halskov & Lundqvist, 2021). As well as it is defined as traditionally as “the aggregation of all possible design solutions in a given task”, it is also seen as the changing space of potentialities created by a designer while designing (Goldschmidt, 2015; Kan & Gero, 2018). The design space concept is also defined as a network of the structure of related designs that are visited in the exploration process (Woodbury & Burrow, 2006). Although the term is mainly considered as a “descriptive metaphor” for collections of design ideas (Halskov et al., 2021), the concept takes different roles related to its definition in various design and computation-related literature; including engineering, architecture as well as visual communication, and interactive design realms. In that context, the conceptual network graph of the design space is visible in Figure 2.2, in which the nodes correspond to the keywords found in the revisited publications. The authors' nodes are indicated with blue color, whereas the articles written in collaboration are highlighted with light blue edges.

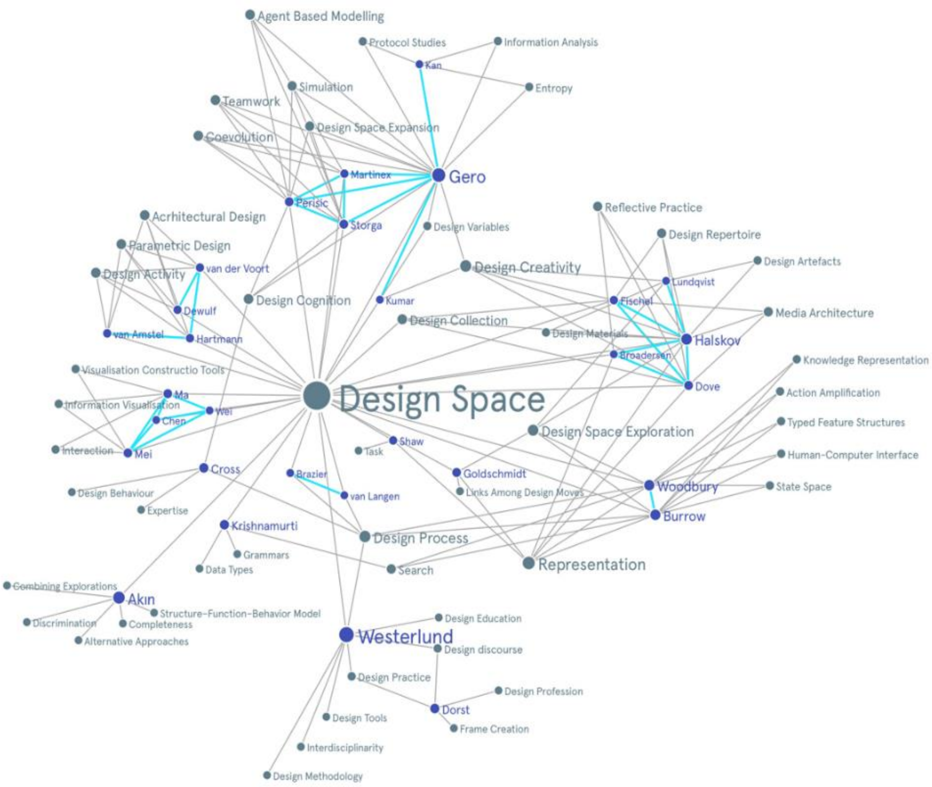


Figure 2.1: Conceptual network of the design space.

In each context, different characteristics of the concept get highlighted, but at the same time, the main focuses remain almost the same in terms of; including the activities of a designer in the process of interacting with the conceptual space, as well as generating alternative solutions to revisit and deliver new designs. However, acknowledging the sub-spaces underlying the concept demonstrate deterministic differences about the role of design space in the design process, about whether it enables the designer to display and interact with the process or not.

One thought of line takes the design space concept as a combination of problem space and solution space, therefore including the design process as a binder of those subsets (Krishnamurti, 2006). On the other hand, another group of researchers takes the term as only forming out of solution space of the alternatives generated under the design brief. Therefore, to guide the readers’ understanding, it is important to revisit the previous works in the literature that deal with the design space conception under two main groups of understandings: First the design space as merely solution space, and secondly design space as the reciprocal formation of problem and solution spaces.

Figure 2.2 shows the inclusion of the sub-spaces graph in the design space concept of the revisited publications.

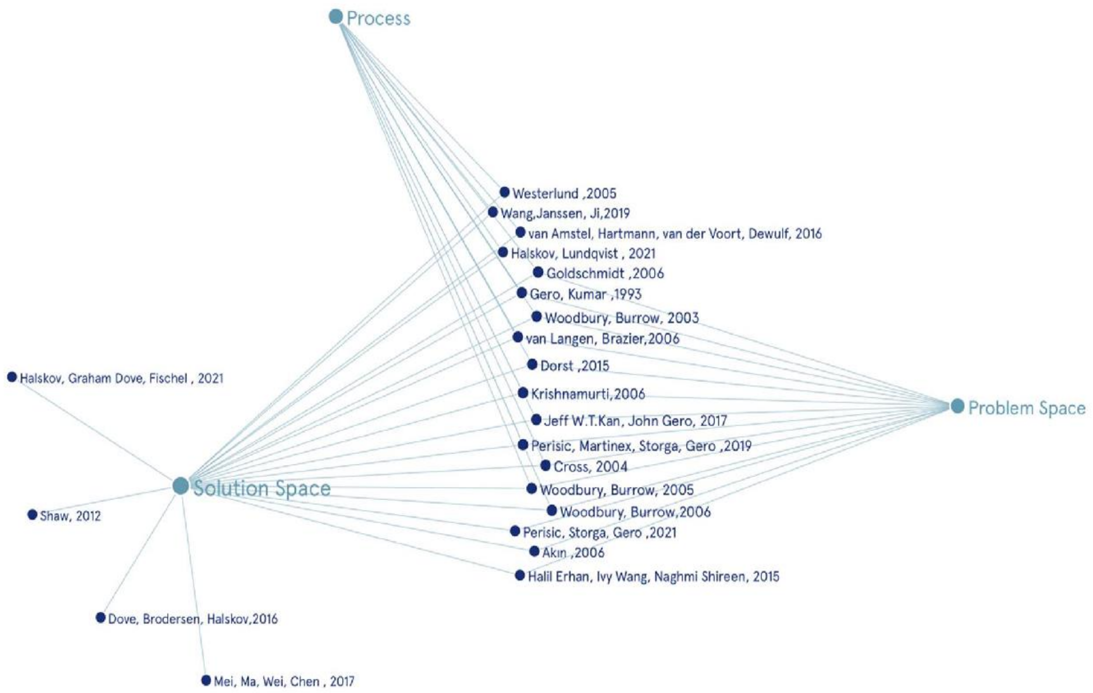


Figure 2.2: Inclusion of problem, solution, and process in design space definition.

2.2.1.1 Design space as a problem and solution space

The intricate point of difference between the conceptions of the design space is the inclusion of the problem space, which might be associated directly with the definition of design problems as ill-structured or wicked problems. Since both definitions suggest that the design problem only gets formulated after certain intents are performed or actions are taken by the designer due to their ambiguous nature, the further steps cannot get foreseen easily as the well-defined ones in other scientific domains(Coyne, 2005; Rittel & Webber, 1973; Simon, Herbert, 1975). Therefore, it could be said that problem space evolves during the whole design process with every cognitive action taken for reframing or reconstructing the given design problem (Purao et al., 2001).

As Dorst states in the same context, since the whole process is not limited to problem reconstruction, as the main aim is to deliver a design solution, the solution space also coevolves with the problem space (Dorst,2015). So, the design research theorists that consider the problem space as an inherent part of the design space concept imply that, since the defined problem gets reconstructed iteratively, the generated set of alternatives in the solution space is also get altered or enhanced in terms of numbers as well as their qualities.

Similarly, Cross takes this ambiguous nature of the design problems directly related to the difference between expert and novice designers(Cross, 2004). Novice designers have no previous experience to be able to know how to deliver a solution to a problem that is not clearly formed. Therefore, the generated solution space remains highly limited since the problem space is not yet fully explored. The reason behind this claim gets enlightened in his paper as the exploration and discovery process of the designer. The designer starts by exploring the problem space and finds, discovers, or recognizes a partial structure, which enables him/her to generate some initial ideas to form a solution space (Cross, 1982).

Woodbury and Burrow (2006) state a significant point parallel to Cross's perspective, to underline the importance of representing the problem space in their keynote article devoted to understanding the structure of the design space. As they refer to enabling and assisting the designers to make new designs by moving amongst the previously discovered ones in the network. The important point here is moving among the previous examples in the problem space to generate new solutions, which can also get explained by the see-move-see pattern of understanding the design process. The designers generally develop their design ideas on top of the previous moves that had been made on the medium of reflection-in-action, therefore seeing a myriad of alternatives of the previous moves in the problem space would expand the solution space, if they both can get represented to be seen. By using computational structures designers might be capable of representing the "vast" set of alternative problem reconstructions in the design space.

Dennet (1995) clarifies that this vastness is only useful when the accessibility of the designer is enabled to reach "unsound" designs from the potential points in the contingent historical accounts defined in the space. The term unsound, underlined in that context can be considered as resembling the ambiguities occurring in the process, due to the perceptual and visual changes. The ambiguities which cannot get well-represented in the process might be valuable in the design space concept to reach unsound, creative, undiscovered solutions (Figure 2.3). Following that as both researchers suggest, the amplification of the number of solutions that answer the given design problem and enhance the already generated ones is only possible by looking through the perspective that takes design space inseparable from the problem space.

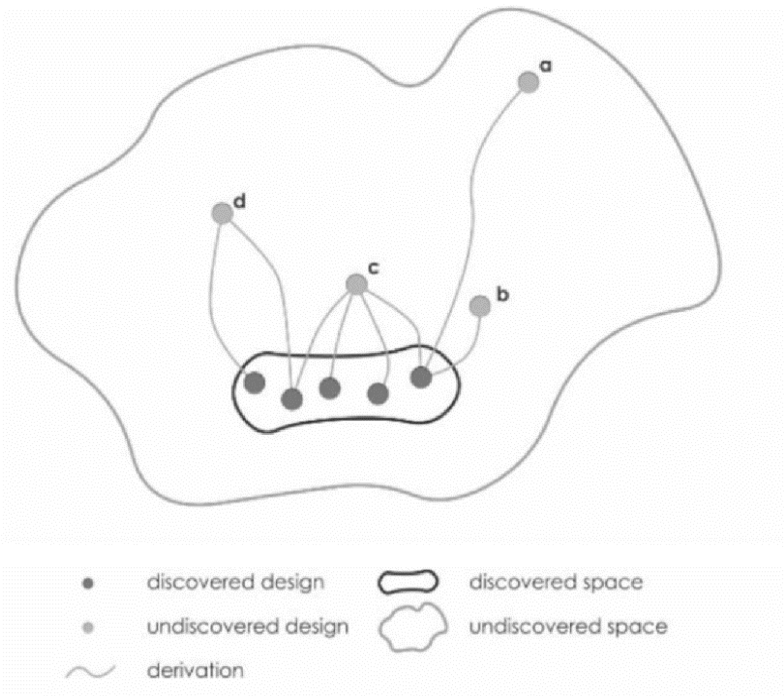


Figure 2.3: Design space accessibility (Woodbury and Burrow, 2003).

Furthermore, Goldschmidt states in her response to the same keynote article, that the attitude of the designer moving amongst the previously generated solutions in the design space not only provides essential feedback regarding the solutions but also highlights the process of design (Goldschmidt, 2006). As her research mainly holds on the design reasoning associated with the design moves and their interconnected links, she underlines the need for consideration of the non-represented actions in the process, in both problem/solution space, to formulate a more comprehensive understanding of the design space including the process.

Agreeing with Goldschmidt (2006), Ömer Akın pointed out in his response to the same keynote article the tasks, that remains still incomplete in terms of the design space framework drawn by Woodbury and Burrow (Akin, 2006). He persisted that the nongraphic content of a design is often considered in the context of design requirements, but still not yet get represented on the medium itself.

In the response of van Langen and Braziers to the mentioned keynote article, the understanding of the design space concept including problem and solution space gets elaborated under three subsets of the design process. At first, they regard the partial descriptions of the design artifacts. Secondly, the space of design requirements and the space of design objectives (van Langen, Brazier, 2006). Following that, the design requirements, and the design space objectives can be considered as the outliers of the problem space since they define the characteristics of the given design brief that needs to get answered. As well as the partial descriptions of the generated design artifact can be directly assessed with the solution space.

Besides the theoretical debates on the concept of design space devoted to understanding the inherent coexistence of problem and solution space, there are also practical researches in the literature that aims to provide a solid connection between them.

As a first instance, Erhan et al. (2017) propose a new methodology to discover the "unsound" alternatives by enabling the interaction of the designer with a large number of alternatives in the design space by a similarity-based exploration. They have modeled a task environment as both encompassing the problem and solution space, which aims to enable the designer to change the characteristics of the pre-defined task environment in the beginning. Therefore, the dynamic alterations of the problem space became visible, which resulted in an immediate expansion of the solution space.

Secondly, Perisic, Martinec, Storga, and Gero presented the results of a computational design experiment that had been conducted on the design teams to demonstrate the effects of experience in the exploration of problem and solution spaces (Perisic et al., 2019; Perisic, 2021). On the same line of thought as Nigel Cross, they have stated that the buildup experience in the design space exploration helps to develop solutions that answer the design problems in less time, as well as the ongoing collaborative work, enhances the design situation. With the agent-based simulation experiment, they demonstrated the results of the process of design space expansion to provide solid evidence for the discussion.

As well, Gero and Kumar discuss the issue of introducing new design variables and constraints to the problem space (Gero and Kumar, 1993). They illustrated how new solution spaces emerge with the introduction of new design variables by giving exemplary design experiments. Those experiments were held in a variety of contexts including mathematical problem space conducted on cartesian geometry, a small-scale housing design, and a structural beam design to demonstrate the solution spaces expansion through adding new constraints to the problem space.

Problem spaces defined in constrained contexts of a design space

Before examining the second set of research that takes the concept as mere solution spaces, it is crucial to acknowledge the existence of literature that explores the conceptual framework of it within the constrained context of a "problem space".

As a first instance, in the case of the social production of the design space, van Amstel et al. have tried to define the design space concept in the context of a socio-material medium rather than a cognitive process of the individuals. Thus, the collective action of designing became the main focus of the research, which highlights the constantly changing parameters that cannot get represented in the problem space due to the ever-changing task environment defined by a group of designers. Therefore, they have interrogated the dialectical relation to the design space and the design activity and highlighted a question that remains unsolved: Whether the contradictions are related to the process, or the solution space indeed (van Amstel et al., 2016).

In the case of "Filtering and Informing the Design space" Halskov and Lundqvist have reconstructed the concept of design space merely as a showcase of the generated design prototypes. However, they have also discussed the limitations as opposed to not including the problem space in terms of the filtering issue of the generated design solution space (Halskov, Lundqvist, 2021). Similarly, Halskov underlines the situation more with Dove and Hansen, in the conference paper named "An Argument for Design Space Reflection": Although the problem space could not get represented explicitly, the solution space increases our awareness about the problem space. In terms of filtering the design space by the design activities, challenging these constraints, and reconsidering the disregarded opportunities (Dove et al., 2016)

Likewise, Wang, Janssen, and Ji's research on the efficiency issue of the computational design of design search spaces, discuss the problems and limitations opposed by inappropriate modeling methods. They have exemplified the situation with case studies that, there are two common types of misusage in the current practice of design. The first one is the lack of proper constraints defined in the problem space and the second one is related directly to the design search space fixed by the conventional design knowledge (Wang, Janssen, Ji, 2019).

2.2.1.2 Design space as a mere solution space

Another group of design theorists elaborates on the design space concept as only containing the alternative solutions represented in the design process. Westerlund (2005) defines that kind of understanding of a design space concept as a conceptual tool for designing an explorative and experimental design process with the generated design solutions. He eliminates the inclusion of the problem space in the concept, in terms of suggesting that the generated alternatives are enough for representing the challenging design process. By claiming that, due to the wicked nature of the design problems the problem space can never get fully explored even if it is tried to get represented on the medium of the design space, since also the medium of it is not defined clearly. Instead, the solutions displayed in the design space comprise a variety of characteristics to be able to set forth what the design work is about.

In a similar line of thought, Halskov, Dove, and Fischel presented recent research which has built on the concept of design space as a display case of alternative solutions. In the context of the research, the design space is referred to as a tool to construct and analyze the precedent design challenges, in terms of the knowledge process (Halskov et al.,2021). They have presented a case study of a design space constructed with 54 examples taken from the Media Architecture Biennale, which have been deconstructed according to the inherent common patterns of characteristics in between, to compose a holistic design space for viewing, navigating, and filtering purposes.

Similarly, in the work of Mei et al. (2017) the design space concept got reconstructed as a tool for visualizing a literature review that has been conducted on the information visualization tools. They have classified the cases in the literature constructing the design space medium by predefined dimensions such as degree of abstraction, presentation medium, supported data source, and action type (Mei et al., 2017). Following that, they have achieved a comprehensive view of the characteristics of the information visualization tools at the current state of the art, to make the statement of the review clearer.

Another recent example of design space as a solution space is brought by Ma Shaw to the discussion table in terms of the role, benefits, and risks of using it in the design process. She has conducted practical research on traffic signal simulators to identify and organize the decisions to be made, by considering the alternative solutions (Shaw,2012). Therefore, the designer might be considered as assisted under the guidance of the design space, which enables them to produce alternative artifacts or a framework to compare them.

2.3 Problem Space

The problem space is a subset of the design space and plays a crucial role in the generation process of solutions(Goel, Pirolli, 1992). To understand the problem space in the design thinking field, it is important to review the relevant literature and explore the various definitions of design problems in terms of the ill and well-structured ones (Goldschmidt, 1997). The problem space comprises a multidimensional space in which each dimension represents a design variable or constraint. Designers can use various methods, such as brainstorming, morphological analysis, decision matrices, and design heuristics, to explore and search the problem space and find the best solution (Murray et al., 2019).

Maedache and others (2019) describe the problem space as a key concept in the design process that defines the constraints and requirements that designers must consider when creating a solution. Understanding and navigating the problem space is crucial for developing creative and effective solutions to design challenges, especially in basic design education. Yoon (2001) discusses the role of the problem space in interaction design, where designers should start by identifying the needs and goals of the user, and then consider the technical and functional constraints of the design context.

Although the ambiguous nature of design problems can be defined in various connotations, as mentioned earlier (i.e., ill-defined, well-defined, tamed, wicked, etc.), a concise framework for the further steps of the research is sought. In this regard, the perspective of novice designers is taken into account, and the two-fold design problems are referred to as ill- and well-defined design problems. The ill-defined design problem statements are reframed as implicit design brief statements that require the elaboration of multiple and interrelated aspects of the problem simultaneously, which generally challenges student to understand the process in the earlier stages of the studio. Conversely, the well-defined problems are reframed as those that indicate explicit directional steps for anyone and provide clear information about the material properties of design elements or the visual field. Thus, reframing the problem space with its inherent subspaces in basic design education is deemed necessary, so that students can be exposed to both types of design problems and have their problem-solving skills and design-thinking abilities developed.

2.3.1 Well-defined design problems

A well-defined design problem is generally defined as one that has a clear solution or path forward. These types of problems typically have a specific goal or objective, and the necessary information and resources needed to solve the problem are identified.

Well-defined design problems can be useful in design education, as they provide students with a clear understanding of what is expected of them and can help them develop specific skills and knowledge(Dorst and Cross, 2001). These types of problems may not always be as challenging or engaging as ill-defined problems, which are more open-ended and require students to think critically and creatively to find a solution.

2.3.2 Ill-defined design problems

As defined in the design thinking literature an ill-defined design problem is a problem that lacks clear and specific goals, constraints, or requirements (Cross, 1982). It may be difficult to articulate or understand, and it may not have a clear or agreed-upon solution (Dorst and Cross, 2001). This can make it challenging for designers to come up with creative solutions, as they may not have a clear direction or framework to work within (Sternberg and Frensch, 1991). These types of problems are often complex and open-ended, and they can be difficult for designers to tackle, particularly for novice designers. However, the ability to effectively address ill-defined design problems is an important skill for novice designers to develop. Since they challenge the students to think critically and creatively about design processes and can help them develop problem-solving skills and collaborative work habits.

To address ill-defined design problems is to use design thinking methods, design methodologists offer a structured approach to problem-solving that involves empathy, experimentation, and iteration, which can be effective for tackling ill-defined design problems because it allows designers to explore a wide range of potential solutions and to iterate on their designs until they arrive at a satisfactory solution (Cross, 2004).

Several studies have explored the use of ill-defined design problems in architectural design education. Hernández-Leo et al. (2017) conducted a comparative study that found that ill-defined design problems can help students develop problem-solving skills and encourage them to think more deeply about design processes. It is found that students can learn to effectively navigate and solve these types of problems with proper guidance and support. Similarly, Goncher (2009) conducted a study on the impact of ill-defined design problems on creativity and design performance in architectural design education. They found that while some students may struggle with ill-defined design problems, with proper support, they can learn to effectively navigate and solve these types of problems.

Thus, it is possible to state that according to the revisited studies, ill-defined design problems are valuable tools in basic design education, helping students to develop critical thinking and problem-solving skills, as well as encouraging them to think creatively more deeply about design processes. On the other side, the ill-defined problem poses an obstacle for first-year students since their level of comprehension is not yet adequate to understand the necessities of the implicit problem (Arum et al., 2018; Saranlı, 1998).

3. GENERATIVE DEEP LEARNING MODELS

In this section of the thesis, the literature on image-generative AI algorithms was reviewed in terms of the implication of the models in design education and the theoretical grounds of the deep learning models. Since it is aimed to generate synthetic design solution spaces to evaluate the impact of design problem definitions in the scope of this research, reviewing the literature on deep learning models in the computational design field is significantly important to highlight the preliminary differences between the computational architectures. After reviewing these differences, the selection criteria for the suitable AI model as the text-to-image of Diffusion Models (DM) were discussed.

3.1 AI Agents in Design Education

The number of researchers that focuses on the implementation of deep learning models or AI tools in design education is limited, particularly in basic design studio framework. However, recently several studies had explored the implementation ways of AI-aided tools into design education to shed light on different aspects of integration including pedagogical experiments, knowledge translation, and interdisciplinary communication.

Tong et al. (2023) present a study that explores the integration of traditional design representation techniques with AI algorithms in the context of an assignment-based course named Visual Communication 1. The assignment involved 64 freshmen students from different departments, aiming to enhance interpretation and composition skills through the use of AI-generated images and technical drawings. The findings indicate the text-to-image AI models positively affect the students' design representations and their ability to combine techniques and contribute to their interpretation and composition skills. Likewise, Kavakçıoğlu et al.(2022) presented a pedagogical experiment of an implementation of an image-to-image GAN model in the early stages of design education, to promote student-design representation, student-

student, and student-artificial intelligence (AI) interactions. They discussed the role of AI in these intricate relations as an external medium to act in a see-move-see pattern of design, in which the students learn from the design solutions delivered by someone else, particularly by synthetic agents.

Gönen Sorguç et al. (2022) try to demystify the machine learning concept for graduate design students by offering a course that emphasizes data literacy, patterns, and various models with student-led projects. Despite the challenge of introducing relatively new subjects, they stated that the students quickly adapted to the material through a problem-based learning approach. The range of project topics varied widely, covering areas such as coloring a painting, predicting building eras, and optimizing daylight gain. The documented outcomes highlight the interdisciplinary nature of incorporating computer science, engineering, and statistics into architectural design.

Similarly, Khean et al. (2018) proposes the development of a novel educative framework to teach architecture students how to implement machine learning in their design processes. To inform the conceptualization of the educative module, student-centered pedagogical strategies were explored. Subsequently, the module was implemented in an undergraduate computational design studio, and its effectiveness in teaching designers machine learning was evaluated aiming to bridge the knowledge gap and foster technological adoption in the architectural industry.

Sciannamè (2022) emphasized the potential benefits of leveraging machine learning systems for designers. By harnessing the transformative influence, empathy, and system-level thinking of ML, designers can conceptualize and develop meaningful solutions. The need for designers to acquire ML-related knowledge is emphasized in terms of language, skills, and competencies. Ethical considerations are also underlined in the integration of ML systems into design education.

3.2 Image Generative Models

In the computational design field, the usage of machine learning-based algorithms and tools has significantly increased. The development of novel design outputs using Artificial Neural Networks (ANNs) is becoming a significant threshold in the design discourse since it has started to become acknowledged by a wider research community as a field that can learn from the existing data to offer a generative synthesis (As et al., 2018). Designers tend to generate 2D and 3D design alternatives and expand their design solution spaces in remarkably shorter times compared to conventional methods of designing, with the introduction of various deep learning algorithms such as Generative Adversarial Networks (GAN), Variational Autoencoders (VAE), Convolutional Neural Networks (CNN), and Diffusion Models (DM).

Deep learning is a specialized subfield of machine learning that deals with artificial neural networks that have multiple layers (Goodfellow et al., 2016). Deep learning algorithms are designed to automatically learn hierarchical representations of data, and they are effective in a variety of applications such as image and speech recognition, natural language processing, and generative models. Inspired by the ANN architecture, Deep Neural Network (DNN) concepts are defined as "deep" because there are numerous hidden layers between the input and output layers, which are also connoted as the latent space (Goodfellow et al.,2014). An abstract representation of the DNN's inherent layer structure is displayed in Figure 3.1.

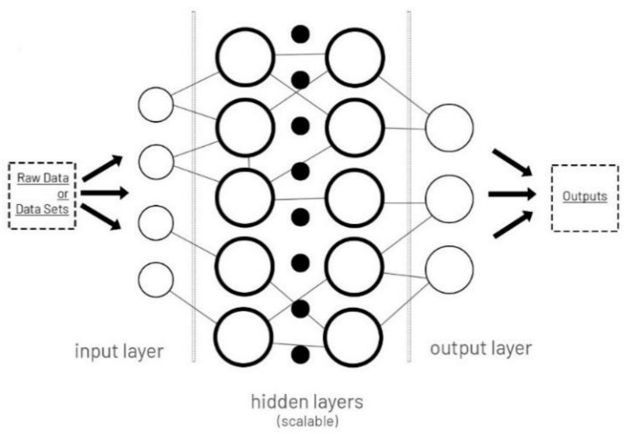


Figure 3.1 : Abstract representation of layer structures of a DNN.

The potential design solutions are discovered by the hidden layers in the latent space through training in the case of DNNs. Unlike generative design systems that are structured on rules or prior algorithms such as Shape Grammars or L-Shape Systems (Stiny, Gips 1972; Lindenmayer,1968), DNNs do not require such rule-based generative applications, as the source of generation is the hidden patterns of the provided data. Therefore, there is no need to define any rule-based generative applications besides training the model.

In this wide framework, Diffusion Models (DM) and Generative Adversarial Network (GAN) models are considered to outperform other deep learning algorithms in terms of image generation performance. GAN algorithms are considered the pioneers of image-generative machine learning models, with their two interacting bodies of DNN structures in the form of discriminator and generator blocks (Brock et al., 2018; Dhariwal and Nichol, 2021). The different variations of image-to-image GAN architectures allow the designers to provide paired and unpaired datasets, to train the machine to generate novel solution instances for various applications.

Although the limited scope of the study aims to generate the synthetic design solution instances from textural data of the assignment briefs, the literature review also included the computational architecture of the image-to-image GAN models, as they stand as the prior for the further development of the text-to-image DMs. Following that, the literature on the text-to-image diffusion models was reviewed to highlight their contributions to the field, and the selection criteria of the DM were explained in the following sections

3.2.1 Image-to-image generative adversarial networks

Generative Adversarial Networks are a type of deep learning model, proposed by the pioneer publication of Goodfellow et al. in 2014 (Goodfellow et al., 2014). Generative Adversarial Networks (GANs) have emerged as a promising approach for image-to-image synthesis, where the goal is to learn a mapping from an input image to an output image with a desired property. Since then, GANs hold the state of the art on most image generation tasks in a wide range of contexts as measured by sample quality metrics (Wang et al., 2020).

The computational architecture of a GAN model consists of two main components: a generator and a discriminator. The generator tries to produce synthetic data that resembles real data, while the discriminator tries to distinguish between the synthetic data generated by the generator and the real data. The two networks are trained in an adversarial manner, with the generator network trying to generate images that fool the discriminator network and the discriminator network trying to correctly identify generated images (Goodfellow et al., 2014). In Figure 3.2 the abstracted GAN architecture is displayed.

One of the important terms in this GAN architecture is the backpropagation, that is used to update the weights of both the generator and discriminator networks. The backpropagation process is repeated multiple times, alternating between updating the discriminator and generator networks (Han et al.,2016). Over time, the generator network learns to produce images that are more similar to real images, and the discriminator network becomes better at identifying generated images. Thus, the generator losses and discriminator losses, and total loss decrease at the end of the training process, significantly.

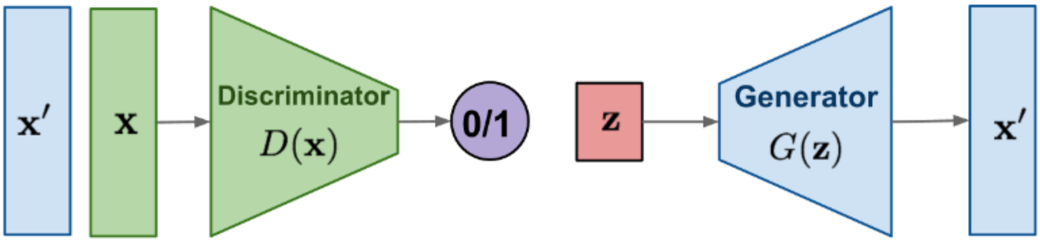


Figure 3.2 : Abstract representation of GAN model architecture (Weng,2021).

Recently, several variants of image-to-image GANs have been proposed, including Pix2pix (Isola et al., 2017), CycleGAN (Zhu et al., 2017), StarGAN (Choi, Lee, Kim, Choe, 2018), SPADE (Park et al., 2019), CoGAN (Liu, Tüzel, 2016) and MUNIT (Huang et al., 2018) among others. These models have been applied to a wide range of tasks, including image translation, style transfer, and super-resolution. The success of image-to-image GANs has been attributed to their ability to capture high-level semantic information and generate images that are both visually appealing and semantically coherent (Salimans et al., 2016).

3.2.2 Text-to-image diffusion models

The selection of text-to-image Diffusion Models was critical for the study since the impact of the ill definitions and well definitions as combined problem definitions were expected to be enlightened as a result of this research. The proposed methodology requires the generation of a synthetic solution space from the textual description of an assignment brief.

In the current state of the art, DMs as a part of deep generative models, stand from the others as being capable of generating high-quality image samples in a multi-modal working environment (Dhariwal and Nichol, 2021).

The DM shows similarity In terms of the computational architecture with the GAN models, regarding the inherent DNN structure found in common. The main differences between are provided data type and the generation workflow. While the image-to-image GAN models take the visual data as the input and generate the outputs by transforming information between the discriminator and generator blocks “real” and “fake”; the diffusion models learn to generate images by the noising process of the input data. In which the text-to-image diffusion models, process the information taken from the text inputs into defined a Markov chain of diffusion steps to slowly add random noise to data and then to construct desired data samples from that noise (Weng, 2021).

The general understanding in the current state in the field is that the text-to-image diffusion models have advantages compared to the other image-generative DL models including the GAN models, regarding the three aspects mentioned below:

Data Availability: The amount of the image data mined from the provided textual data available is larger compared to the corresponding image data sets. Because usually the GAN models are trained with specific datasets collected from various sources, whereas the text-to-image diffusion models are often speculated to be connected to the world wide web, which allows the algorithm to access wider data within a framework of controlled environment systems.

Semantic Representations: Textual descriptions tend to provide more explicit and detailed information about the desired image output in various contexts. Thus, it makes it easier to generate an image that meets the criteria that are trying to be achieved.

Attention mechanism: Text-to-image models can be designed to incorporate an attention mechanism that focuses on specific parts of the input text when generating the image, leading to more fine-grained control over the generated image. It is possible to find a certain mechanism to assign “weight” to the text prompts and image prompts in those diffusion model interfaces (Midjourney Docs, 2022; OpenAI 2023, Dreamstudio AI, 2022).

Besides, implementation of the DM in a variety of different contexts and tasks is possible, ranging from computer vision, natural language processing, temporal data modeling, multi-modal modeling, and interdisciplinary applications (Yang et al., 2022).

The variations of the DM can be grouped under three predominant formulations, denoising diffusion probabilistic models (DDPMs), score-based generative models (SGMs), and stochastic differential equations (Score SDEs) (Ho et al., 2020; Yang et al., 2022). Although in the scope of this research, only text-to-image DMs are taken into consideration, which are considered as a type of generative denoising diffusion probabilistic models (DDPMs).

Text-to-image DMs are a type of generative model that uses natural language descriptions to generate images that combine techniques from natural language processing (NLP) and computer vision to generate images from textual descriptions (Cao et al., 2020). The basic architecture of text-to-image DM models can be conceived as consisting of two main bodies: Text Encoding (integration of the NLPs), Image Generation (diffusion process). (Figure 3.3)

At a high level, text-to-image diffusion models work by first encoding the input text description into a latent representation using an NLP model. There are various networks inherited by different NLP models such as RNN (Recurrent Neural Networks), CNN (Convolutional Neural Networks), and Transformer Networks, etc (Özdil et al., 2021). However, the introduction of the transformer network architecture made a significant advance in the field, since the prior RNN and CNN algorithms, have certain limitations for handling long sequences of text. The Transformer model consists of an encoder and a decoder, which are both made up of a stack of identical layers. Each layer contains two sub-layers: a self-attention mechanism and a feed-forward neural network (Guo et al., 2022).

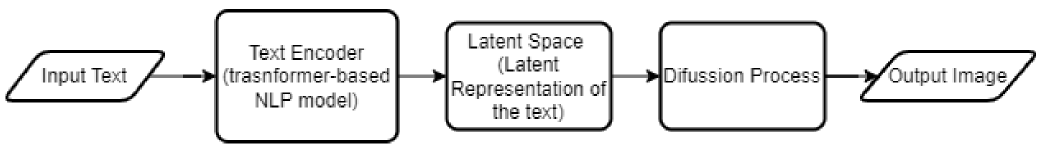


Figure 3.3 : A simplified text-to-Image diffusion model flowchart.

As Vaswani (2017) states in the paper “Attention is all you need”, the attention mechanism implemented in the transformer network, enables the text-to-image DM models to focus on various parts of the input text during encoding, allowing it to capture long-range dependencies between words in a sentence. Moreover, the self-attention mechanism used in the Transformer architecture allows the model to compute attention weights for each word in the input sequence, which is used to weigh the contributions of different words in computing the output representation (Vaswani et al., 2017).

Therefore, it is possible to generate images that closely match the input text description, even for complex and nuanced descriptions. This aspect is one of the most important features of the model to underline since the initial aim is to generate synthetic design spaces with the inherent ill-definitions of design problems given in the assignment briefs.

After the input text is encoded into a latent representation with the help of a transformed-based NLP model, this latent representation is used to generate a sequence of image features, which are iteratively improved to create a final image using a diffusion process (Radford et al., 2018). This diffusion process is built up to generate instances from a data distribution by progressively removing noise from a noisy data sample, which is done by sequentially applying the same model to the original data (Zbinden, 2022; Dhariwal, Nichol, 2021). In other words, inspired by non-equilibrium thermodynamics, they define the Markov chain of diffusion steps to slowly add random noise to data to learn to reverse the diffusion process to generate data samples from the initial noise (Ho et al. 2020; Weiss et al., 2015; Weng,2021). The attention mechanism in the transformer network can also aid in capturing long-range dependencies in the input text, which can help the model to create more accurate image representations (Touvron et al., 2020). Figure 3.4 illustrates the image generation process of denoising diffusion probabilistic models.

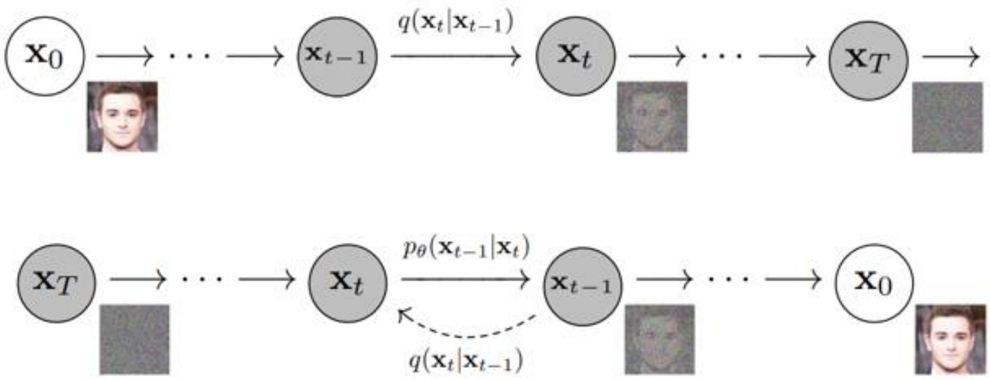


Figure 3.4 : Workflow of DDPMs (Ho et al., 2020).

3.2.2.1 State-of-the-art text-to-image diffusion models

In the field of image-generative machine learning models, text-to-image DMs are considerably new, although there are several text-to-image diffusion models released publicly. Three of these models had gained significant popularity among the image generative DM's, regarding their capability of generating images with astonishing quality (Borji,2022). In the scope of this research these models, DALL-E 2, Stable Diffusion, and Midjourney, are reviewed; regarding their image generation capacities, model architectures, domination of them in the field regarding the style of the generated visuals, user interfaces, and availability. Table 3.1 compares these three models in terms of the aspects mentioned above. As well as in Figure 3.5 all model architecture's image generation processes were displayed as a flowchart, which was originally found in a preprint article (Ploennings, Berger, 2022).

The related lIterature of those models is not as wide as one would expect in an academic domain. Because some of these models released in the current state of the art are not fully open-sourced, they only allow users to generate images from their user interfaces without supplying comprehensive information about the algorithms employed and data sources. Following that the three models are reviewed by taking into consideration of research papers in the publication processes, the blog posts and internet articles are also considered valuable sources during this literature research. Since the user experiences and generation documentations are the only solid evidence to guide the author to select a text-to-image DM.

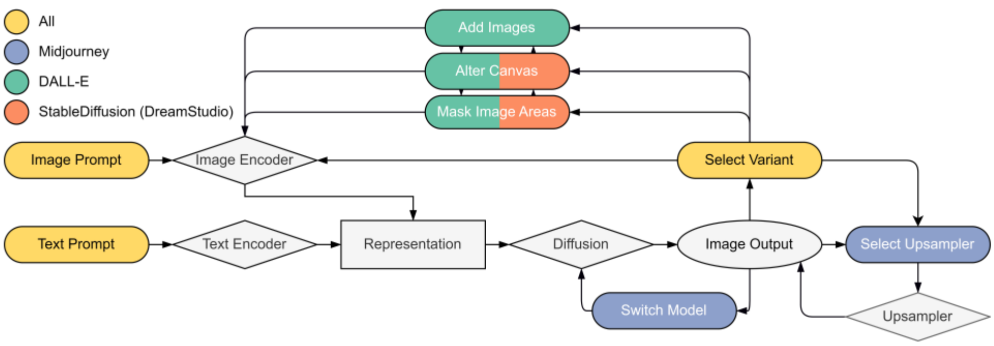


Figure 3.5 : The model architecture of the state-of-the-art DMs and image generation process flowchart (Ploennings and Berger, 2022).

Dall-E 2

Developed by the OpenAI group, DALL-E was announced to the public in January 2021 as the first text-to-image diffusion model, that is capable of generating novel images from text prompts. However, until the beta release of DALL-E 2 on July 2022, the users were not able to generate images. After one million waitlisted individuals had accessed the model, the text-to-image diffusion models received extensive attention, in terms of "beating the GAN models", which surpassing the prior generative design realm (Dwarfial, Nichol, 2021). However, the source codes of both models, DALL-E and DALL-E 2, haven't been released to the public, yet. Therefore, certain information about the model's architecture is limited, especially about the training data set. Although the data sources are still unknown, the research lab stated that the initial training includes everyday objects, animals, and scenes as well as more abstract concepts such as emotions and relationships. As stated by OpenAI (2023), the model's architecture is based on a transformer-based neural network, that was trained using a variant of GPT-3, a highly complex NLP algorithm, which allows generating novel image outputs by combining concepts, attributes, and styles. Besides the text-to-image generation function, DALL-E models also offer image-to-image translation opportunities.

However, this process is strictly limited to only the image editing process of in and out-painting. Using the in-painting tool the users can erase the parts of the generated image and replace the erased part with the objects generated by secondary prompts or can enlarge the original size of the image by generating new instances for the frame by out-painting. One of the main constraints of the model is the aspect ratio of the generated images, which only allows users to generate square formatted images in 1024x1024 resolution. Besides, the user interface of the model depends on OpenAI's web page, which is often recorded as being suspended due to server limitations.

Stable Diffusion

Released in August 2022, the Stable Diffusion model is developed by the CompVis group at Ludwig Maximilian University (LMU) Munich (Rombach et al., 2021). Unlike the other text-to-image DM's the source code is available to the users, that can be implemented on various applications. The model's architecture is based on a latent DM that resembles the others in terms of inheriting three main computational bodies; text encoding by VAE, denoising process by U-Net block, and optional process of text encoding for conditioning the text prompt. The model enables users to give reference images as image prompts. The training data are composed of the images and captions taken from the LAION-5B dataset, which is publicly available since it is retrieved by data crawling from the web (Schuhmann, 2022). Since this large database also includes artworks that are subjected to copyright, the Stability AI is harshly criticized by the public, especially artists in terms of authorship and authenticity issues (Vincent, 2019). Secondly, it is reported that, due to an insufficient amount of data in specific domains such as human anatomy, the model produces fail to produce high-resolution images for certain applications (Neuroflash, 2023). Although it is possible to train the model with new datasets provided by users, the model requires fine-tuning in terms of the sensitivity of the quality of the new data. Because low-resolution images generally make the machine fail to learn new tasks and degrade the overall performance of the model (Rombach et al., 2021).

Midjourney

Developed by an independent research lab that shares the same name with the model, Midjourney, released to the public in March 2022 (Edwards, 2023). Likewise the DALL-E model, the source code is not open to the public yet, but it is highly speculated that the Midjourney uses a similar system to the Stable Diffusion model (Ajaay, 2023). The founder of the Midjourney, David Holz (2022), states in an interview that, the training dataset of the model is scraped from the public datasets available on the Internet. Although he stated that, artistic copyright issues are still a valid concern for the model since the generated images by the model are not embedded with metadata that clarifies the copyright issues. One of the major advantages provided by the Midjourney is the simple user interface accessed through a Discord server, which enables users to control the main characteristics of the generated images i.e. quality, style, and aspect ratio. Unlike Stable Diffusion, it does not require any coding skill to generate images with the pre-trained model, and also a larger variety of options are provided for the end user to change the aspects of the generated image compared with DALL-E models. Besides, from various public user channels, it is possible to see the other user's generations and prompts, which are also displayed in the "Community Showcase". In the current state of the art, there are five different versions of the model released to the public available in the same discord server, which has been developed on top of the others to enhance the image quality, besides adding new stylistic features to the model. From the key parameters provided to users, it is possible to change the images' stylistic qualities, and aspect ratios, as well as it allows to assigning weights to prompts and negative prompting. Besides, the ability to generate images from text prompts, the model also takes image references as a body of the prompt, to generate a novel instance. Another aspect of the Midjourney that differs from the other competitors is the stylistic characteristics of the generations. Midjourney is said to be proficient at adapting actual art styles to create an image of any combination of things, whereas DALL-E and Stable Diffusion models are more focused on generating photorealistic outputs (King, 2023).

Table 3.1 : Comparison of the state-of-the-art text-to-image DM's.

	Training data	**Model Architecture**	**Image Quality**	**Availability**	**Image Operation Possibilities**
DALL-E 2	Large and diverse dataset (data sources unknown)	Transformer-based, with inherent CLIP and GLIDE models	Highly detailed and complex, photorealistic outputs. The aspect ratio is limited to a square format of 1024x1024 resolution.	As a research project, it was not yet publicly available until July 2022. Between July to September 2022, the users had to sign on a waitlist to use the model.	Image editing operations with in-and out-painting. Users can replace the details of images by prompting with an inpainting tool. Out-painting is used to enlarge the boundaries of the original frame.
Stable Diffusion	LAION-5B	Transformer-based, VAE and U-Net models	Highly detailed and complex, photorealistic outputs, limited to context. The aspect ratio is flexible.	A publicly available open-sourced model since the initial release in August 2022.	Image prompting is available with custom prompt weights. Image editing services are provided, as an in-painting tool.
Midjourney	Open-source databases from Web	Transformer-based	High-resolution with artistic styles, abstract representations, and game environments. The aspect ratio is flexible	Publicly available since the initial release in March 2022, commercial usage is required to have a license.	Image prompting is available, with the possibility to assign image and prompt weights. Although no editing services are provided.

3.2.2.2 Selection of a suitable DM: Midjourney

Following the initial findings through the review, the Midjourney model is selected to conduct the study in terms of the generation of a second synthetic design space, according to the different aspects of the models discussed previously. Firstly, the availability of the models was a determinant factor for the selection of the model, as during the initial phases of this research only the Midjourney model was publicly available.

Secondly, the image prompting operation provided by Midjourney (image-to-image translation with text prompts) is one of the most important criteria for the selection. Since the design briefs often define a sequential task, that is the final design output is generated from further developing the design on top of the previous outcomes of assignments/stages. Therefore, it is required to embed the visual output of the previous stage, as the input of the following stage as a parent image. Since the DALL-E models are primarily focused on editing or enlarging the given visual input, rather than taking image input as the prompt. Thus, the Stable Diffusion model and Midjourney model are considered the only option that enables the user to use reference images. However, since the stable diffusion models image database is limited to the LAION-5B dataset in the current version, the performance of the model would not be sufficient to generate image outputs in the specified context of the study. Although, it is possible to train the model as it is currently open-sourced with the customized image dataset. However, in the current scope of the thesis, the required amount of the context-based data of the basic design works was insufficient, to train a model that would generate legible outputs. Therefore, the Midjourney model is considered the most suitable option among the other competitors in terms of its diverse range of datasets and enabling image-prompting.

Besides, the Midjourney community showcase page dedicated to this study would provide a controllable environment to reach out to these parent images and their prompts during the generation processes. Additionally, the user interface of the Midjourney provides a significant advantage to conduct the study, because it is relatively faster as it does not require any coding environment to use the pre-trained model.

Thirdly, the quality and resolution of the generated images is an important criterion for the selection of the model. Since the initial aim is to generate a synthetic design solution space that is guided by the direct translation of the design briefs into text prompts, in which different ratios of design canvases are required. Besides, as stated by many users on the web, the Midjourney model is more powerful generate abstract, artistic outputs compared to the others, whereas DALL-E and Stable Diffusion are more successful to generate photo-realistic images. Since the design outputs expected from the basic design studio briefs are expected to be abstract, design objects, and compositions; the image generation performance of the model in terms of stylistic quality is more important rather than photo-realistic quality.

4. METHODOLOGY

The aim of this thesis research was defined as analyzing and assessing the impact of the problem definitions on the design space of a basic design studio and searching for a tool to help students better understand the ill-defined design problems. As discussed within the theoretical background, the design space of the conventional basic design studio was reframed as follows: Problem Space (PS) was reframed as consisting of the written design tasks as given in the form of assignment brief in the basic design studio, which contains both ill- and well-defined design problems. Design Solution Space (DSS) was considered as the solution process outputs that are developed under the guidance of the design briefs.

The study encompassed a comparative perspective in terms of the two sets of assignment brief data collected from different timeframes and design institutions, to explore the visual impacts of the implicit and explicit problem definitions in the PSs. The first PS, assignment brief data, was collected from the Middle East Technical University ARCH 101 Basic Design course between the academic years 2003-2007. Whereas the second PS was collected from the Izmir University of Economics FFD 101 Arts and Design studio from the 2022-2023 academic year. The PSs of these design institutions were selected consciously as the cases to conduct the research, since both basic design studios shared multiple commonalities, in terms of the grounded ecole of Bauhaus and the conduction way of the studio. However, the observed sequential pattern of the assignment briefs indicated a significant difference, in terms of the definition way of the problems.

A series of synthetic solution spaces generated by a text-to-image AI tool for both PS taken from METU and IUE. The generated DSSs differentiated among themselves in terms of being generated under the solo guidance of the brief, or through the implementation of a feedback mechanism.

As displayed in the study flowchart in Figure 4.1. each set of data was analyzed and used as follows. Firstly, the collected data was analyzed, and the selection criteria of the related assignment briefs were defined. Then, the assignment brief definitions are identified in terms of the inherent ill- and well-defined problems. The second step of the method is dedicated to the generation of the synthetic solution spaces by using various types of prompts. Lastly, the performances of the DSSs were assessed by design expert interviews.

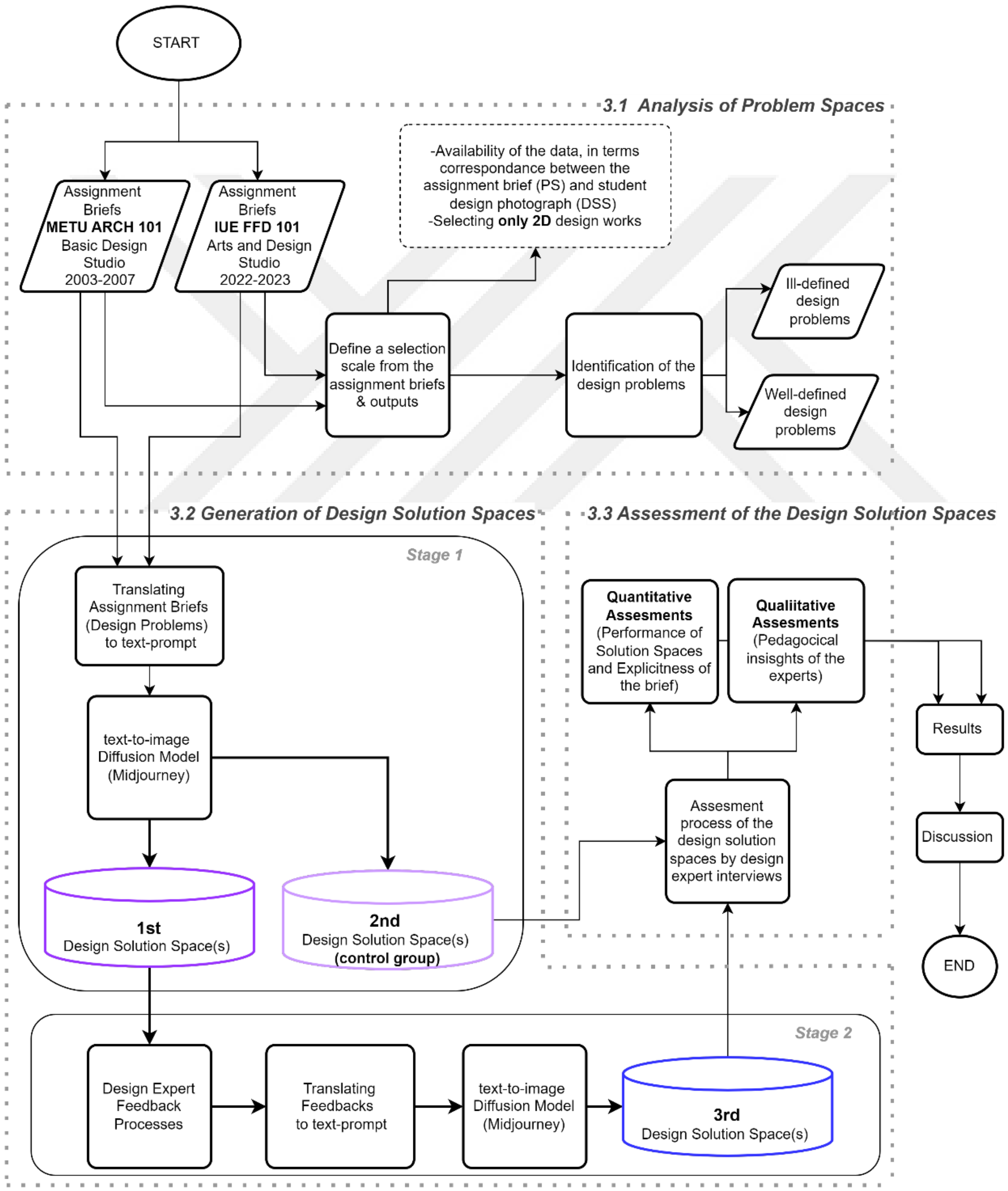


Figure 4.1 : Research flowchart.

For each PS, the assignment briefs were translated into the text prompts, by preserving the semantic structure of the brief. Using these initial prompts 1st and 2nd DSS were generated for each set. Then, the solution instances in the 1st DSS were subjected to a series of feedback sessions held with three design experts. Whereas the 2nd DSS was kept as the control group for the further assessment process. The feedback sessions held with the three design experts enabled to revise the prompts according to the common points highlighted for each solution instance in the 1st DSS. (Figure 4.2)

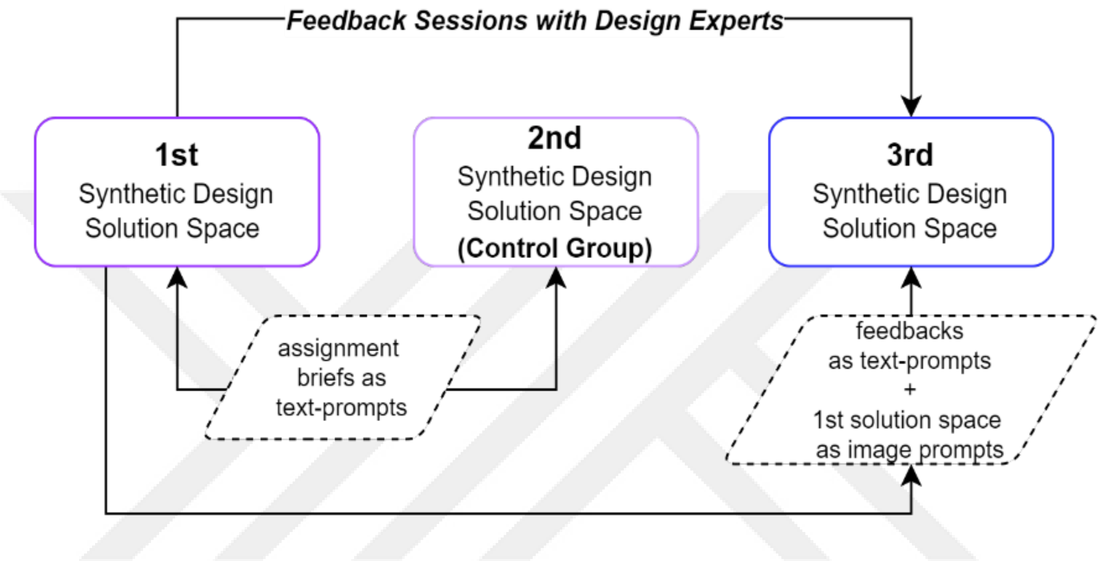


Figure 4.2 : Design solution space generation methods.

The reason for implementing an additional step feedback procedure in the method was to document the visual differences in the solution instances generated by the AI tool, by solo guidance of the briefs and the revised briefs through the feedback mechanism. It also shed light on the potential implementations of the tool in the studio, alluding to the critique sessions held in the studio.

In the third step of the method, the instances of 2^{nd} and 3^{rd} DSS were evaluated by the same design experts with semi-structured interviews. The first part of the interview consisted of three close-ended questions assessing the performance of the solution instances and the explicitness of the brief by ordinal scale rating. Whereas in the second part, three open-ended questions were posed to gather the pedagogical insights of the experts by comparing the synthetic generation method with their observations in the organic solution generation processes in the studio; in order to highlight the potential of the implementation of the method as a tool in the basic design studio.

4.1 Analyses of the Problem Spaces

In this section, the analyses and selection criteria of the assignment brief from the archival data of two first-year design studios were explained. Firstly, the data collected from the Middle East Technical University “ARCH 101: Basic Design Studio” between the academic years 2003-2007 was introduced. Secondly, the data of Izmir University of Economics “FFD 101: Arts and Design Studio” of the 2022-2023 academic year was introduced briefly.

The two sets of assignment brief data were discussed in terms of implicit patterns in the assignment brief sequences and pedagogical strategies highlighted during the interview sessions. Both sets of archival data were subjected to a series of analyses, to identify the ill- and well-defined problems stated in the briefs and to highlight the common patterns.

4.1.1 Introduction of the METU basic design archive data

The original archival documentation contains analog and digital data between the years 1986-2007 provided by Tuğyan Aytaç Dural and Mine Özkar, who both taught at METU ARCH 101 Basic Design Studio. However, to restrain the research in the practical limits of the main inquiry, the materials used in the analysis were selected between the years 2003 and 2007, by considering the common sequence observed in the selected time frame. As explained in the following in detail, the stages of this common pattern can be defined as; abstraction, the definition of the design elements, transformation into another medium, and creation of a 2D composition.

In the analyzed timeframe it was noticed that the assignment briefs were mostly defined in a consequent order. In most cases, the stages of the assignment briefs require development on top of the previous stage with new problem definitions. During the problem identification and DSS generation process, all stages of the brief descriptions were considered. However, to limit the number of cases in practical limits, only certain cases selected from the analyzed timeframe were further assessed by design expert interviews.

One of the data selection criteria was the dimension of the design medium. The offered method of the research proceeds with the generation of 2D images as the design solution space instances according to defined briefs, therefore the assignment requires

3D compositions to be eliminated from the dataset. Because understanding the qualities of the design works would not be possible, due to a lack of photographic data that corresponds to each view of the designed object.

The similarity between the main themes explored in the 2D works produced by the students and the brief descriptions given at the beginning of the semester was also considered an important factor in the assignment brief selection process. Upon analyzing the common themes and requirements across the assignment briefs, it was observed that there is a certain sequence implied in the production of the 2D works.

The sequence started with the abstraction of real-life objects or body parts, and each student was required to interpret the described scene or act or object to be utilized as a design element in the upcoming stage. During the design interviews with Aytaç-Dural, it was recorded that, then there was a pedagogical attempt to use the body as the design element to encourage students to socialize with their fellows during the photoshoots (Aytaç-Dural, personal communication, 12 April 2023). In some of the cases, it was noted that various bodily senses were also used as an element of design that needs to be abstracted and transferred into a visual design medium:

> Think of a number of sounds with a single syllabus and find the proper positions of the entire human body that will best represent these sounds. You are expected to present this work on your own body. (METU ARCH 101 Archival Data, 2004-2005, Assignment No.2, Stage. 01)

The common pattern generally continued in the second step with the implementation of these abstracted forms or sounds as the design elements into a composition or a pattern. The properties of abstracted design elements were in most cases defined explicitly in the assignment brief in terms of the size, color, material, and number:

> Select 3 sounds/positions among these. Ask one of your friends to act as a model to document them. Take photos of your model for each position in front of both a window and a column along the northwest wall of the studio. Present these photos, printed in black and white, on A4 sheets." (METU ARCH 101, 2004-2005, Assignment No.2, Stage. 02)

The third step of the observed common pattern in the brief data was making a geometric analysis of the composition (or pattern) on a tracing paper by drawing. The importance of the analysis stage was highlighted during the interview sessions as encouraging the novice designers to make use of the regulating lines to find out the formal relations of the design elements. Also, the analysis stage was consciously designed for enhancing the definitions of the design elements in terms of their reproducibility (Aytaç-Dural, personal interview,2023):

> Enlarge two of your photographs with two different backgrounds to A3 size. Transform these photographs into measurable and reproducible geometric entities. The regulating lines, which will help you to make this geometrical study, should be visible on your drawings. Work them out by overlaying A3 size sketch paper on your photographs." (METU ARCH 101, 2004-2005, Assignment No.2, Stage. 03)

After improving the formal definitions of design elements, the following step was usually requiring the translation of the design work onto a new design medium, in terms of extracting the reproducible shapes and forms from the analysis:

> Translate the two studies you have made on sketch paper into a new medium: cartridge paper. Use black for one and gray for the other. Obtain the number of shapes by extracting the black and gray cartridge paper." (METU ARCH 101, 2004-2005, Assignment No.2, Stage. 04)

The final step of the sequence generally continues with the utilization of the refined elements on the visual field by repeating them multiple times and various scales in the later stages. In some cases, the number of the element also increases in the stages of the same assignment brief:

> Make a two-dimensional composition on white cartridge paper of A3 size using the black and gray elements you have already produced. There will be a total of 13 elements in your composition. You will also submit the work you have done in Stage 01." (METU ARCH 101, 2004-2005, Assignment No.2, Stage. 05)

The expert interviews indicated an implicit agenda in the final stages of the briefs for guiding the students to explore the "grouping" issue of the formal relations and design elements. These initial groups formed are further encouraged implicitly to be organized in the composition by the gestalt principles, although these principles were not mentioned in the assignment briefs.

The selection of the assignment cases that follows the sequence described above was an important determiner to limit the scope of the study. Since the basic design education at METU holds on to the strong design traditions that can be traced to Bauhaus Ecole (Acar, 2003; Bayırlı, 2015), similar studio procedures might be also visible in the former years in the archive starting from 1986. However, in the selected period, specifically from the year 2003, it is possible to see the implicit agenda of implementation of the visual rule schemas that helps to isolate the essence of the problem explicitly, in terms of the formal relations in the 2D organization (Özkar, 2005).

This implicit reference given to the algorithmic process of design is one of the key determiners of the selection process. Therefore, the selection of the data collected between 2003 and 2007 is a significant discriminator for creating a certain control mechanism, for the inquiry that tries to computationally generate various design solution spaces.

In total 28 stages of the assignments brief were analyzed, and solutions were generated. However, only selected 16 stages of the briefs were further evaluated in feedback sessions and assessed by the design experts.

4.1.2 Introduction of IUE archival data and selection criteria

The second set of archival data used in the scope of the study was taken from the Izmir University of Economics FFD 101: Arts and Design Studio consisting of the assignment briefs given to the first-year students from the 2022-2023 academic year fall semester. It is important to note that, the course is not only designed for first-year architecture students, unlike the METU ARCH 101 course. The FFD 101 course is one of the compulsory courses that is required to be taken by all the design students of the IUE, Faculty of Fine Arts and Design. Therefore, the curriculum was designed not only for first-year architecture students but also for freshman industrial design, visual and graphic communication design, fashion and textile design, and interior architecture students.

Assignment selection criteria were similarly set as in the previous case. The assignment briefs and stages that require a generation of the 3D design work were eliminated. A total number of 5 assignment briefs were analyzed and assessed with their interrelated 24 stages.

In the initial analysis procedure of the assignment brief sequences, a common pattern was observed similar to the set of METU assignment briefs. The overall structure of the studio was designed on the Bauhaus grounds similar to the METU case. This similarity can be assumed as a result of the common METU backgrounds of the studio coordinators', and designers' of the assignment briefs. However, there were several alterations observed between the two sequences and the overall explicitness of the design briefs.

As raised during the interview sessions by Aslankan (2023), the initial step of the sequence of the METU that had started with the abstraction of the body and senses was eliminated from the sequence structure. Instead, the real-life frames or objects within their surrounding context were given to the students as the composition to be analyzed:

> Make an analysis on all 10 images (aerial photographs of the urban texture) (4x4cm each) focusing on; elements and their organization, and compositional guidelines. Use tracing paper, define "reproducible elements" that come out of the visual field (4x4 cm) of each image. (IEU, FFD 101, 2022-2023, Assignment No.4, Stage A)

The aim of this alteration was further explained as easing the students' comprehension process of the element properties by analyzing an image by drawing regulating lines, extracting shapes, and grouping the design elements. Because the current generation of students generally has difficulty in understanding and creating a composition from an abstraction, since they have not understood what composition is or what it requires (Aslankan, 2023). Hence, the first step of the sequence generally starts with an analysis of a finished, non-man-made composition on a tracing paper by drawing to extract the element properties.

Secondly, these analyses done on the tracing paper were required to be reproduced by changing the scale and increasing the number of the initial analysis. Those copies of the analyses act as a design element to be organized on the visual field, to let the students discover the relations of the design elements by using regulating lines to control the visual field:

> Select 2 out of 10 "analysis". Reproduce both "analyses" on tracing paper to have 12 copies (2x12=24 pieces). Organize the identical 4 copies within an 8x8

visual field following 3 different operations separately: Operation 1. Mirror/flip, Operation 2. Copy-paste, Operation 3. Rotate (IEU, FFD 101, 2022-2023, Assignment No.4, Stage B)

Similar to the case of METU the sequence continues with the translation of the study on a new design medium by extracting the shapes and forms from cartridge paper through the element definitions from the analysis drawings:

> Revise the initial unit (8x8) if necessary, and make A3-size Full-Pattern using cartridge paper with tones (4-5 tones) of a single color (monochromatic). (IEU, FFD 101, 2022-2023, Assignment No.4, Stage D)

4.1.3 Identification of the problem spaces

The problem definitions stated in the assignment briefs of the PSs of two design schools were identified in this chapter of the study. These identifications were further used in the assessment procedure to evaluate the performance of the synthetic solution spaces in answering various definitions of the problems.

As discussed in the theoretical background, the definition of the design problem is connoted as ill, well, tamed, or wicked, due to the ambiguous nature of the design problems. Well-defined design problems refer to design challenges that have clear and specific parameters, objectives, and constraints. They are typically structured and offer designers a clear understanding of the problem and its context (Cross, 2011; Dorst, Cross, 2001). Whereas the ill-defined problems lack clarity and present uncertainty and ambiguity for designers. These problems are often complex and multifaceted, with a range of potential solutions that may vary depending on the designer's perspective and approach (Buchanan, 1992)

In the scope of the thesis, in terms of focusing on the assignment briefs given in the basic design studio, the two of the design problem definitions in the design thinking literature were reframed as follows:

1. Well-Defined Problems: The statements that explicltly indicate the properties of the design elements and the visual field i.e. color, size, number of elements, material type, texture, etc.

2. Ill-Defined Problems: The statements define abstract concepts and notions impliciltly, that could challenge novice designers to fully understand the requirements of the solution process.

Table 4.1 exemplifies the identification of the problems stated in the assignment briefs taken from METU and, whereas Table 4.2 represents the IUE problem spaces.

Table 4.1 : Identification of the second brief given to the students in the studio of METU in terms of the problem definitions (Y: Year, A: Assignment no., S:Stage).

Y	A	S	BRIEF DEFINITION	ILL-DEFINED PROBLEMS	WELL DEFINED PROBLEMS
2004-2005	2	1	Think of number of sounds with a single syllabus and find the proper positions of the entire human body that will best represent these sounds. You are expected to present this work on your own body.	Representing a sound with a single syllabus by finding proper body positions presenting the work on the human body	NA
		2	Select 3 sounds/positions among these. Ask one of your friends to act as a model to document them. Take the photos of your model for each position in front of both a window and a column along the northwest wall of the studio. Present these photos, printed in black and white, on A4 sheets.	Selecting three sounds for the following step	black and white photo prints in different exposures
		3	Make a two-dimensional composition using half size of these photos. You can use each photo only once; that is you will have 6 photos to be composed. On the occasion of dissatisfaction with the initial photos you have the chance to modify them.	making a composition by using half-sized photos	6 photos as design elements
		4	Enlarge two of your photographs with two different backgrounds to A3 size. Transform these photographs into measurable and reproducible geometric entities. The regulating lines, which will help you to make this geometrical study, should be visible on your drawings. Work them out by overlaying A3 size sketch paper on your photographs.	enlarging the scale of photographs as design elements with two different backgrounds on A3-sized paper use of regulating lines	transforming the photographs into new design medium measurable and geometric entities making a geometrical study

Table 4.2 : Identification of the second brief given to the students in the studio of IUE in terms of the problem definitions (Y: Year, A: Assignment no., S:Stage).

Y	A	S	BRIEF DEFINITION	ILL-DEFINED PROBLEMS	WELL DEFINED PROBLEMS
2022-2023	2	a	The pool of elements is the 9 elements (fruits) from Ex 01 Final Submission. Make a 2D achromatic composition by using all nine (9) elements on an A3-size visual field with only black, white and gray paper. You are free to change the SIZE of each element except the visual field	making a composition using various scales of design elements	-9 design elements, free scale -achromatic: black, gray, and white paper -A3-sized visual field
		c	Revise previous exercise by increasing the number of elements to 11. New elements should be from the same pool.	making a composition by increasing the number of the elements	11 design elements
		d	Revise previous by using black, white, gray, and a single-color paper.	making a composition by revising the previous stage with the use of color	black, white, gray, and a single color paper
		e	Make an analysis on Ex 02d submission by using pencils and colored pens on tracing paper studying HOW to revise Ex 02d. Produce at least 3 alternative revisions on tracing paper.	making an analysis of how to revise the previous stage	pencil and colored pencil drawing on tracing paper

From the observed sequence patterns of two first-year design studios, it is possible to state that both studios share multiple common points in the curriculum. On the other hand, the degree of the implicitness of the brief varies, as reframed as ill-defined design problems, in the scope of the study. The element properties were usually defined explicitly in both sets, the organization types and the gestalt principles were not mentioned in the briefs. This implicit agenda in the studio procedure is considered an intricate part of the basic design pedagogy, for encouraging the novice designer to learn by doing in terms of discovering the implicit relations and visual rules on their design mediums (van Dooren et al., 2014).

However, the elimination of the abstraction process from one of the problem spaces indicates a substantial difference for the expliticiness between the briefs, when comprehension skills of the first-year design students are considered.

As illustrated in METU basic design studio assignment no.2, stage no. 1 in Table 4.1, this difference can be exemplified. Although the brief describes an explicit process to be followed by the student to create a design solution, the statement "representing a sound of a syllable" can be considered as ambiguous for a novice designer to understand especially in the beginning stages of the studio. Whereas, in the second PS taken from the IUE first-year design studio, it can be seen that the directional steps were more explicitly defined. The impact of these various ways of problem definitions was expected to be highlighted on the synthetic DSS as one of the results of the study.

4.2 Generating the Design Solution Spaces with Diffusion Model

In this chapter of the thesis, the generation procedures of the DSSs were explained, in terms of the translation of the briefs and feedback into text prompts. As discussed within the theoretical background chapter, the Midjourney model was selected to conduct the study, to generate a design solution by translating assignment briefs into text prompts.

Firstly, to generate design solutions by using the assignment briefs as text prompts with the Midjourney model, a certain syntactic and semantic structure of the text prompts was required. Besides, since the methodology requires not only the generation of a single solution space from a single set of assignment briefs but multiple sets, a control mechanism was implemented into the translation procedure of all assignment briefs into text prompts. During the translation process of the assignment briefs, several alterations were made to the syntactic structure of the briefs, by preserving the semantic structure. These translations of the briefs as text prompts were used to generate 1st and 2nd synthetic design solution spaces. The first solution space instances were further evaluated by the design expert feedback sessions, the experts were guided to give written critiques to the instances displayed under three codes defined by the researcher. Whereas the second design solution space was kept as the control group for the further assessment procedure. Thus, the feedback sessions procedure and revision process of the text prompts were explained to have the revised problem spaces to generate the 3rd DSS.

4.2.1 Translating assignment briefs into text-prompts

The alterations made to implement a control mechanism in the generation procure were explained under three subtitles: syntactic alterations, usage of parameters and versions, and image prompting for sequencing the assignment briefs. It is important to underline it one more time, the semantic structure of the briefs was preserved during the translation since one of the aims of the thesis is to evaluate the impact of the problem space over the generated solution spaces. As discussed in detail as follows, Table 4.3 exemplifies the alterations made to the briefs during the translation of a case.

Table 4.3 : Translation of original written statement in assignment briefs into text prompts (Y: Year, A: Assignment no.).

	Y	A	Design Brief	Text-Prompt
METU	2003-2004	5 (Stage 1)	You are expected to choose three glasses of distinctly different forms. Then, you will produce a positive and negative mirror images of each glass on three separate sheets (25x35cm); half black, half white, by cutting and pasting. | Sheet size: 25x35 cm.	/imagine: choose three glasses of distinctly different forms. Then produce a positive and negative mirror image of each glass on three separate sheets, using half of the black paper and half of the white paper by cutting and pasting --ar 35:25 –v 3
IUE	2022-2023	1(a)	You will analyze the properties of the 3 fruits of your choice separately by using technical drawing equipment (ruler & compass). Your analysis should identify: * the formal (by shape) components; * the visual properties (textures, tones, etc.); * the proportional relations between different components and the whole; * the organization of the individual elements that compose the fruit.	/imagine: Analysis of formal properties of a (strawberry) using technical drawing equipment. Analysis should identify formal components by shape, the visual properties with textures and tones, proportional relations between different components and the whole, identify the organization of the individual elements that compose the fruit, technical drawing, black and white pencil drawing --ar 29:21 --v 5

4.2.1.1 Syntactic alterations

The term syntax is defined as the set of rules that determines how words and phrases are combined to form grammatically correct and meaningful sentences that convey the intended message (Radford, 2004). It involves various linguistic features, such as word order, sentence structure, and grammatical markers. Direct usage of the assignment briefs would not have been effective since the diffusion model does not share the same syntactic rules as humans, making it incapable of comprehending the information in its original form. As a result, the necessary syntactic modifications were made to ensure that the text prompts provided the essential information and were formulated in a manner that the diffusion model could comprehend.

Firstly, the punctuation of the brief statement was altered. As explained by the user manual of the Midjourney, the text prompts given into the model get separated by using commas or double columns, to maintain the semantic hierarchy of the prompt (Midjourney, 2023). When the assignment tasks are analyzed, it becomes visible that there were many commas used in the sentence cases written in the design briefs. Therefore, to hold on to the initial definition's semantic hierarchy, these commas were either eliminated or changed with "and". If the brief was defined as a paragraph, that contains two or three sentences, a full stop sign was used in order not to interrupt the description process of the task.

Secondly, the user manual published online by the Midjourney research lab documents that, the users should give the numerical information into the prompts by using verbal descriptions rather than numbers. Therefore, the statements that defined the numerical properties (i.e. repetition time of design elements, size of the elements) using numbers were changed with verbal descriptions.

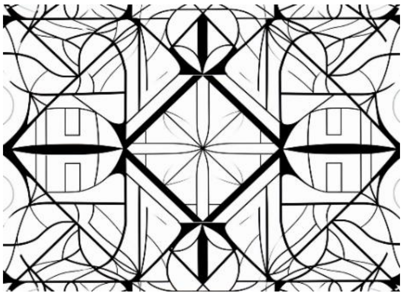
Thirdly, the expressions stated in the briefs by using personal pronouns or indications (i.e. "you", "you're", "a group of students") were eliminated, to avoid misinterpretations. During the experimentation, it was noticed that the pronouns used in the prompts, deflect the model to depict the designer instead of depicting the design work itself. Instead, these sentences were changed into a passive voice to describe the expected outcome. This deflection of the model was exemplified in Table 4.4 about the usage of the pronouns.

Besides, it is visible that generally design brief depicts the material qualities and sizes of the design elements, as defined in the scope of this research as well-definitions, in the middle part of the sentence cases. However, the initial experimentation proved that giving the materialistic information in a separate form by using commas from the rest of the definition usually generates images that fit better into the context. Table 4.5 illustrated the mentioned deflection of the model, in terms of the elements' material properties.

Table 4.4 : Deflection of the image generation due to the usage of pronouns while prompting (2004-2005 Fall Semester, Assignment no.5, Stage 1).

	(a)	(b)
Prompts	Using paper-tape of twelve mm **you are** asked to make a composition in which contrast is the most perceptible quality. **Your** paper-tape elements should start and end only at the edges of the cartridge paper and they should not be adjacent.	Using paper tape of twelve mm make a composition in which contrast is the most perceptible quality. Paper-tape elements should start and end only at the edges of the cartridge paper and paper tapes should not be adjacent, black cartridge paper, paper tape
Generated Image		

Table 4.5 : Prompting hierarchy of the material qualities.

	(a)	(b)
Prompt	**(image prompt from the previous stage),** make a full-pattern using cartridge paper with the tones of blue --ar 42:29 --v 5	**image prompt from the previous stage),** make a full-pattern using cartridge paper with the tones of blue, **four tones of blue paper cut elements, blue cartridge paper** --ar 42:29 --v 5
Generated Image		

4.2.1.2 Usage of the versions of the model and parameters

In the current state, Midjourney provides five versions of the model, that enables users to generate images in various contexts. During the initial experimentation in the generation process, all versions of the models and the usage of the parameters were tested. Although there is a lack of academic literature for the comparison of the versions of Midjourney in the current state, users state worldwide that there are severe differences between the versions regarding the visual styles of the generated images (Sky, 2022; Merzmensch, 2022).

The latest versions of the model, versions 3, 4and 5 considered superior to the earlier versions of the model in terms of the generated image resolution and the stylistic quality. For instance, v1 provides 256x256 resolution images as the starting grid, whereas version 5 can generate 1024x1024 images. Also, the users stated that the overall performance of the model to comprehend the semantic structure of the text prompt had been strengthened by the release of later versions (Uni Matrix Zero, 2023).

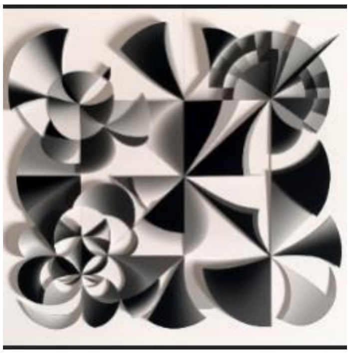
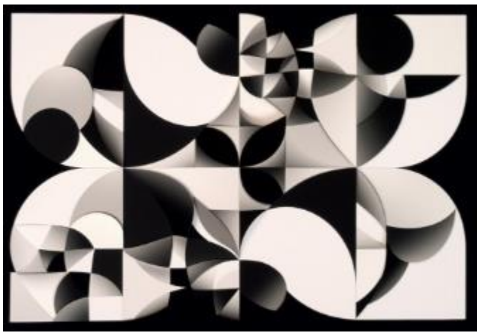
There are also stylistic differences documented on the generated images between the different versions of the model by using the same text prompt with different prompts. For instance, versions 4 and 5 are able to generate more photorealistic and extremely detailed outputs, version 3 performs well in generating abstract artwork. Although version 4 is considered as one of the most powerful versions by public opinion, the model has its limitations in terms of the parameters. Because in the current state, the fourth version does not allow the user to generate image outputs with aspect ratios different than 1:1,3:2 and 2:3. And since the selected design briefs generally require a variety of canvas ratios besides the ones listed above, the usage of the version 4 is eliminated for the scope of the study. Therefore, during the generation process, only two versions of the model were used: Version 5 was preferred for the stages that require taking image references from the exterior context of the studio (i.e. analysis of a real-world object). Whereas version 3 was used for the abstraction and composition processes.

Secondly, the Midjourney model provides a variety of built-in parameters to alter the dimension of the generated image or to enhance the quality of the image and correspondence level to the text prompt:

1. Aspect Ratio: One of the most frequently used parameters during the generation process was the aspect ratio parameter. In the default mode, the model generates all the solution instances in a square format (1:1) (Midjourney, 2023). Since the dimension of the visual mediums were defined variously in

the briefs, the size of the design medium was controlled by the aspect ratio parameter as prompted as "—ar X: Y" . While the numerical input of "X" defines the width of the generated image, "Y" defines the height. Table 4.6 illustrates the case with the usage of different aspect ratio parameters from the PS of IUE, Assignment 2, Stage A.

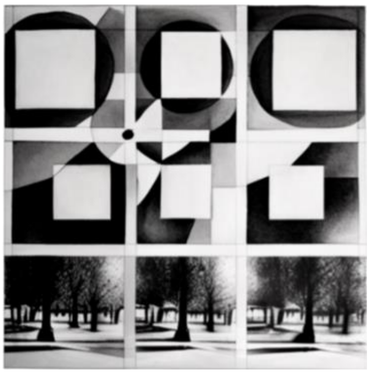
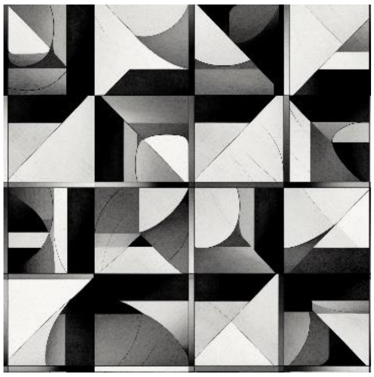
Table 4.6 : Usage of the aspect ratio (--ar) parameter.

	(a)	**(b)**
Prompts	**(image prompt from the previous stage),** The pool of elements is the nine elements from the image prompt, Make a 2D achromatic composition by using all nine elements on visual field with only black, white and gray paper. It is free to change the size of each element except the visual field --seed 584003524 --iw 2 –v5	**(image prompt from the previous stage),** The pool of elements is the nine elements from the image prompt, Make a 2D achromatic composition by using all nine elements on visual field with only black, white and gray paper. It is free to change the size of each element except the visual field --seed 584003524 --iw 2 **--ar 42:29** –v5
Generated Image Instances		

2. Prompt Weights and Negative Prompting: Diffusion models work by conditioning the cross-attention layers of the diffusion model with contextualized text embeddings (Hugging Face, 2023). In other words, the Midjourney model enables users to emphasize or de-emphasize certain parts of the prompts, by the inherent transformer-based attention mechanism of the model. As the documentation guide states, the default weight for each text prompt separated by the usage of commas is set to 1. During the solution generation with longer text prompts that describe multiple requirements for the design task, it was noticed that the model starts to deflect by adding irrelevant objects to the generated scenes. To avoid that situation in those cases, both positive and negative prompt weights were used. The prompts weights were increased by the usage of double columns (i.e. xxx ::2, xxx) and negative prompts were used by adding the "—no" parameter at the end of the prompt. It enabled the model to perform to generate output that corresponds better to

the defined context of the brief. Table 4.7 illustrates the impact of using the prompt weights on an exemplary case.

Table 4.7 : Usage of the prompt weights.

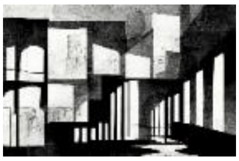
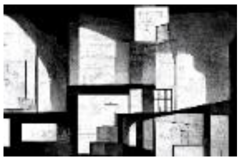
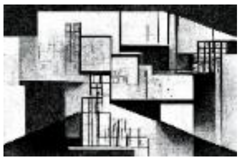
	(a)	(b)
Prompts	(image prompt from the previous stage), Make a geometrical study by drawing regulating lines on the composition. Reproduce this study on white cartridge paper. Work on alternative rendering of chosen areas in between the regulating lines. Produce nine copies each of which to act as one unit of the coming stage, white cartridge paper –seed 43846387 –v3	(image prompt from the previous stage), Make a geometrical study by drawing regulating lines on the composition. Reproduce this study on white cartridge paper. Work on alternative rendering of chosen areas in between the regulating lines. Produce nine copies each of which to act as one unit of the coming stage ::2, white cartridge paper --iw 4 –no tree –seed 43846387 –v3
Generated Image Instances		

3. Seed Value: Seed value in the diffusion models is a random number used to initialize the generation unless it is not specified (Midjourney, 2023). Since the diffusion models are able to produce myriad variations of the images with a single prompt, the seed parameter enables a control mechanism to produce similar ending images. Thus, the same seed values were used for the generating instances for interrelated stages of the briefs.

4.2.1.3 Sequencing the briefs by image prompting

In addition to the text prompts, image instances were used as reference images by image prompting. As discussed before within the introduction of the assignment brief data the problem spaces were consisting of the assignment sequences with interrelated stages. Hence, the design solution of the previous stages evolves into a part of the design problem for the upcoming stage as a reference. To keep the same understanding of the studio, while generating a synthetic design solution space by a diffusion model, the assignment briefs are given as following the same sequence. Therefore, the prior design output generated by the brief of the previous stage was given in to model as an image prompt with the text-prompt version of the brief of the upcoming stage. Thus, it is possible to follow up the development process of the design idea within the defined sequence. Table 4.8 illustrates the usage of image prompts in the sequential assignment briefs.

Table 4.8 : Sequencing the assignment briefs with image references.

A	S	BRIEF	PROMPTS	1ST DSS	2ND DSS
	a	Choose one of the routes/areas below. 1. Alsancak – Pasaport 2. Karşıyaka – Bostanlı 3. Kemeraltı. Walk within the boundaries of the area you selected. Take various photographs by paying attention to any type of “rhythm and repetition” you might observe. Take at least 50 photos and print 5 photographs (black & white) by scaling on A4 size paper (fit-to-paper). Bring the photographs to the class.	Walk within the boundaries of the {Alsancak – Pasaport, Karşıyaka – Bostanlı, Kemeraltı}. Take various photographs by paying attention to any type of rhythm and repetition. Print five black and white photographs, black and white photographs, rhythm and repetition, photorealistic --ar 29:21 --v 5		
2	b	Put A5-size tracing paper on photograph and make a compositional analysis focusing on the repeating elements and their organization. Use your drawing equipment and as many tracing sheets as you need. You are free to use any type of hatching technique to identify the elements/groups.	**(image prompt from the Stage 2a output)**, make a compositional analysis focusing on the repeating elements and their organization. Use drawing equipment and tracing paper, hatching techniques to identify the elements and groups, analysis on tracing paper --iw 2 --ar 21:29 --v 3		
		Make 5 identical copies of the analysis with black marker (or a similar pen). Make a rhythmic composition by overlapping all 5 copies (of A5) on an A3-size white visual field.	**(image prompt from the Stage 2b (1) output),**make five identical copies with black marker. Make a rhythmic composition by overlapping five transparent tracing paper, black and white, marker drawing on tracing paper --ar 42:29		
	c	Considering the panel critique, revise Ex 03a (both the analysis and the composition). You may change the photograph if necessary. Transfer the overall composition by drawing it on a separate A3-size white visual field.	**(image prompt from the Stage 2b (2) output**), Transfer the overall composition by drawing it on a white visual field --ar 42:29		

4.2.2 Feedback sessions

After generating the first and second synthetic design solution spaces by prompting the assignment briefs into a diffusion model, a series of feedback sessions were conducted with three design experts to collect the feedback. The review sessions were conducted one by one and each session lasted three hours, approximately. The instances of the first design solution spaces were displayed to the reviewers, whereas the second solution spaces generated through the same text prompts were kept as the control group for the following assessment stage.

The total number of 40 synthetic design solution space instances were evaluated by each design expert during the feedback sessions individually. 16 of these solution instances were generated by the assignment brief data taken from the METU ARCH 101 archive, whereas the rest 24 solution instances were generated through the IUE FFD 101 archive.

All three design experts chosen for the feedback procedure had experience in teaching the foundational design studio for more than ten years. Also, three design experts share a common Bachelor of Architecture Education background from METU from different timeframes. Besides, it is significantly important to highlight that, all three design experts were also involved in the design process of at least one set of the assignment briefs used in the scope of this thesis. Hence, each design expert was already familiar with the sets of assignment briefs. As well as they had observed the solution-generation process of the first-year design students during at least one of the studio procedures.

Participant 1 has experience in instructing in the first-year design studio for 15 years and has been coordinating the IUE, FFD 101: Arts and Design Studio since 2017. The first participant was also familiar with the assignment set of the METU since the selected timeframe of the assignment briefs coincides with his undergraduate and graduate studies in METU.

Participant 2 is the most experienced first-year design studio instructor among the other participants in the focus group, with more than 25 years of teaching experience in both METU and IUE. The expert had involved in the design process of the METU ARCH 101 assignment briefs in the analyzed timeframe. Besides, the expert was the lead designer of the IUE FFD 101 course curriculum during the initial setup phases of the IUE Faculty of Fine Arts and Design and coordinated the studio until 2017.

Participant 3 has also teaching experience in FFD 101 first-year design studio for more than five years and had been the design process of the assignment briefs in the selected time period.

At the beginning of each session, the aims and scope of the thesis were explained briefly. Also, the generation method of the solution spaces was explained. The design experts were guided by the researcher to give feedback for each solution instance by the guidance of the three following codes:

1. Element Properties: The definitions of the elements of the design work, in terms of using the full potential of the material, scale, color, and texture properties.

2. Organization: The skills of organizing the design elements on the visual field, in terms of searching for formal relations between the elements and overall control mechanism for the composition through the operations and transformations derived from the gestalt principles.

3. Design Themes: The visual implication of the design themes such as dominance, balance, contrast, hierarchy, rhythm, etc.

After the feedbacks were collected through three semi-structured interview sessions with the design experts, the common points mentioned by the design experts are highlighted by a congruency analysis. The feedbacks given for each solution instance under three main codes are identified using spreadsheets, to analyze the collected feedback data. The feedbacks given for each code were composed into one, considering the common points highlighted by reviewers. Table 4.9 exemplifies one of the cases from METU briefs and the corresponding 1st DSS instance, whereas Table 4.10 displays the feedback outputs.

Table 4.9 : Assignment brief and the corresponding synthetic solution instance of 1st DSS of METU (2006-2007, Assignment 7, Stage 2).

Assignment Brief	… Now that you have a better understanding of the parts and the whole of your composition, derive from your tracing study six abstract elements for a new two-dimensional composition.Keeping in mind the ordering principles in your previous composition, make a two dimensional composition with the newly derived elements on a sheet of 35 cm x 50 cm. Work with one of **contrast** *(selected for the case)*, balance, harmony, or hierarchy as the dominant theme of the composition. You may use the elements in varying size.Materials: Paper, grey, craft paper, one other two dimensional material of your choice

Table 4.9 (continued): Assignment brief and the corresponding synthetic solution instance of 1st DSS of METU (2006-2007, Assignment 7, Stage 2).

1st DSS instance	

Table 4.10 : Composing the feedbacks according to the defined three codes (DE: Design Experts).

DE	(1) Element Properties	(2) Organization	(3) Design Themes
1	The number of the elements should have been decreased, by grouping the elements.	The visual field should have been controlled. The composition organization is linear, different formal relations are encouraged. Formal relations of the elements are arbitrary.	Intention of creating a contrast between the black circles and white linear elements are legible, but other relations should have been searched to highlight the "contrast" as design theme.
2	The number of the elements should have been decreased, by grouping. Employing the group of elements in various scales can contribute to the design theme.	The order of the composition is not visible, therefore the composition is not reproducible.	Applying the design theme by using contrasting colors of black and white is visible, however its needs to be enhanced by other types of formal relations.
3	Scale of the elements needs to be controlled. Element number should be decreased, by grouping.	Transition from the previous work is not visible. Overlapping relations of the elements should be reconsidered by controlling the proximity.	The contrast as the dominant design theme is visible in the overall composition.
Composed Feedback	The **number of elements** used in the composition should have been decreased by **grouping** them together. Employing these groups in various scales can contribute to the design theme.	The composition should be organized in a way that controls the visual field and formal relations between elements that is reproducible. Transitions from previous work should be apparent. The proximity and overlapping relations of the elements should be reconsidered.	The design theme of contrast between black and white is visible in the composition but needs to be enhanced by exploring other types of formal relations to highlight it more effectively.

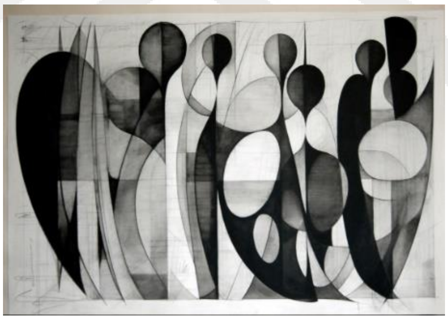
4.2.2.1 Revision of the text-prompts

Following the congruency analyses, the new text prompts were structured by revising the original assignment brief statements according to the composed feedback for each code defined in terms of the element properties, organization, and design theme. The keywords were extracted from each composed feedback and added to the original briefs by reconsidering the semantic structure of the brief.

The main difference in between the translation process into text-prompts from the initial stage was re-formulating the sentence cases in the brief. Since one of the aims is evaluating the impact of the problem definitions in the assignment briefs on the generated solutions, the semantic organization of the briefs were not altered during the generation process of 1^{st} and 2^{nd} DSSs. However, during the generation of the 3^{rd} DSSs the required revisions were made by adding the keywords obtained from the feedback sessions and also restructuring the sentence cases.

Following the composed feedback displayed in Table 4.10, Table 4.11 demonstrates the extracted keywords from the feedback, the revised new text prompt, and the generated solution instance.

Table 4.11 : Revision of the text prompts through the composed feedback.

Composed feedback	1	Less number of elements, grouping, various scales
	2	Controlling the visual field, consideration of the formal relations, reproducibility, control of the proximity, no overlap, transition from previous work (image weight increased)
	3	contrasting formal relationships, black and white contrast
Revised text-prompt	(image prompt from previous stage), two-dimensional composition using less number of elements derived from the image prompt in various scales, groups of elements, consider ordering principles, control of the visual field, contrast as the dominant design theme, black and white and gray and craft paper –ar 50:35 –iw 2 –no overlap –v 5	

4.3 Assessment of Synthetic Design Spaces of the Basic Design Studios through the Design Expert Interviews

In order to highlight the impact of the design problems stated in the assignment brief, the suggested methodology intends to evaluate the visual implications of ill-defined and well-defined problems on the generated synthetic solution spaces. The problem definitions of the given briefs were translated into text prompts to generate synthetic solutions by preserving their semantic structure. Since the design solution generation is not only bounded by the assignment briefs given in the studio but also by the feedback of the studio instructors, a layer of feedback process was also added to the generation mechanisms. Therefore, the initial generations of the synthetic design space were reviewed by a design expert, alluding to the conventional studio procedure. Then a revised set of design solutions were generated, by transforming those feedbacks into the text prompts, in addition to the initial solutions as given as image-prompt.

Thus, in total three different design solution spaces were generated in the scope of the research, aiming to elucidate different aspects of the design problems and the process of the design solutions delivered. These three synthetic design solution spaces were:

First Design Solution Space: Generated through the solo guidance of the assignment briefs.

Second Design Solution Space: Generated through the solo guidance of the assignment briefs and kept as the control group for the assessment without any alteration or revision.

Third Design Solution Space: Generated through the guidance of the revised text prompts by reconsidering assignment briefs through the feedback outputs.

The first and second solution space instances were expected to show the visual aspects of only the problems defined in the assignment briefs. Whereas the third solution space was expected to show the impact of the implicit requirements that the problem states, which conventionally get explained to the students in the studio procedure.

Thus, the performance of the 2nd and 3rd solution spaces were assessed by the same design experts in semi-structured interviews conducted in two parts. The first part of the interview is designed to retrieve the quantitative data by asking the participants to rate each case on an ordinal scale (1 = poor; 2 = poor-average; 3 = average; 4 = average-excellent; 5 = excellent), in terms of three questions asked. Whereas the second part focuses on retrieving the implications of the participants on the various design spaces provided by the open-ended questions in detail.

4.3.1 Materials

For both assessment procedures, the provided materials consist of the second and the third design solution space instances given with the corresponding total number of 40 cases of assignment briefs and interrelated stages of the two design institutions. All reviewers evaluated the design solution spaces following the same chronological order, starting from the 16 METU cases, and continued to evaluate the 24 cases of IUE. Two sets of visual material displaying the assignment briefs and the corresponding design solution instances of the 2^{nd} and 3^{rd} DSS were distributed to the participants, in addition to the rating sheet for the quantitative part.

Table 4.12 displays a part of the visual material for the assessment procedure that demonstrates the 2^{nd} and 3^{rd} solution space instances of METU and Table 4.13 shows similarly the IUE solution space instances.

Table 4.12 : A part of the visual material displaying 2nd and 3rd design solution space instances and corresponding briefs of METU from 2004-2005.

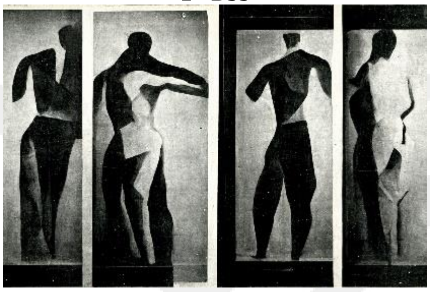
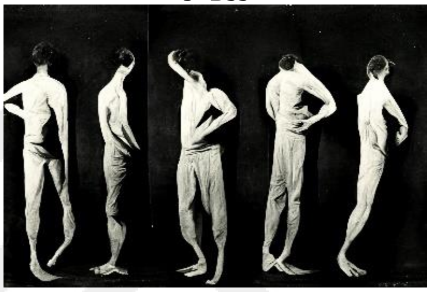
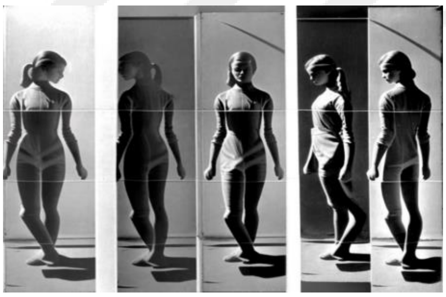
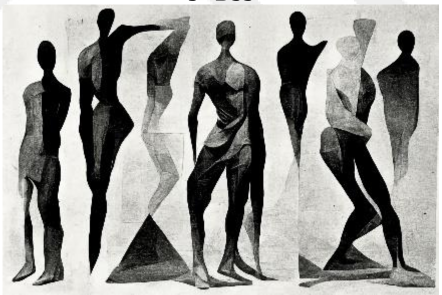
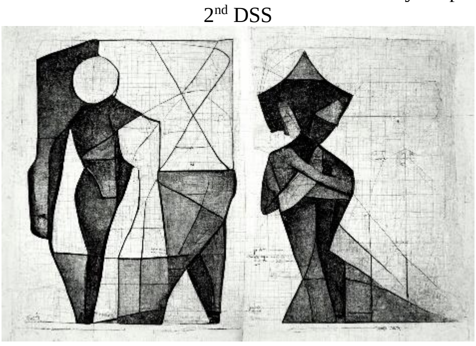
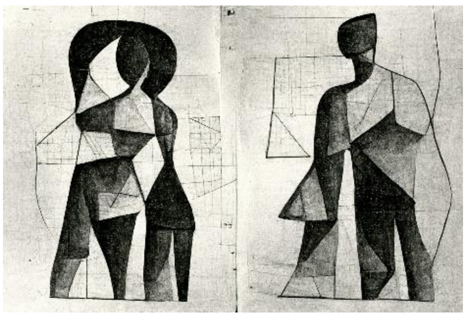
A.	S.	Brief
2	2	Select 3 sounds/positions among these. Ask one of your friends to act as a model to document them. Take the photos of your model for each position in front of both a window and a column along the northwest wall of the studio. Present these photos, printed in black and white, on A4 sheets. 2^{nd} DSS  3^{rd} DSS 
		Brief
2	3	Make a two-dimensional composition using half size of these photos. You can use each photo only once; that is you will have 6 photos to be composed. On the occasion of dissatisfaction with the initial photos you have the chance to modify them. 2^{nd} DSS  3^{rd} DSS 
		Brief
3	1	Enlarge two of your photographs with two different backgrounds to A3 size.Transform these photographs into measurable and reproducible geometric entities. The regulating lines, which will help you to make this geometrical study, should be visible on your drawings.Work them out by overlaying A3 size sketch paper on your photographs. 2^{nd} DSS  3^{rd} DSS 
		Brief
	2	Translate the two studies you have made on sketch paper into a new medium: cartridge paper. Use black for one and gray for the other. Obtain number of shapes by extracting the black and gray cartridge paper.

Table 4.12 (continued): Part of the visual material displaying 2nd and 3rd design solution space instances and the corresponding briefs of METU from 2004-2005.

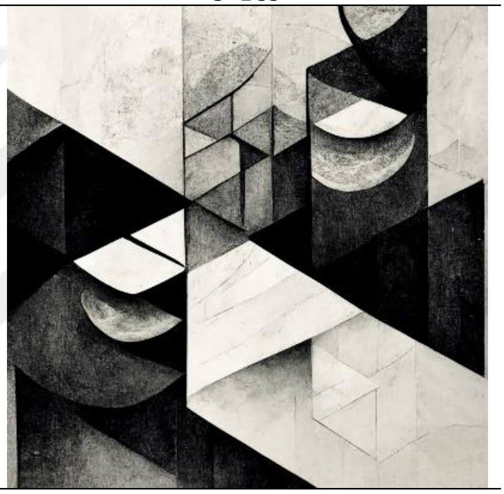
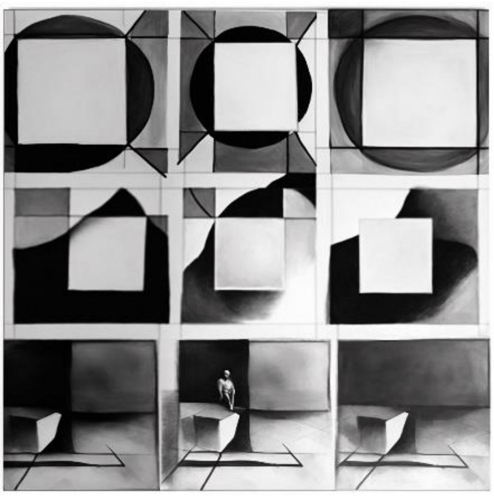
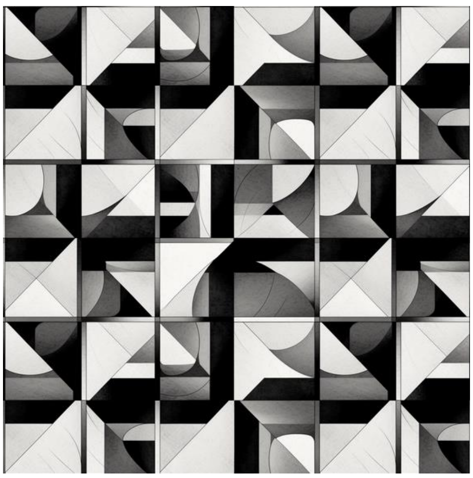
		2nd DSS	3rd DSS
3	2		
		Brief Choose three elements among the ones you have produced for the second stage of your previous assignment. Make a composition with these on a 29.7x29.7 cm cartridge paper. You can change the size of these three elements.	
		2nd DSS	3rd DSS
	1		
		Brief Make a geometrical study by drawing regulating lines on your composition that you have made in Stage 01. Reproduce this study on a 21.2x21.2 cm white cartridge paper. Work on alternative rendering of chosen areas in between the regulating lines. Produce nine copies, each of which to act as one unit of the coming stage.	
4		2nd DSS	3rd DSS
	2		

Table 4.13 : A part of the visual material displaying 2nd and 3rd design solution space instances and the corresponding briefs of IUE from 2022-2023.

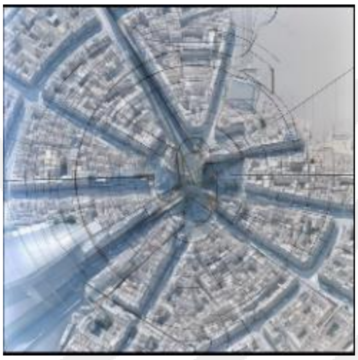
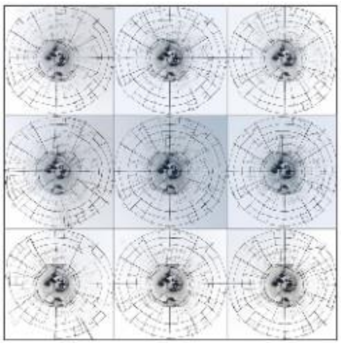
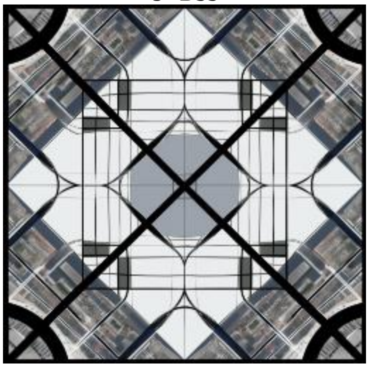
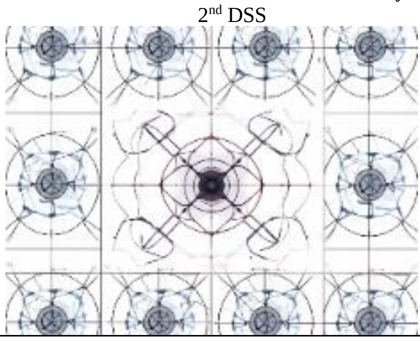
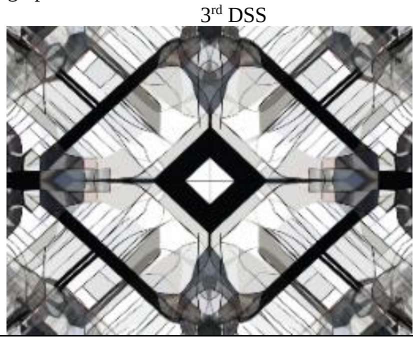
A.	S.	Brief	
4	A1	Make an analysis on all 10 images (4x4cm each) focusing on; Elements and their organization, compositional guidelines. Using tracing paper, define “reproducible elements” that come out of the visual field (4x4 cm) of each image. 	
		2nd DSS 	3rd DSS 
		Brief	
	A2	Select 2 out of 10 “analysis” > Reproduce both “analysis” on tracing paper to have 12 copies. (2x12=24 pieces) > Organize the identical 4 copies within a 8x8 visual field following 3 different operations separately: Operation 1. Mirror/flip, Operation 2. Copy-paste, Operation 3. Rotate	
		2nd DSS 	3rd DSS 
		Brief	
	A3	Enlarge two of your photographs with two different backgrounds to A3 size.Transform these photographs into measurable and reproducible geometric entities. The regulating lines, which will help you to make this geometrical study, should be visible on your drawings.Work them out by overlaying A3 size sketch paper on your photographs.	
		2nd DSS 	3rd DSS 

Table 4.13 (continued): Part of the visual material displaying 2nd and 3rd design solution space instances and the corresponding briefs of IUE from 2022-2023.

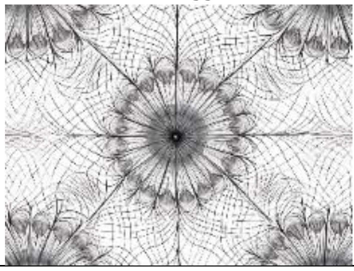
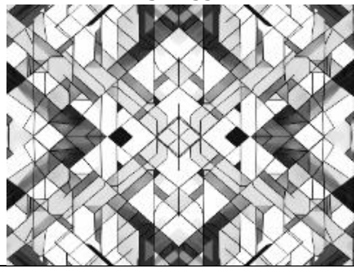
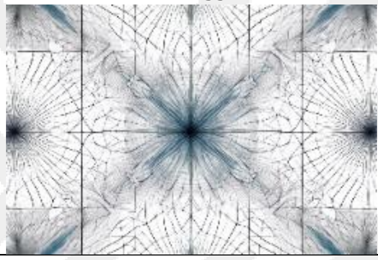
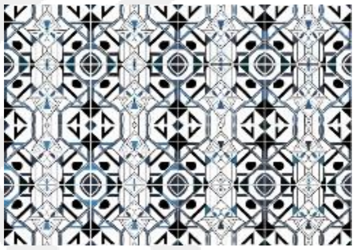
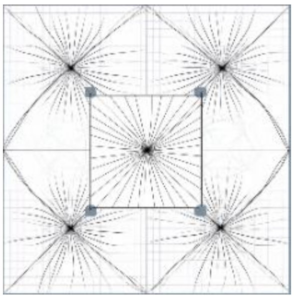
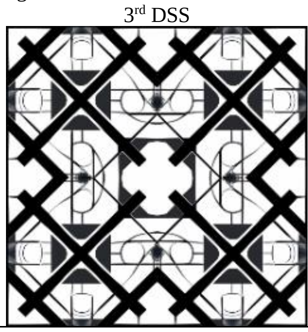
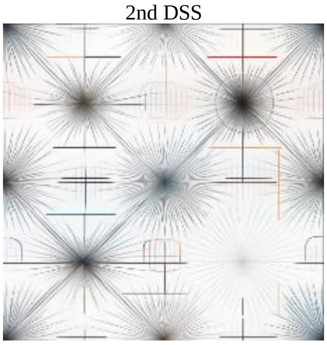
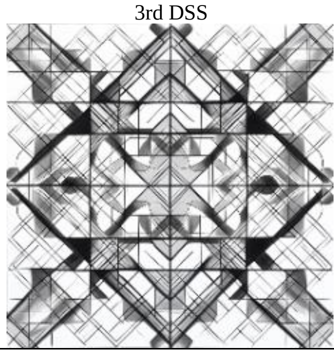
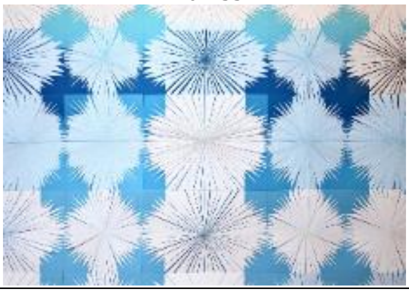
<table>
<tr><td rowspan="12">4</td><td rowspan="3">b
1</td><td colspan="2">Brief</td></tr>
<tr><td colspan="2">*Revise the image or the 4x4 element if necessary.
*Make a full pattern by using the selected 8x8 unit element on an A4-size white visual field (fill all the VF). Produce two-copies of A4:
(1) shading with regular drawing pencils with 5 different tones (H, HB, B, 2B, 3B)</td></tr>
<tr><td>2nd DSS
</td><td>3rd DSS
</td></tr>
<tr><td rowspan="3">b
2</td><td colspan="2">Brief</td></tr>
<tr><td colspan="2">*Revise the image or the 4x4 element if necessary.
*Make a full pattern by using the selected 8x8 unit element on an A4-size white visual field (fill all the VF). Produce two-copies of A4:
(2) shading with color pencil (5 different tones of a single color)</td></tr>
<tr><td>2nd DSS
</td><td>3rd DSS
</td></tr>
<tr><td rowspan="3">c
1</td><td colspan="2">Brief</td></tr>
<tr><td colspan="2">Following critiques;
Revise the initial unit - 8x8 on a separate tracing paper. Pay attention:
Reproducibility of the elements that compose the unit,Network of relations generated by the chosen operation on four 4x4 units ,Emerging new elements.</td></tr>
<tr><td>2nd DSS
</td><td>3rd DSS
</td></tr>
<tr><td rowspan="3">c
2</td><td colspan="2">Brief</td></tr>
<tr><td colspan="2">Fill an area of 24x24cm by drawing full units on a new tracing paper.
Using a regular drawing pencil, give a code of shading for each element and shade the central 8x8 initial unit.</td></tr>
<tr><td>2nd DSS
</td><td>3rd DSS
</td></tr>
</table>

Table 4.13 (continued): Part of the visual material displaying 2nd and 3rd design solution space instances and the corresponding briefs of IUE from 2022-2023.

	Brief	
	Revise the initial unit (8x8) if necessary, Make A3-size Full-Pattern using cartridge paper with tones (4-5 tones) of a single color (monochromatic).	
	2nd DSS	3rd DSS
c3		

4.3.2 Quantitative assessments

The first part of one-to-one interviews with the design experts started by explaining the difference in the generation method of the 2^{nd} and 3^{rd} synthetic solution spaces that would be displayed. In order to assess the impact of the implicitness of the brief definition on the solutions generated, design experts were asked to evaluate the overall explicitness of the design problem as first. The required explanation was made to guide the raters regarding definitions of the ill- and well-defined problems as reframed in the scope of the thesis as follows:

[*1] Ill-Defined Problems: The statements that define abstract concepts and notions implicitly. In which, each designer might interpret the problem variously and attempt multiple ways of solution generation.

[*2]Well-Defined Problems: The statements that define the properties of the design works and design elements i.e., dimension of the visual field; number, material, texture, color, and scale of the elements; creation method (drawing, cutting and pasting) etc.

Secondly, three design experts were asked to rate the solution spaces performances. The three questions posed to the participants, as follows:

(Q1) Please rate the overall explicitness of the brief definition in terms of the inherent ill-defined problems.

(Q2) Please rate the performance of the solution instances of the 2^{nd} and 3^{rd} design solution space in terms of answering the “well-defined problems” on the design solution.

(Q3) Please rate the overall compositional (design work) quality of the solution instances of the 2nd and 3rd design solution spaces.

4.3.3 Qualitative assessments

After the first stage had been completed and the rating for all cases collected, the second part of the interview started with open-ended questions. Following four open-ended questions posed to each participant, to evaluate the performance of two design spaces in terms of the visual impacts of the feedback process and design problems on the generated solutions:

1. Do you think that the clarity of the assignment briefs has an impact on the overall performance of the synthetic design solution spaces? Based on your experience in the first-year design studio, how do you compare the solution-generation process of students and AI-tool in terms of the impact of the brief?

2. Can you comment on the following statement: If current deflections of the model are disregarded in terms of answering the requirements of the well-defined problems (element numbers, materials, scales, lack of transitions of the solutions from the previous stages), the implication of the model as a tool in the studio would help students better understand the abstract concepts and principles of the basic design studio, as reframed in the scope of this study as, ill-defined problems.

3. Can you comment on the potential advantages and disadvantages of the hypothetical case of integration of the text-to-image diffusion models as a tool of basic design studio, for enlarging the design space of the studio during the panel critique sessions?

4.3.4 Assessment of the interview data

For assessing the quantitative data outcomes of the first stage of the interviews, an inter-rater agreement is used. As the inter-rater agreement parameter is commonly used in the design education research methodologies to understand to the extent which raters assign the same score for each case being rated (Taneri, 2021). The interrater agreement defined by standard deviation is calculated for each question, in terms of two design experts' ratings by for each solution space evaluated under each question asked. For each case, the overall evaluation that has less than one standard deviation is considered similar.

In order to evaluate the qualitative assessments, the second part of the interview is voice-recorded with the consent of the participants. The audio is auto-transcribed into the written format by AI-aided Speech-to-Text API by Google Cloud.

5. RESULTS AND DISCUSSION

The results of the interview were evaluated to highlight the aims of the research defined initially as, evaluating the impact of the problem space on the synthetic design solution spaces in terms of the inherent ill- and well definitions of the briefs; and elucidating the potential of integrating text-to-image AI tools into the basic design studio to help the students better understand the implicit concepts conveyed in the studio process.

The explicitness of the assignment briefs and the performance of design solutions in answering the well-defined problems and the overall quality of the design works were assessed by design expert rates according to the questions asked.

Firstly, the overall results displaying the mean rates given by each design expert for two design spaces were discussed. Secondly, the assessment results were evaluated in terms of two comparative methods to elucidate the two primary aims of the research. The impact of the explicitness of the briefs on the overall quality of the generated solutions was evaluated by comparing the results of two design spaces of METU and IUE. Following that, the impact of the feedback process on the design solution spaces was measured, by comparing the performance of the 2nd and 3rd design solution spaces that they differ in terms of including and excluding a feedback mechanism. Hence, it is possible to make an inference from the assessment results to highlight the current limitations of the AI tool in certain contexts and discuss the future potential.

Moreover, the qualitative assessments were used to indicate and discuss potential advantages and disadvantages of the implementation of the text-to-image AI tool into the basic design studio from a pedagogical perspective.

5.1 Evaluation of the Quantitative Data

The results of the quantitative data were evaluated for each design space separately, by calculating the mean of the design experts' rates given for the explicitness of the brief and each design solution performance. Table 5.1 displays the design experts' average rates of the 16 displayed cases from the design space of METU, according to the three questions asked. Similarly, Table 5.2 demonstrates the mean rates of 24 cases of design space of IUE.

Table 5.1 : Quantitative assessment results of the design space of the METU.

METU					
		2nd Design Solution Space		3rd Design Solution Space	
Design Expert	The explicitness of the brief **(Q1)**	Performance of answering well-definitions **(Q2)**	The overall quality of the design solution **(Q3)**	Performance of answering well-definitions **(Q2)**	The overall quality of the design solution **(Q3)**
1	2,5	1,7	1,3	2,4	2,5
2	3,9	1,3	1,3	1,6	2,3
3	3,3	1,3	1,7	1,6	2,7
Mean	**3,2**	**1,4**	**1,4**	**1,9**	**2,5**

Table 5.2 : Quantitative assessment results of the design space of the IUE.

IUE					
		2nd Design Solution Space		3rd Design Solution Space	
Design Expert	The explicitness of the brief **(Q1)**	Performance of answering well-definitions **(Q2)**	The overall quality of the design solution **(Q3)**	Performance of answering well-definitions **(Q2)**	The overall quality of the design solution **(Q3)**
1	4,3	2,0	2,0	2,9	3,0
2	3,9	1,7	2,0	2,3	2,4
3	4,4	1,6	2,3	2,1	3,2
Mean	**4,2**	**1,8**	**2,1**	**2,4**	**2,9**

The overall results displayed in Table 5.1 and 5.2 indicates that, all synthetic design solutions generated by the text-to-image diffusion model performed below the average for both answering the design problem requirements in terms of the well definitions and the overall quality of the design solution. However, the feedback mechanism applied in the generation method of the 3rd solution space increased the performance of the design solutions for overall quality and performance in answering the problem requirements.

However, the comparative evaluations of the data in terms of the two institutions' design spaces and the performance of 2nd and 3rd DSSs contributes to the research findings and valuable insights into the importance of the problem definition and feedback process.

5.1.1 Impact of the problem space on the design solution spaces

The assessment made clear that the text-to-image AI model is limited to providing solid answers to the well-defined design problems in the current state, due to the limitations of the model. However, the comparison of design spaces of two different time frames contributes to the discussion in terms of the impact of the brief definitions on the generated solution performances. Figure 5.1 demonstrates the assessment results of METU and IUE problem spaces comparatively.

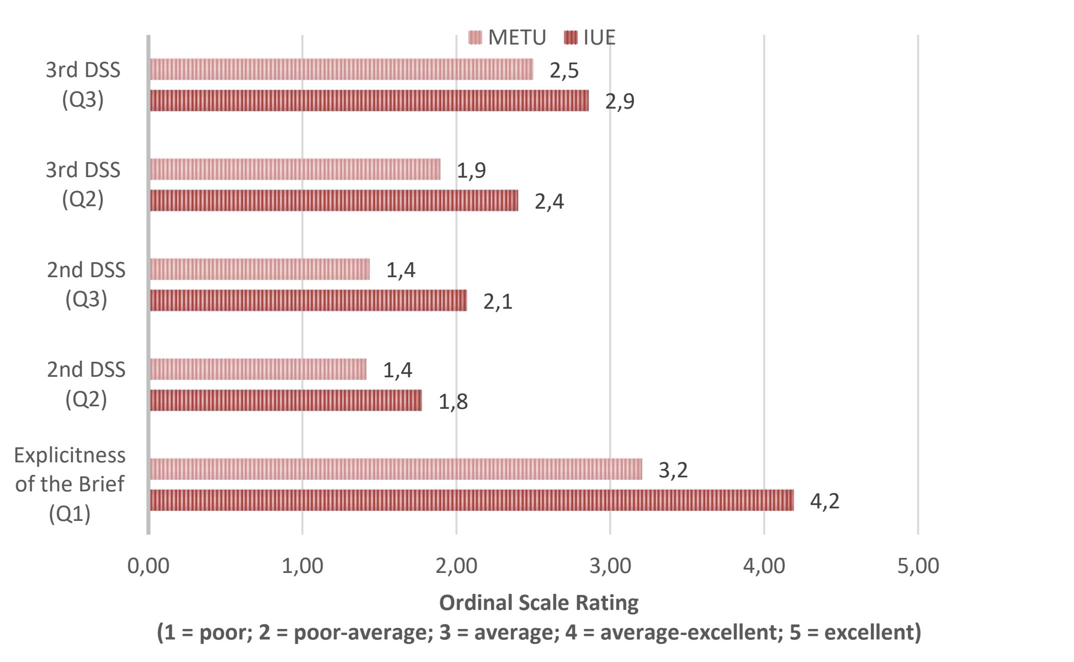


Figure 5.1 : Comparison of two design spaces in terms of the mean rates of the design experts.

Firstly, the average of the design expert rates indicates that definitions of the IUE problem space were more explicit than the problem space of METU in overall by 1 point difference in ordinal scale.

Secondly, as assessed by the second question, the performance of both the 2nd and 3rd design solution spaces of the IUE case was more sufficient in terms of answering the well-defined problems stated in the briefs. Regardless of the different generation methodologies applied for the 2nd and 3rd DSS in terms of prompting various text prompts regarding the inclusion of a feedback mechanism. The difference in the performances of the DSSs of IUE and METU for answering question 2 (Q2) assessed for the 2nd DSS as 0.4 and for the 3rd DSS as 0.5.

Similar results were obtained for the in-between the performances of the problem spaces of both institutions for the third question that aims to assess the overall quality of the design solution assessed by question 3 (Q3). The 2nd DSS of IUE was assessed 0,7 points higher on an ordinal scale than the 2nd DSS of METU. Likewise, the 3rd DSS of IUE assessed 0,4 points higher than the 3rd DSS of METU.

Thus, by considering the evaluations made by calculating the mean rates of each design expert, it is possible to state that the explicitness of the design briefs correlates with the overall performance of the design solutions.

Although the mean score ratings measured for the design spaces of the two institutions were not significantly different from each other, this correlation becomes clear also in the individual assessments of each design expert as well, as shown in Figure 5.2.

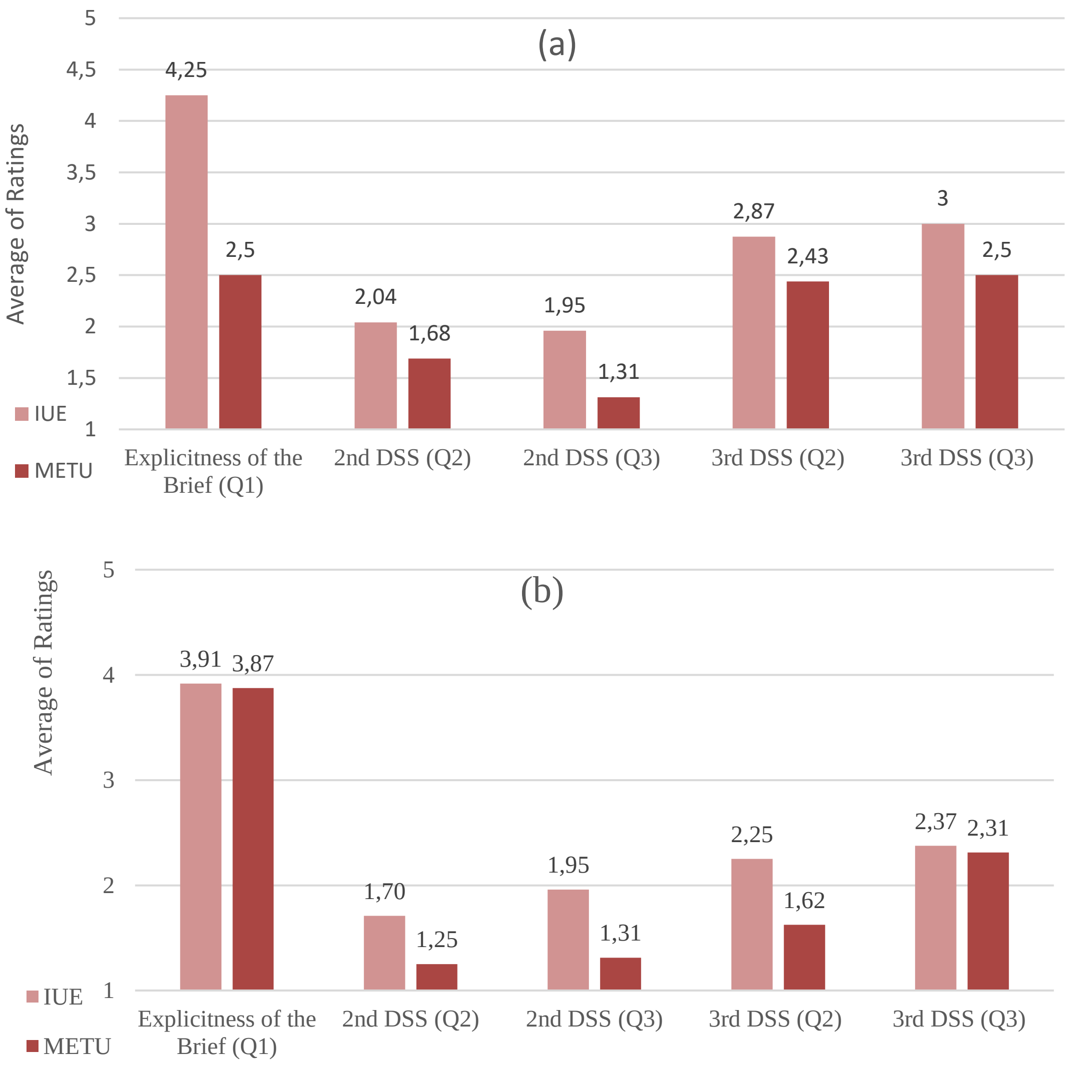


Figure 5.2 : Individual comparison of two design spaces by the design experts rates: (a) Design expert no.1. (b) Design expert no.2. (c) Design expert no.3.

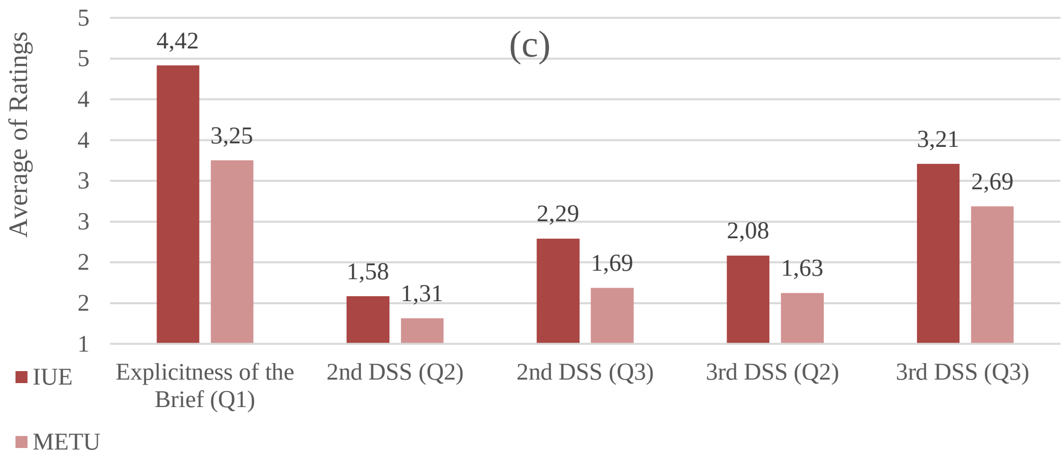


Figure 5.2 (continued) : Individual comparison of two design spaces by the design experts rates: (a) Design expert no.1. (b) Design expert no.2. (c) Design expert no.3.

5.1.2 Impact of the feedback process on the performances of design solution spaces

The overall results demonstrated previously by the tables and graphs that the 3rd DSS performed better than the 2nd DSS in terms of answering Q2 and Q3, regardless of the two-design space analyzed in the scope of the study. In other words, the design solution instances that had generated through the revised text prompts, answer the well-defined design problems better and their overall qualities are higher compared to the solutions generated through only brief guided text-prompt. This situation can be discussed and considered as related to the explicitness of the brief definition, as the feedback processes had highlighted the implicit agenda in the design briefs. Hence the overall performance of the solution spaces of both design spaces regarding the cases of IUE and METU, was increased, as displayed in Figure 5.3.

Comparing the increasement rates of the performances of the design solution spaces under the Q3, it is visible that the overall compositional quality of the design works in the METU design space had improved better in comparison to the IUE cases. This difference between the design spaces can be considered as related to the impact of initial brief definitions. Since the explicitness of the assignment briefs in the problem space of the METU was evaluated less than in the IUE problem space, it can be assumed that the feedback process was more effective on the METU briefs in terms of elucidating the design agendas given implicitly in briefs.

Besides, a difference was noticed between the overall improvement rates of performance of the design solutions under two questions asked in Q2 and Q3. Figure 5.4 displays a line chart that shows the difference in incensement rates by considering the overall rates average of both design spaces in terms of METU and IUE.

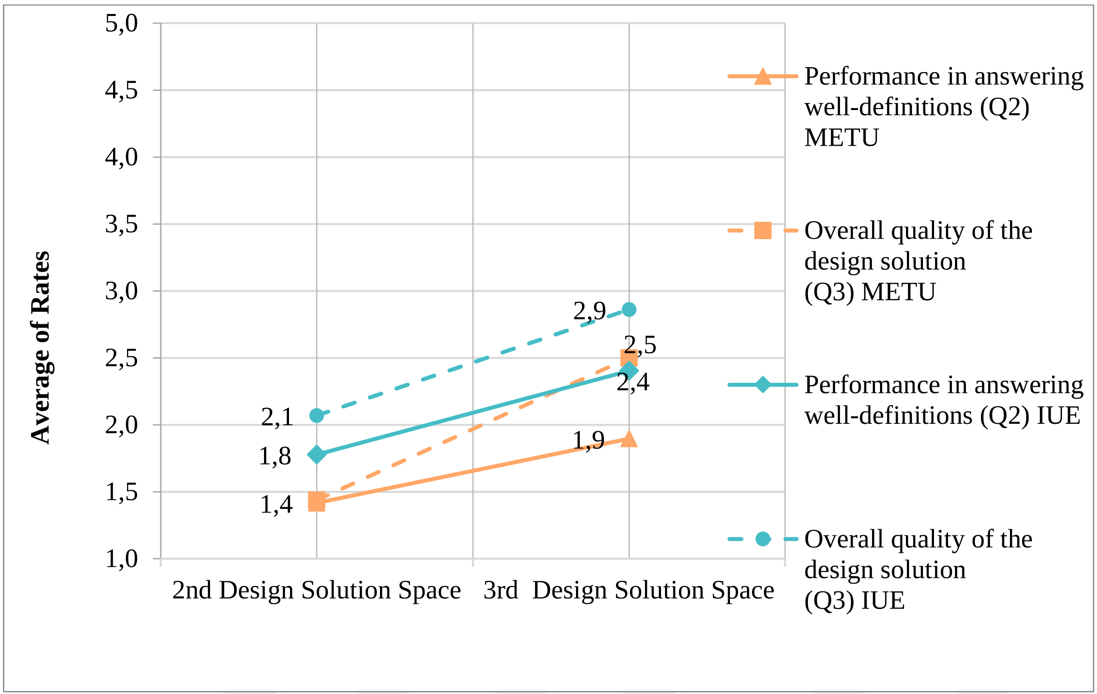


Figure 5.3 : A comparative line graph that displays the increasement in the performances of the analyzed DSSs of METU and IUE under Q2 and Q3.

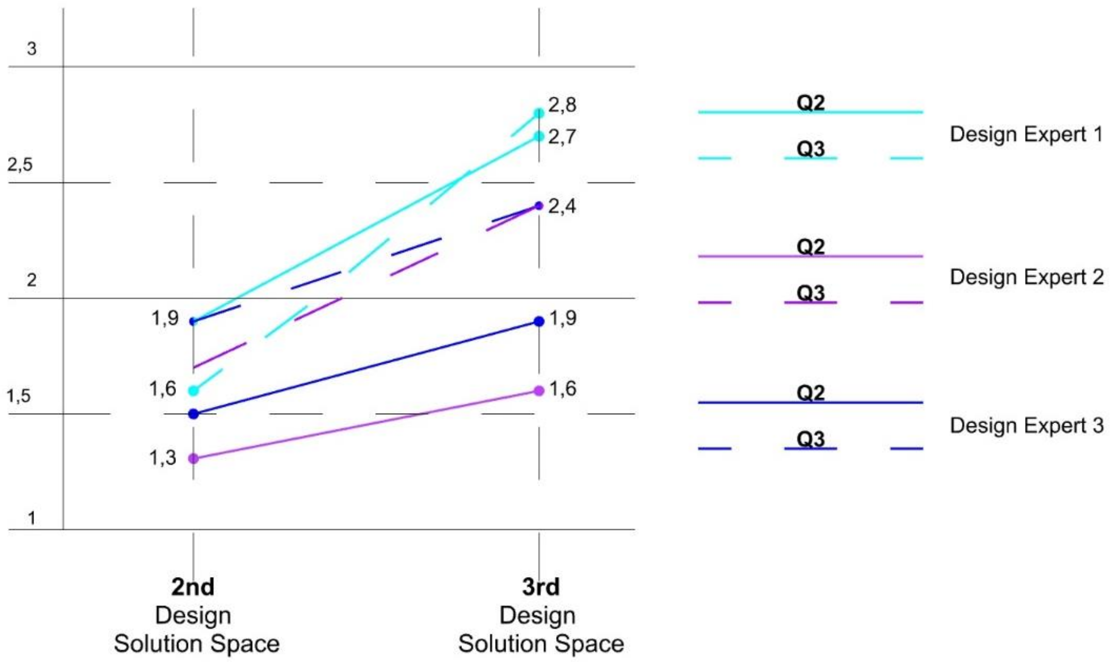


Figure 5.4 : Comparing the increasement rate of the performances of DSS in terms of overall quality (Q3) and well-defined problem-answering capability (Q2).

As the line graph demonstrates, all three-expert ratings answers correlate and indicate that the overall quality of the solutions assessed by Q3 had improved sharper than the performance of answering the well-defined problems, assessed by Q2 (Figure 5.4). That is to say, the performances of DSSs in answering well-defined problems are limited in a certain extent to represent element properties in comparison to the overall quality of the composition. On the other hand, the overall qualities of the design solutions have a greater potential for improvement by implementing a series of feedback layers in the process.

5.2 Evaluation of the Qualitative Data

For the evaluation of the qualitative data, the answers of the three-design expert for three open-ended questions asked during the semi-structured interviews were discussed by the common points raised during the sessions.

5.2.1 Comparing the impact of the problem space on organic and synthetic processes

The first open-ended question was asking the design experts to comment on the relation between the brief definition and the performance of the design solutions. Although the question can be considered as already answered with the quantitative results of the study, the open-ended question was designed to include the experts' insights and experiences of conventional studios, which were valuable in understanding the relationship between the assignment briefs and the performance of the students' design works. Therefore, they were asked to comment also on the relation between the definition way of the assignment briefs and students' design works performance, by considering the solution generation process under the guidance of the same briefs that they observed in the studio. Thus, the synthetic and organic processes were compared, and the significant differences were highlighted.

The first design expert emphasized the importance of explicitness in the design brief, both for students and for the text-to-image AI model. According to Expert 1, an explicit brief is crucial to prevent design works from being disqualified. The expert mentioned the importance of reviewing and revising the brief definitions each semester to address any confusing aspects raised by the students. Even though the instructors of the studio consider the initial brief solid, incorporating feedback from students and refining the brief can further enhance its clarity and effectiveness in guiding student design work.

The second and third design experts agreed with the first expert on the point that a certain degree of explicitness is required in briefs, to guide the students to deliver solutions in the desired format. However, they pointed out that the level of explicitness needs to be consciously constrained to embrace the student's creativity and to encourage them to develop their self-interpretations of the concepts. The concrete definitions that don't embrace any implicit agenda, often guide each student to a single way of solution generation. Hence, all the instances share similar aspects at the end, as if they are variations of a single design work.

Another significant point raised by the first expert was about the difference between the organic and synthetic solution generation processes, in terms of building upon the acquired knowledge. The expert had observed that the text-to-image AI model lacked the ability to derive interpretations of the problems based on previous stages of the process, which would be normally possessed by students with the help of the discussions made in the studio. Therefore, in a conventional studio, the performance of the student generally tends to increase, even the brief statements remain at the same degree of explicitness. However, synthetic solutions did not demonstrate similar performance gains throughout the various stages of the process and only improved as a result of feedback, similar to the traditional studio setting.

5.2.2 Elucidating the ill-defined problems of briefs as a tool in the studio setup

The second and third open-ended questions posed during the sessions aimed at consulting with the design experts regarding the potential of the AI model to clarify ill-defined problems for students. After observing the production processes and performance of the examples generated by the model, all three experts agreed that the current state of the model has limitations and deflections, particularly representing the element properties. However, the capability of the model to generate well-organized compositions through the implicit brief definitions founded very positive. Besides, each expert made their critical reflection from various perspectives on the implementation of the text-to-image AI tool in the basic design studio.

During the feedback and interview sessions, the first design expert frequently stated that, in some cases, the synthetic design solutions were able to visually represent the ill-defined problems better than first-year design students, spesifically in the earlier stages of the assignment sequences. This suggests that, in the beginning phases of the studio, the tool could be implemented to generate solutions and expand the design space of panel discussions, which would benefit the students. However, it is important to carefully select and explain the discussion material from the synthetic design solution space, highlighting their inherent strengths and weaknesses. This is to prevent the students from being guided strictly towards the same solution path or being influenced by the deflections of the solutions instances displayed during the discussion sessions.

The second design expert shared a similar perspective to the first expert and raised an important question about the pedagogical impact of incorporating the AI tool in panel discussions. Based on her extensive experience teaching in first-year design studios for more than 25 years, she noted that students are more motivated and interested in discussion sessions when their work is selected for panel critiques. However, interest tends to decrease among students whose work is not presented. Therefore, the pedagogical effects of displaying AI-generated design solutions in panel discussions need to be further investigated with a case study. Since these solutions have an anonymous quality that is not attributed to a specific student, it may affect student motivation both positively and negatively, depending on how well the students internalize the discussion.

Agreeing with the other experts, design expert 3 expressed a positive evaluation of the hypothetical implementation of the tool to elucidate the ill-defined problems. Besides, the expert highlighted another potential implementation way of the model in the studio, as an alternative assessment for the clarity of the briefs. As observed during the interview sessions, the performance of the generated design solutions was highly correlated with the explicitness of the brief definition Therefore, the instructors of the first-year design studio could make use of the tool as an alternative assessment method for the clarity of the briefs. By prompting the brief as text-prompt, alluding to the AI model as a novice design student, the instructors can identify potential issues in the briefs and improve their clarity to benefit the overall design process.

5.3 Discussion: Synthehic Design Space Generation Process

The results managed to shed light on the main inquiries of the thesis defined in the limited scope study in terms of, evaluating the impact of the design briefs on the design solutions of a first-year studio, and searching for a method to ease the students' comprehension and solution generation processes for the ill-defined design problems.

As shown by the results of the design expert interviews, there is a certain correlation between the explicitness of the design briefs and the overall performance of the solutions generated by an AI model, likewise the student designer's performance in a conventional first-year design studio. Secondly, the quantitative assessment results proved that the overall performance of the solution spaces is able to increase by implementing a feedback process in the generation mechanism. That is to say, the feedback process is essential for both synthetic and organic design solution generation processes to underline the ill-defined design problems and implicit design agendas covered in the briefs. Although the evaluations indicated that in the current state performance of the AI tool is limited in representing well-defined problems, it has the potential to help the students to understand the ill definitions of the problems by generating a myriad of solutions that they can see and learn, as long as the process is supported by expert guidance.

However, it is highly crucial to underline the limitations of the study in terms of the method and applied generic AI model. In order to uncover the full potential of implementing text-to-image AI models as a tool in the first-year design studio to ease the novice designers' understanding of processes of the implicit design problems. Therefore, in this section of the thesis starting from the limitations of the model, the significant points raised during the research process regarding the theoretical background of the basic design education were discussed to speculate on the potential implementation of the text-to-image AI tools in the basic design studio.

5.3.1 Limitations of the generic text-to-image AI-model

Although the assessment results highlighted to main findings according to the main aims of this thesis, they have also indicated that the text-to-image AI tool is not yet sufficient to perform above the average in terms of the questions asked. To identify the potential causes of these deflections, the limitations of the generic AI model used in the scope of the study were discussed in this chapter.

5.3.1.1 Representing element properties

The results of the quantitative assessments demonstrated that the performance of the design solution space is able to increase when the ill-defined design problems in briefs are elucidated through the feedback process. However, the overall results of the performance of all solution spaces were assessed below the average in terms of both Q2 and Q3. However, it is clear from Figure 5.5 that the text-to-image AI model performance of representing the element properties (Q2), as encoded as well-defined problems, is lower than the overall quality of the generated composition (Q3).

As highlighted in both feedback and interview sessions by the experts and observed during the DSS generation process, the text-to-image diffusion model has certain limits for representing the properties of the design elements in terms of number of the elements, size, scale, color, texture and technique. Although the prompt weights of the briefs were increased to overcome this issue during the generation process of the 3rd solution space, the increase of the performance of the DSSs for Q2 remained less than the increase in Q3 (Figure 5.4).

On the contrary, the overall compositional qualities of the design solution spaces were assessed remarkably higher by the experts. Besides, during the quantitative part of the interview sessions, all three-design experts commented similarly that in some of the cases, the compositional qualities of the generated solution could have been rated higher (with almost 5 points corresponding to excellent performance in the ordinal scale). However, since the generated solution did not fulfill the well-defined requirements of the briefs in terms of element properties, and since this situation is often considered a reason for disqualification in a conventional studio, the ratings of Q3 were decreased concerning the ratings of Q2. Table 5.3 demonstrates one of these cases in that each reviewer expressed the same issue mentioned above.

As displayed in the exemplary case with Table 6.1, even though the brief defined the number of the design elements as nine as explicitly as possible, the AI model was not able to employ nine elements in both solution instances. Yet all design experts agreed that it is possible to trace the visual impact of each identified ill-defined problem on both DSS instances, especially in the 3rd one. However, since the element properties also affect the overall quality of the composition, the reviewers' rates for the Q3 also had to decrease.

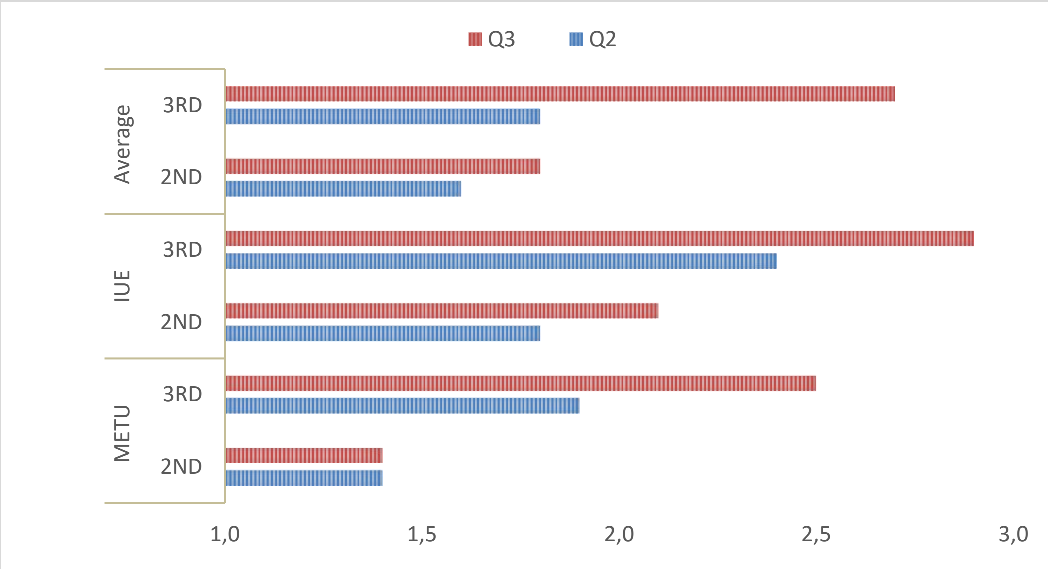
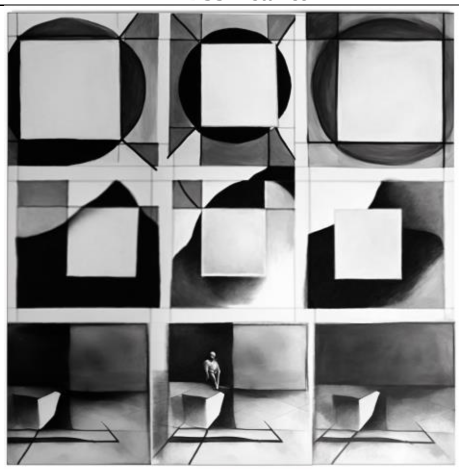
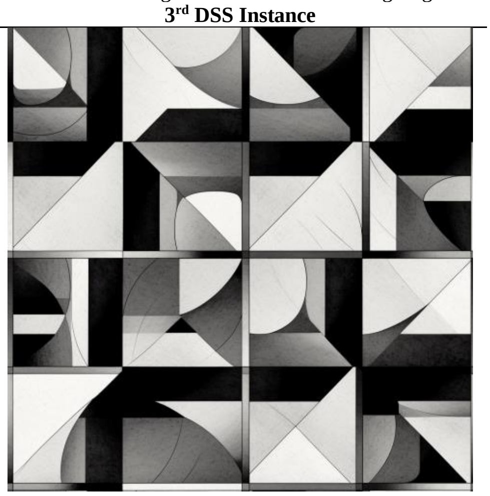


Figure 5.5 : Comparison of the results of the performance of DSSs under Q2 and Q3.

Table 5.3 : Impact of model deflection to represent well-defined problems on the assessment results.

	Brief (METU, 2004-2005, Assignment 4, Stage 3)	
Brief	Make a geometrical study by drawing regulating lines on your composition that you have made in Stage 01. Reproduce this study on a 21.2x21.2 cm white cartridge paper. Work on alternative rendering of chosen areas in between the regulating lines. Produce nine copies, each of which to act as one unit of the coming stage.	
Identifi cations	**Well-Defined Problems** 21.2 x21.2 white cartridge paper visual field **9 copies of the design element**	**Ill-Defined Problems** reproducing the study on new design medium working on alternative renderings elements acting as one unit of the coming stage
DSS Instances	**2nd DSS Instance** 	**3rd DSS Instance** 

Assessment Results

D.E	**Q2**	**Q3**	**Q2**	**Q3**
1	2	4	1	4
2	1	2	1	3
3	1	2	1	4

This deflection in representing element properties can be considered as one of the main limitations of the generic text-to-image diffusion model, due to its context-free database. As explained previously, the information about the sources of the training dataset of the Midjourney model is not accessible to public users. However, the co-founder of the research lab, Holz (2022) stated that they scraped image data from open-source repositories on the internet to build the training dataset, including photographs of real-world objects, animals, humans, buildings, etc.

Assuming that the amount of contextual image data from the design educational setups is not significant in the training dataset compared to the other contexts, the deflection of the model in reflecting the element properties in the context of the basic design studio might be unavoidable by using a generic AI model.

Although in the initial phases of this thesis, collecting contextual data from the student design works to train an open-sourced text-to-image DM (i.e. Stable Diffusion) was considered, the amount of the available archival data of the student design work photographs was insufficient to train the model.

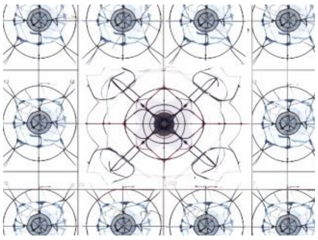
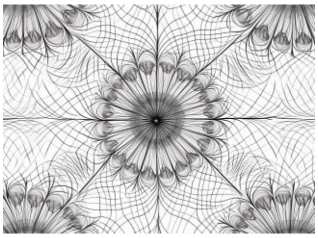
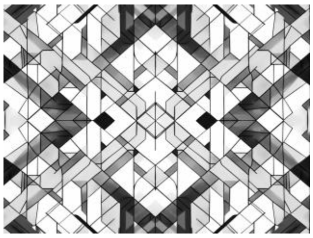
5.3.1.2 Lack of transition

As expressed by the design experts and observed in the generation process, in the current state of the art the text-to-image AI tool is not able to ensure a traceable transition between the stages of the sequential assignment brief definitions.

It was often recorded that the outputs of interrelated stages of the briefs lacked the important characteristics (i.e. element definitions, organizational scheme) of the image prompts (output of the previous stage), and the reference points were not legible enough. This issue had been tried to be solved while generating the 3rd DSS by increasing the prompt weights of the reference images and using the same seed values. Although certain characteristic resemblance in the sequence was obtained in terms of the style of the generated image, the problem often persisted in capturing the reference points of the element or initial unit definitions. Table 5.4 demonstrates the issue from one of the cases.

This deflection of the model can be discussed as the second limitation of the generic diffusion model in terms of not being able to understand the image prompts as the reference point for the next generation. The reason behind this issue might be related to the limited ability of the Midjourney model to utilize the image prompt as visual data since the image prompts enter the generation mechanism of the model as in a translated form of a text prompt

Table 5.4 : The loss of element/initial unit references during the transition (IUE, 2022-2023, Assignment 4, Stage A, B).

Brief	2ND DSS Instance	3rd DSS Instance
Choose one of the 8x8 units. This will be your “unit element” to generate a pattern. Fill an area of 12x16cm (white paper) with your unit element using pencils or/and color pencils.		
Make a full pattern by using the selected 8x8 unit element on an A4-size white visual field (fill all the VF). Produce two copies of A4: (1) shading with regular drawing pencils with 5 different tones (H, HB, B, 2B, 3B) …		

5.3.2 Learning curve

As raised by design expert 1 during the interview session, current versions of the model are unable to construct knowledge upon the obtained knowledge from the previous stages. This issue might be the most crucial limitation of the AI tool compared to the novice designer, in terms of not being able to build a reasoning mechanism. Therefore, the learning curve of the model remains stable, whereas the abilities of the novice designers enhance during the semester with the help of obtained reasoning mechanisms in the studio.

As discussed within the theoretical background, one of the fundamental aims of the basic design studio is teaching the novice designer how to reason. This ability was obtained in the studio by a learning-by-doing paradigm supported by the feedback loops with the studio instructors. However, since the text-to-image AI tool is deprived of inheriting a reasoning mechanism conveyed in the basic design studio, it is not possible for it to build upon the constructed knowledge.

To partially overcome this issue, the feedback mechanism was implemented in the generation procedure of 3rd DSSs. As the results proved that the feedback process was effective to increase the individual performances of the outcomes, likewise the students of a typical basic design studio. However, since the feedback processes only strengthen the qualities defined implicitly or explicitly in the brief definitions within a single brief case, the improvement of the performance of the model during the sequential stages of the task remained limited. In other words, the text-to-image AI model had to start from scratch for each new prompt entered, whereas the students in the basic design studio would improve their performance in generating design solutions and also their abilities to understand the brief definitions. Figure 5.6 exemplifies the learning curve of the AI model with two sequences taken from the assessment results of the 3rd DSS of IUE.

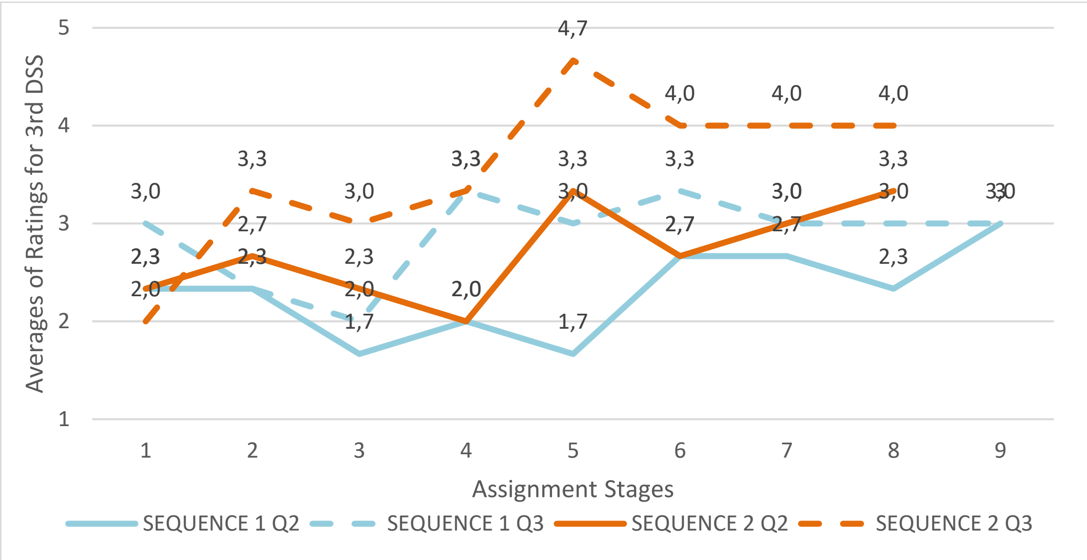


Figure 5.6 : The learning curve of the models during two different assignment sequences (Sequence 1: Assignment 1, Sequence 2: Assignment 4).

Although the answer to this particular problem of implementing a reasoning mechanism into AI relies on the depths of theoretical debates on the vast artificial intelligence theme, there are recent studies that aim to partially overcome this issue by implementing a sequence-to-sequence architecture into the diffusion models (Bakhtiarnia, Zhang, Iosifidis, 2023). Thus, it might be possible in the near future to train a text-to-image DM that learns through the prompt history, likewise, the conversation history trackability implemented in the NLP base Generative Pre-trained Transformer (GPT) models. Thus, the model might be able to develop its understanding of the design problems and improve its solution generation performance by providing an incremental learning curve.

5.3.3 Potentials of implementation of the text-to-image ai model as a tool in the first-year design studio

One of the main inquiries of the thesis was searching for a method to ease the comprehension process of first-year design students to generate solutions under the various definition types of design problems. After evaluating the performance of text-to-image AI models in answering design problems and discussing the current limitations of the model, the potential implementation strategies as a tool for basic design studios were considered. Pedagogical concerns highlighted during the expert interviews were taken into account during these discussions.

5.3.3.1 Expanding the design space of the novice designer

The findings indicated that text-to-image AI model models can generate a myriad of design solutions to a brief in a short period of time, albeit with limitations preventing them from fully addressing the well-defined problems in the briefs in their current state. However, the experts assessed the performance of the model as promising, as it was capable of generating quality compositions under the guidance of expert input to solve the ill-defined problems presented in the briefs. Therefore, novice designers could potentially benefit from the implementation of the tool into the basic design studio as a tool to elucidate abstract, ambiguous concepts stated in the briefs with ill-defined design problems.

One potential implementation strategy of the tool could involve expanding the design space of panel discussions/critiques by the expert selection of synthetic solution instances that address the same problem in various ways. This approach aligns with the collective learning culture often emphasized in the studio through discussions of a variety of student works to address specific points raised by the brief. Through the discussion of synthetic design solutions, students can learn about the different solutions offered by AI.

Moreover, the implementation of the tool may contribute to panel discussions by increasing the pace of the student reasoning process. The time required to create a design solution varies from hours to weeks depending on the assignment or studio work. Generally, panel discussions are held after students complete their submissions, leaving students uncertain whether their solution aligns with the brief's requirements. In some cases, the design brief may contain ill-defined problems that are beyond the comprehension level of novice designers, resulting in no solution being generated. If the students are guided to generate synthetic design solution instances based on the brief statement, panel discussions could occur immediately after the assignment is given. This approach could enhance student performance by helping students understand the requirements of the design problems and the points they need to avoid before delivering design solutions through their interpretation of the briefs.

In other words, the implementation might contribute to the students' reasoning process alluding to the “see-move-see" pattern defined by Schön (1992). This entails students first “seeing” the synthetic solutions, then “moving” to generate their own solutions with the interpretations obtained from the seeing process, and finally see how their solutions compare and contrast to those generated by the AI model.

5.3.3.2 Alternative assessment tool for assignment briefs

As raised during the interview session with the third expert, the model could also have another potential besides enlarging the design space of novice students. It could also serve for the studio instructors as a tool for fine-tuning the degree of the ambiguities inherent in the briefs.

As highlighted repeatedly by both experts, it is highly crucial to define the brief explicitly for the students to understand, but also implicit enough not to guide them towards the same solution path.

Even though the synthetic solutions perform better under the explicit directions in terms of the results obtained in the limited scope of the study, this doesn’t necessarily mean that novice designers perform the same way. However, during the initial phases of the first-year design studio, the novice designers can be compared to the current limited state of the AI tool, as neither of them has developed contextual knowledge or reasoning mechanisms.

Hence, utilizing the text-to-image DM as a tool to evaluate the clarity of early-stage briefs might be beneficial, in terms of prompting the brief as the text prompt and analyzing the potentials and deflections of the synthetic solution, and revising the brief if needed. In a way that treats the AI model as a novice designer and adjusts the level of explicitness of the brief according to the performance of generated synthetic solutions.

6. CONCLUSION

The main inquiry of the thesis was exploring the impact of the problem space on the design space of the basic design studio to search for a method to help students better understand ill-defined design problems. The concept of design space was assumed as promising medium to reconstruct and reinterpret these problems, in order to generate solutions. As it was defined as the combination of problem and solution sub-spaces bonded with the design process (Krishnamurti,2006). In that scope, the design space concept was reframed in the context of the basic design studio setup: as the assignment briefs constitute the problem space, whereas the design solution space involved the design process outputs that aim to answer these briefs.

As the aim was to explore the impact of various definitions of the design problems, two sets of the assignment brief data from different institutions were analyzed retrospectively to identify the statements of ill- and well-defined design problems. Secondly, to explore the impacts of these problem spaces visually, synthetic design solution spaces were generated by using a text-to-image diffusion model by translating assignment briefs into text prompts and implementing a feedback process. These solution spaces varied in terms of generation mechanisms. The first and second solution spaces were generated through the solo guidance of the assignment briefs, and the semantic structures of the briefs were not altered in the text prompts. Whereas, the third solution instances were generated through the revised set of text prompts, which underlines the implicit definitions stated in briefs as keywords with the help of feedback sessions held. Therefore, to evaluate the impact of the problem definitions the solution instances of the two different solution mechanisms were assessed by the design expert interviews quantitatively and qualitatively.

The interviews consisted of two parts; quantitative and qualitative assessments. In the quantitative part design experts were asked to rate the explicitness of the assignment briefs and the performances of 2nd and 3rd DSSs in terms of answering the well-defined problems and overall quality of the design work. The results were evaluated to elucidate the impact of the problem space on the design space of the basic design studio, by comparing the obtained data in different scales and contexts. Whereas the three open-ended questions posed to the design experts in the qualitative part of the assessment were designed to retrieve the design experts' implications of the process to search for the potential contributions of implementing the text-to-image AI tools into the basic design studio.

Overall results indicated that there is an apparent correlation between the explicitness of the brief definitions and the overall performances of all synthetic solution spaces. Besides the feedback sessions improved the performance of all design solution spaces. Especially the performance of generating quality composition under the ill-defined design problems was increased more than the well-defined problem-answering capacity of the solutions. This finding was discussed as an impact of the ill-defined design problem statements of the briefs that became clearer through the feedback sessions. Whereas it also underlined the AI model's limited ability to represent well-defined problems in terms of the properties of design elements, due to the limitations of the generic diffusion model used in the current state of the art in terms of lack of context-based training data and reasoning mechanism. Albeit the limitations of the generic diffusion model for representing the well-defined problems in the current state, the design experts commented repeatedly that, the ability to represent the ill-defined design problems is promising. Thus, the method might have the potential to be implemented in a basic design studio as a tool for elucidating novice designers' understandings of ill-defined problems.

Based on the design experts' insights gathered during the interviews, potential implementation strategies for the AI model as a tool in the basic design studio were discussed. It was speculated that despite the limitations of the current state-of-the-art generic AI tool, implementing the tool could be beneficial for novice designers in terms of clarifying ill-defined design problems stated in the assignment briefs and helping them develop problem-solving abilities through the reasoning mechanism obtained in the basic design studio. The students can learn by seeing a myriad of solutions to the same problem, hence they can move on to their organic solution generation processes from these experiences and interpretations gained by the exposure of expanded design space. Besides, the method can also offer a tool for the instructors as an alternative assessment for the assignment briefs, which would provide a chance for instructors to fine-tune the briefs for the novice designers' comprehension levels beforehand.

In future studies, the limitations of the study related to the use of generic AI model can be solved, by developing an open-source text-to-image diffusion model with the contextual data collected from the educational setups of the basic design studio. Besides it might be possible to implement a feedback mechanism into the model's computational architecture to the model as reinforcement learning to improve the performance of the generated solutions, as alluding to the instructor critique sessions in the basic design studio.

REFERENCES

Acar, A. (2003). *The construction and execution of beginning design education at the Middle East Technical University Department of Architecture between 1956-2000* (Unpublished Master's thesis). Middle East Technical University.

Akcay Kavakoglu, A., Almac, B., Eser, B., & Alacam, S. (2022). AI driven creativity in early design education – A pedagogical approach in the age of industry 5.0. In *Proceedings of the 40th International Conference on Education and Research in Computer Aided Architectural Design in Europe*, Belgium.

Akin, Ö. (1984). An exploration of the design process. In Cross, N. (Ed.), *Developments in Design Methodology*. Wiley & Sons.

Akin, Ö. (2001). “Simon Says”: Design is representation. Arredamento Mimarlik. Pittsburgh, PA.

Akin, Ö. (2006). The whittled design space. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM*, *20*(2), 83–88. doi:10.1017/S0890060406060069

Arum, D.P., Kusmayadi, T.A., & Pramudya, I. (2018). Students’ difficulties in probabilistic problem-solving. *Journal of Physics: Conference Series*, *983*.

As, I., Pal, S., & Basu, P. (2018). Artificial intelligence in architecture: Generating conceptual design via deep learning. International Journal of Architectural Computing. *16*(4). doi:10.1177/1478077118800982

Aslankan, A. (2023). Personal Interview. 4 April and 25 April, İzmir.

Ajaay. (2023, April 7). Does Midjourney use Stable Diffusion? *Nerds Chalk Blog*. Retrived May 19, 2023, from https://nerdschalk.com/does-midjourney-use-stable-diffusion/

Aytaç-Dural, T. (2002). *Theatre architecture education: Theatre as a paradigm for introductory architectural design education*. METU Faculty of Architecture Press.

Aytaç-Dural, T. (2023). Personal Interview. 14 April and 24 April, İzmir.

Bayırlı, Ü. (2015). *Evaluation of basic design education at METU department of industrial design* (Unpublished master’s thesis). Middle East Technical University.

Besgen, A., Kuloglu, N., & Fathalizadehalemdari, S. (2015). Teaching/learning strategies through art: Art and basic design education. *Procedia - Social* *and Behavioral Sciences, 182,* 428-432. doi:10.1016/j.sbspro.2015.04.813

Borji, A. (2022). Generated faces in the wild: Quantitative comparison of stable diffusion, midjourney and dall-e 2. *ArXiv*. https://arxiv.org/abs/2210.00586

Boucharenc, C. G. (2006). Research on basic design education: An international survey. *International Journal of Technology and Design Education*, *16*(1), 1–30. doi:10.1007/s10798-005-2110-8

Buchanan, R. (1992). Wicked Problems in Design Thinking. *Design Issues, 8*(2), 5–21. doi:10.2307/1511637

Brock, A., Donahue, J., & Simonyan, K. (2018). Large scale GAN training for high fidelity natural image synthesis. *ArXiv*. /abs/1809.11096

Cao, H., Tan, C., Gao, Z., Chen, G., Heng, P., & Li, S. Z. (2022). A survey on generative diffusion models. *ArXiv*. /abs/2209.02646

Casakin, H. (2002) Well-defined versus ill-defined design problem solving: The use of visual analogy. In Durling, D. and Shackleton, J. (eds.*), Common Ground - DRS International Conference 2002*, 5-7 September, London, United Kingdom

Chase, S.C. (2003). Revisiting the use of generative design tools in the early stages of design education. In *Proceedings of the 21st International Conference on Education and Research in Computer Aided Architectural Design in Europe*. Graz, Austria.

Choi, Y., Choi, M., Kim, M.S., Ha, J., Kim, S., & Choo, J. (2017). StarGAN: unified generative adversarial networks for multi-domain image-to-image translation. *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*.

Coyne, R. (2005). Wicked problems revisited. *Design Studies*, *26*(1), 5-17. doi: 10.1016/j.destud.2004.06.005

Cross, N. (1982). Designerly ways of knowing. *Design Studies*, *3*(4), 221-227. doi:10.1016/0142-694X(82)90040-0

Cross, N. (1993). Science and design methodology: A review. *Research in Engineering Design, 5*(2). doi:10.1007/BF02032575

Cross, N. (2004). Expertise in design: An overview. *Design Studies, 25*(5), 427–441.

Cross N. (2013). *Design thinking : understanding how designers think and work*. Bloomsbury.

Çakmakli, A. B., Gursel Dino, I., Komez Daglioglu, E., Pinar, E., & Yoncacı Arslan, P. (2022). The diagonal axis from verb to void: Interdisciplinarity in basic design studio education. Archnet-IJAR: *International Journal of Architectural Research*. doi:10.1108/arch-12-2021-0337

Demirbaş, O. O., & Demirkan, H. (2003). Focus on architectural design process through learning styles. *Design Studies*, *24*(5), 437–456. doi:10.1016/S0142-694X(03)00013-9

Dennet C. Daniel. (1995). *Darwin's dangerous idea: evolution and the meanings of life*. Simon & Schuster.

Dewey, J. (1916). *Democracy and Education*. New York: Free Press.

Dhariwal, P., & Nichol, A. (2021). Diffusion models beat GANs on image synthesis. *ArXiv*. /abs/2105.05233

Doğu, T. (2023). Personal Interview. 31 March and 1 May. İzmir.

Dorst, K. (2004). On the problem of design problems - problem solving and design expertise. *Journal of Design Research*, *4*(2), 0. https://doi.org/10.1504/jdr.2004.009841

Dorst, K. (2005). Studying Design Problems. In H. Achten, K. Dorst, P. J. Stappers, & B. de Vries (Eds.), *Design Research in the Netherlands 2005 – Proceedings*. Eindhoven: Technische Universiteit Eindhoven, Faculteit Bouwkunde.

Dorst, K. (2015). Frame creation and design in the expanded field. *She Ji*, *1*(1), 22–33. doi:10.1016/j.sheji.2015.07.003

Dorst, K., & Cross, N. (2001). Creativity in the design process: Co-evolution of problem–solution. *Design Studies*, *22*(5), 425–437. doi:10.1016/s0142-694x(01)00009-6

Dove, G., Hansen, N. B., & Halskov, K. (2016). An argument for design space reflection. *ACM International Conference Proceeding Series*, 23-27-October-2016. doi:10.1145/2971485.2971528

Economou, A. (2001). Shape grammars in architectural design studio. *Proceedings of the 2000 ACSA Technology Conference: The Intersection of Design and Technology*, MIT, Cambridge, USA

Erhan, H., Wang, I. Y., & Shireen, N. (2017). Harnessing design space: A similarity-based exploration method for generative design. *International Journal of Architectural Computing*. *12*. 217-236. doi:10.1260/1478-0771.13.2.217.

Gaver, W. W., Beaver, J., & Benford, S. (2003). Ambiguity as a resource for design. *Conference on Human Factors in Computing Systems - Proceedings*. doi:10.1145/642611.642653

Gero, J. S., & Kumar, B. (1993). Expanding design spaces through new design variables. *Design Studies*, *14*(2), 210–221. doi:10.1016/0142-694X(93)80048-H

Ghom, P.V., & George, A. (2020). Pedagogy for basic design studio in learning architecture: A qualitative exploration. *Journal of Education and Practice*, *11*, 169-172.

Goel, V., & Pirolli, P. (1992). The structure of design problem spaces. *Cognitive Science*, *16*(3), 395-429. doi:10.1016/0364-0213(92)90038-V

Goldschmidt, G. (1997). Capturing indeterminism: Representation in the design problem space. *Design Studies*, *18*(4), 441-455. doi:10.1016/S0142-694X(97)00011-2

Goldschmidt, G. (2006). Quo Vadis, design space explorer? *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM*, *20*(2), 105–111. doi:10.1017/S0890060406060094

Goldschmidt, G. (2015). The pagoda design space: extending the scope of design. In Taura, T. (Ed.), Principia Designae — *Pre-Design, Design, and Post-Design* Springer, Tokyo. doi:10.1007/978-4-431-54403-6_5

Goldschmidt, G., & Weil, M. (1998). Contents and structure in design reasoning. *Design Issues*, *14*(3), 85–100. doi:10.2307/1511899

Goncher, A.M. (2009). Creativity under constraints: the affect of problem space on design learning among engineering students. *Proceedings of the seventh ACM conference on Creativity & Cognition*.

Goodfellow, I. J., Mirza, M., Xu, B., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial networks. *ArXiv*. /abs/1406.2661

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Green, A. (2023, March 8). AI-imager Midjourney v5 stuns with photorealistic images—and 5-fingered hands. *Ars Technica*. Retrieved 20 May, 23 from https://arstechnica.com/information-technology/2023/03/ai-imager-midjourney-v5-stuns-with-photorealistic-images-and-5-fingered-hands/

Guo, M. H., Xu, T. X., Liu, J. J., et al. (2022). Attention mechanisms in computer vision: A survey. *Computational Visual Media*, *8*, 331-368. doi:10.1007/s41095-022-0271-y

Halskov, K., & Lundqvist, C. (2021). Filtering and informing the design space: Towards design-space thinking. *ACM Transactions on Computer-Human Interaction, 28*(1). doi:10.1145/3434462

Halskov, K., Dove, G., & Fischel, A. (2021). Constructing a design space from a collection of design examples. *She Ji: The Journal of Design, Economics, and Innovation*, *7*(3), 462–484. doi:10.1016/j.sheji.2021.07.001

Han, T., Lu, Y., Zhu, S.-C., & Wu, Y. N. (2017). Alternating back-propagation for Generator Network. *Proceedings of the AAAI Conference on Artificial Intelligence*, *31*(1). doi:10.1609/aaai.v31i1.10902

Hernández-Leo, D., Agostinho, S., Beardsley, M., Bennett, S., & Lockyer, L. (2017). Helping teachers to think about their design problem: a pilot study to stimulate design thinking. In *EDULEARN17 Proceedings* .

Ho, J., Jain, A., & Abbeel, P. (2020). Denoising diffusion probabilistic models. *ArXiv*. /abs/2006.11239

Holz, D. (2022, September 16). Midjourney founder david holz on the impact of ai on art, imagination and the creative economy. *Forbes*. Retrieved 15 March,23 from: https://www.forbes.com/sites/robsalkowitz/2022/09/16/midjourney-founder-david-holz-on-the-impact-of-ai-on-art-imagination-and-the-creative-economy/?sh=7a27ccab2d2b.

Horst W. J. Rittel, & Webber, M. M. (1973). Dilemmas in a general theory of Planning. *Policy Sciences*, *4*(2), 155–169. http://www.jstor.org/stable/4531523

Huang, X., Liu, M., Belongie, S., & Kautz, J. (2018). Multimodal Unsupervised Image-to-Image Translation. *ArXiv*. /abs/1804.04732

Isola, P., Zhu, J., Zhou, T., & Efros, A. A. (2016). Image-to-Image translation with conditional adversarial networks. *ArXiv*. /abs/1611.07004

Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, & Surya Ganguli (2015). Deep unsupervised learning using nonequilibrium thermodynamics. *CoRR*, abs/1503.03585.

Kan, J. W. T., & Gero, J. S. (2018). Characterizing innovative processes in design spaces through measuring the information entropy of empirical data from protocol studies. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM*, *32*(1), 32–43. doi:10.1017/S0890060416000548

Kelly, N., & Gero, J. S. (2021). Design thinking and computational thinking: a dual process model for addressing design problems. *Design Science*, *7*. doi:10.1017/dsj.2021.7

Khean, N., Fabbri, A., & Haeusler, M. H. (2018). Learning machine learning as an architect, how to? *In Proceedings of eCAADe 2018: Computing for a better tomorrow*. doi:10.52842/conf.ecaade.2018.1.095.

King, M. (2023, February 10). Midjourney vs Stable Diffusion vs Dall-E: the battle royale of ai image models — comparison test with prompts. *Medium*. Retrieved May 19, 2023, from https://medium.com/@neonforge/midjourney-vs-stable-diffusion-vs-dall-e-the-battle-royale-of-ai-image-models-comparison-test-ef50f6b4cbc8

Knight, T. (1999). Applications in architectural design and education and practice. *Report for the NSF/MIT Workshop on Shape Computation*, Cambridge, Mass., 25-26 April.

Kocadere, S.A., & Ozgen, D. (2012). Assessment of basic design course in terms of constructivist learning theory. *Procedia - Social and Behavioral Sciences*, *51*, 115-119.

Krıshnamurtı, R. (2006). Explicit design space? *AI EDAM*, *20*(2), 95-103. doi:10.1017/S0890060406060082

Lindenmayer, A. (1968). Mathematical models for cellular interactions in development II. Simple and branching filaments with two-sided inputs. *Journal of Theoretical Biology*, *18*(3), 300-315. doi:10.1016/0022-5193(68)90080-5

Liu, M., & Tuzel, O. (2016). Coupled Generative Adversarial Networks. *ArXiv*. /abs/1606.07536

Lloyd, P., & Scott, P. (1994). Discovering the design problem. *Design Studies*, *15*(2), 125-140. doi:10.1016/0142-694X(94)90020-5

Maedche, A., Gregor, S.D., Morana, S., & Feine, J. (2019). Conceptualization of the problem space in design science research. *International Conference on Design Science Research in Information Systems and Technology***.**

Mei, H., Ma, Y., Wei, Y., & Chen, W. (2018). The design space of construction tools for information visualization: A survey. *Journal of Visual Languages & Computing*, *44*, 120–132. doi:10.1016/j.jvlc.2017.10.001

Merzmensch. (2023, May 4). Midjourney evolution V1–5.1. *Medium*. Retrieved May 11, 2023, from: https://medium.com/merzazine/midjourney-evolution-v1-5-1-f18632600bf3

Midjourney (2023). *Midjourney documentation*. Retrieved March 24, 2023, from: https://docs.midjourney.com/docs/models

Murray, J. K., Studer, J. A., Daly, S. R., McKilligan, S., & Seifert, C. M. (2019). Design by taking perspectives: How engineers explore problems. *Journal of Engineering Education*, *108*(2), 248-275. doi:10.1002/jee.20263

Neuroflash. (2023, March 8). Understanding stable diffusion: Advantages and limitations. *Neuroflash Blog*. Retrieved May 19, 2023, from https://neuroflash.com/blog/understanding-stable-diffusion-advantages-and-limitations/

Newell, A., & Simon, H. A. (1972). *Human Problem Solving*. Englewood Cliffs, NJ: Prentice-Hall.

OpenAI. (2023). *DALL·E 2.* Retrieved 11 January 2023 from https://dallery.gallery/the-dalle-2-prompt-book/.

Özdil, U., Arslan, B., Tasar, D.E., Polat, G., & Ozan, S. (2021). Ad text classification with transformer-based natural language processing methods. *ArXiv*, abs/2106.10899.

Özkar, M. (2005). Lesson 1 in design computing does not have to be with computers. *Proceedings of the 23rd International Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe).* doi: 10.52842/conf.ecaade.2005.311

Özkar, M. (2007). Learning by doing in the age of design computation. In: Dong, A., Moere, A.V., Gero, J.S. (eds) *Computer-Aided Architectural Design Futures (CAADFutures)* 2007. Springer, Dordrecht. doi:10.1007/978-1-4020-6528-6_8

Park, T., Liu, M.-Y., Wang, T.-C., & Zhu, J.-Y. (2019). Semantic image synthesis with spatially adaptive normalization. *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR*). doi:10.1109/CVPR.2019.00244

Perisic, M. M., Martinec, T., Storga, M., & Gero, J. S. (2019). A computational study of the effect of experience on problem/solution space exploration in teams. *Proceedings of the International Conference on Engineering Design, ICED*, 2019-August 11–20. doi:10.1017/dsi.2019.4

Perisic, M. M., Štorga, M., & Gero, J. S. (2021). Computational study on design space expansion during teamwork. *Proceedings of the Design Society*. doi:10.1017/pds.2021.69

Ploennigs, J., & Berger, M. (2022). AI art in architecture. *ArXiv*. doi:10.48550/ARXIV.2212.09399

Purao, S., Bush, A.A., & Rossi, M. (2001). Problem and design spaces during object-oriented design: an exploratory study. *Proceedings of the 34th Annual Hawaii International Conference on System Sciences*

Radford, A. (2004). *English Syntax: An Introduction*. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511841675

Reed, S. K. (2015). The structure of ill-structured (and well-structured) problems revisited. *Educational Psychology Review*, *28*(4), 691–716. doi:10.1007/s10648-015-9343-1

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2021). High-resolution image synthesis with latent diffusion models. *ArXiv*. /abs/2112.10752

Salimans, T., Goodfellow, I.J., Zaremba, W., Cheung, V., Radford, A., & Chen, X. (2016). Improved techniques for training GANs. *ArXiv*, abs/1606.03498.

Saranlı, T. (1998). başlangıçtan bugüne temel tasarım. In N. Teymur & T. Aytaç Dural (Eds.), *Temel Tasarım / Temel Eğitim*. ODTÜ Mimarlık Fakültesi Yayınları.

Sciannamè, M. (2022). Introducing ML in design education preliminary experiments. In C. Stephanidis, M. Antona, & S. Ntoa (Eds.), *HCI International 2022 Posters. HCII 2022. Communications in Computer and Information Science*, vol 1580. Springer, Cham. doi: 10.1007/978-3-031-06417-3_60.

Schön D. A. (1985). *The design studio, an exploration of its traditions & potential*. London: RIBA publications Limited.

Schön, D. A. (1987). *Educating the reflective practitioner: Toward a new design for teaching and learning in the professions*. Jossey-Bass.

Schuhmann, C., Beaumont, R., Vencu, R., Gordon, C., Wightman, R., Cherti, M., Coombes, T., Katta, A., Mullis, C., Wortsman, M., Schramowski, P., Kundurthy, S., Crowson, K., Schmidt, L., Kaczmarczyk, R., & Jitsev, J. (2022). LAION-5B: An open large-scale dataset for training next generation image-text models. *ArXiv*. /abs/2210.08402

Shaw, M. (2012). The role of design spaces. *IEEE Software*, *29*(1), 46–50.

Simon, H.A. (2019). *The sciences of the artificial*. Ed. John E Laird. 3rd ed. Cambridge, MA: The MIT Press.

Simon, H.A (1975). The functional equivalence of problem-solving skills. *Cognitive Psychology, 7*.

Simon, H. A. (1957). *Models of man: social and rational*. New York: John Wiley and Sons.

Sky, S. (2022, October 5). Evolution of Midjourney. *Medium*. Retrieved 4 Aprial,2023 from https://medium.com/mlearning-ai/evolution-of-midjourney-bd741564e218.

Sorguç, A., Kruşa Yemişçioğlu, M., & Yetkin, O. (2022). Demystifying machine learning for architecture students. Eskişehir Technical University *Journal of Science and Technology A - Applied Sciences and Engineering, 23,* 60-67.

Stability AI (2023). Dream studio: basics of prompt engineering. Retrieved 6 May,2023 from: https://beta.dreamstudio.ai/prompt-guide

Sternberg, R. J., & Frensch, P. A. (Eds.). (1991). *Complex problem solving: Principles and mechanisms*. Lawrence Erlbaum Associates, Inc.

Stiny, G. (2015). The critic as artist: oscar wilde's prolegomena to shape grammars. *Nexus Network Journal*, *17*(3), 723–758. doi:10.1007/s00004-015-0274-4

Stiny, G. & Gips, J. (1972). Shape grammars and the generative specification of painting and sculpture. *In Information Processing 71*, 1460–1465. North-Holland Publishing Company.

Taneri, B. (2021). *An investigation into architecture students' creative performance while using associative and rule-based reasoning strategies: exploring a dual process approach in design education*. (Doctorate Dissertation). İzmir Institute of Technology, Architecture. https://hdl.handle.net/11147/12042

Tong, H., Ülken, G., Türel, A., Şenkal, H., Yagci Ergun, S. F., Güzelci, O., & Alaçam, S. (2023). An attempt to integrate AI-based techniques into first year design representation course. *Paper presented at Cumulus Antwerp 2023 - Connectivity and Creativity in times of Conflict*, Antwerp.

Touvron, H., Cord, M., Douze, M., Massa, F., Sablayrolles, A., & J'egou, H. (2020). Training data-efficient image transformers & distillation through attention. *International Conference on Machine Learning*.

van Amstel, F. M., Hartmann, T., van der Voort, M. C., & Dewulf, G. P. (2016). The social production of design space. *Design Studies*, *46*, 199-225. doi:10.1016/j.destud.2016.06.002

van Dooren, E. (2020). Making the design process in design education explicit: two exploratory case studies. *Design and Technology Education: An International Journal.*

van Dooren, E., Boshuizen, E., van Merriënboer, J., Asselbergs, T., & van Dorst, M. (2014). Making explicit in design education: Generic elements in the design process. *International Journal of Technology and Design Education*, *24*(1), 53–71. doi:10.1007/s10798-013-9246-8

van Langen, P. H. G., & Brazier, F. M. T. (2006). Design space exploration revisited. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM*, *20*(2), 113–119. doi: 10.1017/S0890060406060100

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. *ArXiv*. /abs/1706.03762

Vincent, J. (2023, February 6). Getty Images sues AI art generator Stable Diffusion in the US for copyright infringement. *The Verge*. Retrieved May 19, 2023, from https://www.theverge.com/2023/2/6/23587393/ai-art-copyright-lawsuit-getty-images-stable-diffusion

Wang, L., Chen, W., Yang, W., Bi, F., & Yu, F. (2020). A state-of-the-art review on image synthesis with generative adversarial networks. *IEEE Access*, *8*, 63514-63537.

Wang, L., Janssen, P., & Ji, G. (2019). Reshaping design search spaces for efficient computational design optimization in architecture. *International Conference on Innovative Computing and Cloud Computing*.

Weiss, E. A., Maheswaranathan, N., & Ganguli, S. (2015). Deep unsupervised learning using nonequilibrium thermodynamics. *ArXiv*. /abs/1503.03585

Weng L. (2021, July 11). What are diffusion models? *GitHub page*. Retrieved September 25, 2023, from: https://lilianweng.github.io/posts/2021-07-11-diffusion-models/.

Westerlund, B. (2005). Design space conceptual tool – grasping the design process. In Binder, T., & Redström, J. (Eds.), *Nordes 2005: In the making*, 29-31 May, Royal Danish Academy of Fine Arts, Copenhagen, Denmark.

Woodbury, R. F., & Burrow, A. L. (2006). Whither design space? *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM*, *20*(2), 63–82. doi:10.1017/S0890060406060057

Yang, L., Zhang, Z., Song, Y., Hong, S., Xu, R., Zhao, Y., Shao, Y., Zhang, W., Cui, B., & Yang, M.H. (2022). Diffusion models: a comprehensive survey of methods and applications.*Arxiv*.

Yoon, W. C. (2001). Identifying, organising and exploring problem space for interaction design. *IFAC Proceedings Volumes*, *34*(16), 69-74. doi:10.1016/S1474-6670(17)41503-5

Zbinden, R. (2022). Implementing and experimenting with diffusion models for text-to-image generation. *ArXiv*. /abs/2209.10948

Zhu, J.-Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In 2017 *IEEE International Conference on Computer Vision (ICCV)*, Venice, Italy. doi:10.1109/ICCV.2017.24

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- **Çiçek S.,** Turhan G.D., Özkar M. 2023: Reconsidering Design Pedagogy through Diffusion Models. *41st Education and Research in Computer Aided Architectural Design in Europe (eCAADe) Conference.* Graz, Austria: University of Technology (TU Graz) *(In press)*
- **Çiçek, S.,** & Özkar, M. 2023: Elucidating the Design Space of Basic Design Studio: Synthetic Solution Space Generation by a Diffusion Model. *In _ International Graduate Research Symposium 2023 (IGRS'23)*, Istanbul Technical University (ITU), Turkey. *(In press)*

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Çiçek, S**., Turhan, G. D., & Taşer, A. 2023: Deterioration of pre-war and rehabilitation of post-war urbanscapes using generative adversarial networks. *International Journal of Architectural Computing*. https://doi.org/10.1177_14780771231181237
- Başarır L., **Çiçek S**., Koç M. 2023: Demystifying the Patterns of Local Knowledge. *41st Education and Research in Computer Aided Architectural Design in Europe (eCAADe) Conference*. Graz, Austria: University of Technology (TU Graz) (In press)

- Turhan G.D, **Çiçek S**., Özbengi Uslu F. 2023: Bio-base material computation and digital fabrication for bacterial cellulose based biofabric. *41st Education and Research in Computer Aided Architectural Design in Europe (eCAADe) Conference*. Graz, Austria: University of Technology (TU Graz) (In press)
- **Çicek, S**., & Turhan, G. D. 2022: Computational generation of a spatial layout through syntactical evaluation and multi-objective evolutionary optimization. *International Journal of Architectural Computing*, 20(3), 610-629. DOI: 10.1177/14780771221120576.
- **Çiçek, S**., Koç, M., Körükçü , B. 2022: Urban map generation in artist's style using generative adversarial networks (GAN). In *ASCAAD 2022: Hybrid Spaces of The Metaverse* (pp. 286–305). Beirut, Lebanon; Beirut Arab University.
- Turhan, G. D., **Çiçek, S**. 2022: A framework for creating a hybrid experience for NFT artworks through 3d printing. In *ASCAAD 2022: Hybrid Spaces of The Metaverse* (pp. 111–120). Beirut, Lebanon; Beirut Arab University.
- **Çiçek, S.** 2022: Türk Evi Biçim Gramerleri: Mekân Sözdizimi ve Evrimsel Algoritma ile Alternatif Plan Şeması Üretimi. In *MSTAS: Mimarlıkta Sayısal Tasarım Ulusal Sempozyumu XVI: Sayısal ekosistemler ve mimarlık* . Eskişehir; Eskişehir Teknik Üniversitesi.
- **Çiçek, S.** 2021: Kamusal Mekânların Covid-19 Pandemisi'ne Karşı Dayanıklılığını Değerlendirme Modeli. *Journal of Computational Design*, 2 (1), 313-334.