Düzce University Journal of Science and Technology
Düzce Üniversitesi Bilim ve Teknoloji Dergisi

14 (3), 2026, 666-679.
https://doi.org/10.29130/dubited.1740484

e-ISSN: 2148-2446
https://dergipark.org.tr/en/pub/dubited

Research Article

Investigating Attitudes of Design Students Toward Parametric Design: Parametric Design Attitude Scale (PDAS)

Hasan Tastan[1*], İhsan Erdem Er[1]

[1] Department of Architecture, Faculty of Architecture, Yildiz Technical University, İstanbul, Türkiye.
ror.org/0547yzj13

*Corresponding author:
hasantastn@gmail.com

Received: 11.07.2025
Revision: 02.03.2026
Accepted: 13.04.2026
Online: 24.07.2026

Abstract: This study aims to develop a valid and reliable measurement tool to evaluate architecture students' attitudes toward parametric design. Adapting items from three established instruments on design technologies and programming, a four-phase methodology was employed. In the first phase, relevant attitude scales from the literature were examined and adapted to parametric design. The second phase involved administering the adapted scale to architecture students and conducting exploratory factor analysis and confirmatory factor analysis, resulting in a four-dimensional structure: perceived usefulness; interest and preferences; functionality and application areas; and practicality and challenges. In the third phase, the finalized scale was applied to twenty-three students after a parametric design course alongside four affective measures. In the final phase all five survey results and students course performances are analyzed for correlations. The results showed that while PDAS shows strong relationships with self-confidence and design thinking variables, moderate correlation with task performance and other variables. This indicates that parametric design education requires balanced and sustainable pedagogical approaches.

Keywords: *Parametric design, Attitude scale, Computational design, Architectural education*

I. INTRODUCTION

Parametric design is an algorithmic process where parameters represent design decisions that shape the solution. In this context, design can be viewed as problem-solving, and the decision-making steps align with algorithmic logic. While simple design problems are linear and mathematically solvable, architectural problems are typically complex, lacking clear right or wrong answers (Rittel & Webber, 1973). Architectural design, therefore, involves selecting the most suitable alternative based on the designer's priorities. Parametric design supports this by enabling procedural thinking, automation, rapid iteration, and computational exploration (Dissaux & Jancart, 2022). Oxman (2008) highlights that digital media has reshaped architectural design through new knowledge forms and performance-based models, moving beyond traditional analysis, synthesis, and evaluation. While architectural education is adapting to digital culture, fully integrating parametric and algorithmic tools into curricula and practice remains a challenge.

Parametric design has become a prominent approach in architectural education and practice in recent years. Its capacity to generate complex forms and rapidly produce design variations enhances students' creative expression (Sunarya et al., 2023; Yiwei & Xia, 2010). From early design stages, it supports time management by aligning construction constraints with form generation (Monteiro et al., 2020). Combined with augmented reality (AR) (Shaghaghian et al., 2021; Shaghaghian et al., 2022) and virtual reality (VR) tools (Tastan et al., 2022), parametric design helps students understand 3D modeling and parameter changes. These technologies also foster spatial abilities, algorithmic thinking, and offer valuable opportunities for interdisciplinary studio work and collaborative projects, preparing students for professional teamwork through interactive change simulations (Joklová & Pifko, 2015; Riggio & Cheng, 2021). However, integrating these methods and tools into architectural education and practice presents challenges. Students often struggle with core concepts, and in the absence of proper guidance, rely on trial-and-error (Shaghaghian et al., 2022). The need for programming skills and tool complexity limits active participation in parametric design (Abdalla & Kandil, 2017; Sunarya et al., 2023). Applied training and workshops, however, help overcome these (Sunarya et al., 2023). Similar issues exist in practice, where new graduates' lack of practical skills causes difficulties (Holzer, 2015). Additionally, collaboration challenges may arise, as effective parametric design requires strong coordination among architects, engineers, and other stakeholders (Monteiro et al., 2020; Riggio & Cheng, 2021).

Parametric design requires computational thinking, and students' attitudes toward it are closely tied to their confidence and motivation in using algorithmic and digital tools. Algorithmic thinking involves understanding a problem and planning steps to solve it (Turan et al., 2017). Integrating these skills into architecture education is key to addressing related challenges. This highlights the need for reliable tools that assess not only technical knowledge but also attitudes toward parametric design and digital methods. While existing scales focus on design tools (Tarakçı Eren & Yılmaz, 2022), computer

Cite as: Tastan, H., & Er, İ. E. (2026). Investigating attitudes of design students toward parametric design: Parametric design attitude scale (PDAS). *Düzce University Journal of Science and Technology, 14*(3), 666–679. https://www.doi.org/10.29130/dubited.1740484

This is an open access paper distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License.

use (Tasli Pektaş & Erkip, 2006), or programming (Godbole, 2014; Hutchinson et al., 2008; Wiebe et al., 2003), there is no dedicated scale for parametric design in architecture education. Yet, like programming, parametric design depends on algorithmic thinking and coding, both critical to student progress, motivation, and professional satisfaction (Godbole, 2014). Therefore, a valid and reliable scale that systematically measures architecture students' attitudes toward parametric design can lead to more productive research in this field. This study aims to develop such a scale, as no existing tool directly addresses this need, though related scales on computer use and programming exist. The parametric design attitude scale (PDAS) was created using exploratory and confirmatory factor analyses based on sub-factors from three established attitude scales. Its relationships with other affective measures such as computational thinking (CT) (Korkmaz & Bai, 2019), computational thinking self-efficacy (CTSE) (Kukul & Karatas, 2019), self-confidence (Li et al., 2023) and design thinking (DT) (Tsai & Wang, 2021), as well as task performance scores obtained via the consensual assessment technique (CAT).

II. THEORETICAL BACKGROUND

Parametric design education involves processes in which students attempt to achieve complex design objectives by focusing on rules and relationships rather than static objects. This requires knowledge and experience in the use of nodes-based visual programming interfaces, such as Grasshopper or Dynamo, or textual programming languages. It also requires higher degree of abstraction and systematic thinking (Lee & Ostwald, 2019) about how to translate complex design parameters into final design outcomes. However, these procedures can present significant challenges for novice designers, particularly in comprehending the underlying logic of the parametric workflow. When reviewing the literature, there are a significant number of studies focusing more on the parametric design process itself rather than on factors affecting learning performance or learners' cognitive affective situations in parametric design education (Er et al., 2025). These studies aim to reveal designers' cognitive processes, interactions with tools, and training models by examining parametric design processes through protocol analyses, linkography, and experimental methods. Gürel & Şenyapılı Ozcan (2023) evaluated data by using a content-oriented coding scheme and protocol analysis to compare cognitive processes between digital and traditional instruments. They argued that Grasshopper is not merely a form-finding tool but also supports the conceptual stage by enhancing physical and perceptual cognitive actions (Gürel & Şenyapılı Ozcan, 2023). In a similar comparison, Öztürk Kösenciğ & Özbayraktar (2025) used linkography and jury evaluations comparatively to identify cognitive interruptions and synthesis deficiencies in the process; they determined that sketching is more effective for synthesis, while the parametric environment creates technical gaps despite serving as an external memory. Lee & Ostwald (2019) aimed to quantitatively measure designers' cognitive complexity by combining protocol analysis with linkography and entropy measurements, demonstrating that this method successfully reveals individual differences in designers' cognitive levels and processes. All these studies focus on how the parametric design process can be carried out and what factors need to be considered. On the other hand, very few studies have focused, even indirectly, on the effect of the parametric design production process on students.

Alalouch (2018) evaluated the series of planes method he developed to avoid the learning curve of software through surveys and statistical tests measuring students' intellectual skills, cognitive strategies, and attitudes. This approach positively influenced attitude but that technical control varied depending on prior computer-aided design experience. Alalouch (2018)'s study suggests that teaching methods in challenging parametric design education can change students' attitudes. While other studies focus on cognitively understanding students' activities in the parametric design process (Gürel & Şenyapılı Ozcan, 2023; Lee & Ostwald, 2019; Öztürk Kösenciğ & Özbayraktar, 2025), Alalouch (2018)'s research focuses more on the effects of a teaching method. More concrete evidence is needed regarding the relationship between students' affective state, the parametric design teaching method, and design performance for more effective parametric design teaching. Various studies in the field of design have revealed that there may be a relationship between students' affective states and other factors. For example, one study showed that in surveys administered to design students, their deep interest in and engagement with the design process directly increased their belief in their ability to successfully complete design tasks (self-efficacy), while superficial approaches such as fear of failure undermined this belief (Lun et al., 2025). This study directly reveals the interactions between students' affective states and various factors in design education (Lun et al., 2025). The inclusion of new challenges not present in traditional design methods, such as the use of node-based abstract interfaces and algorithmic thinking, in parametric design processes necessitates a comprehensive and multidimensional examination of student attitudes. Indeed, a negative attitude can hinder parametric design learning; as Alalouch (2018) also points out, effective pedagogical methods can positively develop the attitudes of novice students, especially those new to this field. In this context, the development of a detailed parametric design attitude scale (PDAS) encompassing different dimensions will lay the foundation for in-depth analysis of affective factors as well as cognitive factors in future studies.

Previous studies showed that attitudes play a significant role in effective learning (Nolan et al., 2012). In line with this, numerous attitude scales were developed in the field of education to evaluate students' perceptions toward specific subjects. Some of these scales (Hongwarittorrn & Krairit, 2010; Hutchinson et al., 2008; Wiebe et al., 2003) are derived from the mathematics attitude scale originally developed by Fennema & Sherman (1976). Similarly, Anastasiadou (2011) developed a five-factor scale to measure students' attitudes toward statistics, while Rees et al. (2002) introduced a six-factor attitude scale to evaluate medical students' attitudes toward communication courses. Within engineering

education, students' attitudes toward programming have been found to be essential in understanding their academic satisfaction, long-term success, and motivation to learn (Godbole, 2014). Some studies (Garrett & Walker, 2008; Godbole, 2014) have examined attitudes toward visual programming. Overall, identifying students' attitudes enables educators to design introductory programming courses that promote more positive and engaging learning experiences. Given that programming is often perceived as a difficult subject to grasp, analyzing students' attitudes can help improve both their learning outcomes and their engagement with the subject (Godbole, 2014). For example, Başer (2013) used the scale developed by Wiebe et al. (2003) to investigate students' attitudes toward computer programming. They validated the scale's reliability and validity and demonstrated the need to enhance students' attitudes to improve their overall perspectives on programming, which in turn may enhance achievement. As previously mentioned, programming attitudes which is similar to those in other educational fields affect learners' academic performance. Therefore, strengthening students' confidence and their perceptions of programming's usefulness is of critical importance.

In the field of design education, Tarakçı Eren & Düzenli (2021) used the environmental attitude scale by Uzun & Sağlam (2006) to examine landscape architecture students' environmental attitudes. Tarakçı Eren et al. (2018) employed a four-factor attitude scale to assess students' perceptions of biomorphic and parametric design approaches. In architectural education, (Baysen & Akçay, 2017) studied students' attitudes toward information-seeking behaviors. While there is no unique attitude scale specifically addressing parametric design in the architectural education literature, research exist relating attitudes toward digital design tools (Tarakçı Eren & Yılmaz, 2022) and computer usage (Tasli Pektaş & Erkip, 2006). Understanding students' attitudes of parametric design is critical for assessing the influence of emerging computational technologies in architecture education. Attitudes focuses on emotive dimensions such as perceived usefulness, interest, and confidence, it is methodologically important to investigate its link with other established affective scales. Examining its relationships with paradigms such as computational thinking (Korkmaz & Bai, 2019), computational thinking self-efficacy (Kukul & Karatas, 2019), self-confidence (Li et al., 2023) and design thinking (Tsai & Wang, 2021) dispositions provides an expanded view of how students emotionally and cognitively engage with parametric approaches. This multi-scale comparison not only ensures PDAS' internal consistency but also places it in a larger educational guidelines where emotional, cognitive, and creative dimensions intersect. Wing (2006) introduced computational thinking (CT) as a method for problem-solving through reasoning across layers of abstraction, especially in design systems. CT is a fundamental cognitive skill relevant to all disciplines, not just computer science. (Henderson et al., 2007) emphasized its broad importance across modern fields. Design thinking (DT), initially developed in design disciplines, aims to solve complex problems and has become central to design education by fostering creative problem-solving. DT combines analytical and creative approaches, emphasizing empathy, divergent thinking, iteration, prototyping, and testing (Razzouk & Shute, 2012). It is viewed as a mindset, structured process, and innovation tool (Brenner & Uebernickel, 2016). Stanford University's five-stage DT model including empathize, define, ideate, prototype, and tests are widely used in education to enhance creative thinking (Tsai & Wang, 2021).

III. METHODOLOGY

The methodology of this study is structured into four main phases, as illustrated in Figure 1. In the first phase, relevant attitude scales from the literature were reviewed and adapted to the context of parametric design. The second phase involved the development and validation of a new attitude scale through exploratory and confirmatory factor analyses. In the third phase, this newly developed instrument, along with other selected affective scales, was implemented following a parametric design course to evaluate students' task performance. Finally, in the fourth phase, correlations were analyzed between the new attitude scale, course performance scores, and other affective factors.

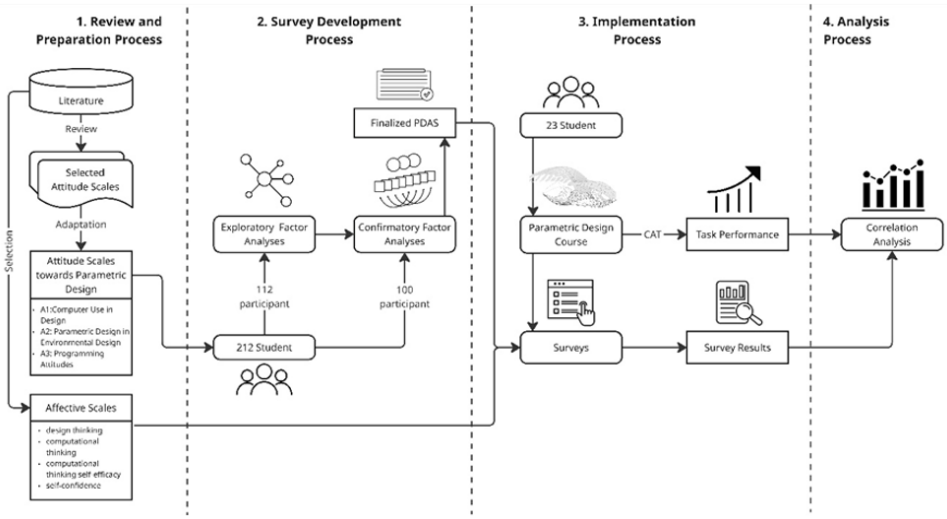


Figure 1. Flowchart of the study.

A. Review and Preparation

In the first phase, a comprehensive literature review was conducted to identify established attitude scales that could form the foundational item pool for the PDAS. Three specific instruments were selected to capture the technological, disciplinary, and algorithmic aspects of parametric design:

- Scale 1 (Computer Use in Design): A 20-item, two-factor instrument by Tasli Pektaş & Erkip (2006) focusing on students' general technological orientation in design studios.
- Scale 2 (Parametric Design in Environmental Design): A 23-item scale by Tarakçı Eren et al. (2018) that provided the specific disciplinary terminology for parametric and biomorphic approaches.
- Scale 3 (Programming Attitudes): A 16-item, four-factor scale by Godbole (2014) used to capture the algorithmic and logic-based challenges inherent in parametric workflows.

These original items were qualitatively adapted by the researchers to ensure conceptual alignment with architectural education. For instance, items referencing general "programming" were recontextualized as "parametric design" to better reflect the visual programming environments (e.g., Grasshopper) used by architecture students. All items were unified under a five-point Likert scale format. Items in the adapted scales were rated on a five-point Likert scale ranging from 1 to 5: “strongly disagree,” “disagree,” “neutral,” “agree,” and “strongly agree.”

In addition, four more affective scales related to parametric design were identified from the literature. To measure students’ design thinking (DT) abilities, the study employed an adapted DT disposition scale developed by Tsai and Wang (Tsai & Wang, 2021). This scale reflects the five phases of DT: empathy, define, ideate, prototype, and test, comprising a total of 19 items. For assessing computational thinking, the study used a modified version of the CT scale (Korkmaz & Bai, 2019), which consists of 20 items. Additionally, Kukul & Karatas (2019)’s computational thinking self-efficacy scale was utilized, which comprises 18 items. The last affective scale that was used was the 4-question self-confidence scale (Li et al., 2023). Both scales employ a 5-point Likert format for item responses, from strongly disagree (1) to strongly agree (5).

B. Scale Development

In the second phase, the combined and adapted version of adapted three different attitude scales specified in the first phase resulted in a survey designed to assess attitudes toward parametric design, which was administered to a sample of 212 architectural design students. That the collected data was divided for exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). To determine the internal validity and factor structure of the scale, an EFA was first conducted using responses from 112 participants. Subsequently, a CFA was conducted with data from 100 participants to validate the factor structure derived from the EFA. At the end of this analysis, a new scale that measures attitudes toward parametric design in architecture was developed. During this step, the scales were administered to architecture students at one university via an online survey.

C. Implementation

In the third phase, this new PDAS and other four selected affective scales were implemented to 23 architectural design students after parametric design course. For measuring task performance, Amabile (1982)’s consensual assessment technique (CAT) was employed. This technique, which relies on the independent and subjective evaluations of domain experts, is considered a reliable method for assessing creativity in design. Given the limitations of standardized tests within design contexts (Suh & Cho, 2020), this approach was chosen.

Students completed one parametric design exercise, which was assessed based on CAT with five key criteria: (1) originality (the innovation and creativity of the design), (2) appropriateness (the extent to which the design meets functional requirements), (3) 3D spatial richness (the use of diverse volumes and spatial depth), (4) clarity (the transparency of the design presentation and process), and (5) overall creativity. These evaluation criteria were established based on prior research (Cho & Suh, 2019). This exercise required a parametric system that can transform with movement and fulfill multiple functions. This system was expected to fulfill functions such as seating, storage, and lighting by transforming with movements in different directions. The transformation of individual elements was not allowed in the design; the transformation had to be achieved by the holistic movement of the surface. Within the scope of this task, students were asked to prepare a 50x70 cm presentation board with Rhino-Grasshopper files. The sheet should include two or three different perspective images showing that the system responds to multiple functions. These perspectives should clearly express which functions the surface fulfills. The process steps reflecting the design process were also expected to be included in the sheets. All designs were randomly ordered and individually assessed by experts using a five-point Likert scale. Some task outputs according to this evaluation are shown in Figure 2. This study was conducted in accordance with ethical standards and was approved by the relevant ethics committee (Approval No: 2023.06)

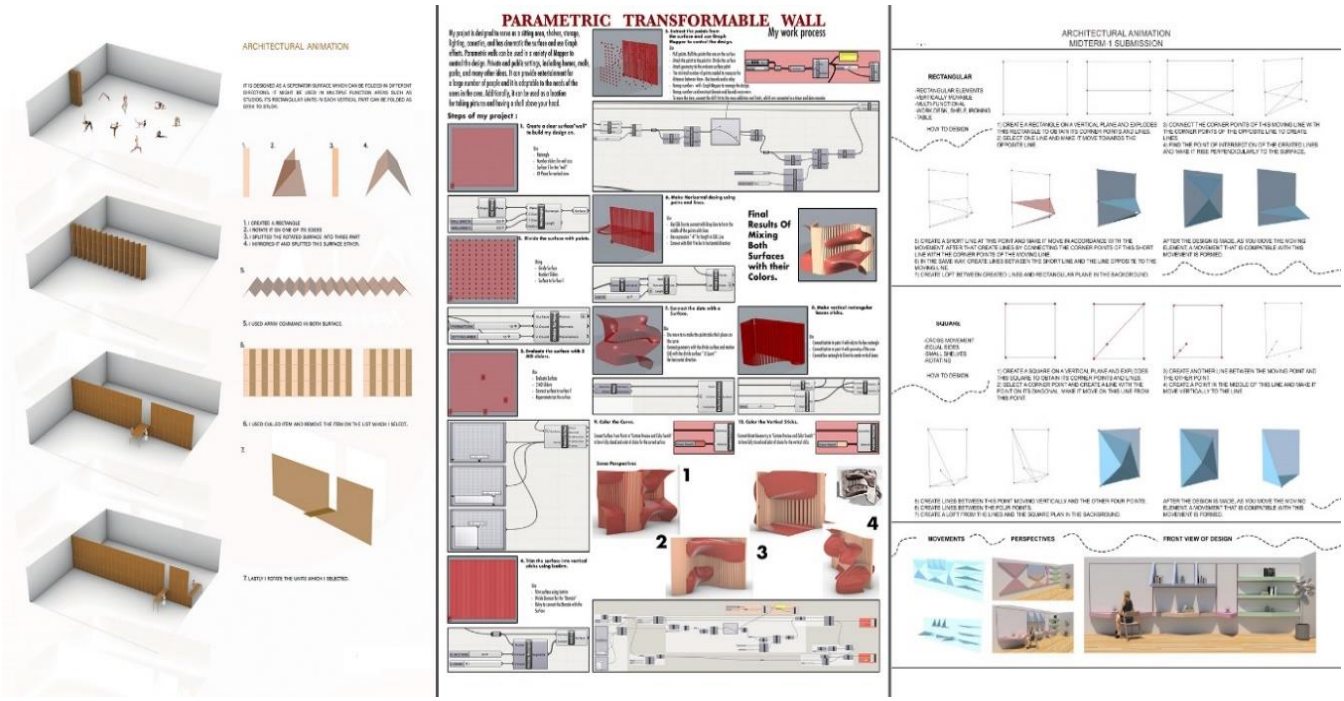


Figure 2. Examples of student projects.

IV. FINDINGS

For the EFA, the principal components extraction method and direct oblimin rotation technique were used. The principal components method was chosen because it is the most widely used method in literature and is relatively easy to apply compared to other techniques (Costello & Osborne, 2005). The direct oblimin rotation was employed based on the assumption that the factors are correlated. SPSS software was used for EFA, while AMOS 24 was utilized for confirmatory factor analysis (CFA). The scale items were labeled according to their source and sequence using the format "A (Survey No) (Item No)." Items adapted from Tasli Pektaş & Erkip (2006) were coded as A1, those from Tarakçı Eren et al. (2018) as A2, and those from Godbole (2014) as A3. Prior to analysis, the scores for negatively worded items were reverse-coded.

A. Exploratory Factor Analysis (EFA)

As a result of the initial EFA conducted with all 54 items of the scale, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was found to be **.778,** indicating that the sample size was sufficient for factor analysis. Additionally, as shown in Table 1, the Bartlett's test of sphericity was statistically significant at the $p < .001$ level, confirming that the items possessed an adequate correlation structure for factor analysis.

Table 1. Bartlett sphericity test.

Kaiser-Meyer-Olkin Sample Fit Measure		**,778**
Bartlett Sphericity Test	x2	4210.6
	df	1431
	p	**<,001**

In the initial solution, twelve components with eigenvalues above 1 explained 74.07% of the total variance. However, the Pattern Matrix showed that several items loaded significantly (≥ .30) on multiple factors, obscuring the factor structure. After removing these items, a second factor analysis was conducted with 27 items. The KMO value rose to .816, and Bartlett's test was significant, $\chi^2(406) = 1880.53$; $p < .001$, confirming the suitability for factor analysis. Promax rotation revealed a six-factor structure, with most items loading strongly (> .50) on a single factor, supporting statistically and theoretically coherent subdimensions. Since factor loadings above .40 are considered ideal (Hair, 2010), the retained items were deemed valid contributors. Table 2 shows item distributions and loadings.

Table 2. Factor structure of the items, identified through exploratory factor analysis.

	A26	A29	A25	A21	A22	A17	A23	A14	A16	A10	A12	A18	A17	A19	A20	A33	A34	A36	A17	A16	A18	A12	A10	A13
F1	.86	.84	.84	.81	.80	.78	.76																	
F2								.85	.84	.75	.71													
F3												.84	.77	.73	.70									
F4																.92	.85	.82						
F5																			.88	.79	.77			
F6																						.83	.78	.77

Initially, the structure consisted of twelve factors explaining 74.07% of the variance; however, through the step-by-step elimination of items with cross-loadings and low factor loadings, the number of factors was reduced to six, and the overall sampling adequacy was improved. In the resulting six-factor scale, item loadings ranged from .52 to .89, with no item falling below .50, indicating that each item made a meaningful contribution to its respective factor. This refined structure not only enhanced the explanatory power of the factors but also strengthened the internal consistency of the scale. Cronbach's coefficients for each factor ranged between .78 and .87, demonstrating a high level of internal reliability.

B. Confirmatory Factor Analysis (CFA)

To validate the six-factor structure obtained through Exploratory Factor Analysis (EFA), a Confirmatory Factor Analysis (CFA) was conducted using AMOS 24 with data from 100 participants. In the initial model, several items demonstrated inadequate performance due to factor loadings falling below .50 and issues with cross-loadings. Accordingly, 11 items—coded as A2_5, A1_7, A1_4, A1_2, A1_18, A1_17, A1_19, A1_20, A2_17, A2_16, and A2_18—were removed from the model. As a result, the factors F2 and F5, previously identified in the EFA stage, were entirely excluded from the final structure. The revised model, based on the remaining items, was tested with a four-factor structure, as shown in Figure 3. To improve model fit, error covariances were added between the following item pairs due to their conceptual proximity: A2_6–A2_2, A2_2–A2_3, and A2_2–A2_1. The model fit indices for the final model are presented in Table 3.

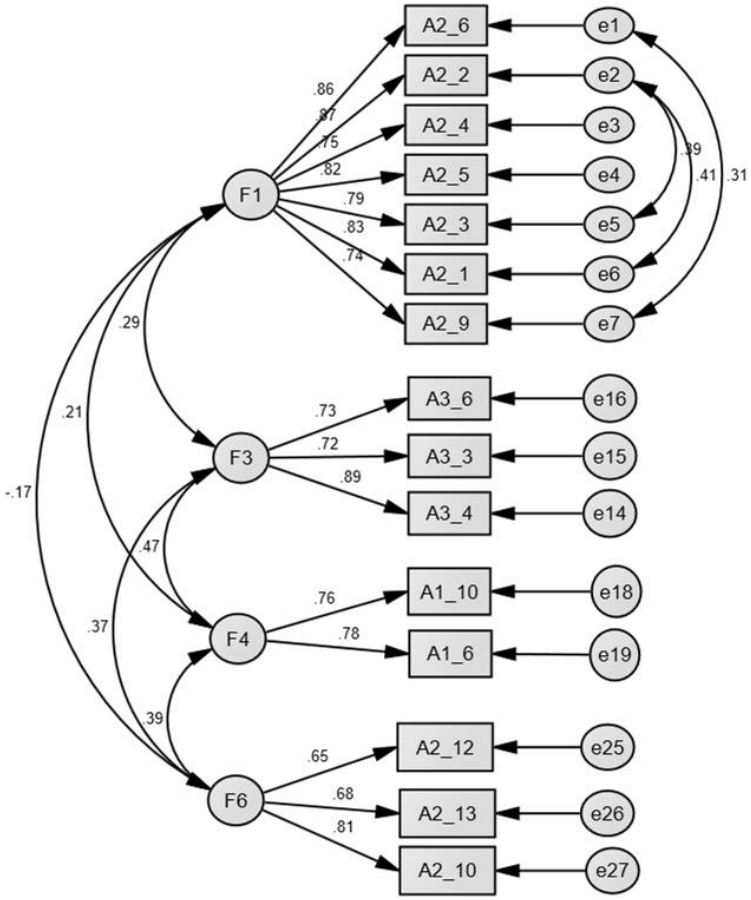


Figure 3. Confirmatory factor analysis model for the retained items in the final stage.

Upon examining the results, the CMIN/df value satisfied the ideal threshold of CMIN/df < 3**,** and the AGFI exceeded the standard of AGFI > 0.85. Among the other indices expected to be above 0.90**—**GFI**,** NFI**,** CFI**,** IFI**,** and TLI—all except GFI met this criterion. The GFI, measured at 0.899, was found to be very close to the acceptable threshold. Additionally, the RMSEA value was 0.035, which is well below the **0.08** threshold, indicating good fit between the factors.

Table 3. Fit Indices of the confirmatory factor analysis.

CMIN/df	AGFI	GFI	NFI	CFI	IFI	TLI	RMSEA
1.123	,850	,899	,901	,988	,988	,984	,035

The standardized factor loadings further supported the model's structural validity, with values ranging from .74 to .87 in F1, .72 to .89 in F3, .76 to .78 in F4, and .65 to .81 in F6. These results demonstrate that the initial six-factor model identified during EFA could be refined into a more coherent and parsimonious four-factor model: (F1) Perceived Usefulness, (F3) Interest and Preferences, (F4) Functionality and Application Areas, and (F6) Practicality and Challenges. Furthermore, to assess the reliability of the finalized 15-item scale resulting from CFA, a Cronbach's alpha analysis was conducted, and the results are presented in Table 4. As all subdimensions of the scale exceeded the .60 threshold (Hair, 2010), the scale can be considered a reliable measurement instrument. The final version of the validated and reliable scale, along with its factor distribution, is provided in Appendix 1.

Table 4. Cronbach's alpha reliability coefficients for each factor and the overall scale.

	F1	F3	F4	F6	Overall Scale
Item Count	7	3	2	3	15
Cronbach Alpha	,934	,823	,745	,756	,821

C. Correlation of PDAS with Other Factors

In this study, Pearson correlation analyses were conducted across ten core variables. Each relationship was marked using asterisk symbols based on p-values: * ($p \leq 0.05$), ** ($p \leq 0.01$), and *** ($p \leq 0.001$). The results are important as they demonstrate both inter-item consistency and how the subdimensions of the scale relate to each other and to course performance scores. Table 5 presents all correlation relationships.

Table 5. Correlations between PDAS and other factors (r values and significance levels).

	Task Per.	PU (F1)	IP (F3)	FAA (F4)	PC (F6)	PDAS	CT	Self Confidence	DT	CTSE
Task Per.	1.00	0.42*	0.28	0.24	0.30	0.50*	0.64***	0.27	0.07	0.28
PU (F1)		1.00	0.44*	0.29	0.19	0.77***	0.27	0.47*	.27	0.39
IP (F3)			1.00	0.05	0.04	0.58**	0.20	0.15	0.09	0.06
FAA (F4)				1.00	0.01	0.66*	0.37	0.72**	0.72**	0.40
PC (F6)					1.00	0.38	0.33	0.23	0.33	0.17
PDAS						1.00	0.49*	0.54**	0.56**	0.44*
CT							1.00	0.17	0.41*	0.52**
Self Confidence								1.00	0.52**	0.41*
DT									1.00	0.40*
CTSE										1.00

*p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001, PU: Perceived Usefulness, IP: Interest and Preferences, FAA: Functionality and application areas, PC: Practicality and challenges

When examining the relationships between task performance and other variables, the strongest and most significant correlation was found with CT ($r = 0.64$; $p < 0.001$). This suggests that students with higher computational thinking performance tend to achieve higher scores in course exams or related assessments. Additionally, there was a moderate positive correlation between task performance and perceived usefulness (F1) ($r = 0.42$; $p < 0.05$), while a moderate correlation was observed with the PDAS ($r = –0.50$; $p < 0.05$). No significant relationships were found between task performance and interest and preferences (F3), functionality and application areas (F4), practicality and challenges (F6), self-confidence, DT, or CTSE scale.

When analyzing the relationships among the sub dimensions, a strong and highly significant negative correlation was found between perceived usefulness (F1) and PDAS ($r = –0.77$; $p < 0.001$). Similarly, a significant correlation was found between interest and preferences (F3) and PDAS ($r = 0.58$; $p < 0.01$), and a strong and significant correlation between functionality and application areas **(**F4) and PDAS ($r = 0.66$; $p < 0.001$). Regarding the PDAS and its relationship with other variables, a significant correlation was observed with CT ($r = –0.49$; $p < 0.05$). Moreover, moderate to strong and significant correlations were found with self-confidence ($r = –0.54$; $p < 0.01$) and DT ($r = –0.56$; $p < 0.01$). A similar but lesser connection was detected with CTSE mean ($r = -0.44$; $p < 0.05$).

Examining the correlations between CT and other scale components revealed a strong and significant relationship with CTSE ($r = 0.52$; $p < 0.01$). This suggests that participants who perform well in computational thinking also perceive themselves as more competent in this area. A moderate and statistically significant positive correlation was also found between CT and DT ($r = 0.41$; $p < 0.05$), indicating that individuals with high computational thinking performance can also tend to perform relatively better in design thinking.

With regard to self-confidence**,** a significant correlation was found with DT ($r = 0.52$; $p < 0.01$), and similarly with CTSE ($r = 0.41$; $p < 0.05$). These results show that participants with higher levels of self-confidence also tend to achieve higher performance in both design tasks and computational thinking self-efficacy. Finally, a significant correlation was observed between DT and CTSE ($r = 0.40$; $p < 0.05$), suggesting that individuals who perform well in design thinking also tend to have a stronger perception of their computational thinking self-efficacy.

V. DISCUSSION

A. The Content of PDAS

PDAS was intended to investigate architecture students' perceptions of parametric design employing a multidimensional structure. The scale items were adapted from three previously validated attitude studies (Godbole, 2014; Tarakçı Eren et al., 2018; Tasli Pektaş & Erkip, 2006) and, through exploratory and confirmatory factor analyses, were grouped under four main factors: (F1) perceived usefulness, (F3) interest and preferences, (F4) functionality and application areas, and (F6) practicality and challenges. This instrument evaluates attitudes toward parametric design not only technologically, but also pedagogically, psychologically, and operationally.

Perceived usefulness (F1) is an indicator of how students perceive parametric design's contribution to the design education process. Students reported that parametric design encourages creativity, improves project quality, and keeps them interested in the course. These findings align with similar themes identified in Tarakçı Eren et al. (2018), suggesting that parametric design tools go beyond being technical instruments and can play a transformative role in learning processes. Interest and preferences (F3) assesses students' willingness to engage voluntarily with parametric design and their motivational levels for learning. Items in this dimension reveal that some students display reluctance or indifference toward learning parametric design. Godbole (2014) emphasizes that early-stage attitudes toward programming play a crucial role in long-term success and motivation to learn.

Functionality and application areas (F4) explores whether students view parametric design as merely a visual or technical tool or as an integrated approach that supports decision-making processes in design. This factor reveals that reductive perceptions of parametric design persist. Some students perceive parametric tools as assistants for speeding up drawing processes, rather than as enablers of decision-making, alternative generation, or problem-solving. This indicates a lack of full internalization of parametric design's role in the design process and indicates the need for framing these tools not only as output generators but also as modes of thinking (Abdalla & Kandil, 2017).

Practicality and challenges (F6) reflects how students evaluate parametric design in terms of infrastructure, available resources, time, and skill levels. Negative perceptions, such as "extra workload" and "technical difficulty" suggest that students experience cognitive load related to the process. This finding echoes the results of Tasli Pektaş & Erkip (2006) regarding digital tools. Furthermore, the effective dissemination of parametric design in education critically depends on technical infrastructure (hardware, software, support staff). Thus, broader implementation of parametric design in education requires not only pedagogical adjustments but also structural and technological investments. Furthermore, the technical gaps identified by Öztürk Kösenciğ & Özbayraktar (2025) in parametric workflows align with the findings in F6 factor. These technical issues indicate that although students may leverage the parametric environment as an external memory, the natural cognitive interruptions may significantly impede the effective synthesis of complex design concepts. Thus, it is essential to overcome these challenges through effective pedagogical support and infrastructure to avoid a disconnect between students' technical efforts and their ultimate design accomplishments, requiring further longitudinal research to track the evolution of these perceived challenges as students gain more experience.

B. The Relationship between the PDAS and Other Factors

In addition to the development process, this study also examined the relationships between students' attitudes toward parametric design and their levels of CT**,** DT**,** CTSE, and self-confidence. To begin with, a strong and significant correlation was found between students' task performance and their CT ($r = 0.64$; $p < 0.001$). This result aligns with Wing (Wing, 2006) emphasis that computational thinking is not limited to computer science but contributes to problem-solving across disciplines. The findings demonstrate that computational thinking skills can positively influence academic performance even in design related fields such as architecture. This supports Oxman (Oxman, 2008)'s findings regarding the intuitive and constructive nature of the design process.

The weak direct correlations observed in Table 5 between task performance and affective factors like design thinking ($r = 0.07$) or self-confidence ($r = 0.27$) suggest that high emotional readiness does not automatically translate into high design scores. This distinction is contextualized by the findings of (Lun et al., 2025), who demonstrated that deep engagement and interest are primary drivers of a student's self-efficacy within the design process. However, in the context of our research, the gap between these affective states and task performance suggests that interest is not enough without the necessary computational foundations. As (Alalouch, 2018) pointed out, even if teaching methods are successful in changing attitudes, technical proficiency is an important variable that is affected by experience. This is further made difficult by the technical gaps that have been identified by (Öztürk Kösenciğ & Özbayraktar, 2025); although the parametric environment serves as an external memory, the cognitive interruptions that are created by technical problems may affect the synthesis of design ideas, thus preventing even highly motivated students from attaining immediate academic success.

The significant correlation between CT and CTSE ($r = 0.52$; $p < 0.01$) suggests that individuals with strong computational thinking skills also tend to feel more confident in their ability to use those skills. It can be said that this finding is consistent with Bandura and Wessel (Bandura, 1997)**'s** self-efficacy theory. Similarly, correlations were found between other affective factors indicating that design thinking not only supports creative processes but also contributes to cognitive and affective competence perceptions (Razzouk & Shute, 2012).

The significant correlations found in this study between F4 and design thinking ($r = 0.72$; $p < 0.01$) provide compelling empirical evidence for the necessity of shifting the pedagogical focus from technical tool-use to a cognitive-based design approach. This necessitates a shift from perceiving parametric software as mere output generators to framing them as integrated modes of thinking that enable complicated decision-making and alternative exploration. These findings indicate that students with greater creative development and confidence are more likely to see parametric design as a comprehensive framework for issue solving rather than a superficial modeling utility. This finding is supported by Gürel & Şenyapılı Ozcan (2023) who argue that node-based environments like Grasshopper are not merely form-finding instruments but critical supports for the conceptual design stage by enhancing physical and perceptual cognitive actions.

These findings clearly demonstrate that, in architectural education, it is essential to consider not only technical skills but also affective dimensions such as attitude, interest, and motivation. This suggests the need for more balanced approaches in the pedagogical integration of parametric design tools. Future research should employ longitudinal methods to examine the effects of long-term exposure to parametric design education on cognitive load, learning motivation, and creative output. Such investigations could help develop sustainable strategies for evaluating the technical and pedagogical effectiveness of parametric tools in architectural education.

In this study, no strong correlations were observed between task performance and some affective factors such as DT,

self-confidence, or CTSE. This is a observed phenomenon in literature. Academic achievement is often more closely related to prior knowledge, cognitive strategies, and effective instructional methods than to affective attitudes alone (Köller et al., 2001). In structured teaching models such as direct instruction, systematic content delivery and teacher guidance can lead to high performance even in cases of low student engagement (Kirschner et al., 2006). In such contexts, success tends to be shaped more by structural interventions in the learning process than by individual motivation.

Furthermore, students' interest or self-efficacy may increase after experiencing success, which blurs the direction of the correlation (Kirschner et al., 2006; Yokoyama, 2018). Therefore, high achievement does not always result from high motivation. On the contrary, success may foster interest and confidence. From a motivational standpoint, perceived usefulness or interest may contribute to achievement if such attitudes translate into effective study strategies (e.g., self-regulation, time management) (Nauzeer & Jaunky, 2021). Even if a student is interested, without strategic learning skills, that interest may not result in performance gains. In conclusion, the influence of affective factors on academic performance is context-sensitive and often indirect. In effective learning environments, cognitive support mechanisms can compensate for affective deficiencies. Thus, the weak correlations observed in this study indicate that the impact of students' attitudes on academic outcomes is conditional and complex.

C. Limitation of Study

This study has several limitations. First, the sample consisted solely of students from the department of architecture at a single institution, which may limit the generalizability of the findings to other universities, educational models, or student populations. Expanding the sample size and including participants from different institutions and design-related disciplines would strengthen the external validity of the scale.

Second, because this research primarily focused on the adaptation and validation of an attitude scale, no comparative or experimental testing was conducted. The absence of intervention-based or longitudinal designs means that the scale's responsiveness to instructional strategies and its predictive power for learning outcomes could not be evaluated. Future research could utilize pre-post evaluations or controlled trials to investigate how attitudes evaluated by the PDAS relate to changes in student performance over time.

Third, using self-reported data can increase the risk of subjective misreporting. Including behavioral data such as interviews or observations as well as quantitative metrics might improve the findings and provide a better understanding of students' real involvement with parametric design. Finally, while the PDAS was created primarily for architecture students, parametric design tools can be frequently utilized in other fields such as landscape architecture, interior design, and urban planning. The scale's applicability in certain situations has still to be demonstrated.

VI. CONCLUSION

This study aims to develop a valid and reliable attitude scale to measure architecture students' perceptions of parametric design. The PDAS was developed and evaluated using both exploratory and confirmatory factor analyses, drawing on existing literature-based instruments. The validated scale comprises fifteen items distributed across four dimensions reflecting usefulness, motivational orientation, functional application, and practical constraints. These items represent the comprehensive nature of parametric design in architecture education, which includes not only technology but also instructional, motivational, and operational components.

The structural validation analyses demonstrate that the PDAS possesses a robust and coherent factor structure supported by satisfactory sampling adequacy (KMO = .816), strong item loadings, acceptable model fit (CFI = .988; RMSEA = .035), and high internal consistency (α = .745–.934). The exploratory factor analysis initially indicated a six-factor structure, which was subsequently refined into a more parsimonious four-factor model through confirmatory factor analysis. This refinement strengthened both the explanatory clarity and structural coherence of the survey, suggesting that students' perceptions of parametric design cluster around four dominant dimensions rather than fragmented sub-constructs.

The scale provided valuable insights on how students perceive parametric design not merely as a technical drafting tool but as a pedagogical and cognitive component of architectural education. While students generally expressed positive feelings about the creative and pedagogical possibilities of parametric approaches, difficulties relating to usability and infrastructure were also recognized. Furthermore, the study found that attitudes toward parametric design are moderately associated with constructs such as computational thinking, self-efficacy, and design thinking, suggesting that affective, and motivational factors interact in shaping students' experiences with emerging design technologies.,

The correlation analyses further clarify the structure of these perceptions. The strongest relationship observed in the study was between CT and task performance, indicating that computational reasoning skills play a central role in design performance within parametric contexts. PDAS and its subdimensions were moderately associated with CT, design thinking, self-confidence, and computational thinking self-efficacy. However, none of these affective variables demonstrated strong direct correlations with task performance. This pattern suggests that attitudes alone do not directly translate into measurable academic outcomes. Instead, computational reasoning skills appear to function as primary determinants of performance, while affective dispositions operate in a more conditional and supportive manner.

From a pedagogical perspective, the PDAS serves as a diagnostic tool for identifying motivational barriers, perceived difficulty, and conceptual misunderstandings related to parametric design. Students' concerns about workload, usability, and infrastructural limitations suggest that operational conditions significantly shape their learning experiences. At the same time, parametric design does not appear to be fully internalized as a mode of reasoning; it is at times perceived primarily as a technical tool rather than as a generative design approach. Integrating parametric design into architectural curricula therefore requires more than software training. It necessitates structured pedagogical support that positions parametric tools as cognitive instruments for analytical reasoning, iterative exploration, and systematic problem-solving.

This study contributes to the literature by addressing a specific gap in the assessment of attitudes toward parametric design through the development of the PDAS, which has previously been addressed only indirectly through broader digital or programming-focused scales. This scale offers educators a practical tool to evaluate student attitudes, identify areas of resistance or misunderstanding, and design more targeted instructional strategies. It can also be used in future research to investigate the effects of long-term exposure to parametric design tools, the impact of different pedagogical interventions, and the evolution of design-related attitudes over time.

DECLARATIONS

Acknowledgements: The authors do not wish to acknowledge any individual or institution.

Author Contributions: Conceptualization, H.T. and İ.E.E.; Methodology, H.T. and İ.E.E.; Validation, H.T. and İ.E.E.; Formal Analysis, H.T. and İ.E.E.; Investigation, H.T. and İ.E.E.; Resources, H.T. and İ.E.E.; Data Curation, H.T. and İ.E.E.; Writing—Original Draft, H.T. and İ.E.E.; Writing—Review & Editing, H.T.; Visualization, H.T. and İ.E.E.; Supervision, H.T. All authors have read and approved the final version of the manuscript.

Conflict of Interest: The authors declare no conflict of interest.

Supporting Institutions: This research received no external funding.

Ethical Approval: This research was carried out with the permission of the Yıldız Technical University Rectorate Social and Humanities Scientific Research and Publication Ethics Board dated June, 01, 2023 and numbered 2023-06.

Plagiarism Statement: This article has been evaluated for plagiarism and no instances of plagiarism were detected.

Use of AI Tools: The authors declare that no Artificial Intelligence (AI) tools were used in the creation of this article.

REFERENCES

Abdalla, M. R., & Kandil, B. M. E. L.-S. (2017). Parametric and its roles in the design process. *Journal of Engineering and Applied Science*, *64*(5), 345–363.

Alalouch, C. (2018). A pedagogical approach to integrate parametric thinking in early design studios. *Archnet-IJAR: International Journal of Architectural Research*, *12*(2), 162–181. https://doi.org/10.26687/archnet-ijar.v12i2.1584

Amabile, T. M. (1982). Social psychology of creativity: A consensual assessment technique. *Journal of Personality and Social Psychology*, *43*(5), 997–1013. https://doi.org/10.1037/0022-3514.43.5.997

Anastasiadou, S. D. (2011). Reliability and validity testing of a new scale for measuring attitudes toward learning statistics with technology. *Acta Didactica Napocensia*, *4*(1), 1–10. https://files.eric.ed.gov/fulltext/EJ1054957.pdf

Bandura, A. (1997). *Self efficacy: The exercise of control*. W. H. Freeman and Company.

Başer, M. (2013). Developing attitude scale toward computer programming. *International Journal of Social Science*, *6*(6), 199–215. http://dx.doi.org/10.9761/JASSS1702

Baysen, F., & Akçay, A. Ö. (2017). Architecture students attitudes toward information search process. *Information World, 18*(1), 125–142. https://doi.org/10.15612/BD.2017.596

Brenner, W., & Uebernickel, F. (Eds.). (2016). *Design thinking for innovation: Research and practice*. Springer. https://doi.org/10.1007/978-3-319-26100-3

Cho, J. Y., & Suh, J. (2019). Understanding spatial ability in interior design education: 2D-to-3D visualization proficiency as a predictor of design performance. *Journal of Interior Design*, *44*(3), 141–159. https://doi.org/10.1111/joid.12143

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research and Evaluation*, *10*(1), Article 7. https://doi.org/10.7275/jyj1-4868

Dissaux, T., & Jancart, S. (2022). Architecture students' search behavior in parametric design. In *Co-creating the Future: Inclusion in and Through Design: Proceedings of the 40th Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 2022)* (Vol. 1, pp. 171–181).

https://doi.org/10.52842/conf.ecaade.2022.1.171
Er, I. E., Arabacıoğlu, F. P., & Tastan, H. (2025). Cognitive processes in parametric design: A systematic literature review of methods, models, and future directions. *Megaron*, *20*(1), 37–51. https://doi.org/10.14744/megaron.2025.52893
Fennema, E., & Sherman, J. A. (1976). Fennema-Sherman mathematics attitudes scales: Instruments designed to measure attitudes toward the learning of mathematics by females and males. *Journal for Research in Mathematics Education*, *7*(5), 324–326. https://doi.org/10.2307/748467
Garrett, J., & Walker, T. (2008). Student attitudes towards the use of graphical programming languages. In *Proceedings of the 2008 Annual Conference & Exposition* (pp. 13.1105.1–13.1105.11). https://doi.org/10.18260/1-2--3239
Godbole, S. (2014). *Impact of a visual programming experience on the attitude toward programming of introductory undergraduate students* [Master's thesis, Purdue University]. Purdue e-Pubs. https://docs.lib.purdue.edu/open_access_theses/327/
Gürel, A., & Şenyapılı Ozcan, B. (2023). Cognitive Comparison of design methods in the conceptual phase. *International Journal of Architectural Computing*, *21*(4), 581–601. https://doi.org/10.1177/14780771231188474
Hair, J. F. (2010). *Multivariate data analysis*. Prentice Hall.
Henderson, P. B., Cortina, T. J., Wing, J. M., & Hazzan, O. (2007). Computational thinking. In *Proceedings of the 38th SIGCSE Technical Symposium on Computer Science Education* (pp. 195–196). https://doi.org/10.1145/1227310.1227378
Holzer, D. (2015). BIM and parametric design in academia and practice: the changing context of knowledge acquisition and application in the digital age. *International Journal of Architectural Computing*, *13*(1), 65–82. https://doi.org/10.1260/1478-0771.13.1.65
Hongwarittorrn, N., & Krairit, D. (2010). Effects of program visualization (jeliot3) on students' performance and attitudes towards java programming. In *Proceedings of the 8th International Conference on Computing, Communication and Control Technologies (CCCT 2010).* https://www.iiis.org/CDs2010/CD2010IMC/CCCT_2010/PapersPdf/TA750PM.pdf
Hutchinson, A., Moskal, B., Cooper, S., & Dann, W. (2008). The impact of the Alice curriculum on community college students' attitudes and learning with respect to computer science. In *Proceedings of the 2008 Annual Conference & Exposition* (pp. 13.1238.1–13.1238.14). https://doi.org/10.18260/1-2--3306
Joklová, V., & Pifko, H. (2015). Innovation in architectural education-OIKONET experience. *Global Journal of Engineering Education*, *17*(3), 124–131. https://www.wiete.com.au/journals/GJEE/Publish/vol17no3/04-Joklova-Pifko.pdf
Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist*, *41*(2), 75–86. https://doi.org/10.1207/s15326985ep4102_1
Korkmaz, Ö., & Bai, X. (2019). Adapting computational thinking scale (CTS) for Chinese high school students and their thinking scale skills level. *Participatory Educational Research*, *6*(1), 10–26. https://doi.org/10.17275/per.19.2.6.1
Köller, O., Baumert, J., & Schnabel, K. (2001). Does interest matter? The relationship between academic interest and achievement in mathematics. *Journal for Research in Mathematics Education*, *32*(5), 448–470. https://doi.org/10.2307/749801
Kukul, V., & Karatas, S. (2019). Computational thinking self-efficacy scale: Development, validity and reliability. *Informatics in Education*, *18*(1), 151–164. https://doi.org/10.15388/infedu.2019.07
Lee, J. H., & Ostwald, M. J. (2019). Measuring cognitive complexity in parametric design. *International Journal of Design Creativity and Innovation*, *7*(3), 158–178. https://doi.org/10.1080/21650349.2018.1555492
Li, Q., Liu, Z.-x, Wang, P., Wang, J.-j, & Luo, T. (2023). The influence of art programming courses on design thinking and computational thinking in college art and design students. *Education and Information Technologies*, *28*(9), 10885–10902. https://doi.org/10.1007/s10639-023-11618-7
Lun, S., Ho, H. N. J., Shih, M., Perng, Y. H., Tsaih, L., & Liang, J. C. (2025). Exploring learning approaches and self-efficacy among design students in Taiwan. *International Journal of Technology and Design Education*, *35*(4), 1717–1740. https://doi.org/10.1007/s10798-025-10004-3
Monteiro, V., Januário, P., & Veloso, M. (2020). Design collaboration towards constructibility in parametric design process: A design experiment with architecture students. In *Anthropologic: Architecture and Fabrication in the Cognitive Age: Proceedings of the 38th Conference on Education and Research in Computer Aided Architectural Design in Europe (eCAADe 2020)* (Vol. 1, pp. 305–314). https://doi.org/10.52842/conf.ecaade.2020.1.305
Nauzeer, S., & Jaunky, V. C. (2021). A meta-analysis of the combined effects of motivation, learning and personality traits on academic performance. *Pedagogical Research*, *6*(3), Article em0097. https://doi.org/10.29333/pr/10963
Nolan, M. M., Beran, T., & Hecker, K. G. (2012). Surveys assessing students' attitudes toward statistics: A systematic review of validity and reliability. *Statistics Education Research Journal*, *11*(2), 103–123. https://doi.org/10.52041/serj.v11i2.333
Oxman, R. (2008). Performance-based design: Current practices and research issues. *International Journal of Architectural Computing*, *6*(1), 1–17. https://doi.org/10.1260/147807708784640090
Öztürk Kösenciğ, K., & Özbayraktar, M. (2025). Unveiling interactions among architectural sketching, parametric design,

and digital fabrication using linkography. *International Journal of Design Creativity and Innovation*, *13*(1), 1–22. https://doi.org/10.1080/21650349.2024.2426646

Razzouk, R., & Shute, V. (2012). What is design thinking and why is it important? *Review of Educational Research*, *82*(3), 330–348. https://doi.org/10.3102/0034654312457429

Rees, C., Sheard, C., & Davies, S. (2002). The development of a scale to measure medical students' attitudes towards communication skills learning: The Communication Skills Attitude Scale (CSAS). *Medical Education*, *36*(2), 141–147. https://doi.org/10.1046/j.1365-2923.2002.01072.x

Riggio, M., & Cheng, N. Y.-w. (2021). Computation and learning partnerships: Lessons from wood architecture, engineering, and construction integration. *Education Sciences*, *11*(3), Article 124. https://doi.org/10.3390/educsci11030124

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155–169. https://doi.org/10.1007/BF01405730

Shaghaghian, Z., Burte, H., Song, D., & Yan, W. (2022). Learning geometric transformations for parametric design: an augmented reality (AR)-powered approach. In D. Gerber, E. Pantazis, B. Bogosian, A. Nahmad, & C. Miltiadis (Eds.), *Computer-Aided Architectural Design: Design Imperatives: The Future Is Now* (Communications in Computer and Information Science, Vol. 1465, pp. 515–527). Springer. https://doi.org/10.1007/978-981-19-1280-1_31

Shaghaghian, Z., Yan, W., & Song, D. (2021). Towards learning geometric transformations through Play: An AR-powered approach. In *Proceedings of the 2021 5th International Conference on Virtual and Augmented Reality Simulations (ICVARS '21)* (pp. 1–6). https://doi.org/10.1145/3463914.3463915

Suh, J., & Cho, J. Y. (2020). Linking spatial ability, spatial strategies, and spatial creativity: A step to clarify the fuzzy relationship between spatial ability and creativity. *Thinking Skills and Creativity*, *35*, Article 100628. https://doi.org/10.1016/j.tsc.2020.100628

Sunarya, W., Seputra, J. A. P., & Zakariya, A. F. (2023). Parametric modeling practice for the first-year architecture students learning. *ARTEKS: Jurnal Teknik Arsitektur*, *8*(2), 293–304. https://doi.org/10.30822/arteks.v8i2.2189

Tarakçı Eren, E., & Düzenli, T. (2021). Determination of the difference between environmental attitudes of 1st and 4th year students of landscape architecture. *A|Z ITU Journal of the Faculty of Architecture*, *18*(3), 551–565. https://doi.org/10.5505/itujfa.2021.23855

Tarakçı Eren, E., Düzenli, T., & Akyol, D. (2018). Attitudes of landscape architecture students towards biomorphic and parametric design approaches in environmental design. *Sanat ve Tasarım Dergisi*, *8*(1), 126–143. https://doi.org/10.20488/sanattasarim.510285

Tarakçı Eren, E., & Yılmaz, S. (2022). The student attitudes towards digital and conventional drawing methods in environmental design studios and the impact of these techniques on academic achievement in the course. *International Journal of Technology and Design Education*, *32*(1), 617–644. https://doi.org/10.1007/s10798-020-09605-x

Tasli Pektaş, Ş., & Erkip, F. (2006). Attitudes of design students toward computer usage in design. *International Journal of Technology and Design Education*, *16*, 79–95. https://doi.org/10.1007/s10798-005-3175-0

Tastan, H., Tuker, C., & Tong, T. (2022). Using handheld user interface and direct manipulation for architectural modeling in immersive virtual reality: An exploratory study. *Computer Applications in Engineering Education*, *30*(2), 415–434. https://doi.org/10.1002/cae.22463

Tsai, M.-J., & Wang, C.-Y. (2021). Assessing young students' design thinking disposition and its relationship with computer programming self-efficacy. *Journal of Educational Computing Research*, *59*(3), 410–428. https://doi.org/10.1177/0735633120967326

Turan, B. O., Şahin, K., & Işıkdağ, Ü. (2017). An investigation on the attitudes towards adopting the design by coding paradigm. *A|Z ITU Journal of the Faculty of Architecture*, *14*(1), 1–11. https://doi.org/10.5505/itujfa.2017.18209

Uzun, N., & Sağlam, N. (2006). Development and validation of an environmental attitudes scale for high school students. *Hacettepe University Journal of Education*, *30*(30), 240–250. https://izlik.org/JA45DW48NF

Wiebe, E., Williams, L. A., Yang, K., & Miller, C. S. (2003). *Computer science attitude survey*. North Carolina State University, Department of Computer Science. https://repository.lib.ncsu.edu/items/f79abb75-cca8-4e39-85b0-4142bfec772e

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, *49*(3), 33–35. https://doi.org/10.1145/1118178.1118215

Yiwei, R., & Xia, R. (2010). Interpretation of parametric design. In *2010 IEEE 11th International Conference on Computer-Aided Industrial Design & Conceptual Design (Vol. 1*, pp. 1458–1461). https://doi.org/10.1109/CAIDCD.2010.5681935

Yokoyama, S. (2018). Academic self-efficacy and academic performance in online learning: A mini review. *Frontiers in Psychology*, *9*, Article 2794. https://doi.org/10.3389/fpsyg.2018.02794

APPENDIX

Perceived Usefulness

- I consider parametric design approach beneficial for project education to reach its goals.
- I consider parametric design approach improves the achievements.
- I consider using parametric design approach increases student creativity.
- I consider parametric design approach improves the quality in design.
- I consider using the parametric design approach in design projects increases interest.
- I consider parametric design approach beneficial for project education to reach its goals.
- I consider parametric design approach is necessary for more effective design education

Interest and Preferences toward Parametric Design

- I am not interested in learning parametric design concepts.
- I do not think that I will take additional parametric design courses.
- I would not take additional parametric design courses if I were given the opportunity.

Functionality and Application Areas of Parametric Design

- Parametric design cannot help designers while making decisions.
- Parametric design can help designers only for drawing purposes.

Feasibility and Challenges of Parametric Design

- Parametric design can be challenging to implement given the current resources and technical infrastructure.
- I consider use of parametric design approach in design projects is difficult.
- Parametric design approach introduces extra workload.