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A Survey of Personalized Interior Design

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Abstract

Interior design is the core step of interior decoration, and it determines the overall layout and style of furniture. Traditional interior design is usually laborious and time-consuming work carried out by professional designers and cannot always meet clients' personalized requirements. With the development of computer graphics, computer vision and machine learning, computer scientists have carried out much fruitful research work in computer-aided personalized interior design (PID). In general, personalization research in interior design mainly focuses on furniture selection and floor plan preparation. In terms of the former, personalized furniture selection is achieved by selecting furniture that matches the resident's preference and style, while the latter allows the resident to personalize their floor plan design and planning. Finally, the automatic furniture layout task generates a stylistically matched and functionally complete furniture layout result based on the selected furniture and prepared floor plan. Therefore, the main challenge for PID is meeting residents' personalized requirements in terms of both furniture and floor plans. This paper answers the above question by reviewing recent progress in five separate but correlated areas, including furniture style analysis, furniture compatibility prediction, floor plan design, floor plan analysis and automatic furniture layout. For each topic, we review representative methods and compare and discuss their strengths and shortcomings. In addition, we collect and summarize public datasets related to PID and finally discuss its future research directions.

Keywords: Methods and Applications

CCS Concepts: • Computing methodologies → Computer graphics; • General and reference → Surveys and overviews; • Human-centred computing → Interaction design

1. Introduction

Home is not only a place for people to live but also a medium in which people express their personalities and tastes. Therefore, the interior decoration should not only meet residents' practical functional needs but also reflect their pursuit of aesthetics and personality. This aims means that personalization has become an important factor that merits serious consideration in modern interior design. Personalized interior design (PID) is a technology used to create a reasonable, comfortable and graceful interior environment to meet people's functional needs and aesthetic intent according to their personalized requirements for the furniture and floor plan. Personalization in PID consists of two main aspects, that is, furniture selection and floor plan preparation, and is ultimately reflected in a stylistically matched and functionally complete interior layout result.

On the one hand, furniture selection reflects people's subjective personalization in their aesthetic pursuits. The two most important attributes of furniture are function and style. On the basis of meeting functional requirements, personalized furniture selection should be as close as possible to the preferences of residents. The selection of furniture should not only focus on their style preferences but also consider whether the styles of furniture are compatible with each other; for example, Baroque furniture and Modernist furniture are obviously not compatible. Therefore, it is meaningful to conduct furniture style analysis, which can guide residents to select furniture with matching styles according to their individual preferences.

On the other hand, floor plan preparation also reflects the objective personalization embodied in floor plan design and planning. There are usually two cases in practical applications. When residents do not have a floor plan, they can design personalized and

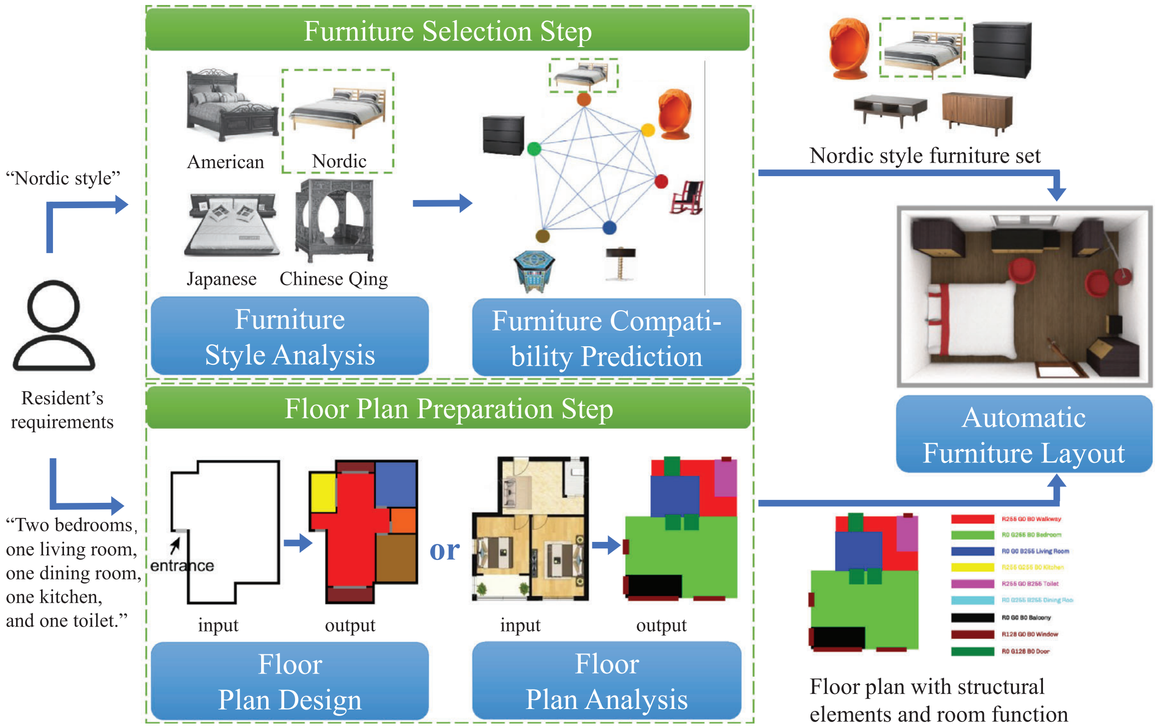

Figure 1: *PID pipeline.*

reasonable floor plans according to their needs while meeting functional requirements such as room function. If the resident already has a floor plan, which is usually in the format of a raster image provided by the developers, it is necessary to identify its structural elements, including walls, doors and windows, and room functions; these factors guide the realization of automatic furniture layout. For example, cabinets should be placed against the wall, and a bed should not be present in the kitchen. This step is challenging because it requires joint optimization of various functional and spatial constraints within a limited interior space.

Overall pipeline

The input to the PID is divided into two aspects: the style preference for the furniture (European, Rococo) and the house boundary or floor plan. The PID output is a style-matching and well-laid-out interior furniture layout result. Based on the above discussion, this paper reviews the research progress of PID from two perspectives, as shown in Figure 1, that is, furniture selection and floor plan preparation. The former reflects people’s subjective personalization in their aesthetic pursuits, while the latter reflects the objective personalization embodied in floor plan design and planning. The furniture selection step contains two tasks, that is, furniture style analysis and furniture compatibility prediction. These two tasks are serially related. The former determines the style of the furniture and furniture design, while the latter analyses how well the furniture matches each other. The floor plan preparation step eventually aims to obtain a well-defined and structured floor plan. There are two cases in which the input is the house boundary or the original floor plan, corresponding to two tasks: floor plan design and floor plan analysis. The inputs to the automatic furniture layout task are the results of the furniture selection step and floor plan preparation step. The furniture selection step helps residents select style-matching furniture according to their personalized preferences; the floor plan preparation step identifies structural elements and room functions that constrain the furniture layout. Finally, the automatic furniture layout task generates a stylistically matched and functionally complete furniture layout result based on the selected furniture and prepared floor plan. Representative methods of each task in PID are listed in Table 1. Overall, the contributions of our work can be summarized as follows:

- For the computer-aided interior design problem, we propose to organize the existing work into a PID pipeline from two aspects of personalization, that is, furniture selection and floor plan preparation.
- We split the PID pipeline into five tasks and discuss the ideas, advantages and disadvantages of previous work and the connection between tasks.
- We collected relevant datasets in PID and compared and summarized them from the perspective of their form, scale and application.
- We discuss current applications of PID, current limitations of PID research and possible directions for future efforts.

This survey is organized as follows: Sections 2 and 3 review representative methods in furniture style analysis and furniture compatibility prediction. Sections 4 and 5 discuss recent literature on floor plan design and floor plan analysis. Section 6 reviews the work

Table 1: *Personalized interior design algorithm overview.*

Tasks	Methods	References (Year)
Furniture style analysis	Furniture style classification	Hu et al. [HWL*17] (2017), Hu et al. [HLK*17] (2017), Yu et al. [YZX*18] (2018), Ting et al. [TTKYHQ19] (2019), Schwartz et al. [SWACC21] (2021)
	Furniture style transfer	Xu et al. [XLZ*10] (2010), Li et al. [LZW*13] (2013), Ma et al. [MHS*14] (2014), Han et al. [HLHB15] (2015) , Lun et al. [LKWS16] (2016), Berkiten et al. [BHS*17] (2017), Segu et al. [SGST20] (2020)
Furniture compatibility prediction	Binary group-based methods	Bell et al. [BB15] (2015), Aggarwal et al. [AVSY18] (2018), Weiss et al. [WYA*20] (2020)
	Triple group-based methods	Liu et al. [LHLF15] (2015), Lun et al. [LKS15] (2015), Dev et al. [DL15] (2015), Lim et al. [LGK16] (2016), Pan et al. [PDTH17] (2017), Pan et al. [PDHC19], Liu et al. [LTR19] (2019)
	Multivariate group-based methods	Polania et al. [PFNL20] (2020)
Floor plan design	Boundary-constrained floor plan design	Bahrehmand et al. [BBM*17] (2017), Wu et al. [WFLW18] (2018), Wu et al. [WFT*19] (2019), Wang et al. [WZC*21] (2021), He et al. [HHW22] (2022), Sun et al. [SWL*22] (2022)
	Graph-constrained floor plan design	Nauata et al. [NCC*20] (2020), Chen et al. [CWT*20] (2020), Hu et al. [HHT*20] (2020), Nauata et al. [NHC*21] (2021), Xu et al. [XXR*21] (2021), Wang et al. [WXL*21] (2021), Para et al. [PGK*21] (2021)
Floor plan analysis	Structural element identification	Mace et al. [MLVT10] (2010), Ahmed et al. [ALWD11] (2011), Dodge et al. [DXS17] (2017), Ziran et al. [ZM18] (2018), Surikov et al. [SNBS20] (2020), Wu et al. [WSC*21] (2021), Song et al. [SY21] (2021),
	Room function prediction	Liu et al. [LWKF17] (2017), Huang et al. [HZ18] (2018), Zeng et al. [ZLYF19] (2019), Lu et al. [LWG*21] (2021), Lv et al. [LZYZ21] (2021)
Automatic furniture layout	Case reasoning-based methods	Akase et al. [AO13] (2013), Xu et al. [XCF*13] (2013), Song et al. [SZJ17] (2017), Fu et al. [FFY*20] (2020)
	Rule constraint-based methods	Xu et al. [XSF02] (2002), Sanchez et al. [SLRLG03] (2003), Yu *et al.* [YYT*11] (2011), Merrell et al. [MSL*11] (2011), Kan et al. [KK18] (2018), Vitsas et al. [VPGV20]
	Deep learning-based methods	Wang et al. [WSCR18] (2018), Ritchie et al. [RWL19] (2019), Yang et al. [YLS*19] (2019), Zhou *et al.* [ZWK19] (2019), Wang et al. [WLW*19] (2019), Zhang et al. [ZYM*20] (2020), Luo et al. [LZWT20] (2020), Wang et al. [WLY20] (2020), Wang et al. [WYN21] (2021), Paschalidou et al. [PKS*21] (2021), Ostonov et al. [OWM22] (2022)

related to automatic furniture layout, and Section 7 introduces several tasks that are included in PID but that have been studied less. Section 8 compares relevant public datasets in PID. Future research directions and conclusions are discussed in Sections 9 and 10.

2. Furniture Style Analysis

Furniture style analysis is one of the key tasks in PID and the basis of furniture selection. Furniture style analysis includes two parts: furniture style classification and furniture style transfer. The former can identify the style of the input furniture image or shape, such as European or Victorian. Meanwhile, the latter allows residents to create new furniture according to style, providing more possibilities for PID furniture selection. In this section, we start with a style classification study for a single piece of furniture, and then discuss the style transfer between two pieces of furniture. Table 2 summarizes various furniture styles involved in previous studies.

2.1. Furniture style classification

Furniture style classification aims to predict the style category of furniture, such as European court or Chinese classical. In practice, there are significant appearance differences between furniture with the same style but different functions (as shown in Figure 2a), and the boundaries between different styles of the same function may be vague or overlap (as shown in Figure 2b). This objective factor makes accurate classification of furniture styles difficult. This section introduces three furniture style classification methods:

Table 2: *Categories of furniture styles introduced in various papers.*

Reference	Venue	Furniture style
Hu et al. [HWL*17]	TIST 2017	American, Baroque, Empire, Gothic, Renaissance, Rococo, Chinese Ming, Chinese Qing, Neo-Classicism, Mediterranean, Rural, Modern French, Japanese, Modern Chinese, Southeast Asia, Modernist
Hu et al. [HLK*17]	TOG 2017	Children, European, Japanese, Ming
Ting et al. [TTKYHQ19]	ICSAI 2019	European, Baroque, Royal, Gothic, Neaclassicism, Rococo, Simplicity, Classical, Rustic, Japanese, Literary
Schwartz et al. [SWACC21]	CDNA 2021	Modern, Coastal, Traditional, Cottage

Figure 2: *Difficulties of the furniture style classification task. (a) Ming. (b) Baroque and Rococo.*

Figure 3: *Examples of furniture style definition elements [HLK*17]. (a) European. (b) Ming.*

deep neural networks (learning high-level style features) and style-defining elements (mining low-level elements features).

2.1.1. *Deep neural network based methods*

With the development of artificial intelligence, deep neural networks have also been applied to furniture style classification. Thanks to their excellent feature extraction ability, they perform well in the furniture style classification task.

The first study on furniture style classification [HWL*17] realized a classification of 16 common furniture styles. They concatenated hand-crafted features with convolutional features extracted by AlexNet and input the mixed features into a SVM to train a furniture style classifier. Inspired by the human eye's attention mechanism, Ting et al. [TTKYHQ19] combine interest factors and CNN features to achieve furniture style classification, which effectively suppresses the influence of less visually pleasing areas. They calculated interest factors based on colour, brightness and contour features, compensating for the shortcomings of traditional CNNs with a single feature. Schwartz et al. [SWACC21] utilized deep neural networks to achieve end-to-end learning without using explicit feature extraction steps. They used a siamese network with VGG16 as the backbone, which avoids the complex hand-crafted feature extraction steps.

2.1.2. *Style-defining element-based methods*

A furniture style-defining element set refers to the collection of all of the elements that distinguish a furniture style. For example, the colour area in Figure 3 represents the extracted style-defining elements used to determine the furniture style, namely, the tubular structure and relief decorative elements of furniture in the Ming style and curved lines in the European style.

As shown in Figure 4, Hu et al. [HLK*17] proposed a method for co-locating style-defining elements on a set of 3D shapes. They collected an initial set of elements from the shape and obtained the style-defining elements by sampling and combining the elements. Then, they detected the style-defining elements for a new furniture image and classified furniture styles using a simple classifier. Similarly, Yu et al. [YZX*18] proposed a semi-supervised co-analysis method. They learned the style of 3D furniture models from projected feature lines and used weak supervision to achieve style patch (style-defining elements) localization; then, they extracted the style patches on the 3D furniture model by back projection to analyse furniture styles.

These methods can improve the accuracy of style classification and localization of style elements, but they have a limitation in that the style-defining elements they extract are local. They focus on local elements and analyse furniture styles based on local structure; for example, they classify furniture styles based on details that appear in the type and shape of chair legs. Their analysis does not account for structural features and more global characteristics, which are also important factors that influence furniture style.

2.2. Furniture style transfer

Personalized furniture customization is a furniture synthesis process based on the premise of preserving furniture function while achieving style transfer. According to the specific implementation methods, we divide the existing furniture synthesis methods based on style transfer into two categories: methods based on style content separation and methods based on analogy.

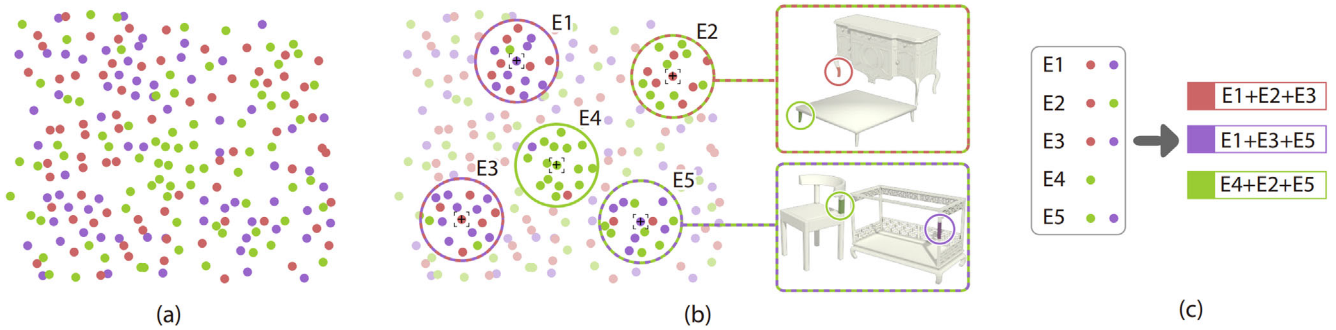

Figure 4: *Extract style-defining elements of the furniture style analysis [HLK*17].*

Figure 5: *Furniture style transfer result (the image in the box is the original image) [XLZ*10].*

2.2.1. *Style content separation-based methods*

Furniture generation based on style transfer generates new furniture with a specific style while ensuring that the furniture's function is not affected. Existing methods attempt to analyse the style and content (functional structure) of furniture independently and then achieve style transfer of the retained content.

Xu et al. [XLZ*10] proposed a style content separation algorithm for 3D furniture models and realized furniture synthesis based on style transfer. They obtained the inter-style and intra-style part correspondence through style classification and co-segmentation. Based on the part correspondence, they deformed the components to achieve furniture synthesis of style transfer. The result of furniture synthesis in Figure 5 shows that this method generates new shapes based on scale transformation only, with no significant change in shape structure and lack of diversity. Later, Han et al. [HLHB15] also proposed a similar method to achieve 3D model style transfer. Since some complex shapes are difficult to segment, they implement style-content separation without semantic segmentation.

Li et al. [LZW*13] proposed an unsupervised algorithm to identify a curve's style and separate its style and content by analysing the feature-shape association matrix. They then synthesized the new 2D shape by replicating the feature curve. However, this approach fails when the segment-level resolution is too coarse to capture source-to-target relationships. Lun et al. [LKWS16] transferred the exemplar style to the target through a series of element-level operations; they progressively updated the target shape with compatible operations, increasing its stylistic similarity to the example while strictly maintaining its functionality at each step.

Previous methods based on style-content separation have obvious limitations. First, it is difficult to establish dense correspondence between shapes with large geometric changes because the shape comparison strategy of these methods is based on dense correspondence. Second, when generating a new model, the recombination of two adjacent parts often leads to the problem of connecting parts, and improper connections often result in an unnatural model.

Recently, Segu et al. [SGST20] proposed the first learning-based method to achieve style transfer of 3D objects, 3DSNet. 3DSNet uses a shared content encoder and two domain-specific style encoders, both of which were implemented based on PointNet [QSMG17] to implicitly separate the style and content in the feature space. The decoder is used to reconstruct 3D objects from the selected content and style encoding. However, 3DSNet inherits the limitations of the 3D reconstruction method, and some significant details are lost in the reconstructed shapes; this loss may be due to the loss of high-frequency feature components caused by the maximum pool layer in the PointNet encoder.

2.2.2. *Shape analogy-based methods*

Different from the method based on style content separation, furniture style transfer based on the shape analogy method calculates the analogical relationship between a source model and a target model and applies it to the exemplar model to synthesize a new furniture model according to the exemplar style.

Figure 6 illustrates the analogy-driven style transfer method framework [MHS*14]. Given three input shapes: a source $\mathcal{S}$, a target $\mathcal{T}$, and an exemplar $\mathcal{E}$, the model synthesized an output model $\mathcal{O}$. They first restore the transformation relationship $\mathcal{M}$ and $\mathcal{A}$. The example-to-output transformation relationship $\mathcal{A}^*$ is approximated as $\mathcal{M}\mathcal{A}\mathcal{M}^{-1}$ and then refined further using simultaneous alignment and deformation processes to obtain the desired output shape. Berkiten et al. [BHS*17] attempted to implement transferring model

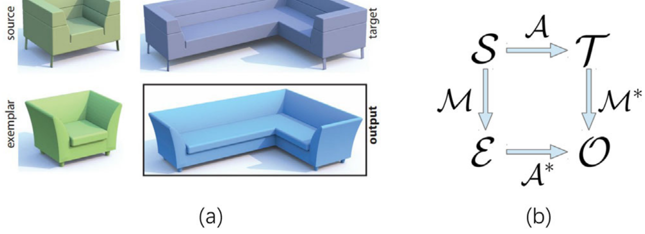

Figure 6: *(a) Style transfer example. (b) Analogy model [MHS*14].*

details, for example, textures and shapes. They performed the analysis entirely in the source model and creatively used metric learning to optimize the feature representation. The learned metrics are then used to guide the output model's texture synthesis.

Compared with the style transfer method based on style content separation, shape-analog-based approaches can capture fine hierarchical styles features such as part shapes or geometric textures and process source and target models with different structures. Style transfer is achieved by calculating source-to-target analogies, which define structural differences between models in geometric terms. However, the per-patch transformations used to assemble the analogies are restricted to rigid similarity transformations, and there is still a significant gap between the more complex, free-form organic shape deformation effect that is achieved manually.

Discussion. Style is the main attribute that needs to be considered when selecting furniture, and the current furniture style classification method has been able to accurately judge furniture style, but, furniture design is still a field that has been studied less. Although the furniture style transfer method introduced in this section is also a furniture design method, it relies on the existing furniture and has considerable limitations. Future work could employ cross-modal learning, for example, to generate 3D furniture models based on the resident's textual description of the furniture to better reflect 'personalization'.

3. Furniture Compatibility Prediction

A natural requirement of interior design is finding style-matching furniture. As furniture style studies have advanced, researchers have gradually transitioned from single furniture style classification to quantitative descriptions of matching relationships between furniture. Furniture compatibility prediction specifically refers to the calculation of compatibility scores for multiple furniture images or models to determine their degree of style matching. Furniture compatibility prediction is mostly based on metric learning, which measures the similarity between two or more pieces of furniture and determines their compatibility. Depending on the form of the data used during learning, methods based on binary group, triple group and multivariate group are discussed in this section. For ease of understanding, it is specified that A, B, C represent furniture and x_A, x_B, x_C represent their style feature embeddings.

3.1. Binary group-based methods

Binary group data are commonly used in siamese networks for furniture compatibility prediction. Bell et al. [BB15] inferred furniture compatibility based on visual similarity, trained siamese network models using contrast loss, and applied them to furniture retrieval. Aggarwal et al. [AVSY18] trained a siamese network based on binary groups (A, B, Y), where A and B represent two pieces of furniture, respectively; $Y \in \{0, 1\}$ is the compatible label, where $Y = 1$ represents a positive compatible pair and $Y = 0$ represents a negative one. They trained a CNN model to learn furniture style embeddings by applying the following contrast loss:

$$L(x_A, x_B, Y) = Y \cdot D(x_A, x_B)^2 + (1 - Y) \cdot \max{[0, m - D(x_A, x_B)]^2} \tag{1}$$

where $D(x_A, x_B)$ is a measure of the distance between furniture A and B such that the obtained embedding brings the matched furniture closer and pushes the mismatched furniture further away, and m is the margin hyperparameter.

In contrast, the binary group in [WYA*20] can be expressed in the form $(A, B, l, y^l_{(A,B)})$, where $y^l_{(A,B)}$ is a comparison label. A value of 1 indicates that furniture A is more inclined to style l than furniture B, and a value of -1 indicates the opposite. They used VGG16 as the backbone network and trained the siamese network to predict whether the first image depicts more style-specific characteristics than the second image.

3.2. Triple group-based methods

The methods in this section typically use triplet loss to analyse style compatibility between different categories of furniture based on triplet data [LGK16, PDHC19, PDTH17, LTR19]. They obtained the triplets (A, B, C), which indicate that A and B are more stylistically matched than A and C. VGG16 is used as the backbone network, and the following triplet loss function is used during training:

$$\mathcal{L}(x_A, x_B, x_C) = \max{(D(x_A, x_B) - D(x_A, x_C) + m, 0)} \tag{2}$$

where $D(x_A, x_B)$ indicates the distance between two furniture embeddings and m is an edge hyperparameter.

Other methods propose more innovative approaches to feature extraction or style similarity measurement. Liu et al. [LHLF15] calculate the consistent partitioning of all 3D objects in the same furniture type. Then the geometric features of the parts and the whole are concatenated as a feature representation of the object. They also learned separate projection matrices $W_{c(A)}$ and $W_{c(B)}$ for classes $c(A)$ and $c(B)$ to calculate the asymmetric embedding distance and learned furniture compatibility measures using triple groups (Figure 7).

$$d_{\text{asymm}}(x_A, x_B) = ||W_{c(A)}\, x_A - W_{c(B)}\, x_B||_2 \tag{3}$$

This method addresses the problem of furniture feature representation across categories. However, it ignores the attributes that affect the style compatibility of the furniture's 3D model such as colour and structure. Lun et al. [LKS15] used a weighted combination of feature descriptor distances as a stylistic measure of the 3D model based on the significance, geometric similarity, and prevalence of patches extracted from the object's surface. Then, they introduced triplet supervised data to learn the weights of the

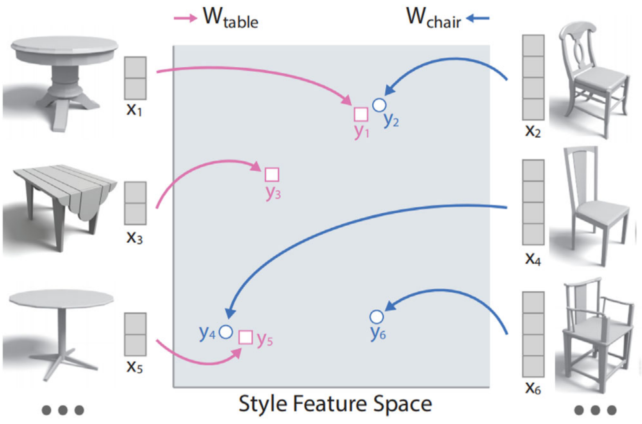

Figure 7: *Mapping into a shared feature space [LHLF15].*

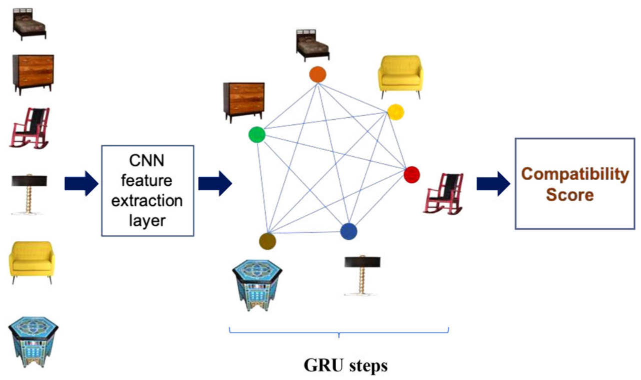

Figure 8: *Furniture compatibility prediction model based on the GNN [PFNL20].*

significance terms and the similarity terms. However, because these methods rely on partially aware geometric features, they require consistent partial segmentation of 3D models within the object classes, which is a challenging step that often requires manual segmentation. To solve the problem that only geometric features are considered in [LHLF15, LKS15], Dev et al. [DL15] added color and texture features to improve the 3D models's style similarity learning.

3.3. Multivariate group-based methods

The approach based on multivariate groups means that the model's input comprises multiple pieces of furniture, but the number is variable. Polania et al. [PFNL20] represented furniture in a matching group as an interconnected graph (Figure 8). They used the CNN feature vector as the initial state of the furniture represented by the GNN nodes and then iteratively updated the nodes' hidden state with a GRU by using the neighbouring nodes' information. Finally, they used the node states to calculate the compatibility score between the furniture. This method takes advantage of the GNN model's excellent feature aggregation capability to simultaneously consider the interactions between multiple pieces of furniture in the scene, instead of considering pairs of data separately.

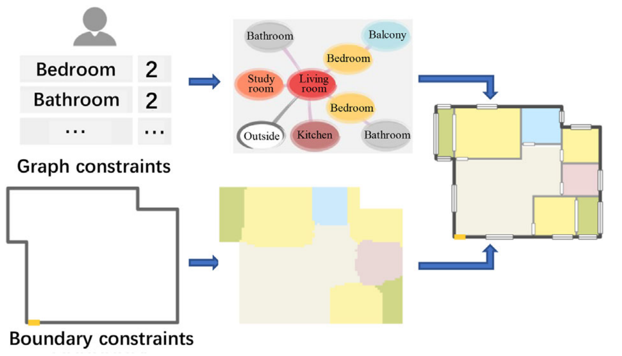

Figure 9: *Implementing a floor plan design based on graph constraints or boundary constraints.*

Discussion. The purpose of this section is to guide residents in the selection of furniture. However, there is still a gap between current compatibility prediction methods and human perception of style collocation, as they rarely consider human factors. One possible approach idea is to introduce human-computer interaction in terms of determining furniture compatibility to generate a judgment result that matches human intuition.

4. Floor Plan Design

The first two sections mainly focus on various innovative methods that help residents select personalized furniture. PID personalization is also reflected in the floor plan, and the furniture layout is usually planned according to the floor plan. In this problem, residents expect to design personalized and reasonable floor plans according to their preferences while meeting requirements such as room division. Depending on the input constraints, this section introduces the floor plan design based on both boundary constraints and graph constraints (Figure 9). We compare the similarities and differences of these methods in Table 3.

4.1. Boundary-constrained floor plan design

Floor plan design based on boundary restrictions achieves a reasonable structural design and room division within the boundaries. Early floor plan generation algorithms [BBM*17] build objective functions based on architectural quality metrics and resident preferences, starting with an initial random floor plan that is iteratively optimized using evolutionary algorithms. Wu et al. [WFLW18] adopted high-level constraints as inputs and generated building interiors based on a mixed integer quadratic programming (MIQP) formulation. The integer variables are used to account for different room configurations. Both approaches consider the generation of floor plans to be a system based on constraints (such as room size and adjacency). However, these constraints rely on professional designers. Wu et al. [WFT*19] simulated the human design process by first locating rooms and then walls while adapting the input building boundaries to generate floor plan designs with high-level requirements. He also used a living room first strategy to predict room locations to improve the reasonableness of the generated floor plans.

Table 3: *Comparison of floor plan design methods.*

Reference	Venue	Methods	Input	Door&Window	Output
Bahrehmand et al. [BBM*17]	GM 2017	Genetic algorithm	Boundary	✓	3D floor plan
Wu et al. [WFLW18]	CGF 2018	MIQP	Boundary	✓	3D floor plan
Wu et al. [WFT*19]	TOG 2019	Encoder-Decoder	Boundary	✓	2D floor plan
Hu et al. [HHT*20]	TOG 2020	GNN, CNN	Boundary, Graph	✓	2D floor plan
Nauata et al. [NCC*20]	ECCV 2020	GAN	Graph	×	2D floor plan
Chen et al. [CWT*20]	CVPR 2020	GCN, GAN	Graph	✓	3D floor plan
Wang et al. [WZC*21]	TVCG 2021	GAN	Boundary	✓	2D floor plan
Wang et al. [WXL*21]	CGF 2021	CNN	Graph	×	3D floor plan
Para et al. [PGK*21]	ICCV 2021	Transformer	Boundary, Graph	✓	2D floor plan
Nauata et al. [NHC*21]	CVPR 2021	GAN	Graph	✓	2D floor plan
Xu et al. [XXR*21]	ICCV 2021	VAE	Graph	×	2D floor plan
He et al. [HHW22]	CVPR 2022	Markov chain	Boundary	✓	2D floor plan
Sun et al. [SWL*22]	TOG 2022	Graph generation	Boundary	✓	2D floor plan

The previous approach required complex problem modelling, and Wang et al. [WZC*21] proposed a simpler human-centred approach to floor plan design. In the first stage, they used a human activity map to guide the generation of floor plans from input boundaries. During the second stage, they converted the pixelwise predictions into vectorized floor plans for convenient usage by architects. Their experiments show that incorporating human activity maps into the guided learning process yields more accurate network predictions. Although the current floor plan design work can be fully automated, design is essentially a procedural process, and this lack of designer interaction may cause the floor plan design to deviate from the original concept. Therefore He et al. [HHW22] proposed a new human-in-the-loop generative model, iPLAN, that automatically generates layouts but also interacts with the designer throughout the process. They decomposed the design procedure into three steps: acquiring the room types, locating rooms and finalizing room partitions. This process allows the model to accept input from the designer at any stage to generate a floor plan that matches the resident's preferences. Sun et al. [SWL*22] designed a wall-oriented approach, WallPlan, which innovatively uses two modules to predict a floor plan's wall and room functions separately. The two modules then alternate to generate partial floor plans until no new walls can be generated. WallPlan can produce high-quality floor plans without postprocessing.

4.2. Graph-constrained floor plan design

Graph-constrained floor plan designs typically represent residents' requirements as relational graphs, using nodes to represent rooms and edges to represent adjacencies. Based on the sparse design constraints provided by the resident, Hu et al. [HHT*20] used generative networks to learn room relationships and automatically generate floor plans. They employed a layout graph to represent these constraints and then input the graph into a deep neural network-based learning framework, Graph2Plan, to generate rough floor plans. Finally, postprocessing is performed to obtain a fine-grained, vectorized floor plan. Based on independent room data from a large 3D scene dataset, Wang et al. [WXL*21] generated new 3D floor plans by stitching together existing 3D rooms based on a relation graph. Many previous methods require heuristic postprocessing to improve the quality of floor plans, but that process is not based on the data and may generate unrealistic results. Para et al. [PGK*21] proposed a floor plan generation model using constraint graphs. The nodes of the constraint graph represent the layout elements, and the edges represent the constraints between the elements. Constraint optimization is then used to solve for the final layout. They used a transformer-based architecture to generate the floor plan without resident input.

The GAN, as a generative algorithm, performs well on a variety of image generation tasks, and there are also many GAN-based methods that can generate a wide variety of floor plans. Nauata et al. [NCC*20] used the bubble diagram as input to generate a set of reasonable floor layouts. The nodes of the bubble diagram encode room types, and the edges encode adjacency. For the floor layout design, they proposed a graph-constrained relation generation adversarial network, House-GAN, which includs a relation generator and a discriminator. Nauata et al. [NHC*21] then integrated a graph-constrained relational GAN and a conditional GAN that accepts the previously generated model as the next input constraint to achieve iterative layout refinement. They also extended the previous application to handle nonrectangular room shapes and generated doors or entrances. Chen et al. [CWT*20] proposed the House Plan Generative Model (HPGM), a creative implementation of text-to-3D house plan conversion. They first designed a Graph Conditioned Layout Prediction Network (GC-LPN), which encodes graphs as feature representations and predicts room layouts using bounding box regression. Then, a Language Conditioned Texture GAN (LCT-GAN) was designed to generate room textures using the encoded text representations as input. Finally, after rendering, a 3D house plan can be generated. Xu et al. [XXR*21] designed a city modelling algorithm based on the variational autoencoder (VAE), which is a generative model. It can also be used to generate floor plans.

Discussion. The floor plan design reflects another aspect of personalization in PID. Some current approaches [PGK*21] can account more for residents' requirements while meeting boundary constraints such as two bedrooms and one bathroom. This additional consideration of the resident's idea for the floor plan design

Table 4: *Comparison of floor plan structural element identification methods.*

Reference	Venue	Methods	Structural elements
Mace et al. [MLVT10]	IAPRW 2010	Hough transform	wall, door, room
Ahmed et al. [ALWD11]	ICDAR 2011	SURF	wall, door, room, window
Dodge et al. [DXS17]	MVA 2017	FCN, Faster R-CNN	wall, sliding door, kitchen oven, door, bath tubs, sink, toilet
Ziran et al. [ZM18]	IAPRW 2018	Faster R-CNN	door, window, furniture
Surikov et al. [SNBS20]	COMS2 2020	UNet	wall, door, window
Wu et al. [WSC*21]	IJGIS 2021	Mask R-CNN	wall, door, window, room, staircase
Song et al. [SY21]	ISPRS 2021	GNN	wall, door, window, room, staircase, lift, hallway

makes considerable sense. There are also some innovative works [CWT*20] that used residents' text descriptions as the only input to guide floor plan generation, which highlights a new direction for subsequent research.

5. Floor Plan Analysis

The floor plan affects the furniture layout, and both structural elements and room function influence the final furniture layout. Specifically, the structural elements influence the position of the furniture, for example, cabinets should be placed against the wall. The room function also limits the type of furniture; for example, a bed should not be present in the kitchen. Therefore, it is necessary to analyse the structural elements and room function in the floor plan to guide the subsequent automatic furniture layout. Based on these two factors, this section discusses structural element identification and room function prediction in floor plan analysis.

5.1. Structural element identification

Structural elements include doors, walls and rooms, which play important roles in dividing rooms and influencing the furniture layout. The representative approaches are summarized in Table 4. As seen from the table, researchers typically use methods such as object detection and semantic segmentation to detect elements such as walls, doors and rooms in floor plans.

Early methods usually use line detection and edge detection to extract walls and then, analyse other structures such as doors, windows and rooms. Mace et al. [MLVT10] used a line detection algorithm based on a combination of the classical Hough transform and image vectorization to achieve wall detection. Door detection is achieved by extracting arcs. Then, the hypothetical extraction results for the walls and doors are logically analysed to detect the rooms in the floor plan. Ahmed et al. [ALWD11] extracted lines of different thicknesses from floor plans, extracted walls from thicker lines, and then segmented the rooms using geometric reasoning. However, these heuristic methods [MLVT10, ALWD11] depend on the data of specific standard floor plans and cannot be applied to different floor plans.

Due to the robustness of CNN models in terms of floor plan noise [SY21], recent studies have typically used deep learning-based algorithms to realize floor plan element recognition. Dodge et al. [DXS17] used wall segmentation, object detection, and optical character recognition (OCR) to analyse floor plans in a step-by-step manner. They also estimated the area of the house by using a combination of OCR and object detection. Similarly, Ziran et al. [ZM18] used a Faster R-CNN model based on ResNet-50 to detect elements in floor plans, thus realizing information analysis of floor plans. Wu et al. [WSC*21] transformed floor plan images into indoor maps and models; they first used Mask R-CNN to vectorize the architectural elements in the floor plan, performed consistent topology optimization, and finally generated rooms, maps, and models. Similarly, Surikov et al. [SNBS20] used the UNet and DeepLabv3+ models to achieve segmentation of floor plans and added morphological filtering, component filtering, contour extraction and contour simplification to optimize the segmentation results and identify structural elements. However, these pixel-level segmentation methods [DXS17, ZM18, WSC*21, SNBS20] have difficulty capturing the exact shape of interior elements, and some of their postprocessing steps may lead to the loss of the original interior elements. In contrast, Song et al. [SY21] innovatively proposed a GNN-based interior element recognition framework. They abstracted the interior elements into polygons and represented them as nodes in the GNN. The nodes are classified by analyzing their inherent features and the relationships between them to achieve recognition of interior structural elements.

5.2. Room function prediction

As we all know, beds should not appear in the kitchen, and sofas are usually placed in the living room. Room function is crucial for furniture layout in practical applications, and it is necessary to analyse the room function in the floor plan. Room function prediction tasks usually use semantic segmentation to divide rooms with various functions [LZYZ21] or use a generative adversarial network to generate room function prediction results [HZ18]. Some algorithms have also introduced the idea of multitask learning to improve the model effect [ZLYF19, LWG*21].

Liu et al. [LWKF17] trained a CNN to detect the connection points in a floor plan, such as the corners, and then applied integer programming to encode the high-level constraints to analyse the floor plan and predict the room function. However, because they rely on the Manhattan world assumption and the wall thickness uniformity, the method cannot handle irregular layouts. Lv et al. [LZYZ21] used YOLOv4 as the basic detection model for the region of interest (ROI) detection module. Then, the segmentation algorithm is used to predict the functions of each room. However, it often incorrectly predicts the room function in an open kitchen, and it also cannot identify curved walls.

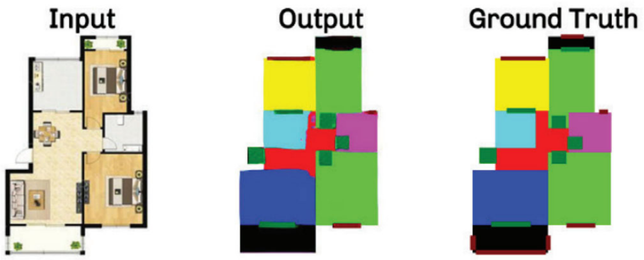

Figure 10: *Results of floor plan analysis [HZ18].*

Zeng et al. [ZLYF19] introduced the multitask learning idea and attention mechanism module to improve the floor plan analysis performance. The following two tasks are learned simultaneously: prediction of the room boundaries' pixels and prediction of the room function pixels. They used the attention mechanism guided by room boundaries to construct spatial context modules to maximize the feature integration for room function prediction. However, the method still fails to correctly address some special room structures (such as long and curved corridors). Lu et al. [LWG*21] also used multitasking learning. Two branches are connected after the VGG16 encoder, a UNet decoder that predicts the room boundaries, and a fast single shot detector (SSD) that detects room-function text. Huang et al. [HZ18] innovatively used the GANs for element recognition and room function prediction of floor plans by using different RGB values to label different regions. This method can achieve the results shown in Figure 10.

Discussion. Floor plan analysis is the basis of automatic furniture layout. Researchers usually use methods such as semantic segmentation or object detection to achieve recognition of structural elements and room function. There are also innovative approaches that use GANs to generate analysis results directly. These approaches have performed well in most scenarios but have difficulty addressing some rare structures, such as open kitchens and curved walls. Some methods calculate both the area and dimensions of a room, and this information is also useful when constructing the subsequent automatic furniture layout.

6. Automatic Furniture Layout

After the furniture style analysis, we can annotate furniture with suitable style labels such as Classical Chinese and European court. This process effectively limits the scope of furniture selection in the automatic furniture layout task, which guarantees a stylistically matched and functionally complete furniture layout result. The floor plan preparation step identifies structural elements and room functions that constrain the furniture layout. Based on the furniture selection results and floor plan preparation, this section introduces the automatic furniture layout algorithm to obtain a stylistically matched and functionally complete interior layout result.

A good furniture layout balances functionality and aesthetics. Mitton et al. [MN21] noted the importance of accessibility of furniture placement when decorating a room, Ching et al. [CB18] showed how the walkway to the door influenced the furniture layout and interior decoration, and Ballast *et al.* [BFN*13] and OShea et al. [OGL13] also provided wealth of aesthetic, ergonomic and functional rules for interior design. These studies are the basis of automatic furniture layout research in PID. This section divides the related work on automatic furniture layouts into three categories: automatic layout methods based on case reasoning, rule constraints and deep learning. Table 5 summarizes and compares the automatic furniture layout methods.

6.1. Case reasoning-based methods

Case reasoning uses the idea of "borrowing" to solve interior design problems by using information from existing layouts. This method usually collects large-scale indoor scene layout data first, conducts learning and training, and then applies the training results to the furniture scene to be determined.

Akase et al. [AO13] used prior information stored in a semantic database and resident preferences to optimize furniture layouts. The system introduced human-computer interaction to update the layout results several times until the resident was satisfied. Xu et al. [XCF*13] calculated the exact positions of all objects in the sketches in 3D space, searched the 3D models corresponding to each object in the model library, and formed 3D scenes. The system only considers small groups of objects, such as a desk scene, rather than the layout of the entire room. Song et al. [SZJ17] decomposed the scene layout problem into a combination of several layout modes (coupling mode, matrix mode and enclosed mode) and solved them separately. This method is fast and can meet the system's real-time response requirements. Fu *et al.* [FFY*20] quantitatively assessed the layout quality of certain objects through human-centred metrics (HCMs) to guide the layout of objects in 3D scenes. The introduction of HCMs makes the furniture layout results more ergonomic and personalized.

6.2. Rule constraint-based methods

The automatic layout method based on rule constraints constructs the energy function or cost function of the overall layout by considering the constraint relationship between layout objects and rooms. Then, various optimization algorithms are used to find the global optimal solution to the energy function or cost function to determine the location of the layout object.

The furniture to be laid out is represented as a cube with attributes such as direction, size, and coordinates in [XSF02]. These objects integrate various layout constraints, such as physical constraints and non-interpenetration of objects, and use semantic database information to automatically place each object in a room. Sanchez et al. [SLRLG03] used cost functions to model principles used in professional interior design practices, optimizing cost functions through genetic algorithms to generate optimal solutions that meet these design principles. Yu et al. [YYT*11] extracted the hierarchical and spatial relations of various furniture objects from a large number of examples of interior scenes as prior knowledge. The cost function was then constructed and solved using a simulated annealing algorithm. However, their approach is based on the assumption that the perimeter of the room is sufficiently large. Violating this assumption

Table 5: *Comparison of automatic furniture layout methods.*

Reference	Venue	Methods	Vertical Space Constraints	Data Representation	Output
Sanchez et al. [SLRLG03]	CGAI 2003	Rule constraint	✓	Unordered set	3D rooms
Yu et al. [YYT*11]	SIGGRAPH 2011	Rule constraint	✓	Unordered set	3D rooms
Merrell et al. [MSL*11]	TOG 2011	Rule constraint	×	Unordered set	3D rooms
Akase et al. [AO13]	CISIS 2013	Case reasoning	×	Unordered set	3D rooms
Xu et al. [XCF*13]	TOG 2013	Case reasoning	✓	Unordered set	3D rooms
Kan et al. [KK18]	VR 2018	Rule constraint	×	Unordered set	3D rooms
Wang et al. [WSCR18]	TOG 2018	Deep learning	×	Object sequence	3D rooms
Ritchie et al. [RWL19]	CVPR 2019	Deep learning	×	Object sequence	3D rooms
Yang et al. [YLS*19]	CW 2019	Deep learning	×	Rectangle set	2D rooms
Wang et al. [WLW*19]	TOG 2019	Deep learning	✓	Relation graph	3D rooms
Zhou et al. [ZWK19]	ICCV 2019	Deep learning	✓	Relation graph	3D rooms
Fu et al. [FFY*20]	GM 2020	Case reasoning	×	Unordered set	3D rooms
Vitsas et al. [VPGV20]	CGF 2020	Rule constraint	✓	Unordered set	3D rooms
Zhang et al. [ZYM*20]	TOG 2020	Deep learning	✓	Unordered set	3D rooms
Wang et al. [WLY20]	TOG 2020	Deep learning	×	Matrices set	2D rooms
Luo et al. [LZWT20]	CVPR 2020	Deep learning	✓	Relation graph	3D rooms
Wang et al. [WYN21]	3DV 2021	Deep learning	×	Object sequence	3D rooms
Paschalidou et al. [PKS*21]	NIPS 2021	Deep learning	×	Unordered set	3D rooms
Ostonov et al. [OWM22]	WACV 2022	Deep learning	×	Object sequence	2D rooms

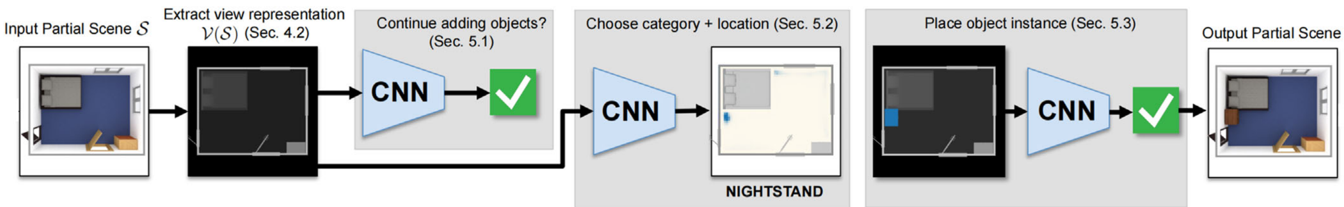

Figure 11: *Automatic furniture layouts based on the CNN [WSCR18].*

can result in local suboptimal layout or layout failure. Merrell et al. [MSL*11] iteratively and randomly optimized the initial layout by specifying the furniture participating in the layout and the initial location of the furniture. They converted layout guidelines into a density function and generated layout recommendations using a Monte Carlo sampler. Kan et al. [KK18] used greedy cost minimization to achieve automated furniture layouts. The model generates layout results in one second in an order from large furniture to scene details. However, the complex rule-based cost function modelling limits the actual performance of this method. Vitsas et al. [VPGV20] innovatively introduced lighting constraints into interior furniture layouts, modelled them as a cost function, and obtained reasonable layout results through hierarchical optimization.

6.3. Deep learning-based methods

Most of the methods in this section use deep neural networks to predict the type, location, and orientation of furniture to complete the layout of indoor scenes in a step-by-step manner [WSCR18, RWL19]. Other methods model the relationship between layout objects as graphs to predict the layout results [WLW*19, ZWK19].

Wang et al. [WSCR18] synthesized indoor scenes based on convolutional neural networks, as shown in Figure 11. They first predicted whether the model should continue to add objects to the scene. The second component selects the object class and the location to be added. They finally instantiated and positioned a specific object and generated the interior scene with a reasonable layout over several iterations. This work is the first attempt to use deep learning to automatically generate furniture layouts, and it still has many limitations. Specifically, it does not model object size, leading to the problem of improperly sized furniture choices, and since hundreds of deep CNN evaluations are used for each scene, it takes several minutes to synthesize a scene, which is very time-consuming. In [RWL19], the team processed the category and location of the objects separately and used the category prediction module to globally infer the scene to solve the problem that the objects may be repeatedly sampled, which was an issue in [WSCR18]. They also introduced the conditional variational autoencoder (CVAE) to optimize the object orientation. Compared with [WSCR18], it reduces the time needed to generate layout scenes from minutes to 2 s. Yang et al. [YLS*19] trained a conditional generative adversarial network (CGAN) model to divide the room into functional areas. Next, an FCN model is used to place the furniture in the corresponding functional areas.

Due to the flexibility and diversity of furniture layouts, some researchers have used graph models to solve this problem. Wang et al. proposed PlanIT [WLW*19], which combines high-level graph representation and spatial prior neural networks. It uses image-based convolutional networks to instantiate a graph and generate furniture layout results. This graph representation provides more modelling flexibility and applicability, but its instantiation module cannot model objects and spaces and may produce some layout results that deviate from reality; it also relies heavily on the quality of the training graph extracted from the input scene dataset and is not robust. However, these furniture layouts generated through iteration are inherently suboptimal, so Zhang et al. [ZYM*20] used a GAN structure that jointly optimizes all factors of 3D synthesis. They also describe the scene space with 3D data but simultaneously use the images to guide the network training, thus integrating the advantages of 2D and 3D data. Other approaches model the relationship between objects as a graph. In [ZWK19], the object to be predicted is represented as a special 'empty' node. After message passing, the MLP is used to predict the target probability distribution of the special 'empty' nodes. Luo et al. [LZWT20] converted the ground truth scene layout and scene graph into a distribution and then generated different scene layouts by sampling from the prior distribution. To automatically transform furniture layouts, Wang et al. [WLY20] proposed Scene Mover, which generates a plan containing a sequence of actions. They used a Monte Carlo tree search method embedded in deep reinforcement learning to solve the problem of planning action sequences.

Wang et al. [WYN21] used a transformer-based architecture to generate rooms by automatically regressing the selection and placement of objects in a scene. This model is flexible and can generate complex scenes based on room or textual descriptions. However, using these processes [RWL19, WYN21] to generate scenes in order of the furniture class frequency impose unnatural restrictions that inhibit practical applications. To address these limitations, Paschalidou et al. [PKS*21] treated scene synthesis as a disordered set generation problem and proposed ATISS, a new autoregressive transformer architecture for modelling this process. ATISS can quickly predict a reasonable layout without any postprocessing. Ostonov et al. [OWM22] presented RLSS, a deep reinforcement learning algorithm for sequential scene generation that can generate a large variety of scenes for the same floor plan while accounting for domain constraints.

Discussion. Early methods for automatic furniture layout were usually based on case reasoning and rule constraints. However, collecting layout cases and rules is a time-consuming task and requires the skills of experienced artists. The latter approach improves the generation speed by producing interior layouts through iterative regression selection and objects placement, but this iterative process imposes unnatural constraints that can lead to discordant placements. Other methods use generative methods or reinforcement learning to generate layouts quickly. In addition to satisfying spatial requirements, future research should give more consideration to generating stylistically consistent interior scenes, which are needed for PID.

7. Other Problems Related to PID

PID is a very large field. In this section, we introduce several tasks that are included in PID but are less studied; they are also an essential part of the PID.

Lighting design. Lighting is one of the most important factors to consider in 3D interior design. The quality of lighting can affect the comfort and safety of residents. Gkaravelis et al. [GP16]generated a hierarchy of light by clustering light sources that contribute similarly to the environment. Based on the complementarity of light contribution, the search space is effectively explored, and a high-quality lighting configuration is quickly generated.

Furniture retrieval. Furniture retrieval can help residents quickly obtain the furniture they want. Tautkute et al. [TMS*17] proposed a multimodal search engine that could retrieve the corresponding furniture using text. More importantly, the furniture it retrieves matches the query visually or stylistically. Therefore, this search engine has important significance for guiding PID. Pardhi et al. [PW17] extracted features from furniture images and realized similar furniture retrieval based on feature similarity.

Wallpaper generation. Wallpapers is commonly used to decorate walls in interior design, and the texture of the wallpaper influences the overall style. However, designing wallpaper is a time-consuming and laborious job, and wallpaper designers need to collect many materials to create new wallpaper. Based on multilabel semantics, using generative adversarial networks and perceptual feature regression, Gao et al. [GFZ*21] proposed a perception-driven wallpaper texture generation model that can generate high-quality wallpaper textures. This tool has significance for guiding the decoration of interior walls in PID.

8. Interior Design Related Datasets

As the basis of PID research, datasets help researchers compare and evaluate the performance of different algorithms and promote the development of related research. In this section, we collect and sort the different types of datasets involved in PID research and discuss the benefits and drawbacks of each dataset. The dataset types include furniture datasets for furniture style analysis and compatibility prediction and floor plan datasets for floor plan analysis and furniture layout.

8.1. Furniture Datasets

Furniture datasets usually use various furniture as the main body and mark furniture according to different tasks. This section introduces two types of furniture datasets with different focuses.

8.1.1. *Furniture Style Datasets*

Furniture data with style labels can be applied to furniture style analysis and furniture style matching. As shown in Table 6, the #Scenes

Table 6: *Summary of furniture datasets.*

Dataset	Venue	#Images	#Scenes	#Categories	#Styles	#Matchings
Singapore [HWL*17]	TIST 2017	2,955	–	6	16	–
NCKU [PDTH17]	Big Data 2017	22,960	–	7	–	–
SZU [HLK*17]	TOG 2017	618	–	5	4	–
Interior Items [TMS*17]	FedCSIS 2017	2,193	298	9	–	298
Bonn [AVSY18]	GCPR 2018	90,298	–	6	17	–
Target [PFNL20]	CVPRW 2020	6,550	–	9	–	1,632
3D-FUTURE [FJG*21]	IJCV 2021	9,992	20,240	34	–	5,000

column records the number of scenes in the dataset, #Styles indicates the number of furniture styles, and column #Matchings records the number of matching sets.

Singapore (2017) [HWL*17]: This dataset is a collection of 2955 furniture images from different sources with both style and function labels. The furniture styles are divided into the most popular 16 categories, and the furniture function labels include six types, that is, bed, storage cabinet, chair, sofa, table and others.

NCKU (2017) [PDTH17]: This dataset includes 420 textured 3D furniture models collected from ShapeNet [CFG*15]and comprises seven types of furniture, that is, beds, bookshelves, lockers, chairs, lamps, sofas and tables. Compatibility between furniture is assessed through crowdsourcing.

SZU (2017) [HLK*17]: This dataset consists of five sub-datasets, including Furniture, Furniture legs, Buildings, Cars and Drinking vessels. The Furniture dataset includes 618 models classified into four styles (Children, European, Japanese, and Ming) and five functions (beds, cabinets, chairs, stools, and tables).

Bonn (2018) [AVSY18]: This dataset is a collection of 90,298 pure furniture images with 17 styles and six functional labels from www.houzz.com. The dataset also provides the corresponding text data for the image, including manufacturer, size, weight, material and other information.

8.1.2. *Furniture matching datasets*

Unlike the previous furniture style datasets, furniture matching datasets emphasize matching or compatibility relationships between furniture. These datasets can be used not only in the field of furniture classification but are also indispensable for furniture style matching studies. They include multiple matching sets of furniture with matching styles. Some of the datasets also provide indoor scene images. The statistics for the dataset are shown in Table 6.

Interior Items (2017) [TMS*17]: This dataset was published by Tautkute et al. for cross-modal furniture style retrieval. The dataset consists of 298 indoor scene images collected from ikea.com and 2193 furniture images and text descriptions from these scenes.

3D-FUTURE (2021) [FJG*21]: 3D-FUTURE is a high-quality interior design research dataset launched by the Alibaba Tao Technology Department. 3D-FUTURE can support researchers in conducting 3D shape retrieval, 3D reconstruction based on a single image and instance segmentation tasks at the same time. The dataset contains 20,240 indoor rendering scene images matched by professional designers and 9992 3D furniture models from the scenes as well as their attribute labels and matching relationships.

Target Furniture Collections (2020) [PFNL20]: This dataset covers a variety of furniture categories and includes approximately 6550 furniture images. The items were arranged by furniture matching experts into 1632 matching sets. The number of pieces in each collection is between 2 and 20 (most collections have no more than eight pieces). Although this dataset is small, it provides more important information about compatibility between furniture.

8.2. Floor plan datasets

The floor plan is one of the important data necessary for interior design. It provides designers and residents with the house structure, size, area and other information. Similarly, the design and analysis of floor plans need considerable floor plan data, and the automatic furniture layout is also completed based on the floor plan. A few public floor plan datasets are introduced below, and a dataset summary is provided in Table 7.

CVC-FP (2015) [dlHTRS15]: CVC-FP is a real floor plan dataset that includes four sub-datasets. The black dataset models the walls in the floor plan as black lines and consists of 90 high-quality two-dimensional floor plans. The textured dataset is composed of 10 low-quality grayscale images, which are computer drawings of floor plans that contain structural symbols, furniture and text information. The textured2 dataset consists of 18 images from a six-story building. The parallel dataset only includes four binary images, and each image includes wall identification depicted by parallel lines for wall segmentation.

Rent3D (2015) [LSK*15]: Liu et al. collected the most popular 215 apartment data from an apartment rental website. The number of photos for each apartment ranges from 2 to 30, and there are 1259 photos of the apartment. They also kept photos of the apartment buildings or utilities in the buildings advertised for rent for a total of 1570 images. This dataset annotates the actual layout and posture of each room in the apartment.

R2V (2017) [LWKF17]: Liu et al. established a large-scale dataset for vectorization of floor plans based on the LIFULL

Table 7: *Summary of floor plan datasets.*

Dataset	Venue	#Images	#Rooms	#Objects	Resolution (pixels)
CVC-FP [dlHTRS15]	IJDAR 2015	122	1,320	50	905-7,383
Rent3D [LSK*15]	CVPR 2015	1,570	1,312	–	–
R2V [LWKF17]	ICCV 2017	870	7,466	27	96-1,920
CubiCasa5K [KYH*19]	SCIA 2019	5,000	68,877	83	50-8,000
RPLAN [WFT*19]	TOG 2019	80,000	–	–	256
Structured3D [ZZL*20]	ECCV 2020	3,500	21,835	–	–
RFP [LZYZ21]	CVPR 2021	7,000	–	–	–
RuralHomeData [LWG*21]	IS 2021	800	–	–	–
3D-FRONT [FJG*21]	IJCV 2021	–	18,968	13,151	–

HOME'S dataset [LIF], which contains 5 million floor plan raster images. They randomly sampled images, annotated room structures and function and collected 870 floor plans with ground truth.

CubiCasa5K (2019) [KYH*19]: This dataset consists of 5000 floor plans (with manual annotations) collected from 15,000 Finnish floor plans. They are divided into three subcategories: high-quality architecture, high-quality, and colourful, with 3732, 992 and 276 floor plans, respectively.

RPLAN (2019) [WFT*19]: RPLAN is a large-scale floor plan dataset from residential buildings with pixel-level semantic annotations. It contains more than 80K real-world floor plans, and each floor plan contains 3 to 9 rooms and is saved as a 256×256 image.

Structured3D (2020) [ZZL*20]: Zheng et al. presented a large synthetic dataset with rich annotations of 3D structures and photorealistic 2D renderings of indoor man-made environments. This dataset contains rich ground truth 3D structure annotations of 21,835 rooms in 3500 scenes and more than 196k photorealistic 2D renderings of the rooms. They also introduced a unified 'primitive + relationship' representation for 3D structures.

RFP (2021) [LZYZ21]: Lv et al. obtained 7000 residential floor plan (RFP) data from an internet search engine, and the data mainly consist of residential floor plans of urban buildings in China. They manually marked the starting point, the end point, and the wall thickness. They also marked the doors, windows and room types.

RuralHomeData (2021) [LWG*21]: Lu et al. provided a new dataset for analysing rural residential floor plans in China. Compared with previous datasets, there are a large number of different types of rooms, hollow walls and curved windows in the rural floor plans. They collected 800 rural house floor plans converted from original CAD files and manually labelled basic architectural elements and 21 room types in the images.

3D-FRONT (2021) [FCG*21]: Fu et al. collected a new, large-scale, and comprehensive repository of synthetic indoor scenes with professionally designed layouts and a large number of rooms populated by high-quality textured 3D models with style compatibility. 3D-FRONT contains 13,151 furniture objects and 6813 CAD houses, including 18,968 diverse rooms.

9. Discussion

The development of PID largely depends on the progress of the relevant algorithms. The current research results have spawned some emerging applications related to interior design. In this section, we discuss the commercial application of computer-aided PID as well as the existing limitations and prospects for future work.

9.1. Application

The previous sections introduced some PID-related algorithms, some of which have been applied to furniture matching, intelligent interior design, and interior model generation. Some websites support these functions, which will greatly lower the threshold for ordinary people to participate in interior design. Table 8 summarizes the services offered by several interior design websites.

IKEA (www.ikea.com): IKEA provides a wide variety of furniture products in terms of function and style. IKEA's 'Inspiration' section provides a large number of sample furniture matching scenarios, and residents can choose furniture in sample scenarios. '3D Exhibition Room' allows residents to view the room from different directions and see the layout and more details online.

Houzz (www.houzz.com): Houzz is a community and photo gallery for indoor and outdoor design enthusiasts. Houzz provides a keyword-based furniture search and several matching sample scenarios. In addition, the resident can implement image-based furniture retrieval in the sample scene.

Planner 5D (planner5d.com): Planner 5D is a simulation tool that helps residents design home decoration effects. It vectorizes resident-uploaded floor plans and then allows residents to implement PID. Residents can add and place furniture, windows, doors or other structures to the floor plan and render them to obtain 3D interior scenes.

HOMESTYLER (www.homestyler.com): HOMESTYLER provides free professional tools and rendering services such as Planner 5D for ordinary residents and home designers. What is more interesting is that the design tool provides a one-click design 'Autostyler' function. Residents can upload a floor plan and select a sample room, and the tool will realize the furniture layout, ceiling design, carpet laying, and painting based on the sample room style; finally, they can obtain a perfect 3D interior design rendering (see Figure 12).

Table 8: *Summary of interior design website.*

Services Provided	IKEA	Houzz	Planner 5D	HOMESTYLER	Kujiale	AiHouse
Furniture matching	✓	✓	✓	✓	✓	✓
Furniture retrieval	✓	✓	✓	✓	✓	✓
Floor plan analysis			✓	✓	✓	✓
Automatic furniture layout			✓	✓		✓
Online interior design			✓	✓	✓	✓

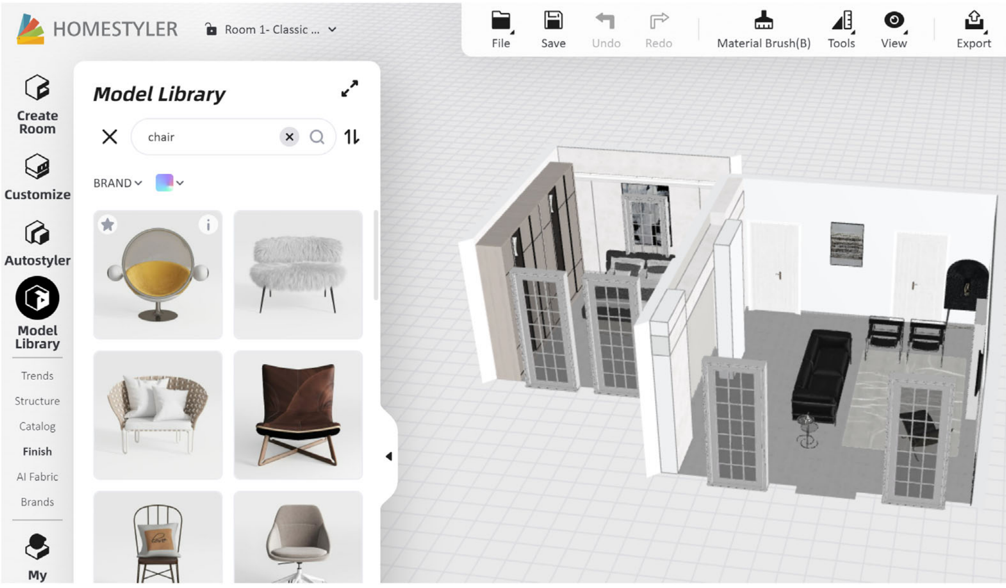

Figure 12: *PID on the HOMESTYLER's website (www.homestyler.com).*

Kujiale (www.kujiale.com): Kujiale is a professional and efficient online 3D intelligent cloud design platform that provides residents with many 3D interior design plan effects, floor plans, 3D model materials, and 3D/2D design template materials. It also allows residents to perform online interior design and supports model upload and CAD import and export.

AiHouse (www.aihouse.com): AiHouse can also convert resident-uploaded floor plans into vector graphics and allows residents to use them to construct an online interior design. Residents can retrieve and select their favourite furniture models from the furniture library and arrange the furniture by dragging and dropping, and it also allows for a basic furniture automation layout.

9.2. Existing limitations

Limited open source code. In contrast to other computer graphics tasks, only some of the PID-related algorithms have published source code. Due to the limitation of manuscript lengths, it is difficult for new researchers to understand an algorithm's implementation details and reproduce the results. This limitation is inconvenient for researchers in terms of understanding the status of research and uniform measurement and limits the development of PID research to some extent.

Connection problem between tasks in PID. PID as described in this paper is a theoretical pipeline in interior design. There may be some problems in practical applications, especially in terms of the connection between tasks. For example, the data used in furniture style analysis and furniture compatibility prediction include both 2D furniture images and 3D furniture models, while the automatic furniture layout mainly uses 3D furniture models. Similarly, most floor plan designs generate 2D floor plans, while automatic furniture layouts based on 3D models require the floor plan's spatial information. Therefore, the connection between tasks in practical applications is still worth studying.

Lack of datasets for PID. We still lack large-scale interior design-related datasets with accurate annotation, including furniture datasets and floor plan datasets. In particular, furniture-matching data and furniture layout datasets with compatibility labels or matching information are important resources for studying furniture-matching recommendations and automatic furniture layout. The 3D-FUTURE [FJG*21] dataset recently launched by the Alibaba Tao Technology Department based on the data from home decoration and home design platforms can support researchers in conducting 3D shape retrieval, 3D reconstruction based on a single image and instance segmentation tasks at the same time. It is a high-quality interior design research dataset. We expect more of these multilabel, furniture-matched, multitask datasets, which will be a strong driver for PID research.

The gap between furniture style analysis and the human perception of style compatibility. Although a series of furniture style studies based on deep neural networks has recently achieved relatively excellent performance, there is still a certain gap between the algorithm and the human definition of style compatibility, especially in terms of the analysis of style compatibility between different types of furniture with significant differences in appearance. In addition, the existing style compatibility research work usually only focuses on the geometric characteristics of furniture, and ignores other rich characteristics such as colour, texture, and structure [LHLF15]. The GNN-based furniture compatibility prediction method [PFNL20] proposed by Polania et al. provides us with a new idea. It is an innovative method for modelling furniture compatibility by combining the excellent feature extraction ability of the CNN and the feature aggregation ability of the GNN.

9.3. Future work

At present, researchers have carried out preliminary exploration and research in the field of PID, and many excellent results have been produced. However, there are some urgent problems to be solved, and they may be important research directions in the future.

Personalized furniture design. The current ‘personalization’ in PID mainly regards the choice of furniture. A higher level of personalization should include automatic furniture design according to the intentions of the resident or designer. The ‘Furniture style transfer’ section introduces some of the relevant content, but the methods in this section rely on existing furniture styles and furniture entities and lack more imagination and creativity. Personalized furniture design should be as close as possible to the ideas and preferences of the residents, and methods to achieve this outcome include designing furniture according to the resident’s requirements for material, texture, style and size, thus improving the quality of PID.

Automatic layout of 3D furniture. At present, automatic layouts for furniture are usually based on a 2D floor plan, and the spatial relationship and support relationship between furniture in automatic layouts is rarely considered (e.g., the lamp on the table), while 3D layouts for furniture are closer to reality. Therefore, modelling spatial constraints and the optimization of 3D furniture layouts in addition to realizing more complex 3D automatic furniture layouts will be a research direction in the future. Li et al. [LPX*19] layered the interior scene using encoders to encode the spatial attributes and structural relations of the objects and then used decoders to generate a hierarchical 3D layout. This work is a meaningful attempt at 3D furniture layout.

Style-matching furniture layouts. Current automatic furniture layout methods typically model furniture sets as unordered sets or sequences of furniture. The layout is guided by optimization algorithms or by introducing human-computer interaction. However, most algorithms consider only the size, type, orientation and other constraints in furniture layout and ignore the problem of style matching among furniture. This limitation may lead to layout results with reasonable locations but mismatched styles. Future work could consider the effect of style compatibility between furniture on layout effects and use furniture compatibility as a constraint to guide automated furniture layout.

End-to-end PID model. This survey divided the PID pipeline into five tasks to guide personalized interior design from the two aspects of furniture selection and floor plan preparation and finally obtained an indoor scene layout result. This process is complex and difficult, and no researchers have modelled it as an end-to-end problem. The purpose of PID is to plan a reasonable furniture collocation and indoor scene layout for residents based on their requirements and preferences, including furniture style preferences and floor plan constraints. This direction should guide researchers in the future. An end-to-end PID model will greatly simplify the process of resident interior design and reduce its cost.

10. Conclusion

This paper reviews and summarizes current research progress in the field of PID. From two aspects of personalization, that is, furniture selection and floor plan preparation, we introduce related research regarding furniture style analysis, furniture compatibility prediction, floor plan design, floor plan analysis and automatic furniture layout. We also compare and discuss relevant furniture and floor plan datasets. This paper also discusses the industry application, current limitations and possible future research directions for personalized interior design. Related applications have realized furniture recommendation, floor plan analysis and automatic layout in PID, promoting the digitalization and intelligence of interior design. Future work should pay more attention to the coordination of furniture styles and floor plan styles, personalized furniture design, and the layout of 3D furniture.

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