PARTICIPATORY SPACE AUTO-ENCAPSULATION

Bridging human relationships to building typology with machine intelligence

YI ZHANG[1], ZIYU PENG[2] and WEISHENG LU[3]
[1,2,3] *The University of Hong Kong.*
[1]*zhangyi0709@connect.hku.hk, 0009-0001-8026-1635*
[2]*ziyupeng@connect.hku.hk, 0000-0002-2541-7537*
[3]*wilsonlu@hku.hk, 0000-0003-4674-0357*

Abstract. Co-living housing is often designed with a high extent of interunit repetitiveness. This characteristic can undermine human well-being and social equality. A participatory system compensates for these stereotypes yet remains defective in the deprivation of expert knowledge and slow algorithmic feedback speed, both of which could restrain the manifested level of collective intelligence in the decision-making process. Therefore, we propose a customized co-living housing design process so that the participatory system can be professionalized and accelerated, simultaneously. With few studies focused on the network-level nexuses in human demands and spatial arrangements, our novel AI-embedded platform, SN2S (Social-Network-to-Space), innovatively transforms spatial social networks into 3D design solutions while employing compound and decentralized decision processes. A knowledge translator will first map the occupancy social networks into spatial correlations through graph-based machine learning. Then, a design generator will expand the spatial graph into a detailed layout, thereby synthesizing 3D shapes. Overall, the proposed data-driven paradigm understands co-living housing design from the social network perspective. It adapts to social dynamics and accelerates design speed, enabling a provocative participatory design system.

Keywords. Social-network-to-space, Machine learning, Participatory system, Co-living housing, Accelerated design.

1. Introduction

Public housing constitutes a substantial segment of living environments, particularly in densely populated cities such as Singapore and Hong Kong. In these locales, collective-living dwellings (e.g., HDB flats) are commonly employed as a response to the housing crisis. Nonetheless, on account of the constraints related to investment, construction timeline, and government policy (Rangiwhetu et al., 2020), co-living housing design often shows excessive prioritization of quantity over quality. This has led to a high extent of design repetitiveness in both exteriors (i.e., facade) and interiors (i.e., unit

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 2, 231-240.

layouts), resulting in minimal dwellings that appear insular, negative, and even counterproductive regardless of their well-intentioned nature. Over time, this architectural isomorphism within co-living housing contributes to a diminished sense of respect and happiness among occupants, jeopardizing their well-being and exacerbating inequity (Hernández & Swope, 2019).

The participatory system presents an opportunity to turn the tide. It incorporates instances from online platforms to gaming systems (Laing, 2018), where the wishes of the population are promptly incorporated and transformed into design metrics. These metrics are processed by human designers or embedded algorithms into design proposals (Di Mascio & Dalton, 2017), which are subsequently refined through users' feedback. Yet two important factors that determine the success of system development are rarely balanced in existing practices: the first one is the quality of the generated design, contingent on the system's internal professionality and integration of expert domain knowledge; and the other is the user-friendliness of the system that dictates the extent of genuine user participation before patience depletion. The two factors often appear as paradoxes, consequently restraining the manifested intellectual level of participants in the decision-making process. Therefore, how to efficiently incorporate guidance into a collective intelligence system has emerged as a major issue.

As a response from both technological and humanitarian perspectives, we propose a customized co-living housing design process: Social Network to Space (SN2S). This approach seeks to professionalize, simplify, and accelerate the participatory system simultaneously. By automatically encapsulating expert knowledge into deep neural networks, we reconcile these once-contradictory visions. This accelerated design process not only enhances their future sense of happiness and belonging but also disseminates architectural education and aesthetics throughout the process.

2. Literature Review

Social networks, composed of individuals, organizations, and ties among them, necessitate exclusive specifications in the field of generative design for collective-living dwellings. Although the occupants are identifiable, the nature of their connections remains less defined. Pertinent research from a spatial community perspective sheds light on this area. Kim & Kim (2020) evaluated the elderly social housing nexuses in the extent of acquaintance (i.e., general, close, and official); Andris and Sarkar (2022) emphasize the need to link social graphs with spatial configurations, suggesting that social relationships can inform the underlying environmental categorizations. As it stands, spatial attributes (e.g., apartment proximity and common space accessibility) continually shape the social networks among occupants.

Nonetheless, less attention was paid to the inverse mechanism, i.e., how initial social networks can deduce spatial relationships in the early design stage of co-living housing. Several top-down models, such as Kalkbreite, subordinate social networks to building design governance, where acquaintances struggle to register for adjacent units, and the co-living quality depends solely on the designer's expertise. Conversely, the bottom-up approach, commonly exemplified in self-built communities (Gupta et al., 2017), uses social relations to dominate spatial arrangements, thereby accommodating occupant interconnections. As a synthesis of these opposing views, Silvonen (2022) stated that compressing free will within a controllable range achieves more balanced performance, yet current research falls short in comprehending collective housing design through a consensus between governance and freedom. This strategy allows us to deductively translate a decentralized social graph into the corresponding topological relation among functional spaces, namely a spatial graph, which will be further elaborated in the next section.

The encapsulation process of social networks into a physical ambient necessitates a typological cognition, wherein the housing spatial models are conceptualized as spatial graphs: the nodes denote rooms and edges record connectivity. In the co-living context, as well as in the critique of minimum dwelling, some architectures have showcased distinctive and evolutionary depictions of spatial typologies. Schindler House (1925) was an enlightening attempt at dual-occupancy living, with two distinct apartments sharing a common kitchen and semi-communal utilities. Teige (1932) proposed combining minimum yet adequate rooms with rich domestic infrastructures for socializing; Several recent cooperative housing designs worldwide, such as Kalkbreite and Urbanus, have reimagined privacy relationships into various cluster flats and community households, creating a new form of luxury without economic burden (Bhatia & Steinmuller, 2018). Communally, a hierarchical paradigm consisting of private, semi-private, and public spaces (e.g., minimum dwelling, shared utilities, and circulation) has emerged as a standardized solution, where occupants blend into a larger mechanism while possessing exclusive enclaves.

Neither graph theory nor machine learning algorithm is new to participatory building design engagements, as evidenced by utensils like Graph2plan (Hu et al., 2020). However, few studies explore these from a collective living perspective. Industrial gaming practices, such as Common'hood (2022), have allowed users to construct housing within a digital production chain. Nevertheless, the extent of participant engagement in the design outcome presents a dilemma. While a lengthy design and feedback process is critically threatening to a participatory system (Ma & Van, 2021), their direct involvement in design is also impractical given that occupant demands are not directly expressible in layouts without sufficient nourishment of professional knowledge. Therefore, there is an urgent need in co-living housing for a gaming system that can automatically and rapidly transform the information directly related to occupants, e.g., social networks, into potential inhabitant possibilities.

To address the aforementioned knowledge gaps, we present SN2S (Social-Network-to-Space). It demonstrates novelty through bridging social relationships to design solutions and contribute further in two aspects: firstly, it ensures solutions that commit to the typological paradigm of hierarchical privacy in collective housing spatial models; Secondly, the platform synergizes bottom-up and top-down decision processes to generate relative efficient and dynamic co-living housing solutions.

3. Methodology

The SN2S design platform follows a two-stage workflow illustrated in Figure 1. In the first stage, a knowledge translator will map the social networks of occupants into sub-spatial correlations through graph-based deep learning. Then, in the second stage, a rule-based diffuser will expand the graph gained from the first stage into a layout of functional divisions within the wall boundary. By doing so, the SN2S can instantly turn consensus graph knowledge into architectural typologies, which accelerates the knowledge transition from occupants to architects. Throughout this process, participants would interact with the system by adjusting individual demands and expressing communal prospects in the network with constant artistic feedback.

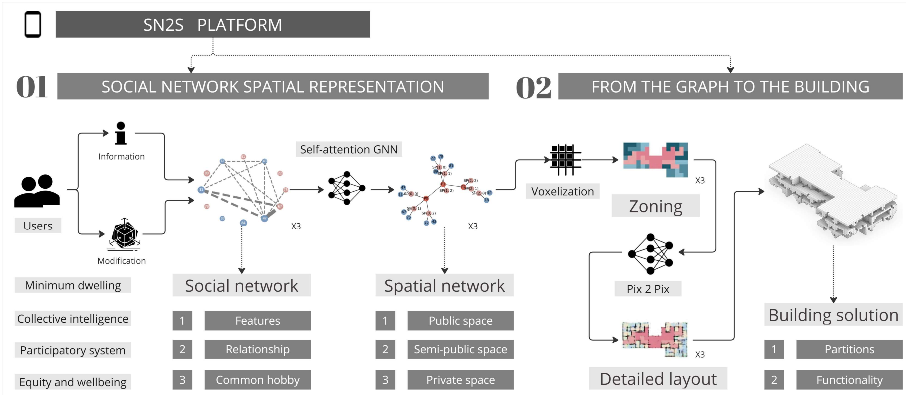

Figure 1. The overall workflow of SN2S

3.1. SPATIAL GRAPH REPRESENTATION OF SOCIAL NETWORK

3.1.1. prerequisites: Social and spatial graph specification

The research carryout necessitates two key aspects, namely the convincing definition of the co-living networks (for both social and spatial), and the training data collection for the machine learning process. Therefore, we first carried out a series of interviews: seventy-five interviewees imagined their family, friends, or acquaintances as potential co-living occupants, and engaged in the following interview from the minimum dwelling (MD) level. By doing so, we collected a population of one hundred MDs, among which a social network substantially took shape.

Under the aforementioned configurations, we make the following efforts to clarify the features and nexuses of MDs. The interviewees first provided several individual information, including the required area in a private apartment, the preferred orientation, the gender and age composition, and their willingness to share extra spaces. Afterwards, we used their top three most common social options as the correlated information, composed by: a) the inner social relationship (i.e., family, friend and acquaintance), represented in an adjacency matrix A_{soc}, whereby the weight values denotes the subjective strength of the relationship; b) the common interest nexuses, for which we gathered the hobbies of each *MD* (e.g., mingling, reading. etc.), and bridged their mutual interests. This eventually forms another adjacency matrix A_{hob}, where the weight values represent the number of shared hobbies among each pair of MDs. As shown in Figure 2.a, these parameters mutually constituted a large social graph, wherein individual and correlated information were used as the attributes in node and edge, respectively. Each node denotes a MD, and connected through A_{soc} and A_{hob}.

Once we have well-established the social network for SN2S, it's crucial to specify the spatial network among MDs in concrete co-living housing. In reference to Domino House by Le Corbusier (1915), the demonstrated physical substrate is identified as a three-storey arbitrary building, with several *MD* residing on each floor. The spatial network follows the typical typology of "private, semi-private, public", where *MD*, representing private proprieties of occupants, are distributed in isolation or around several semi-private spaces (*SPs*). These spaces are subsequently attached to public spaces (*Ps*) and connected through circulation, appearing as tempting spots, e.g., bars, that serve as the altruistic commons for the whole building.

3.1.2. Graph transformation through Graph Neural Network (GNN)

The transformation from social network to spatial graph is an optimization problem: since the functionality of *SPs* and *Ps* would optimize the total well-being when decided through the collective intelligence from adjacent occupants, it raises the possibility of consensual through a proper node classification mechanism, which is beyond mathematical description and takes expert knowledge from architects. In SN2S we use self-attention GNN, namely GATConv (Veličković et al., 2017), to learn expert patterns of MD classification, thereby facilitating an accelerated design process.

To achieve this, a two-step workflow is implemented. The first is the data pre-processing: a) N number of sub-graphs $\{G_i\}_{i=1}^{N}$ are sampled from the population networks (Figure 2.a), attaining sufficient data without relying on numerous interviews. Each sub-graph (Figure 2.b) contains $\{k\}_{k=1}^{12}$ nodes and inherits node features and adjacent relationships from the population. These form the training datasets; b) For each G_i, their attributes are visualized through node colour transparency, size, edge type, and width (Figure 2.c). Five architects were invited to perform labelling (Figure 2.d), categorizing all the *MDs* with (i, j), where $i, j \in \{0,1,2\}$; c) Lastly, for each (i, j), we assign nodes with the label (i, j) to $SP_{i,j}$, attach $SP_{i,j}$ to P_i, and connect P_i to P_{i+1} (Figure 2.e), wherein a series of spatial graphs $\{G_i^s\}_{i=1}^{N}$ were synthesized.

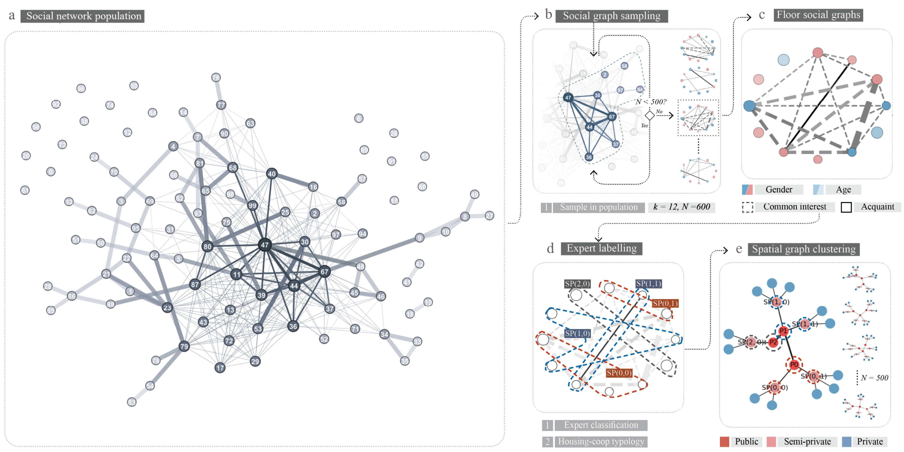

Figure 2. The transformation from social graphs to spatial graphs

The second procedure trains a GNN model to automate the last step. a) Our dataset is formed by 500 pairs of inputs $\{G_i\}_{i=1}^{N}$ and outputs $\{G_i^s\}_{i=1}^{N}$, separated in 80% and 20% for model validation; b) The GNN architecture is threefold, where knowledgepassing layers exchange and update information with attention heads, a SoftMax classifier then assign nodes with (i, j) predictions, and a graph rebuilder lastly output spatial adjacency matrices; c) We calculate the cross-entropy as the loss between predictions and labels, and use the backpropagation process to update parameters; d) GNN minimizes the predictive error throughout iterations until convergence.

3.2. FROM THE GRAPH TO THE BUILDING

With the social graph now endowed with spatial attributes, the focus shifts to using *HouseGenerator*, the second component of the SN2S platform, to synthesize 3D building solutions from $\{G_i^S\}_{i=1}^N$. To prepare for the automation at the later stage, we input the footprint, the floor number, and the corridor position as predefined elements from off-platform architects. Concurrently, we employ a voxel grid representation, whereby each voxel signifies a 5m×5m spatial unit.

We then carry out a series of operations to automate the generation process. To begin with, several rules are deployed to accommodate the spatial graphs (Figure 3.a) into a building voxel grid (Figure 3.b). These rules emphasize whether the voxels should be placed in the vicinity of the central corridor or building boundaries, depending on their space openness. Once the relationships between the graph and voxel grid are fixed, we employed a novel algorithm emulating the human designers, to replicate the spaces of *MD, SP,* and *P* (Figure 3.c). It contains three steps: a) public voxels were activated in the vicinity of the corridor, generating a continuous inner street infused with public functions; b) k groups of voxels are instantiated around each private node in different shapes, and their property rights are delineated with four shades of blue; c) the remaining gaps were filled with semi-public voxels, flexibly interlinking public and private areas. Through the aforementioned computational procedures, we auto-encoded the spatial typology from classical housing cooperatives.

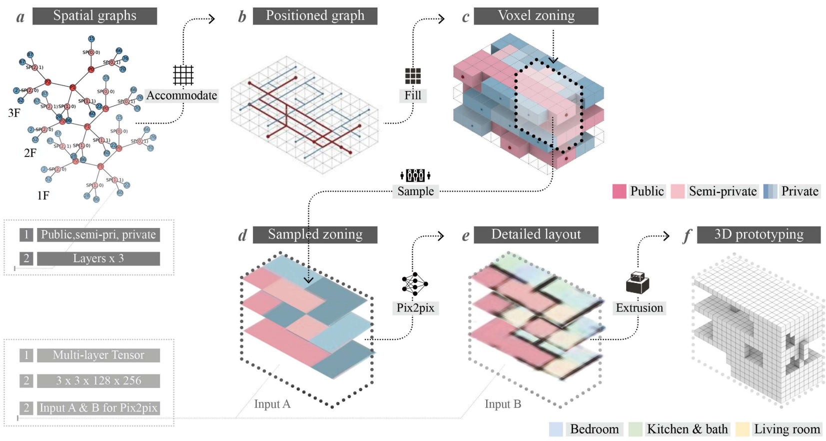

Figure 3. The transformation from graphs to building volumes.

We use generative AI algorithm to instantaneously generalize current floor plans with further details, such as walls and programs, to control complexity. Based on our task specifications, we select Pix2Pix (Isola et al., 2017) for superior performance. The following steps were executed: a) Since the model works better with smaller-sized inputs, 128×256×3-pixel pictures are sampled, as shown in Figure 5.c, forming a dataset comprised of 300 pairs of synthesized voxel-zoning plans (i.e., *Input A*, Figure 3.d) and detailed floor layout (i.e., *Input B*, Figure 3.e, manually labelled); b) A generator G improvises *input A* to output y, and a discriminator D judges the resemblance between y and *input B*. The algorithm places G and D in antagonism, enhancing their ability to establish the correct mapping from *input A* to *B*; c) The trained G is transferred to expedite the design process; d) A rule-based generator extrudes wall areas as 3d-spatial prototypes (Figure 3.f).

4. Result and Discussion

The hardware for computational implementation is a Think Station computer with Intel(R) Core (TM) i9-12900K CPU and NVIDIA GTX A5000 GPU, whereby abundant results have been acquired as justification for our workflow. The first part is the two converged AI models, whose cross-validated training process, spatial graph prediction, and detailed layout predictions are shown in Figures 4 and 5, respectively.

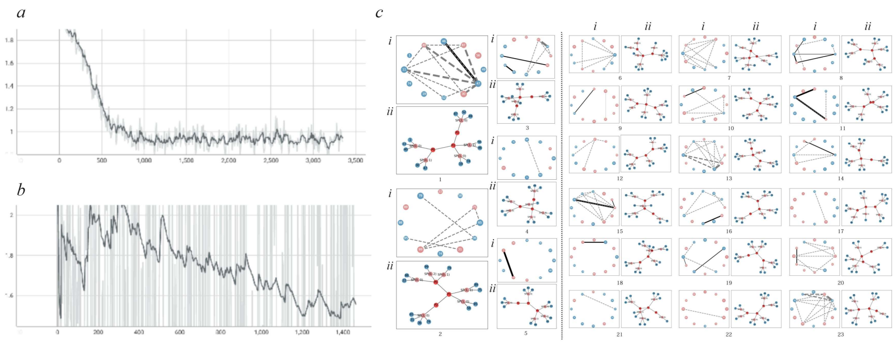

Figure 4. Training results of the first stage in SN2S using GNN.

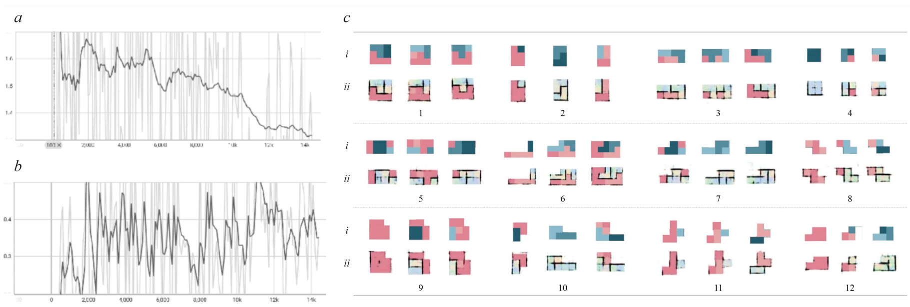

Figure 5. The training results of the first stage in SN2S using Pix2Pix.

In Figure 4, we employed the following hyper-parameter configuration: a batch size of 18, an initial learning rate of 0.01, a training set size of 500, and a training epoch of 150. Combining GATConv layers with multiple residual blocks, we attained a more expressive network structure thus diminishing the loss of predictions to 45% of the random-parametrized model. This showcases discernible evidence in the learned capability of spatial node classification, wherein the train set (Figure 4.a) and test set (Figure 4.b) converged at 87.5% and 61.8% of accuracy, respectively. The predicted results are illustrated in Figure 4.c, wherein the *MD* nodes have been classified according to their local attributes and global connectivity; Figure 5 presents our Pix2Pix training process and results, with hyper-parameters set as batch size equals 10, initial learning rate equals 0.001, training set of 480, and training epoch equals 300. The loss of the *G* decreases to approximately 1.23 (Figure 5.a) while the output of the *D* for fake images (Figure 5.b) bounces periodically, indicating a sufficient learning result for picture transformation. The predicted results are shown in Figure 5.c. Our SN2S algorithm, compared to precedent generative models, innovates in solving multiple layout transformations in collective living scenarios with more spatial fluidity.

We have bridged the complete workflow of SN2S through these converged neural networks, thereby synthesizing numerous 3d building design solutions, as shown in Figure 6. It illustrates the correlation between the social relation, the spatial graph on the zoning tensor, and the final solutions. The size of the input plan is restricted by the increased feature burden from multiple layers, whereas it facilitates adaptivity through its combinatoric possibilities, accommodating multiple-scale occupancy relations. A novel process of inputting multiple floors as one tensor input grants enrichment and structural integrity realized through labelling aligned walls on adjacent floors. The results demonstrate SN2S's capability of generating diverse, intricate, and rational architectural outcomes, wherein the personal dwellings of the most socially related occupants are connected by shared utility spaces (light pink). Meanwhile, occupants with sub-closer social ties are more likely to be connected through larger common interest spots, thus providing more frequent yet optional socializing occasions. These spots are united by corridors, acting as the central artery of the building while promoting a cooperative philosophy of solidarity and collective living.

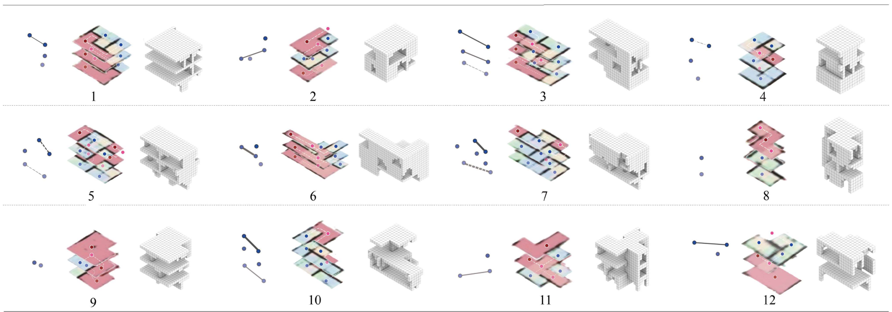

Figure 6. Building prototyping variations from graph inputs

We designed the initial platform prototype, which is shown in Figure 7, as the carrier of the works above. The internal algorithms visualise a social network (Figure 7.d) into building solution (Figure 7.e), enabling users to exchange opinions via group chat (Figure 7.b) while making modifications to profiles (Figure 7.a) and zoning voxels (Figure 7.c). By doing so, the occupants are managed to fully participate in the design process, where they first post-intervention on interconnections, then modify the architectural solutions without the constraints of expert knowledge.

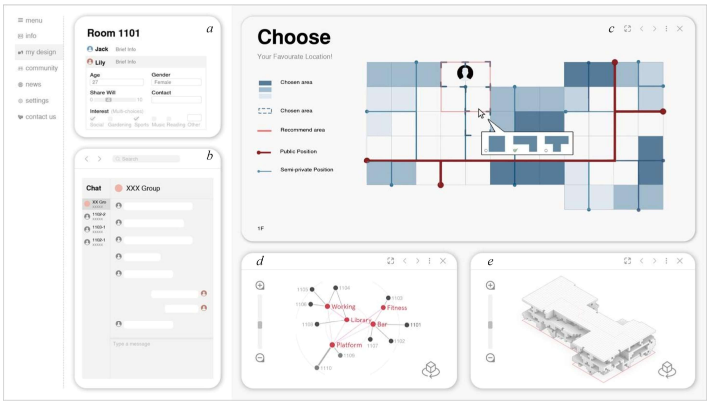

Figure 7. The platform interface for participatory decision-making processes

The two-dimensional constraints in architectural AI design genetically impair the synthesized solutions' sectional enrichness. To mitigate this, we employed strategies using corner detection methods for diagonal bracings; Regarding the additional production costs from design customization, modularization technologies offer a strategy to cover individuality through mass production (Lu et al., 2023), thereby activating the feasibility of platform-based participatory design for co-living housing in the future. Our research focuses more on architectural typological and morphological representations, assuming that different layout combinations in a voxelized environment will not pose a significant additional production burden in the future with the widespread adoption of automation and modularization.

5. Conclusion

Our paper contributes new knowledge to the generative design community in the following three aspects. First, we report a novel paradigm of understanding co-living housing design from the social network perspective. Second, the developed SN2S platform significantly accelerates generation speed for different solutions, forming instant feedback of architectural knowledge to enable the interactive decision-making process. Third, the platform demonstrates adaptivity towards heterogeneous topologies, accommodating components and their nexuses in a changing social dynamic.

Nevertheless, we recognize several limitations. Our platform is incapable of generating cross-layer units (e.g., lofts) due to the sacrifice of sectional diversity for neural network processing; Besides, the size and type of datasets constrained the floor and occupant number to fixed values in our housing, otherwise diminishing expert efficacy; Issues such as dark living rooms, misaligned walls, and structural inconsistencies arise due to the limited scale of the floor plan dataset; While gradually implemented in low-rise communes and self-built communities in Singapore and Denmark. etc., the application of our approach in high-rise public housing faces challenges of expenses and sustainability, etc., limiting its autonomy and applicability, therefore counting on the development of modular and automation techniques for the full realization. In conclusion, our study serves as a demonstration of a workflow that synthesizes 3D building prototypes from social networks, offering insights for future development in the field of public collective housing design.

Acknowledgements

The study is supported by the Collaborative Research Fund (CRF) (Project No.: C7080-22GF) from the Hong Kong Research Grants Council. It is partially developed from the first author's postgraduate study in the Bartlett, UCL, for which we present sincere gratitude to Gilles Retsin, Manuel Jimenez Garcia, Mollie Claypool, Kevin Saey, David Doria, Tongyu Fu, and Hsiumin Lin. Their expertise and insights have been instrumental in shaping this study and enriching its outcomes.

References

Andris, C., & Sarkar, D. (2022). Social networks in space. Chapters, 400-415.

Bhatia, N., & Steinmuller, A. (2018). Spatial models for the domestic commons: Communes, co-living and cooperatives. *Architectural Design*, 88(4), 120-127. https://doi.org/10.1002/ad.2329.

Di Mascio, D., & Dalton, R. (2017). Using Serious Games to Establish a Dialogue Between Designers and Citizens in Participatory Design: The Architectural Portal of People's Narratives. *Serious Games and Edutainment Applications: Volume II*, 433-454. https://doi.org/10.1007/978-3-319-51645-5_20.

Gupta, J. K., Egorov, M., & Kochenderfer, M. (2017). Cooperative Multi-agent Control Using Deep Reinforcement Learning. In G. Sukthankar & J. A. Rodriguez-Aguilar (Eds.), *Autonomous Agents and Multiagent Systems* (pp. 66–83). Springer International Publishing.

Hernández, D., & Swope, C. B. (2019). Housing as a platform for health and equity: evidence and future directions. *American journal of public health*, 109(10), 1363-1366. https://doi.org/10.2105/AJPH.2019.305210.

Hu, R., Huang, Z., Tang, Y., Van Kaick, O., Zhang, H., & Huang, H. (2020). Graph2plan: Learning floorplan generation from layout graphs. *ACM Transactions on Graphics (TOG)*, 39(4), 118-1. https://doi.org/10.1145/3386569.3392391.

Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. *In Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1125-1134).

Kim, J. Y., & Kim, Y. O. (2020). The association of spatial configuration with social network for elderly in social housing. *Indoor and Built Environment*, 29(3), 405–416. https://doi.org/10.1177/1420326X17732612.

Laing, R. (2018). *Digital participation and collaboration in architectural design.* Routledge.

Lu, W., Yang, Z., & Kong, L. (2023). Identification of Learning Effects in Modular Construction Manufacturing. *Automation in Construction*, 154, 105010. https://doi.org/10.1016/j.autcon.2023.105010.

Ma, C. Y., & van Ameijde, J. (2021). Participatory housing: discrete design and construction systems for high-rise housing in Hong Kong. *In The 26th CAADRIA Conference Proceedings (Hong Kong)* (pp. 271-280).

Rangiwhetu, L., Pierse, N., Chisholm, E., & Howden-Chapman, P. (2020). Public housing and well-being: evaluation frameworks to influence policy. *Health Education & Behavior*, 47(6), 825-835. https://doi.org/10.1177/1090198120917095.

Silvonen, T. (2022). Which Came First, Neighbourhood or Community? - Community Construction in a Self-Built Neighbourhood. *Polish Sociological Review*, 217(1), 65-78.

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., & Bengio, Y. (2017). Graph attention networks. *arXiv preprint arXiv:1710.10903.*