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Perspective

Decision Support Systems in Architecture—A Future Perspective

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Abstract: The benefits of design decision support systems (DDSSs) in the architectural planning context have been proven in research and are increasingly used in practice. The sense and purpose are apparent. The weighing of the most diverse ideas and approaches are required for design problems that cannot be solved unambiguously and are characterized by complex, open issues of architectural design tasks, coupled with contradictory criteria. DDSSs support planners/decision-makers with objective information to support the decision-making process with well-founded data and statements. This is becoming increasingly necessary, especially given increasingly complex construction tasks, and thus the difficult-to-predict effects of decisions. Taking this maxim into account, however, also reveals challenges in the planning context, as well as the immense potential and fields of application. Building on these issues, this article presents a perspective for DDSSs. The paper discusses the current focus and advancements of such systems, highlighting the challenges such tools still face, and provides a vision of the perspective future of these systems from reactive systems to proactive assistance.

Keywords: design decision support systems; artificial intelligence; deep learning; assistance systems

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1. Introduction

As early as the 1960s, assistance systems were developed as a contrary movement to automatic design machines in the architectural context [1]. In contrast to automatically acting design systems, the basic idea of assistance systems is to support decision-makers with additional information. These systems include a set of related computer programs and the data required to assist with analysis and decision-making within an organization [2]. In concrete terms, these are usually analytical tools that analyze an existing situation based on predefined criteria and present results to the user in a process-integrated manner. Thus, DDSSs serve to provide decision-makers with supporting data to improve the manageability of decision-making within the design process. For the assessment of the results, the generation of different solution approaches, their subsequent comparison, and the decision itself remain on the human side.

If we look at the type and form of architectural tasks in this context, it becomes apparent that these systems are ideally suited for support in the architectural planning context. Irrespective of the specific forms of architectural tasks, the purpose of design decision support systems can be especially seen in open problems, i.e., questions that cannot be answered unambiguously. Architectural tasks belong to this type of problem and can be counted substantially among so-called "wicked problems", i.e., problems that do not have a clear best solution. This leads to a process of the synthesis, analysis and evaluation of ideas [3]. It is here that the added value of DDSSs can be found. The available calculations present objective aspects to decision-makers so that the phase of evaluation and decision-making can be better founded and, ideally, become better in the long term. The advantages are apparent. Digital systems analyze the design idea and identify the effects a design decision. These not only have to be clear and unambiguous findings, but they can also be long-term aspects that are not directly apparent (e.g., sustainability, comfort, etc.), which can flow into the decision-making process. The concrete requirements for DDSSs can be defined when considering the architectural design process to ensure these advantages and, more specifically, to formulate a visionary approach. These are based, among other things, on the criteria for design tools set out by [4].

1. Interoperability: Design decision support systems are supporting systems. However, support—in the sense of the system—is only possible if the "support" is directly integrated into the work process. The more seamless the integration, the less disruption within the design process. To achieve this, the systems must be able to record the initial design-relevant situation, the design activity and the design itself.
2. Incomplete Input: Ideas are often vague and incomplete in early design phases. Things may only be vaguely sketched or not fully defined. This is independent of the form of representation and the medium. Instead, the ideas are usually not thought out concretely. For DDSSs, even incomplete or erroneous data can be interpreted, utilized and extrapolated upon.
3. Ad hoc: A "seamless integration into the process" requires that the process of designing or deciding is not interrupted. This applies not only to user prompts, e.g., for activation, but also to feedback from the systems. In concrete terms, the results must be made available directly and ad hoc, regardless of the complexity of the design or calculations. Further, user input should be interpreted from their interactions and reactions to the system's feedback.
4. User-Friendliness: A core point relating to user-friendliness is that the supporting feedback needs to be easy to understand, whether visually, through haptic feedback, acoustically, or otherwise. Understanding the effects of the decisions must be as simple and quick as possible. This applies not only to experts but to lay people as well.

As can be seen from the defined requirements for the design tools, DDSSs must function seamlessly without requiring intervention from the user and must not disturb the process—neither through complex input procedures, queries and messages nor through other disruptive factors. Instead, the systems must show the effects of the decisions made by the planner and where problems can occur without interference or user prompting.

The requirements listed above indicate the functional requirements and conditions for DDSSs to be integrated successfully in the early design stages of planning. Considering these requirements, the state-of-the-art research is presented and evaluated. Building upon this research, we hypothesized what challenges modern solutions are facing. In this paper, we propose an approach that will provide a solution to these requirements while simultaneously presenting a paradigm shift in the design of such systems. Leveraging advancement in the field of artificial intelligence (AI), we present a novel concept for the future perspective of DDSSs in the early design stages.

2. State-of-the-Art Research

Since the mid-1960s, decision support systems (DSSs), which support planning and decision-making in complex problems (poorly or partially structured decision problems), have been systematically investigated in various research areas [5]. Based on the purpose of use, different domains of application and types can be identified.

In the field of spatial planning, urban planning and architecture, special DSSs have been established for different planning tasks and planning areas, such as for pre-design solution comparisons and cost estimates by visualizing different solution variants [6]. In combination with the functionalities of a GIS (geographical information system), DSSs represent a spatial decision support system (SDDS), whereby the DSS takes on a spatial dimension [7]. Such systems exist for various planning fields, for example, in spatial planning and nature conservation [8] or waste disposal planning [9]. Planning support systems (PSSs) focus on scenario planning [10,11]. In this context, the LEANkom project, part of the REFINA funding program, investigated the visualization of fiscal impacts of local housing development projects [12]. There are also solutions for spatial planning [13] or energy planning [14]. Design decision support systems (DDSSs) are comparable to PSS systems. Still, the focus is not on finding solutions for long-term planning and planning strategies, but on the limited aspects of the design process. DDSS systems are developed, for example, in the context of a computer-aided knowledge-based design [15] using various aspects of master planning [16], as well as collaboration and visualization [17] for urban planning, transport planning [18], or building law [19]. The goal of group decision support systems (GDSS) in planning scenarios is to support distributed project planning with several planning participants in groups, even over spatial distances [20]. New communication technologies in construction have been investigated with regard to optimizing communicative relationships among the participants [21], and technical foundations for better cooperation between different project partners have been developed [22]. A very prominent modern way of integrating decision support systems into the workflow is through the introduction of so-called "dashboards" that provide the user with overview values based on specific scenarios [23,24]. The challenges of integrating flexible decision support systems have led to the introduction of whole systems [4,25,26], providing a complete workflow system that wraps around the basic design principles. To provide more relevant ad hoc feedback to the user, these systems have focused on developing surrogate models of simulations. Such models offer estimates of the results that can be expected through actual simulation and analysis tools but for a fraction of the required time [27–29], allowing for them to be embedded into established design processes or generative designs.

One challenge that can be observed by such models is the lack of a clear-cut approach, for which a surrogate model for a specific simulation or analysis should be used for different use cases [30–32]. Due to the rapidly changing and growing field of AI and deep learning (DL), a wide range of approaches have been proposed for underlying simulations as well. For example, in the field of computational fluid dynamics, which is the base for the computational wind engineering field, there are several approaches of creating surrogate models—from super resolutions [33] and complex generative adversarial neural networks [34], to multi-neural network approaches [35]. With all these proposed approaches tailored only to specific theoretical application areas, the potential for expanding them on a larger scale remains to be explored.

The scope of various DDSSs that have been developed in research fields or as commercial products has been heterogeneous. In order to evaluate such solutions for their suitability for integration in early design stages, the criteria defined in Section 1 were used to evaluate the proposed solutions. The criteria were graded from (--) for not fulfilling the requirement, over (-) for non-fulfilment of the requirement in part to (+) for meets some of the requirements and (++) for having a requirement ideally fitted for early design stages. The responsiveness column evaluated how the solutions worked, whether reactively—performing their tasks only when triggered by the user—or proactively—anticipating the user input and proposing solutions before being explicitly requested by the user. As shown in Table 1, the majority of the DDSSs proposed in the literature focused on the development of tailored solutions to specific single-criteria optimization problems. Such solutions require a large amount of concrete information from the design model. Due to the complexity of such solutions, they are often developed as full software packages. This causes a more difficult integration into the design tools but provides the advantage of user-friendly interfaces as ad hoc results. On the other hand, the commercial products such as those referenced in [36–38] were either integrated into digital design tools or provided a complete design platform. Such solutions are well suited for working with vague and incomplete data, typically in the early design stages. Furthermore, they can provide ad hoc results and have sufficiently robust, but simple-to-use user interfaces. The main drawback of all the examined solutions is that they rely on the explicit needs of the user, requiring the user to interpret the provided information and generate their own alternatives. This negatively disrupts the design process.

Table 1. Analysis overview of DDSSs.

Name	Interoperability	Incomplete Input	Ad Hoc	User-Friendliness	Responsiveness
PLOOTO-LC [39]	0	--	-	-	Reactive
Design Puzzle [40]	--	+	N/A	++	Reactive
[41]	-	--	+	--	Reactive
[42]	+	--	0	N/A	Reactive
KDSMS [43]	-	-	++	+	Reactive
[44]	--	-	++	+	Reactive
[45]	0	--	0	++	Reactive
Urbanistic [36]	--	++	+	++	Reactive
[46]	--	-	++	+	Reactive
Chameleon.tools [37]	-	0	+	+	Reactive
Cove.tools [38]	++	0	+	+	Reactive

As shown in this literature overview, diverse types of DSSs have attempted to solve different combinations of the requirements set out at the beginning of this paper. However, none have achieved all of them. In the following sections, the paper will introduce a novel concept and paradigm shift in the design of DDSSs.

3. Vision—Reimagining DDSSs

Building upon the current research state, presented briefly in the literature overview, and following the requirements defined in the introduction, a new perspective for DDSSs will be presented in this section. The core element is built upon a direct, close human–machine interface—a seamless connection between the user and the supporting tool. By observing the existing tools in the research and the industry, it can be seen that the DDSS research has mainly focused on the traditional digital tool approach of interacting with the user—focused on a proactive user by activating a specific functionality of the system via the use of various UI Elements, where any functionality is either always present or only available for the user on demand. Comparing this approach to the requirements defined at the beginning of this review, it can be postulated that such solutions lead to a negative disruption of the design process, as the user must interrupt their actions to activate the system or make a suboptimal or misinformed decision due to permanent unnecessary feedback. This issue is further exacerbated by the fact that the definition of which criteria play a crucial role in the design is vague and difficult to define beforehand.

The constant increase in the technical, regulatory and safety requirements towards urban planning leads to the necessity of incorporating them into the design process as early as possible. Accurate predictions based on architectural decisions are needed at all the relevant planning levels. Thus, this sheer quantity of regulations, simulations and design-relevant parameters is no longer manageable by the planner alone. More importantly, it is no longer possible to conduct this process manually. Therefore, the planner must have an omnipresent overview of all the requirements but must also be capable of acting upon this information. This challenge highlights where the future of DDSSs have immense potential for expansion and improvement.

Considering the current state-of-the-art development, the areas of application and the criteria for successful integration, it is clear that DDSSs have been designed primarily as reactive systems. Such systems must be consciously activated and controlled by the user and focus on providing an analysis of the current scenario presented to them. The user must actively request and define how the monitoring of this evaluation is conducted and can only optimize the process based on the respective parameters. This leads to a direct interruption of the planning process to define the analysis parameters and their boundary conditions. Current DDSS tools focus on single-criteria optimization scenarios, making multi-criteria optimizations prohibitively difficult to implement and compounding the previously identified issues.

Ref. [47] accurately stated that "the architect needs a CAAD system that 'looks over his/her shoulder' while designing and that informs about the qualities of the design [. . .]". This is precisely what is needed in the early planning phases. However, DDSSs have been developed as reactive systems to date. The user must interact with them explicitly, defining precisely what is needed and when. A shift in the design of such a system is required for them to promote a broader appeal and realize an "over the shoulder" approach. The focus should center on developing such systems to proactively monitor what the user is doing and propose ideas, suggestions, etc.

Some approaches in this school of thought were already developed and used in the 1990s. This includes, among others, more freely acting solutions such as "Clippy" [48]. The issue that these approaches faced was their limited perception. The system reacted only to predetermined patterns in the text, seldom providing actual value to the user. Furthermore, such "user interface agents" were an integral part of the GUI. This further contradicted the non-disruptive approach required of future DDSSs—focusing more on the agents and their capabilities and less on the interface.

It is clear from the literature overview that such a solution would require a paradigm shift in how such issues are solved. Exploring adjacent research fields for potential novel solutions is a natural expansion of this field. In recent years, AI has shown that it can tackle both the issues faced with complex evaluation, such as runtime and precision, and analyzing behavioral and subjective patterns. Only in this way is it possible to extract and learn the design needs of the user without disruption and build upon them. The relevant regulations and simulations can be analyzed and presented, if necessary.

The design decision support systems of the future need to fulfill a wide range of objective and subjective criteria. The system needs to provide ad hoc results for a wide range of optimization problems, such as wind, solar potential, optimal volume, construction costs, building regulations, etc. At the same time, the user interactions need to be analyzed, and the potential goals and preferences of the user and the context of the scenario need to be inferred. The extracted subjective information, combined with the ad hoc results of the simulation and analysis tools, would enable design alternative generations tailored to the user and the scenario at hand, providing solutions to the user about problems they have not yet discovered.

This leads to the formulation of more concrete criteria for such systems in the context of creative architectural planning.

- Design recognition: understanding the geometry, design tasks and necessary functions.
- Critical area detection: the capability of recognizing the parts of the design area that are most relevant in the design context.
- Critical area analysis: the detection of potential issues generated by the design must be proactively detected and presented.
- Design suggestions: based on the analysis and design recognition, potential solutions must be generated and presented to alleviate the detected issues.

In the following section, a technical system concept will be presented and potential concrete examples of addressing its key features will be discussed.

4. System Concept

Establishing a DDSS in the form of an assistant that overcomes the limitations discussed so far would require a complex system. The sheer scope of the input information and tasks that need to be solved are prohibitive to model using a singular AI model or algorithm. Recent advancements in the open distribution of AI and DL algorithms has led to the possibility of artificial general intelligence (AGI). Ref. [49] found that by leveraging large language models to process complex requests and dividing them into smaller chain of tasks, it is possible to approximate AGI. Building upon this concept, we proposed a design decision support assistant consisting of multiple agents working in concert. The core features can be defined as follows.

- Digital interface—this interface facilitates the scope of the necessary user interactions in the early design stages. It holds the representation of the digital model and all the results provided by the other agents.
- Objective AI—a cluster of agents capable of evaluating ad hoc designs based on a wide range of simulations, regulations and analysis tools.
- Subjective AI—a cluster of agents focusing on understanding the needs of the designer without the need for interactive user feedback.
- Design alternative AI—utilizing both objective and subjective AI agents to provide potential alternatives to the user.

Due to the reusability and adaptability of modern DL and AI approaches [40,41], a modular approach is necessary. This facilitates the possibility of exchanging solutions when better options become available. The introduction of platforms such as HuggingFace [50] and solutions such as ONNX [51] facilitate the possibility of abstracting DL and AI solutions to standard interfaces, which would allow for specific agents of the proposed concept to be integrated into a broader set of digital interfaces. The particular type of solutions and an interaction loop are briefly presented, as shown in Figure 1.

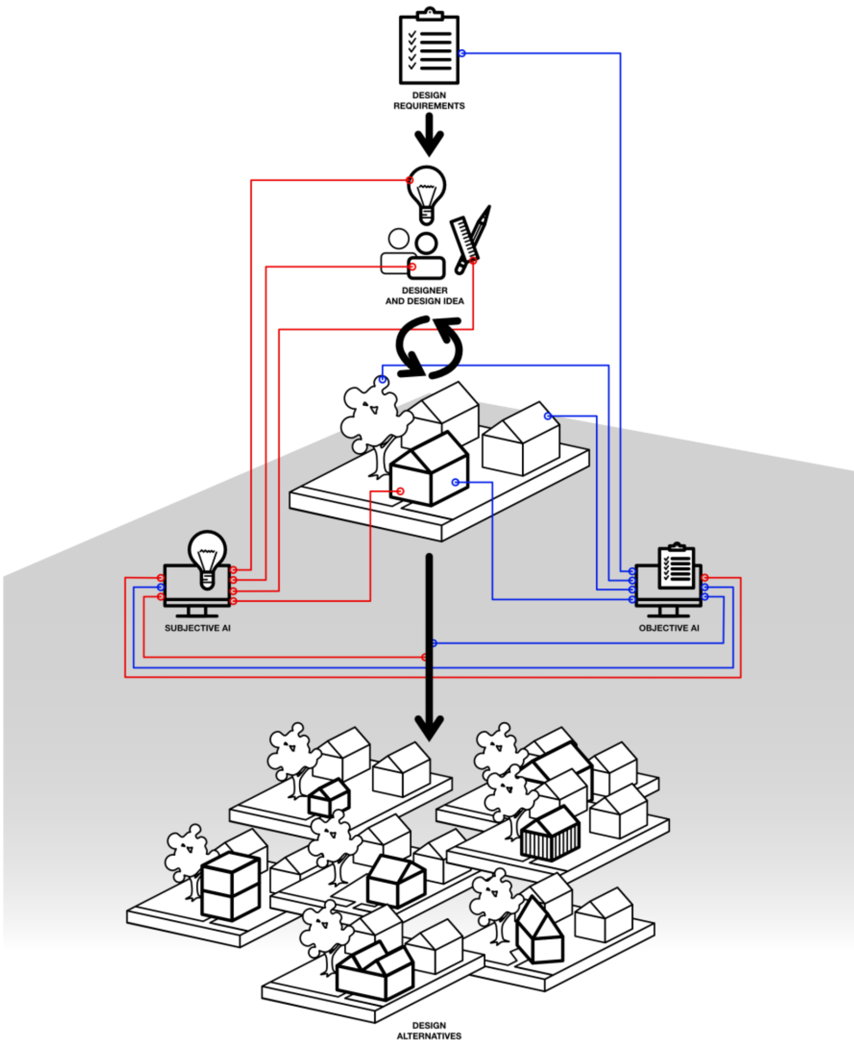

Figure 1. Prototypical interaction flow of the proposed DDSS.

4.1. Digital Interafce

Although solutions have already been developed that merge digital tools with multiple sources of designs that are typical for early design stages, such as physical models and vague sketches [4,52], there is still room for expansion. With the rise of the efficiency of

AI and, specifically, deep learning (DL) approaches, several existing methods could be expanded and improved upon. Examples of object detection [53], object tracking [54], or even 3D object reconstruction [55] with various deep learning algorithms achieved a higher accuracy in their prediction than traditional approaches used in computer vision. The toolset of the digital interface can be further expanded upon with the introduction of more complex tasks, such as 3D gesture recognition [56] and voice commands [57] to facilitate an even more seamless interaction with the digital interface. All these modern approaches focus on the application of convolutional neural networks (CNNs) or transformers to process structured n-dimensional data and provide the necessary predictions in real time, making them ideal for the expansion of the digital interface interaction toolkit. This would allow for even more established tactile planning interfaces to be embedded into the digital interface.

4.2. Objective AI

The goal of objective AI, or more accurately, the several AI agents that form this module, is to process data based on the boundary conditions extracted from the subjective AI module and a given digital model detailed analysis of various regulations, simulations and analysis evaluations. The state-of-the-art research focused on creating "surrogate" models of underlying numerical simulations utilizing various neural network architectures [29,58–60]. After training, such models can provide highly precise results in just a fraction of the standard computation time. The disadvantages, such as being too narrowly tailored to specific scenarios, must be addressed by introducing a more comprehensive range of parameters for describing the scenarios at hand. Furthermore, such models can only be trained and optimized for specific simulations and evaluations before becoming untrainable. This leads to the requirement that robust DDSSs do not have only one DL model but a toolbox of models working in concert.

The backbone of each tool in this toolbox will be a neural network model tailored to the problem. For example, fully connected neural networks can be used for simpler models, such as energy simulations or cost analyses, and more complex neural networks based on convolutions, transformers, or diffusion models can be used for wind or solar potential. These models must be able to receive consistent updates based on the user interactions and the subjective models.

4.3. Subjective AI

While the objective evaluation of the user interaction loop is processed, a second subjective evaluation will be executed in parallel. The goal of this subjective AI module is to anticipate not only the needs of the planner but also extract the subjective design idea and priorities for the specific project. This information can be extracted through the analysis of user interactions based on the feedback they are provided. Since DDSSs are digital systems, the atomic user interactions are finite. This allows for the user's interaction to be abstracted into a set of precise digital values.

The solutions that have already tackled similar challenges, such as keyboard prediction [51], language translation [61], or even chatbots [62,63], have shown that deep learning approaches provide sufficiently strong prediction capabilities. Again, various structures of neural networks can be applied to predict or anticipate the outcome of an unstructured or semi-structured string of inputs [64]. Here, recurrent neural network (RNN) architectures, transformer-based architectures, or long short-term memory (LSTM) architectures have been applied [65–67] to varied degrees of success. Further expanding upon these models, probabilistic architectures such as Bayesian neural networks can be used to rank the probability of the anticipated actions. This would allow for the program to decide on its own whether it should act upon these results, avoiding the potential issues of intruding on the design process with unnecessary feedback. Furthermore, the subjective AI module needs to be capable of extracting the boundary conditions for various objective AI agents. Such feedback can be extracted from user interactions based on the feedback they are presented. Similar solutions have already been explored in the areas of online retail and marketing, where LSTM solutions have been used to capture the evolving interest of users and optimize click-through rates [68]. Using the results from such an approach can approximate the design requirements, ideas and priorities of the planner without needing them to specify such vague and challenging-to-define parameters.

4.4. Design Alternative AI

To combine both the subjective AI and the objective AI modules, a design alternative AI will provide the planner with similar designs. These designs would be based on the design preferences and requirements extracted from the subjective AI module. To correctly provide the user only with the alternatives that would deliver better results regarding the specific design requirements, the objective AI module will provide an ad hoc evaluation for each of requirement and for every simulation, regulation and analysis. The design alternative AI module would then utilize the design requirements from the subjective AI to rank the evaluation and provide only the highest-ranked options to the planner. For the generation of alternative designs, evolutionary and genetic algorithms will be employed. Such algorithms have been widely utilized in urban planning for space and cost optimization problems [69,70]. The inherent disadvantages of high computation costs and minimum evaluation criteria can be overcome due to the ad hoc nature of the objective AI agents.

5. Conclusions

This paper argues the advantages and importance of decision design support systems in the creative context of early planning decision phases.

Based on the research performed on the state-of-the-art solutions, it was highlighted that such systems are purely reactive. Therefore, this paper argued for a shift towards a proactive multi-agent assistance system. This was derived from the observation that the sheer amount of decision-supporting information available, even in the early stages, has become overwhelming for humans to adequately process while maintaining an uninterrupted design thought process.

The paper outlined the base requirements for such systems, compacting them into four main components—interoperability, vague inputs, ad hoc feedback and user-friendliness. It expanded upon these requirements with a proposed system concept for how such a complex system can be developed modularly, allowing for even further flexibility in its integration into existing design processes. Here, the focus fell on the distinction between the objective criteria—such as simulations (wind, solar) and regulations—and the subjective criteria—the specific design requirements and preferences of the planner. By utilizing both sides, a generative approach can be employed so that the assistant provides information regarding the current design and design-specific improvements.

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References

1. Bonini, C.P. *Simulation of Information and Decision Systems in the Firm*; Prentice Hall: Englewood Cliffs, NJ, USA, 1963.
2. Keen, P.G.W. *Decision Support Systems: A Research Perspective*; Elsevier: Amsterdam, The Netherlands, 2018.
3. Lawson, B. *How Designers Think—The Design Process Demystified*; University Press: Cambridge, UK, 2006.
4. Schubert, G. Interaction Forms for Digital Design—A Concept and Prototype for a Computer-Aided Design Platform for Urban Architectural Design Scenarios. Ph.D. Dissertation, Technical University of Munich, Munich, Germany, 2021.
5. Power, D.J. A Brief History of Decision Support Systems. 2007. Available online: DSSResources.com (accessed on 24 July 2023).

6. Sowa, A.; Hovestadt, L. Decision support in architectural strategic planning. In Proceedings of the eCAADe25, Antwerpen, Belgium, 17–20 September 2008.
7. Densham, P.J. Spatial decision support systems. In *Geographical Information Systems: Principles and Applications*, 1st ed.; Wiley: Hoboken, NJ, USA, 1991; pp. 403–412.
8. Czeranka, M. GIS-Basierte Entscheidungsunterstützung in der Naturschutzorientierten Raumplanung, Studien Umweltwissenschaften Vechta. Ph.D. Dissertation, Osnabrück University, Osnabrück, Germany, 1997; p. 1.
9. MacDonald, M.L. A multi-attribute spatial decision support system for solid waste planning. *Comput. Environ. Urban Syst.* **1996**, *20*, 1–17. [CrossRef]
10. Klosterman, R.E. Planning support systems: A new perspective on computer-aided planning. *J. Plan. Educ. Res.* **1997**, *17*, 45–54. [CrossRef]
11. Geertman, S.; Stillwell, J. Planning support systems: An inventory of current practice. *Comput. Environ. Urban Syst.* **2004**, *28*, 291–310. [CrossRef]
12. Preuß, T.; Floeting, H. *Werkzeuge und Modelle der Kosten-Nutzen-Betrachtung. Zusammenfassung und Synthese. Folgekosten der Siedlungsentwicklung. Bewertungsansätze, Modelle und Werkzeuge der Kosten-Nutzen-Betrachtung (Reihe REFINA, Bd. 3, S. 159–174)*; Deutsches Institut für Urbanistik: Berlin, Germany, 2009.
13. Elgendy, H. Development and Implementation of Planning Information Systems in Collaborative Spatial Planning Processes. Ph.D. Dissertation, Karlsruher Institut für Technologie (KIT), Karlsruhe, Germany, 2003.
14. Kaden, R.; Kolbe, T.H. Simulation-based total energy demand estimation of buildings using semantic 3D city models. *Int. J. 3-D Inf. Model. (IJ3DIM)* **2014**, *3*, 35–53. [CrossRef]
15. Langenhan, C.; Weber, M.; Liwicki, M.; Petzold, F.; Dengel, A. Graph-based retrieval of building information models for supporting the early design stages. *Adv. Eng. Inform.* **2013**, *27*, 413–426. [CrossRef]
16. Derix, C. Digital masterplanning: Computing urban design. *Proc. Inst. Civ. Eng. Urban Des. Plan.* **2012**, *165*, 203–217. [CrossRef]
17. Kunze, A.; Burkhard, R.; Gebhardt, S.; Tuncer, B. Visualization and decision support tools in urban planning. In *Digital Urban Modeling and Simulation*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 279–298.
18. Wischmeier, C.; Rinke, N. Ein Soziale-Kräfte-Modell für gemeinsam genutzte Verkehrsflächen. In Proceedings of the 25th Conference "Forum Bauinformatik", Munich, Germany, 18–20 September 2013.
19. Donath, I.D.; González, A.L. Integrated planning support system for low-income housing. *SIGRADI* **2001**, *5*, 113–116.
20. Huber, G.P. Issues in the design of group decision support sytems. *MIS Q.* **1984**, *8*, 195–204. [CrossRef]
21. Schapke, S.E.; Menzel, K.; Scherer, R.J. Towards organisational memory systems in the construction industry. In Proceedings of the e-Smart 2002 Conference, Salford, UK, 23–25 November 2022.
22. Schapke, S.E.; Pflug, C.; Bögl, M. Multi-models: New potentials for the combined use of planning and controlling information. *Transparent-Das Mag.* **2012**, *37*, 4–9.
23. Gadelhak, M.; Lang, W.; Petzold, F. A visualization dashboard and decision support tool for building integrated performance optimization. In Proceedings of the 35th eCAADe Conference, Rome, Italy, 20–22 September 2017; Volume 1, pp. 719–728.
24. Kovacs, A.T.; Micsik, A. Building information dashboard as decision support during design phase. In Proceedings of the 36th eCAADe Conference, Lodz, Poland, 19–21 September 2018.
25. Schubert, G.; Bratoev, I.; Petzold, F. Visual programming meets tangible interfaces-generating city simulations for decision support in early design stages. In Proceedings of the 35th eCAADe Conference, Rome, Italy, 20–22 September 2017.
26. Seifert, N.; Mühlhaus, M.; Petzold, F. Urban strategy playground: Rethinking the urban planner's toolbox. *Int. J. Archit. Comput.* **2020**, *18*, 20–40. [CrossRef]
27. Araújo, G.; Santos, L.; Leitão, A.; Gomes, R. AD-Based Surrogate Models for Simulation and Optimization of Large Urban Areas. In Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, CAADRIA 2022, Sydney, NSW, Australia, 9–15 April 2022; pp. 689–698.
28. Choo, T.S.; Janssen, P.A. Performance-based parametric design. In Proceedings of the 20th International Conference of the Association for Computer-Aided Architectural Design Research in Asia, Daegu, Republic of Korea, 20–22 May 2015; Volume 1, pp. 1–10.
29. Zhang, H.; Feng, H.; Hewage, K.; Arashpour, M. Artificial Neural Network for Predicting Building Energy Performance: A Surrogate Energy Retrofits Decision Support Framework. *Buildings* **2022**, *12*, 829. [CrossRef]
30. Kumari, P.; Toshniwal, D. Deep learning models for solar irradiance forecasting: A comprehensive review. *J. Clean. Prod.* **2021**, *318*, 128566. [CrossRef]
31. Peña-Gallardo, R.; Medina-Rios, A. A comparison of deep learning methods for wind speed forecasting. In Proceedings of the 2020 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 10–12 November 2020; pp. 1–6. [CrossRef]
32. Esteghamati, M.Z.; Flint, M. Do all roads lead to Rome? A comparison of knowledge-based, data-driven, and physics-based surrogate models for performance-based early design. *Eng. Struct.* **2023**, *286*, 116098. [CrossRef]
33. Shu, D.; Li, Z.; Barati Farimani, A. A physics-informed diffusion model for high-fidelity flow field reconstruction. *J. Comput. Phys.* **2023**, *478*, 111972. [CrossRef]
34. Xie, Y.; Franz, E.; Chu, M.; Thuerey, N. tempoGAN: A Temporally Coherent, Volumetric GAN for Super-resolution Fluid Flow. *ACM Trans. Graph. (TOG)* **2018**, *37*, 95. [CrossRef]

35. Hasegawa, K.; Fukami, K.; Murata, T.; Fukagata, K. Machine-learning-based reduced-order modeling for unsteady flows around bluff bodies of various shapes. *Theor. Comput. Fluid Dyn.* **2020**, *34*, 367–383. [CrossRef]
36. "Urbanistic". Urbanistic GmbH. Available online: www.urbanistic.de (accessed on 4 July 2023).
37. "Chameleon.tools". Available online: https://chameleon.tools/ (accessed on 4 July 2023).
38. "Cove.tool". Available online: https://cove.tools/ (accessed on 4 July 2023).
39. Schwartz, Y.; Raslan, R.; Korolija, I.; Mumovic, D. A decision support tool for building design: An integrated generative design, optimisation and life cycle performance approach. *Int. J. Archit. Comput.* **2021**, *19*, 401–430. [CrossRef]
40. Chang, T.W. Supporting Design Learning with Design Puzzles. In *Recent Advances in Design and Decision Support Systems in Architecture and Urban Planning*; Van Leeuwen, J.P., Timmermans, H.J.P., Eds.; Springer: Dordrecht, The Netherlands, 2004. [CrossRef]
41. Bi, G.; Medjdoub, B. Hybrid Approach to Solve Space Planning Problems in Building Services. In *Recent Advances in Design and Decision Support Systems in Architecture and Urban Planning*; Van Leeuwen, J.P., Timmermans, H.J.P., Eds.; Springer: Dordrecht, The Netherlands, 2004. [CrossRef]
42. Guerrero, J.I.; Miró-Amarante, G.; Martín, A. Decision support system in health care building design based on case-based reasoning and reinforcement learning. *Expert Syst. Appl.* **2022**, *187*, 116037. [CrossRef]
43. Rahman, S.; Odeyinka, H.; Perera, S.; Bi, Y. Product-cost modelling approach for the development of a decision support system for optimal roofing material selection. *Expert Syst. Appl.* **2012**, *39*, 6857–6871. [CrossRef]
44. Bakhoum, E.S.; Brown, D.C. An automated decision support system for sustainable selection of structural materials. *Int. J. Sustain. Eng.* **2015**, *8*, 80–92. [CrossRef]
45. Liu, K.-S.; Hsueh, S.-L.; Wu, W.-C.; Chen, Y.-L. A DFuzzy-DAHP Decision-Making Model for Evaluating Energy-Saving Design Strategies for Residential Buildings. *Energies* **2012**, *5*, 4462–4480. [CrossRef]
46. Juan, Y.-K.; Chi, H.-Y.; Chen, H.-H. Virtual reality-based decision support model for interior design and decoration of an office building. *Eng. Constr. Archit. Manag.* **2021**, *28*, 229–245. [CrossRef]
47. Neuckermans, H.; Geebelen, B.; Boeykens, S.; Nagib Callaos, L. Virtual Engineering in Architectural Design. In Proceedings of the 9th World Multi-Conference on Systemics, Cybernetics and Informatics, Orlando, FL, USA, 10–13 July 2005; International Institute of Informatics and Systemics: Winter Garden, FL, USA, 2005; Volume 3.
48. Swartz, L. Why People Hate the Paperclip: Labels, Appearance, Behavior, and Social Responses to User Interface Agents. Ph.D. Dissertation, Stanford University, Stanford, CA, USA, 2003.
49. Shen, Y.; Song, K.; Tan, X.; Li, D.; Lu, W.; Zhuang, Y. Hugginggpt: Solving ai tasks with chatgpt and its friends in huggingface. *arXiv* **2023**, arXiv:2303.17580.
50. Hugging Face—The AI Community Building the Future. Available online: huggingface.co (accessed on 21 June 2023).
51. Open Neural Network Exchange. ONNX. Available online: https://onnx.ai (accessed on 21 June 2023).
52. Schubert, G.; Artinger, E.; Petzold, F.; Klinker, G. A (Collaborative) Design Platform for early design stages. *eCAADe* **2011**, *2011*, 187.
53. Zhao, Z.-Q.; Zheng, P.; Xu, S.-T.; Wu, X. Object Detection with Deep Learning: A Review. *IEEE Trans. Neural Netw. Learn. Syst.* **2019**, *30*, 3212–3232. [CrossRef]
54. Ciaparrone, G.; Sánchez, F.L.; Tabik, S.; Troiano, L.; Tagliaferri, R.; Herrera, F. Deep learning in video multi-object tracking: A survey. *Neurocomputing* **2020**, *381*, 61–88. [CrossRef]
55. Fan, H.; Su, H.; Guibas, L.J. A point set generation network for 3d object reconstruction from a single image. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 605–613.
56. Devineau, G.; Moutarde, F.; Xi, W.; Yang, J. Deep learning for hand gesture recognition on skeletal data. In Proceedings of the 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), Xi'an, China, 15–19 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 106–113.
57. Solovyev, R.A.; Vakhrushev, M.; Radionov, A.; Romanova, I.I.; Amerikanov, A.A.; Aliev, V.; Shvets, A.A. Deep learning approaches for understanding simple speech commands. In Proceedings of the 2020 IEEE 40th International Conference on Electronics and Nanotechnology (ELNANO), Kyiv, Ukraine, 22–24 April 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 688–693.
58. Tan, C.; Zhong, X. A Rapid Wind Velocity Prediction Method in Built Environment Based on CycleGAN Model. In *Hybrid Intelligence: CDRF 2022*; Yuan, P.F., Chai, H., Yan, C., Li, K., Sun, T., Eds.; Computational Design and Robotic Fabrication; Springer: Singapore, 2023. [CrossRef]
59. Yousif, S.; Bolojan, D.; Anastasia, G.; Jeroen, A.; Adam, F. Deep-Performance: Incorporating Deep Learning for Automating Building Performance Simulation in Generative Systems. In Proceedings of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hong Kong, 29 March–1 April 2021; Volume 1, pp. 151–160.
60. Mokhtar, S.; Sojka, A.; Davila, C.C. Conditional generative adversarial networks for pedestrian wind flow approximation. In Proceedings of the 11th Annual Symposium on Simulation for Architecture and Urban Design, Online, 25–27 May 2020; pp. 1–8.
61. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, Ł.; Polosukhin, I. Attention is all you need. In *Advances in Neural Information Processing Systems*; MIT Press: Cambridge, MA, USA, 2017; Volume 30.
62. Weizenbaum, J. ELIZA—A computer program for the study of natural language communication between man and machine. *Commun. ACM* **1966**, *9*, 36–45. [CrossRef]

63. Ouyang, L.; Wu, J.; Jiang, X.; Almeida, D.; Wainwright, C.; Mishkin, P.; Zhang, C.; Agarwal, S.; Slama, K.; Ray, A.; et al. Training language models to follow instructions with human feedback. In *Advances in Neural Information Processing Systems*; MIT Press: Cambridge, MA, USA, 2022; Volume 35, pp. 27730–27744.
64. Xu, M.; Qian, F.; Mei, Q.; Huang, K.; Liu, X. DeepType: On-Device Deep Learning for Input Personalization Service with Minimal Privacy Concern. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2018**, *2*, 197. [CrossRef]
65. Schydlo, P.; Rakovic, M.; Jamone, L.; Santos-Victor, J. Anticipation in Human-Robot Cooperation: A Recurrent Neural Network Approach for Multiple Action Sequences Prediction. In Proceedings of the 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 21–25 May 2018; pp. 5909–5914. [CrossRef]
66. Wang, W.; Peng, X.; Su, Y.; Qiao, Y.; Cheng, J. TTPP: Temporal Transformer with Progressive Prediction for efficient action anticipation. *Neurocomputing* **2021**, *438*, 270–279. [CrossRef]
67. Wu, Y.; Zhu, L.; Wang, X.; Yang, Y.; Wu, F. Learning to Anticipate Egocentric Actions by Imagination. *IEEE Trans. Image Process.* **2021**, *30*, 1143–1152. [CrossRef] [PubMed]
68. Wang, Q.; Liu, F.; Huang, P.; Xing, S.; Zhao, X. A Hierarchical Attention Model for CTR Prediction Based on User Interest. *IEEE Syst. J.* **2020**, *14*, 4015–4024. [CrossRef]
69. Koenig, R.; Knecht, K. Comparing two evolutionary algorithm based methods for layout generation: Dense packing versus subdivision. *AI EDAM* **2014**, *28*, 285–299. [CrossRef]
70. Koenig, R.; Schneider, S. Hierarchical structuring of layout problems in an interactive evolutionary layout system. *AI EDAM* **2012**, *26*, 129–142. [CrossRef]