# Supporting the Development of Designers Rather Than Designs: The Role of AI in Design Decisions for Immersive Analytics

Ingela L. Rossing
Web & Information Systems Engineering Lab
Vrije Universiteit Brussel, Pleinlaan 2
Brussels, Belgium
ingela.rossing@vub.be

Beat Signer
Web & Information Systems Engineering Lab
Vrije Universiteit Brussel, Pleinlaan 2
Brussels, Belgium
bsigner@vub.be

## Abstract

In this position paper, we argue that a primary consideration when introducing AI to immersive analytics should be its impact on designers and its ability to foster the development of their skills. By considering how designers develop their skills and how other AI-based systems aim to positively support user growth, we conclude that AI is currently not serving as an effective teacher. At the same time, there are multiple needs for assistance and teachers in the design process. We exemplify what assisting, while encouraging the development of designers, could look like based on a visionary multisensory extension of AI-driven visualisation recommendation systems used today.

## Keywords

Immersive analytics, design process, skill development, recommendation systems

## 1 Introduction

Regardless of which sensory modality an interface is designed for, a user- and context-centric design process is widely considered the best option. This approach allows designers to gather and understand contextually relevant information. By exploring the problem space and considering multiple design alternatives before converging on a solution, the final choice is often not the first idea that came to mind, but one that better meets users' needs. If a computer knew what would work, these steps and the designer's role in the process could be replaced. However, there are several reasons why this is unlikely to be the case.

First, a design challenge is not an optimisation problem by nature, even though some human perceptual capabilities are more precise than others and hardware may be customised to fit a specific human. Second, the design problem is more complex than we know how to collect data on systematically, with multiple contextual factors inaccessible to the system. This makes a human designer better suited to defining what makes one solution better than another, even if a system can help them explore suitable options, thereby creating a *dependency on the designer's skills and sensitivity.*

With this in mind, we argue that a primary focus of AI tools should be on developing designers' skills rather than merely simplifying the process. At the same time, there are limitations to what one person can be expected to keep in mind, and the interdisciplinary challenge of immersive analytics goes well beyond what is feasible for a single designer to know. Multiple technical challenges risk slowing down the design process without adding value in terms of reusable solutions or design skill development. To consider potential ways forward, we have explored how AI affects skill development, as well as existing AI solutions to support design decisions in visualisation and the role they play in supporting a designer.

## 2 The Development of a Designer

In this paper, we consider designers as lifelong learners with ongoing needs to develop their skills and knowledge. To develop a designer, we must consider what skills and facts they need to learn, as well as what a good learning process looks like. A first challenge in supporting novice designers is to introduce the basics. As pointed out by Parsons [6], other design and art-related fields often educate students in a studio setting. Students do not start by memorising rules from a book, but they learn by doing. The teacher's role is to guide the activity and provide context-relevant advice. Students learn more efficiently when mistakes, as well as design rules, are brought to light and reflected on before pursuing a new, improved solution. From discussing learning in a studio setting with an architect, an additional benefit that came to light is the experience one gains not only from studying others' work, but also from observing their design process.

In a study of the design process of novice hapticians [9], multiple shortcomings in the process itself were found, such as *"reliance on personal experience as inspiration and feedback, a focus on technical factors while neglecting conceptual aspects of the experience, consideration of a narrow part of the available multisensory design space, absence of articulated objectives or criteria, and no plan for iteration"*. In studies on educative strategies where students actively learn by themselves, Vermunt and Verloop [10] suggested that teachers demonstrating good practices open the way for students to efficiently learn a process through reuse rather than invention. In an active learning approach, teachers play an important role in providing the structure and learning materials [3]. This resonates with our personal experience in teaching Computer Science Bachelor's students a human-centric design process, in that "learning by doing" goes further when providing a template to follow, where the values of the activities usually become self-evident. We have further observed that students familiar with humanistic topics seem to internalise the general approach to the design process and understand its benefits more quickly, whereas many of our more technical students remain sceptical of its merits until much later in the course. Even with hands-on guidance, these students are pulled towards creating solutions without asking *why* a solution is suitable, which problem they should solve and how they would validate the solution. For instance, when asked to write down design requirements for their app, they often list a *login function* rather than concrete motivations for choosing a specific solution. For many students, the Human-Computer Interaction (HCI) course we offer is the first in their studies that requires them to consider user requirements rather than focusing primarily on technical novelty and optimisation. After completing the course, many students consider it highly valuable, as it offers new perspectives and practical ways to structure their process.

This highlights the need for resources to take on a teaching role to support novice designers in developing their process skills and the risk of introducing tools that keep them trapped in their drive to create the (often bad) first solution that comes to mind. Instead, we must consider that the iterative design methodology is built around failing forwards [2]. In both industry and research on developing design resources, we want designers to keep developing and learning from mistakes, but not for everyone to keep repeating the same ones. Reusing an established design process, solutions, and design guidelines and heuristics is a good way to reduce time spent on avoidable mistakes and tasks. Some of this reusable knowledge could be built into tools themselves, taking on some of the tasks and input normally provided by a teacher. Many of the good practices are useful for more senior designers too, even if they likely prefer less guidance and use additional functionality that is challenging for beginners. Immersive analytics is interdisciplinary and one person is unlikely to be an expert in all the skills required for a project. It is common to rely on support from other people or tools to learn or execute tasks beyond our expertise.

### 2.1 Challenges in the Design Process

Even when a designer has developed fundamental skills of a design process, multiple additional challenges and bottlenecks remain in creating a good data representation. Immersive analytics comes with multiple challenges related to the many different domains involved in the design, creation and evaluation of an immersive interface for data exploration. Challenges that practitioners have identified as significantly slowing down the process include a reliance on timely input of interdisciplinary knowledge necessary to avoid wasting time on bad solutions, difficulties in accessing relevant information, as well as time, resources and expertise needed to build and evaluate solutions through user testing [8]. To efficiently combine multisensory data representations, designers often must create, refine and debug a solution using various hardware, while considering user safety and enhancing the story being told by the data [9]. Limitations in less specialised software, and in access to resources that inform the design, place a heavy burden on designers to determine what could work.

### 2.2 AI as a Teacher

There are clearly many steps in the design process that could benefit from additional support, possibly from AI systems. Bilda and Candy [1] point out that existing AI solutions often collapse the fundamental architecture of design methodology, for example by skipping ahead while acting on assumptions. These tools are often called a form of assistant to market them as supporting rather than replacing, by engaging in dialogue. However, it seems that rather than learning the behaviours of expert designers, these systems fall into the same traps as someone completely unfamiliar with design methodology. The lack of competence makes them unsuitable to take on the role of an assistant, and even less as a supervising teacher. Other downfalls mentioned are that dialogue systems fail to capture context, suggest solutions while oblivious to potential downstream implications, and never learn the preferences of the designer they converse with. Final suggestions by Bilda and Candy for more successful AI use include focusing on curation, process pacing, and moving beyond verbal communication to step into a multifunctional workspace.

In a recent paper on the impact of generative AI (GenAI) on critical thinking and confidence [4], several considerations regarding approaches that evolve users' skills are presented, as well as aspects that risk inducing a skill regression. A common reason people become increasingly reliant on systems is their lack of self-confidence, which can be undermined by facing overly challenging and time-consuming tasks. At the same time, it is easy to become reliant on the system when it seems to solve things better, so it is important to encourage continued critical customisation and refinement of generated content. The design of an interface can encourage users by making changes easy, suggesting that aspects may be overlooked, as well as promoting the idea that taking action improves the user's professional skills.

To conclude, some aspects that seem to constitute a good (AI) design teacher include that they help facilitate the process while encouraging action, exploration and critical thinking of their students. An excellent teacher helps you learn new things, adapts to each student and possibly most importantly, makes you believe in yourself. The role of teaching is not necessarily bound to a person we can talk with; it is embedded in the space we work in, other people working alongside us and the tools we use.

## 3 Support for Choosing and Creating a Design

A particularly interesting example of AI in the design process that we focus on in this work are the Visualisation Recommendation Systems (VRSs) that exist today. These solutions have the potential to incorporate a vast amount of design knowledge from various domains to quickly filter out low-potential solutions known to be directly misleading or harmful, as well as generate graphs that fit the data at hand. In this section, we discuss what visionary solutions for recommending immersive analytics design solutions could look like, based on designers' executive and educative needs.

### 3.1 Visualisation Recommendation Systems

Nowadays, Visualisation recommendation systems exist to address the narrower problem of suggesting common statistical 2D graphs for tabular data. Figure 1 illustrates a simplified version of the challenge they solve. A foundational work that these systems often build on is *The Grammar of Graphics* [11], which provides a theoretical framework for the design elements available as options and the rules that must be followed when constructing a graph with these elements. This includes available coordinate systems, the channels required for specific marks and the type of data attributes to be encoded by a channel. Channels include variable aspects such as colour, size and position.

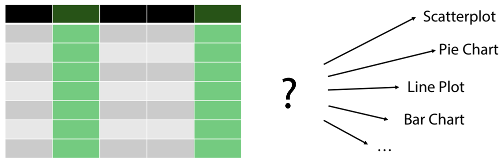


**Figure 1: A visualisation recommendation system provides suggestions on the best way to present a selection of data, with consideration of the characteristics of the data and the task targeted by the user.**

Visualisation recommendation systems rely on a rule-based approach, machine learning (ML), or a combination of both [7]. The rule-based approach relies on an earlier form of AI, known as expert systems, where each rule is defined based on existing design knowledge as a logical expression, often in the format: *If A is true, then B is true*. With a large set of these rules, logical reasoning is used to find all the possible answers to a set of initial facts that apply to a specific design case, such as *B is true*. The facts of a design problem can include data characteristics of selected data items, as well as manually defined parameters, such as a preference for solutions that are optimal for having an overview rather than reading individual values. This can help designers filter out a significant number of non-viable solutions, based on a vast body of theory from domains unknown to them. The results provided are transparent and explainable, though only as trustworthy as the source a rule is based on. There are multiple challenges involved in realising such a solution. First, it relies on formulating rules in a code format that does not conflict with existing ones. Second, VRS solutions have been criticised for lacking access to source materials and for being difficult to refine in light of new findings [13]. If up-to-date knowledge is to be used, VRS relies on a system for managing design knowledge and inserting facts into the system.

A hybrid approach is used by Draco 2 [12], where rules that limit solutions to the correct ones are complemented by additional rules that help suggest which solution is likely to be better. This second type of rules is used for preferences such as mapping time to the x-axis, which is generally good but not a strict requirement, and comes with a cost if violated. A user can explore top alternatives and acquire a transparent list of design concerns for different solutions. The cost for violating different rules is calculated using a model trained on pairwise comparisons. A weakness of this approach is that training data with conflicting findings can cancel each other out, resulting in a different cost estimate [14]. This type of conflict is likely to occur in training data where factors related to the context and elements of the solution are not fully captured. If it already happens for the most common 2D graphs, expecting a useful ranking of solutions in immersive analytics would be highly optimistic. KG4Vis [5] is another VRS that uses a different approach, where machine learning is used to construct a knowledge graph from a dataset of pairwise comparisons. This provides the potential to capture more case-specific optimisations. Moreover, AdaVis [15], a tool built on top of this system, can provide explanations for solutions. For example, a motivation for using a line chart rather than a bar chart might be that *"two column data values are significantly correlated, and data types are numerical-numerical"*. Such explanations appear to offer meaningful reasoning that can help users understand and justify a design choice. On the other hand, a user might hesitate to question the validity of the claim and simply accept this solution without exploring alternatives.

## 3.2 Considering Extensions for Immersive Analytics Designers

Notably, VRSs have been developed not only for smaller design problems but also for laypersons (not designers) interested in analysing or presenting their data. The objective ranking of alternative solutions helps bring more promising solutions to light, but it is not always supported by explanations. Skipping the design steps towards a more final solution would hinder the designer in developing their motivation for *what makes a solution good*. Rather than only extending a recommendation system with more types of solutions, it could be better to envision the algorithms as providing useful functionality within a *design exploration and education system*, where a valuable conversation around a design challenge can take place between the designer and the system through various connected process stages. An example of what such a solution could encompass is shown in Figure 2. Within the design exploration system, the exchange between designer and system could iteratively and strategically explore design alternatives, as well as educate and generate new design knowledge.

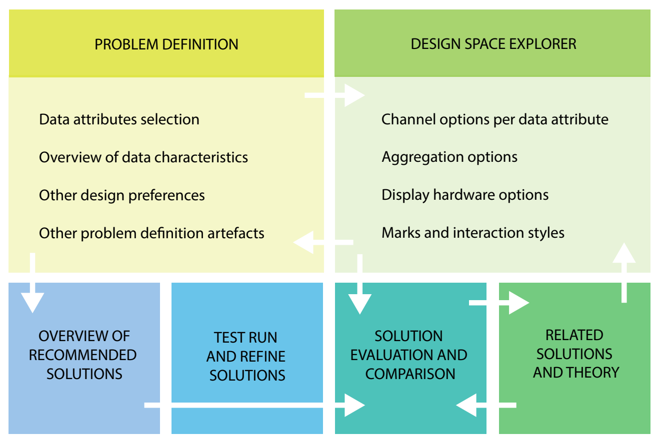


**Figure 2: Components of a visionary system for designers that integrates recommendation algorithms into a more holistic workspace, allowing for iterative development of designs.**

## 3.3 Using an ML-based Solution as an Immersive Analytics Designer

Currently, no dataset of pairwise comparisons is available to train systems for immersive analytics solutions, and even if one existed, the problem of factors not considered in the training data would remain. Gathering large amounts of pairwise comparisons of solutions is challenging without established models to represent the elements of a design, multisensory relations experienced by a user, and task goals used for evaluating the pair. The design goals to which one must optimise a design depend on the unique challenge users are facing and the context, which is up to the designer to understand and define. The difficulty of iteratively expanding on the design specification highlights a clear pitfall with ML-based solutions. The ranking of solutions from pairwise comparisons cannot be easily retrained to incorporate additional requirements defined by a designer, as is common in iterative design practice. This further makes it challenging to encourage designers to broaden their search for a design, which could lead them to accept ML-based solutions even when they sometimes produce poor results.

If data on pairwise comparisons becomes available, generating a knowledge graph as realised by KG4Vis [5] could provide analytical value when exploring design theory, but it would be unsuitable for direct use by a designer. The model could help discover broader trends in design reasoning, but would need to be redesigned to present its reasoning transparently, acknowledging that it cannot validate or recommend a good design on its own.

### 3.4 Using a Rule-based Solution as an Immersive Analytics Designer

A rule-based system can already help address the challenge of avoiding solutions that violate established guidelines, and rankings may also be included, though with the assumption that such rankings are highly unreliable.

After defining the foundations of the design problem, one approach is to generate and quickly explore many good and bad solutions. If linked to a knowledge base, the results may include not just generated results but also existing design solutions that match the criteria. This approach has the potential to lead to unexpected insights in data exploration, but also to let the designer build their sensibility through reflection on the design challenge and qualities of alternative solutions. If additional design preferences are discovered, they may be communicated iteratively to the recommendation system, creating a human-in-the-loop exchange. As the generated weights are linked to concrete rules, they may be manually adjusted if their importance is found to be mismatched to reality or the design. Today, adding new context-specific requirements to the system is challenging and dependent on coding skills. A specialised AI solution could add value by translating preferences expressed through everyday language, or information from other artefacts related to the design problem at hand, into concrete machine-readable rules.

Another challenge in exploring design solutions for immersive analytics is that display devices may differ across cases. A lack of standardisation and defined design recommendations is inevitable for new hardware. In visualisation, solutions can be seen and compared as final renderings side by side, but experiencing a non-visual solution may be difficult without labels or a complementary view of the mapping schema. Exploring a description of a design solution rather than experiencing it would provide easier overviews of alternative solutions, but place high expectations on the user's imagination and depend on the availability of vocabulary for sensory experiences. For example, could we compare a solution using *vibrotactile roughness* with one using the *tempo* of a sound? Rather than only generating a gallery of final-looking results, a rule-based approach might also be used to generate overviews for a design space of options fitting defined requirements, or provide corrections when a proposed solution violates a known design rule. If developed alongside a knowledge base that collects design theory, it could also serve as an entry point for accessing related solutions, research studies and design advice.

### 3.5 The Theory That Informs a Decision

A natural part of exploring and selecting among alternative solutions is drawing lessons from related theory and similar work and applying them to one's own project. Getting acquainted with related work helps grow one's design knowledge by finding relevant work within the vast amount of available information. Simpler access to related information could encourage a designer to learn more and save time in a project. Even within a structured and curated database, it is challenging to develop sophisticated, easy-to-use means of filtering results for contextual relevance. The more a design specification has been narrowed down, the more context-specific information can be provided. An AI tool may take on the role of a teacher by helping steer the designer toward reflections on the design specification, which, as stated in Section 2, novices in particular seem to struggle with.

## 4 Closing Comments

In this position paper, we suggested different types of AI solutions for browsing and selecting among design solutions, focusing on how they encourage or discourage users from using critical thinking and developing their design skills. We found that a useful approach for ideating and evaluating these conceptual solutions is to inspect them using expectations commonly attributed to a teacher. In the future, a more extensive and structured evaluation framework built on this idea could provide additional insights. While our work focuses on VRSs, the approach could prove valuable to the development of other AI tools supporting designers, and there are many other stages of the design process that can benefit from a similar inspection, such as fine-tuning prototypes, conducting user evaluations, as well as documentation.

The solutions we discussed remain visionary and depend on data resources that are also still emerging, though increasingly requested and investigated. An important task moving forward is to evaluate the alternative solutions in their conceptual state and consider how the dependent resources complement one another. For a design to be successful, one cannot ignore certain requirements, but rather hardware, design, ergonomics, storytelling, and many other factors must all come together. Immersive analytics can already begin developing long-term plans for cross-disciplinary knowledge exchange, the design requirements for complementary solutions, and means of evaluating these with different research and design communities. Perhaps one of the early pursuits for AI tools should be to grow and augment the communication skills of designers, developers and researchers.

## Acknowledgments

The work of Ingela L. Rossing is supported by VUB's Strategic Research Programme - Growth Funding (Grant No. SRP92).

# References


[1] Zafer Bilda and Linda Candy. 2026. Beyond Partnership: What Designers Discover Working with AI. *Interactions* 33, 4 (June 2026). https://doi.org/10.1145/3816033

[2] Eden Hennessey and Julie Mueller. 2020. Teaching and Learning Design Thinking (DT): How Do Educators See DT Fitting into the Classroom? *Canadian Journal of Education* 43, 2 (2020). https://www.jstor.org/stable/26954696

[3] Summiyani Hilmi. 2023. Implementation of Active Learning Strategies. *Journal of Curriculum and Pedagogic Studies (JCPS)* 2, 1 (June 2023). https://doi.org/10.30631/jcps.v2i1.1778

[4] Hao-Ping (Hank) Lee, Advait Sarkar, Lev Tankelevitch, Ian Drosos, Sean Rintel, Richard Banks, and Nicholas Wilson. 2025. The Impact of Generative AI on Critical Thinking: Self-reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers. In *Proceedings of CHI 2025, SIGCHI Conference on Human Factors in Computing Systems*. Yokohama, Japan. https://doi.org/10.1145/3706598.3713778

[5] Haotian Li, Yong Wang, Songheng Zhang, Yangqiu Song, and Huamin Qu. 2022. KG4Vis: A Knowledge Graph-based Approach for Visualization Recommendation. *IEEE Transactions on Visualization and Computer Graphics* 28, 1 (January 2022). https://doi.org/10.1109/TVCG.2021.3114863

[6] Paul Parsons. 2023. Preparing Future Data Visualization Designers for Professional Practice. In *Proceedings of EduVis 2023, IEEE VIS Workshop on Visualization Education, Literacy, and Activities*. Melbourne, Australia. https://doi.org/10.1109/EduVis60792.2023.00010

[7] Luca Podo, Bardh Prenkaj, and Paola Velardi. 2025. Agnostic Visual Recommendation Systems: Open Challenges and Future Directions. *IEEE Transactions on Visualization and Computer Graphics* 31, 3 (March 2025). https://doi.org/10.1109/TVCG.2024.3374571

[8] Oliver Schneider, Karon MacLean, Colin Swindells, and Kellogg Booth. 2017. Haptic Experience Design: What Hapticians Do and Where They Need Help. *International Journal of Human-Computer Studies* 107 (November 2017). https://doi.org/10.1016/j.ijhcs.2017.04.004

[9] Hasti Seifi, Matthew Chun, Colin Gallacher, Oliver Schneider, and Karon E. MacLean. 2020. How Do Novice Hapticians Design? A Case Study in Creating Haptic Learning Environments. *IEEE Transactions on Haptics* 13, 4 (January 2020). https://doi.org/10.1109/TOH.2020.2968903

[10] Jan D. Vermunt and Nico Verloop. 1999. Congruence and Friction Between Learning and Teaching. *Learning and Instruction* 9, 3 (June 1999). https://doi.org/10.1016/S0959-4752(98)00028-0

[11] Leland Wilkinson and Graham Wills. 2005. *The Grammar of Graphics* (2 ed.). Springer. https://doi.org/10.1007/0-387-28695-0

[12] Junran Yang, Péter Ferenc Gyarmati, Zehua Zeng, and Dominik Moritz. 2023. Draco 2: An Extensible Platform to Model Visualization Design. In *Proceedings of VIS 2023, International Conference on Visualization and Visual Analytics*. Melbourne, Australia. https://doi.org/10.1109/VIS54172.2023.00042

[13] Zehua Zeng and Leilani Battle. 2023. A Review and Collation of Graphical Perception Knowledge for Visualization Recommendation. In *Proceedings of CHI 2023, SIGCHI Conference on Human Factors in Computing Systems*. Hamburg, Germany. https://doi.org/10.1145/3544548.3581349

[14] Zehua Zeng, Junran Yang, Dominik Moritz, Jeffrey Heer, and Leilani Battle. 2024. Too Many Cooks: Exploring How Graphical Perception Studies Influence Visualization Recommendations in Draco. *IEEE Transactions on Visualization and Computer Graphics* 30, 1 (October 2024). https://doi.org/10.1109/TVCG.2023.3326527

[15] Songheng Zhang, Haotian Li, Huamin Qu, and Yong Wang. 2024. AdaVis: Adaptive and Explainable Visualization Recommendation for Tabular Data. *IEEE Transactions on Visualization and Computer Graphics* 30, 9 (September 2024). https://doi.org/10.1109/TVCG.2023.3316469