"TAL-CAT" a Computer-Aided Tool Prototype to Quantify User Experience in Design Workflow: A Case Study of Teamwork Assessment in Primary Care Clinics

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Abstract. This study introduces a Grasshopper tool prototype that empowers designers, researchers, and managers to evaluate a design's possible impact on users, compare design alternatives and alter them to better support teamwork as a desired qualitative outcome. This prototype, called TALCAT, is part of an approach called Functional Scenario Analysis (FSA) developed in SimTigrate design lab where stakeholders articulate their needs in brief plain-language statements, then the design research team turns these into criteria for design and specific metrics for measuring designs. Here we present the implementation of TALCAT in a number of Mayo primary-care clinic layouts to analyze, compare, and dynamically visualize teamwork affordance of layouts to support informed design decisions. TALCAT allows very rapid assessment of multiple metrics and allows what-if-testing of new designs as well as constructing new metrics. Moreover, it can address the validity issue in the field by providing consistency in data collection across multiple projects.

Keywords: Performance-informed design, Healthcare design, Computation Aided Design, Teamwork Assessment, Computer-aided design

1 Introduction

Research in Evidence-Based Design emphasizes using measurable spatial performance and aims to support designers and managers in choosing the best design alternative to respond to organizational demands (Anne Clyde, 2006;

Etchegaray, 2013). Part of EBD is to specify stakeholder needs and link them to desired outcomes for each project. Functional Scenario Analysis (FSA) is a very specific way to do this evolved at SimTigrate Design Lab that enables researchers to distill complex qualitative needs of stakeholders into measurable parameters, facilitate the evaluation of design affordance, and identify the effective design features to improve desired objectives. However, this process is cumbersome and labor-intensive. Since this multi-step method determines certain rules at each stage, we could use computational design to computerize it and develop Computational Analysis Design (CAD) aids. These digital aids empower researchers to analyze the design alternatives more efficiently and provide consistent yet adjustable measurements that collect and store data across multiple projects with similar goals. Employing such computer-based analysis aids make it possible to develop measurement databases and facilitate validation which is generally very hard in empirical studies concerned with complex architectural experiences.

This paper exemplifies how we performed this method to prototype a digital tool to assess teamwork affordance of layouts in primary care clinics. TAL-CAT (Teamwork Affordance of Layouts Computation Assessment Tool) was designed in Grasshopper, and we used Python to define new Grasshopper components.

1.1 Performance-Based Design in Healthcare Settings

Performance-based design has emerged due to the increasing attention given to assessing project performance before and after building them to ensure that the design accomplishes its determined goals (Kolarevic, 2003; Oxman, 2009; Oxman et al., 2007). One of the areas in which performance evaluation is of great importance and sensitivity is the field of healthcare where built environment proved to associate with the quality of care and patient's health outcomes (Ulrich et al., 2008). Research in Evidence-Based Design emphasizes using data acquired to measure spatial performance and aims to support designers and managers in choosing the best design alternative to respond to organizational demands (Anne Clyde, 2006, 2006; Etchegaray, 2013).

The decisions made in the early stages of the design have a profound impact on the performance of the building (Haq & Pati, 2010). However, in practice, design professionals usually face challenges during this phase in exploring, analyzing, and evaluating design alternatives and their influence on the user's behavior (Anne Clyde, 2006; Martin, 2009). One major reason is that performing the EBD research process is time-consuming and labor-intensive. Also, the findings from one project are not seamlessly applicable beyond the boundaries of that specific project. Moreover, most studies are observational and descriptive, so research findings (as part of EBD) are often lost in translation between the backstage design process and what appears in the actual design (Watkins & Keller, 2008).

With the continuing advancement of computational tools for architectural design, the role of performance evaluation has become more effective as an informing force in early design decisions (Bernal et al., 2015; Dubey et al., 2020). This approach allows designers to incorporate real-world design complexity into computational design prototypes and customize and augment design solutions. It also facilitates communication among different stakeholders and tailors the design alternative based on the specific needs of each project. Besides, employing computational design can speed up the design process and build up a database by providing adjustable tools that collect and store data from various projects (Bernal et al., 2015; Kalay, 1985). Multiple performance-based tools in computational design environments were developed to rapidly estimate various building performances at the early stage of the design process. So far, most of the effort in this realm was dragged to energy performance, structural deflection, daylight analysis, and material assessment (Bhatt et al., 2011; Haghir et al., 2021; Dubey et al., 2020; Goldstein et al., 2020; Sanguinetti et al., 2010).

This paper discusses a case study where we modeled a design-assistive tool to evaluate the teamwork affordance of five Mayo clinic layouts and discuss how developing these tools helps designers, researchers, and decision-makers enhance design performance. The tool captures the logic and process of key needs of stakeholders and computerizes them through Grasshopper in the Rhino platform. Through this translation, not only the outcome of the research can be applied to other case studies/design alternatives faster, with higher accuracy, the tool can collect data over time, provide a database for EBD researchers, enhance analytical precision, and customize the same tool for each project.

1.2 Why Teamwork is Important in Healthcare Settings

Team-based care addresses patients' needs by coordinating groups from different healthcare providers. The main teamwork element, effective communication, directly impacts the success of team-based care by reducing medical errors and cost, and enhancing patient safety, team efficiency, and performance (Kolarevic, 2003; Lim, 2018.; Oxman et al., 2007; Oxman, 2009). Face-to-face interaction is the primary sort of communication, ranging from an unintended encounter in a corridor to planned and organized collaboration (Gharaveis et al., 2018; Rashid et al., 2006).

In a healthcare setting, the layout of a design is known to play a key role in and greatly influence the quality of communication. Collocated team rooms have been shown to improve team efficiency (DuBose et al., 2015; Gharaveis et al., 2018). This finding suggests private offices be removed in many clinics and include larger office areas for providers to cooperate with other care teams. While private offices impose hierarchical models, fragmentation, and limited collaborations, integrating team rooms provides effective communication and collaboration opportunities as the fundamental basis for the Patient-Centered Model of Care (Gharaveis et al., 2018; Gurascio-Howard & Malloch, 2007). Care teams can work together more interactively and share information and knowledge in an integrated shared working setting. Such workspaces also need to offer efficient individual and heads-down work spatial conditions where staff can work effectively, without unnecessary interruptions. These integrated care team rooms can enhance teamwork by meeting four primary objectives: promoting situational awareness and care coordination and improving team communication and individual staff roles (Gharaveis et al., 2018).

Although better communications can improve team performance, collocated spaces have not always led to communication enhancement. Some studies demonstrate less communication among employees and coworkers when moving from individual cellular offices to open-plan ones since they do not want to disturb their coworkers or feel overheard. In some cases, these studies showed more stress and less productivity in such environments. This gap reveals the need to identify those design strategies that improve communication and promote teamwork (Becker, 2007; Gurascio-Howard & Malloch, 2007).

2. Method

2.1 Functional Scenario Analysis Method

As a design assessment approach toward quantifying design objectives and user needs, the Functional Scenario Analysis Method (FSA) suggests metrics to designers, researchers, and decision-makers for evaluating design's potential impact on users and offers design modifications to improve user experience.

The FSA follows five steps:

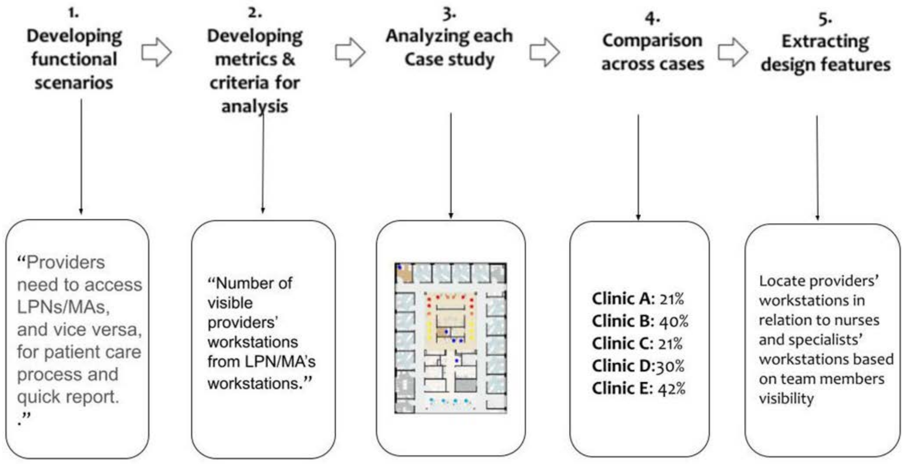


Figure 1. Steps of Functional Scenario Analysis method.

FSA method has already been performed effectively in evaluating the design of healthcare settings such as exam rooms, clinics, ICUs, NICUs, and the design of biocontainment rooms (Denham et al., 2018; Matić et al., 2018). This research extends upon the results of one of our studies at SimTigrate Design Lab that has applied FSA to evaluate the impact of layout on the teamwork performance of Mayo Clinic.

In the following, we will explain how we extracted and processed logical rules after applying the FSA method and how we developed our CAD tool based on these rules.

The first step of the FSA method is to define the user's needs. For this project, we used three data sources to investigate and identify the needs of healthcare team members to deliver care in ambulatory care facilities that could be affected by the physical environment: Published literature, Mayo documents, and field observations. Based on these resources, those needs of the team members that improve performance and are also affected by the physical space were extracted. Figure 2 represents the final statements illustrating the demands of a high-performance team.

In the next step, these needs were translated into measurable metrics. The metrics have to be standardized and general enough to be used among all the clinics in the study. Second, the values of the metrics can be directly evaluated based on the floor plans, thereby allowing the evaluation of design alternatives prior to finalizing a design. Figure 3 represents the metrics developed to assess each functional Statement.

Between team members

Team members need to see:
1. each other throughout the day for patient care in the clinic.
2. other team members with the same role for social learning and to share workload.

Providers need to access:
3. LPNs/MAs, and vice versa, for patient care process and quick report.
4. the specialist providers to make warm hand-offs.

Between team members and space

Team members need to:
1. know the status of specific exam rooms
2. take breaks without feeling isolated from their work flow.
3. do their heads down tasks during the clinical day.
4. Providers and rooming staff need to access exam rooms from their workstations.
5. Registered nurses and rooming staff need to be aware of the status of the overall clinic
6. Schedulers need to access team members in the team area.

Care-team members:
LPN: Licensed-Practice Nurse
Providers
Specialist
MA: Medical Assistant

Figure 2. Functional Scenarios for High Performance Team

2.2 Extracting the Logical Rules

As mentioned before, by applying the FS method we were able to analyze the teamwork affordance of the layouts.

In order to convert the method to several measurable rules, the method has been broken into its constituent elements. The developed scenarios entail rules in three categories; *visibility*, *accessibility*, *and visual integration*. Each of the rules requires a separate algorithm to calculate the related scenarios.

The first criteria category is *visibility* which covers most of the measures of our analysis.

Functional statement	Metrics
1. Interaction Between Caregivers	a. Average number of workstations visible from each workstation.
2. Same Role Interaction within caregivers	a. Average number of providers' workstations visible from each provider's workstation. b. Average number of visible RNs' workstations from each RN's workstation. c. Average number of visible LPNs/MAs' workstations from each LPN/MA's workstation.
3. Access of LPN/MS for fast patient care/report	a. Average number of visible LPNs/MAs workstations from each provider's workstation. b. Average distance between medical assistant and team provider workstations. c. Number of the pathways between provider workstations and exam rooms that pass LPN/MA stations. d. Number of the pathways between LPN/MA workstations and exam rooms that pass provider workstations.
4. Access of Specialist providers to make warm-handoffs	a. Average number of specialist providers that providers can see directly. b. Average shortest walking distance between the specialists' offices/workstations and providers 'workstations.
5. Knowing ability of exam rooms	a. Average number of exam rooms status indicators visible from each team member workstation.
6. Accessibility of exam rooms for providers/ rooming staff	a. Average walking distance between providers and exam rooms. b. Average walking distance between LPNs/MAs and exam rooms.
7. Spatial awareness for RNs/Rooming staff	a. Average visual integration of RNs workstations to the whole clinic area. b. Average visual integration of LPNs workstations to the whole clinic area.
8. Accessibility of team members in team areas for schedulers	a. Average shortest distance between the team area and scheduler work stations.
9. Doing heads down tasks during the clinical day	a. Measure the average shortest distance between the private areas and work station.
10. Taking breaks without disruption of workflow	a. The shortest distance from the break room to the team area.

Figure 3. List of metrics for each functional statement.

Measurements of this category consist of three elements: objects, targets, and visual barriers. Generally, a group of agents needs to see a group of targets, which can be agents from their own team, other teams' agents, patients, or target spaces through the visual barriers, which are walls or partitions. Therefore, assessing the measurements of this category requires two types of rules; In the first one, objects and targets are from the same group, and the other one contains objects and targets entries from different groups. This distinction causes a technical difference in the code which will be described in the next section.

An example of the first type of measurement concerning the visibility within the same group is: "Team members need to see each other throughout the day for patient care in the clinic." In this criterion, the tool has to calculate the percentage of the visible agents for any other agents within the entire care team. In our tool, we apply this rule to measure the following metrics: 1-a, 2-a, 2-b, 2-c (refer to Figure 3 to identify metrics).

The second type of rule for visibility criteria analyzes the same logic for separated entries as a group of targets and a group of objects. Metrics 3.a, 4.a, 5.a fall in this category.

Accessibility can be specified in terms of both visual and physical connection. We covered its visual component in the visibility measurements. As a result, the second recognized category values physical accessibility, which concerns the walking pathway between an origin and a destination. In our research, this category is divided into two different parts. The first part measures the length of walking pathways between two points, and the second one evaluates the intersection possibility of certain walking paths with a specific target/targets.

The first physical accessibility rule estimates the average distance between each member of the agent group as the origin and all of the destination group members as the destination. Following measurements dropped in this category: 3-b,4-b, 6-a, 6-b, 8-a, 9-a, 10-a (refer to Figure 3 to identify metrics).

The second accessibility rule contains two steps. First, it determines the shortest walking pathways between assigned agents and destinations. Second, the tool counts the number of these pathways which pass a specific target. 3-c and 3-d are the calculated measures via this rule (refer to Figure 3 to identify metrics).

The last criteria category that we identified is *visual integration*. This measure calculates the visual distance from all spaces to all others using a simple point visibility test radiating from the current location. The following measures are encompassed in this category: 7-a and 7-b (refer to Figure 3 to identify metrics).

In sum, all of the five rules in the aforementioned criteria categories can be listed as follow:

(1a) The average number of objects visible from themselves.

(1b) The average number of targets visible from the group of objects.

(2a) Average walking distance between the agents and the destination.

(2b) Number of the pathways between the agents and the destination that pass the targets.

(3) Average visual integration of the agents to the whole area.

2.3 Processing the Logical Rules

As we concluded in the previous section, there are five rules in three criteria categories that have to be incorporated into our tool. This part of the study explains the algorithms which we designed for each rule. There is also some lateral information that would be the same across the rules. For example, the tool has to provide visual representations of all the information ultimately, and this action requires a separated algorithm and entry data, primarily similar to all five rules. Besides, the tool has to validate the data type (for example, the user cannot input a line as an agent, and it must always be a point), which is unrelated to the logic. This paper focuses on the specific algorithms of the rules and would not go through the lateral algorithms.

The first rule (1a) attempts to find the number of agents visible to others within the same group. Here, the primary entry data is the 'agents' group and the visual barrier. The algorithm considers every wall, partition, and furniture that can block the axial view as visual barriers and excludes those with a height lower than the sitting eye level. The main output for this rule is a percentage value representing the average percentage of the visible agents for all of the agents, as shown in Figure 3.

The second rule (1b) uses the same logic; however, the agents and the targets would be from different groups. Figure 4 illustrates the logic of this rule.

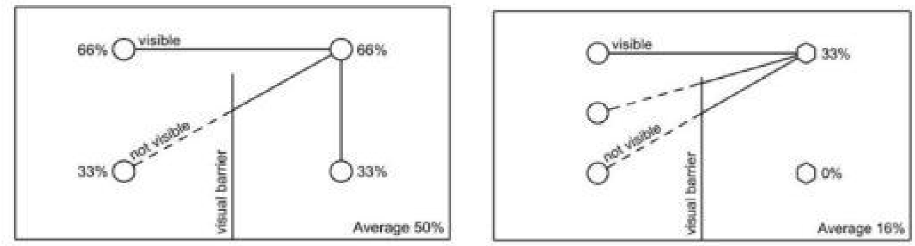


Figure 4. The left image shows the 1a rule and the one on the right shows the 1b.

Both of these rules follow the same logic presented in Figure 5. Although the algorithm output data provides more information like who has the best or the worst situation and the exact number of visible targets for each agent, the tool reports only the main output, the percentage, because a large amount of data would confuse the user. This secondary calculated data would be stored for further analysis that might be added later in the process. Figure 5 demonstrates how the algorithm works.

For implementing the two rules of 1a and 1b, the intersection method was

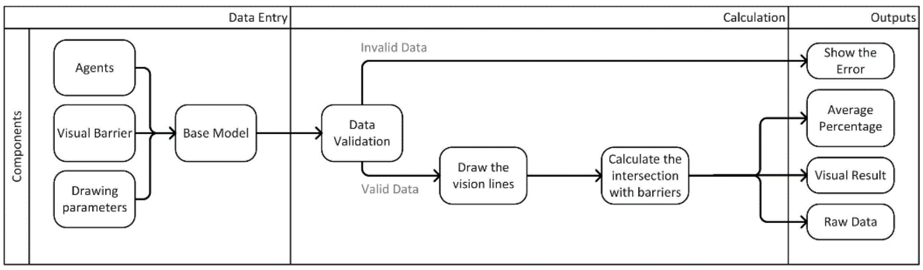


Figure 5. The flowchart for the rules (1a and 1b).

employed, which means if the line between the agents and the target has an intersection with the barrier, which was imputed as curves, the result would be zero. In this case, the agent and the target are not able to see each other.

The second category (2a and 2b) rules use the same inputs, including agents, destinations, walking barriers, and the drawing parameters. This part applies a pathfinding algorithm to find the shortest walking path from a grid for further calculation. Figure 6 represents the function of our rules.

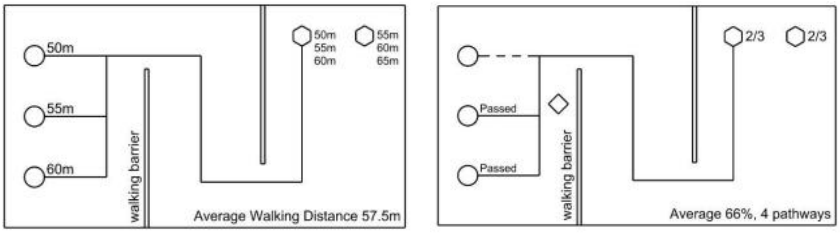


Figure 6. The left image shows the 2a rule and the other one shows the 2b.

The flowchart in Figure 7 illustrates how the algorithm works. The tool calculates the path length and its proximity to the target based on the shortest pathway. To find the path, an orthogonal base grid is considered in the code as a pathway graph. The size of the grid is adjustable by the user; a smaller grid size would be more precise but more complex to solve. As the second step, the code deletes the grid parts, colliding with the pathway barriers and generating the base graph. Finally, the shortest path will be calculated using graph theory.

The third rule (3) uses VGA maps from Depthmap software as the entry data. A JPG file, like Figure 8, enters the code as the map and the tool computes the value of the visual integration at each agent position. Thus, the input data are Agents, Visual Integration Raw Data, and Drawing parameters. In the end, the tool totals the average percent of visual integration for a target group of agents.

After designing the algorithms and categorizing the analyzes, the tool design was finalized in Grasshopper, and we applied it to analyze 5 case studies.

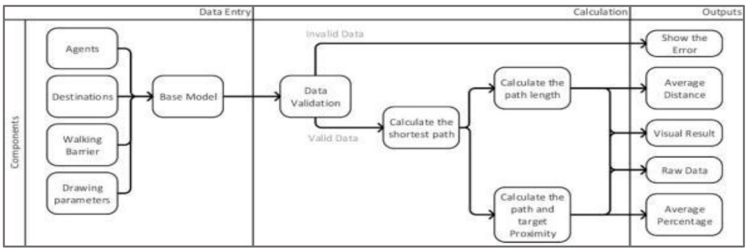


Figure 7. The flowchart used for the rules (2a and 2b).

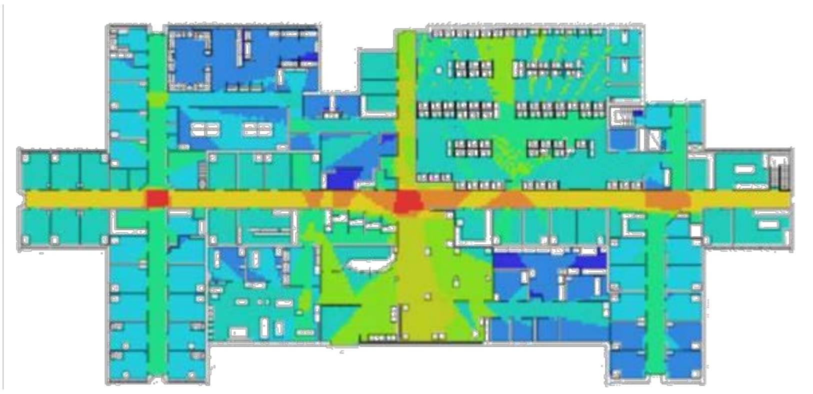


Figure 8. VGA map imported from Depthmap.

2.4 Visualization

Eventually, the script produces 19 sheets for every case study, each corresponding to one of the metrics. After applying this process to all case studies, the script visualizes the comparison results among the clinics and ranks them based on their performances in every defined teamwork requirement. The tool maps the results into a graph which allows us to see where the strengths and weaknesses of each layout are. This lets researchers

And designers return to the design and determine which design feature is responsible for that specific performance outcome.

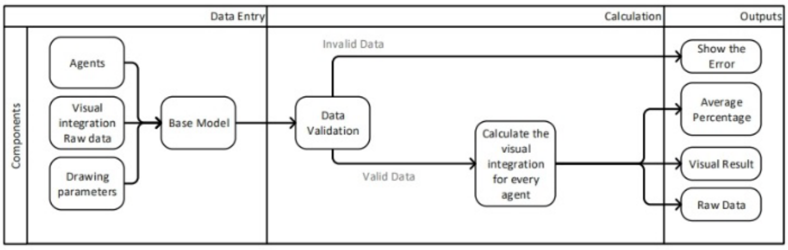


Figure 9. The flowchart used for the rules (3).

3. Discussion:

As the construction of healthcare facilities costs a lot of money, time, and man-force, it is highly critical to ensure the effectiveness and performance of the projects for the clients. Although the evidence-based design has endeavored to evaluate healthcare settings' performance from different aspects effectively, applying this process requires a lot of time and labor. The progress of computational design has widely promoted the development of many Computational-Aided Design tools (Bernal et al., 2015, 2020). The paper shows how computational design can be expanded to design evidence-based analytical tools to evaluate designs' performance. As a case study, this research

discusses a study of assessing clinic layouts in multidisciplinary team-based primary medical care at Mayo Clinic. The stakeholders and previous research literature in medicine, teamwork and evidence-based design led to a focus on how the layout could increase informal interactions by seeing or encountering others and how staff could gain situational awareness of what the larger team is doing and how they can support the work of the team (Dubose et al.,2015; Gharaveis et al.,2018).
To evaluate layout effects on teamwork, we employed Functional Scenario, an evidence-based design method that allows converting the complex spatial needs of stakeholders to measurable components.

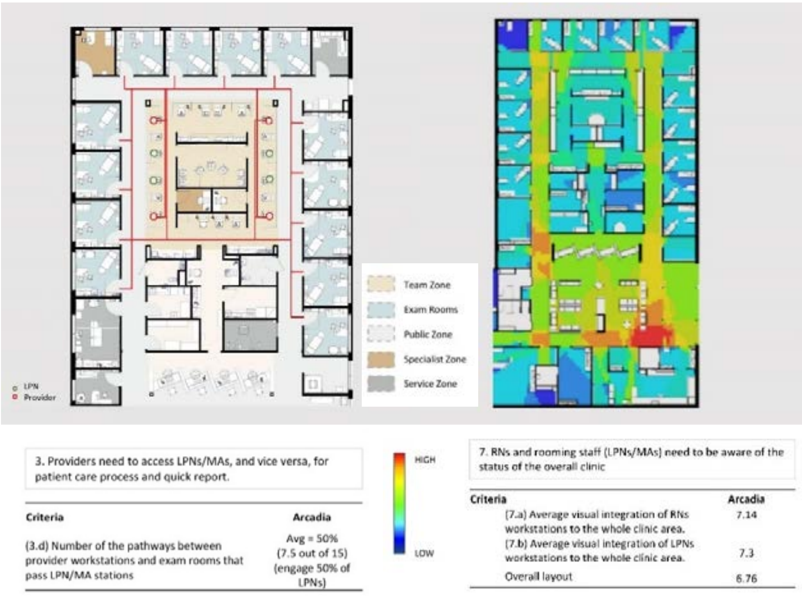
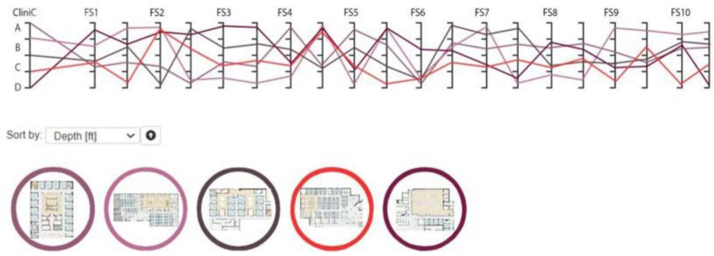


Figure 10. Samples of 19 analysis sheets entirely created by the tool.



Case 1 Case 2 Case 3 Case 4 Case 5

Figure 11. Illustration of the case studies' comparison.

Developed in Grasshopper plugin in Rhino, this research presents the implementation of TALCAT in a number of primary-care clinic layouts to analyze, compare, and dynamically visualize spatial behavioral data to support informed design decisions. We modeled a prototype of such tools to evaluate the teamwork affordance of primary clinic layouts. Utilizing similar assessment tools at early design stages enables researchers to compare different design alternatives, examine the impact of each design strategy on the target outcome/s, and consequently make more informed decisions. We suggest that this approach responds to the growing need to tailor the CAD assessments for each project due to the project complexities while facilitating the application of the tools among projects with similar objectives and developing a database, which later helps extract effective design strategies. Moreover, such an approach can result in accumulating comparable data across projects and tackle the issues of validation and generalization, which are ongoing challenges in EBD empirical studies. We established TAL-CAD based on the small sample of Mayo-Clinic layouts with co-located team rooms. Future research could expand the sample size and add various outpatient clinic layouts, including those with cellular offices rather than a shared-team space. Further research projects might also expand the current list of two-dimensional measurements to cover three-dimensional spatial parameters. Progressively, machine learning algorithms can employ the collected data to capture and detect patterns to extract more effective and goal-directed design typologies.

References

Anne Clyde, L. (2006). The basis for evidence-based practice: *Evaluating the research evidence. New Library World*, *107*(5/6), 180–192. https://doi.org/10.1108/03074800610665194

Becker, F. (2007). Nursing Unit Design and Communication Patterns: What is "Real" Work? *HERD: Health Environments Research & Design Journal*, *1*(1), 58–62.

Bernal, M., Haymaker, J. R., & Eastman, C. (2015). On the role of computational support for designers in action. *Design Studies*, *41*, 163–182.

Bernal, M., Okhoya, V., Marshall, T., Chen, C., & Haymaker, J. (2020). Integrating expertise and parametric analysis for a data-driven decision-making practice. *International Journal of Architectural Computing*, *18*(4), 424–440. https://doi.org/10.1177/1478077120940975

Bhatt, M., Guesgen, H., Wölfl, S., & Hazarika, S. (2011). Qualitative Spatial and Temporal Reasoning: Emerging Applications, Trends, and Directions. *Spatial Cognition & Computation*, *11*(1), 1–14.

Denham, M. E., Bushehri, Y., & Lim, L. (2018). Through the Eyes of the User: Evaluating Neonatal Intensive Care Unit Design. *HERD: Health Environments Research & Design Journal*, *11*(3), 49–65. https://doi.org/10.1177/1937586718761017

Dubey, R. K., Khoo, W. P., Morad, M. G., Hölscher, C., & Kapadia, M. (2020). AUTOSIGN: A multi-criteria optimization approach to computer aided design of signage layouts in complex buildings. *Computers & Graphics*, *88*, 13–23.

DuBose, J. R., Lim, L., & Westlake, R. (2015). Designing team rooms for collaboration in the outpatient clinics. *Georgia Institute of Techonolgy Simtegrate Lab*.

Etchegaray, J. M. (2013). Understanding evidence-based research methods: Confirmatory and exploratory analysis. *HERD*, *6*(4), 169–172.

Gharaveis, A., Hamilton, D. K., Pati, D., & Shepley, M. (2018). The Impact of Visibility on Teamwork, Collaborative Communication, and Security in Emergency Departments: An Exploratory Study. *HERD: Health Environments Research & Design Journal*, *11*(4), 37–49.

Goldstein, R., Breslav, S., Walmsley, K., & Khan, A. (2020). *SpaceAnalysis: A Tool for Pathfinding, Visibility, and Acoustics Analyses in Generative Design Workflows*.

Gurascio-Howard, L., & Malloch, K. (2007). Centralized and Decentralized Nurse Station Design: An Examination of Caregiver Communication, Work Activities, and Technology. *HERD : Health Environments Research & Design Journal*, *1*(1), 44–57.

Haghir, S., Haghnazar, R., Saghafi Moghaddam, S., Keramat, D., Matini, M. R., & Taghizade, K. (2021a). BIM based decision-support tool for automating design to fabrication process of freeform lattice space structure. International Journal of Space Structures, 09560599211033867. https://doi.org/10.1177/09560599211033867

Kalay, Y. E. (1985). Redefining the role of computers in architecture: From drafting/modelling tools to knowledge-based design assistants. *Computer-Aided Design*, *17*(7), 319–328.

Kolarevic, B. (2003). 03 Digital Production. *2003*, 26.

Lim, L. (2018). *Designing Team Rooms for Collaboration in the Outpatient Clinics*. 70.

Martin, C. S. (2009). The Challenge of Integrating Evidence-Based Design: *HERD: Health Environments Research & Design Journal*.

Matić, Z., Wong Sala, M., & Lim, L. (2018, June 7). *Using Functional Scenario Analysis Method for Designing and Evaluating Exam Rooms*.

Oxman, R. (2009). Performative Design: A Performance-Based Model of Digital Architectural Design. *Environment and Planning B: Planning and Design*, *36*(6), 1026–1037.

Oxman, R., Hammer, R., & Ari, S. B. (2007). *Performative Design in Architecture*. 8.

Rashid, M., Kampschroer, K., Wineman, J., & Zimring, C. (2006). Spatial Layout and Face-to-Face Interaction in Offices—A Study of the Mechanisms of Spatial Effects on Face-to-Face Interaction. *Environment and Planning B: Planning and Design*, *33*(6), 825–844.

Sanguinetti, P., Bernal, M., El-Khaldi, M., & Erwin, M. (2010). Real-time design feedback: Coupling performance-knowledge with design iteration for decision-making. *Proceedings of the 2010 Spring Simulation Multiconference on - SpringSim' '10*, 1.

Ulrich, R. S., Zimring, C., Zhu, X., DuBose, J., Seo, H.-B., Choi, Y.-S., Quan, X., & Joseph, A. (2008). A Review of the Research Literature on Evidence-Based Healthcare Design. *HERD: Health Environments Research & Design Journal*, *1*(3), 61–125.

Watkins, N., & Keller, A. (2008). Lost in Translation: Bridging Gaps between Design and Evidence-Based Design. *HERD: Health Environments Research & Design Journal*, *1*(2), 39–46.