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MULTI-ATTRIBUTE DECISION-MAKING AND DATA VISUALIZATION FOR MULTI-DISCIPLINARY GROUP BUILDING PROJECT DECISIONS

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ABSTRACT

With improvements in computer modeling that allow AEC professionals to rapidly simulate trillions of design and construction alternatives, decision-makers need a way to efficiently and effectively interpret and explore the vast design space while building team and organizational consensus around a solution. Multi-attribute decision-making (MADM) and data visualization methods play an important role in successfully achieving these goals. However, while the prescriptive benefits of these methods are widely acknowledged, the precise impact that they have on design team performance and project quality has not been fully described. This paper presents the descriptive findings from four early-stage building design charrettes that implemented normative data visualization and MADM techniques. Key metrics considered are normalized solution quality, level of design exploration, and consensus among multiple decision-makers. Empirically, the results show that MADM is associated with higher rates of group consensus, and that a combination of MADM and visual aids generates the greatest improvement in solution quality over time.

KEYWORDS: Multi-attribute decision-making, simple additive weighting, data visualization, consensus building, design decision support

INTRODUCTION

Throughout a building project, architecture, engineering, and construction (AEC) consultants predict and evaluate the performance of many different design and construction options. The daily design-construction recommendations AEC consultants make to the client have significant impacts on building cost, schedule, and life cycle performance. Often, teams of AEC consultants must collaborate and communicate across disciplines to select the best alternative to recommend to the client, all while under strict budget and schedule constraints.

While architects, designers, engineers, contractors, and building managers have historically relied on the collective experience of AEC consulting teams to efficiently and accurately guide exploration of project design and construction options, such heuristic methods are becoming less capable of guiding design. Improvements in computer modeling are allowing AEC teams to rapidly simulate trillions of design options. (Basbagill et al. 2013), making exploration of design spaces using collective experience or “rules-of-thumb” impractical. Moreover, new design metrics such as CO₂-equivalent footprint, life cycle eco-points, or pollutant emissions can be rapidly modeled for each design option (Basbagill et al. 2013). The

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consideration of these new metrics may negate industry experience, transforming experienced groups of AEC professionals into neophytes.

Thus, AEC consultants need fair, open, and legitimate decision-making processes to meet client goals and deliver high quality design and construction solutions that consider a number of diverse metrics. Multi-attribute decision-making (MADM) methods and data visualization play an important role in successfully achieving this goal (Blasco et al. 2008); yet, there is a lack of agreement and understanding about appropriate processes in research and in practice (Grierson 2008), and the relationship between formal decision methods and visualization tools (Al-Kassab et al. 2014). This paper evaluates the separate and joint implementation of MADM and Pareto front visualization in a team-structured building design charrette with multi-disciplinary objectives, time and resource constraints, and a limited, pre-determined design space. The objective of this work is to determine if such tools can lead to improved decision-making in a limited design space, thus making a case for the potential of such tools in navigating a more massive design space.

This paper begins with the theoretical foundations for decision-making and decision problem visualization. The research methodology, decision problem, and design charrettes are then explained. Empirical findings for the study are summarized, followed by a discussion of results and conclusions.

THEORETICAL FOUNDATIONS

Decision-Making

Multi-Criteria Decision-Making

The multidisciplinary nature of AEC decision-making and the engagement of multiple stakeholders often result in decision problems with multiple, conflicting objectives. This particular structure of decision-making calls for a set of approaches referred to as multi-criteria decision-making (MCDM). MCDM methods structure and model the imprecise goals of multi-dimensional decision problems in terms of a set of individual decision criteria, where each criterion characterizes a single dimension of the problem to be evaluated. Typically, each criterion has a different unit of measurement. (Hwang & Yoon 1981) The general framework for most MCDM involves decomposing the decision problem into components, evaluating each component individually, and reassembling the components to provide overall insights and recommendations. (Seppälä et al. 2002) Decision makers may then evaluate and select the best alternative among a finite set of previously defined alternatives (multi-attribute decision-making (MADM)) or design the best alternative (multi-objective decision-making (MODM)) over all criteria. (Hwang & Yoon 1981)

AEC professionals and researchers are actively investigating MCDM processes in design and pre-construction to select projects for investment (e.g., Lam et al. 2001, Dey 2006), choose project procurement methods (e.g., Kumaraswamy & Dissanayaka 2001, Anderson & Oyetunji 2003, Mahdi & Alreshaid 2005), and enhance early-stage design (e.g., Ugwu & Haupt 2007, Turksis et al. 2009, Flager et al. 2012). The majority of MCDM methods examined in the building design and construction literature and implemented in practice are value-based MADM techniques. Value or utility theory approaches ask decision makers to develop a numerical score or value for each decision alternative and choose the alternative with the highest value. Examples

include multi-attribute utility theory (MAUT) (Keeney & Raiffa 1976), the analytic hierarchy process (AHP) (Saaty 1980), simple additive weighting (SAW) (Hwang & Yoon 1981), and Choosing By Advantages (CBA) (Suhr 1999). While MADM methods are currently being explored academically or applied in AEC organizations, few researchers have considered the impact of these normative methods on building project decision-making, including design decision quality and group consensus-building, or the implications for project team organization.

Simple Additive Weighting

Simple additive weighting (SAW) method is a compensatory MADM technique that weights the contributions from each attribute according to the decision maker's preferences. SAW is a simple, intuitive process that is quick and easy for new decision makers to learn. As such, it is one of the best-known and most widely used MADM methods. To set up the SAW method, the decision maker assigns importance weights to each of the n attributes. These weights are usually normalized so that $\sum_{j=1}^n w_j = 1$. The decision maker also numerically scales the intra-attribute values to be comparable, often normalizing them between 0 and 1. Next, the decision maker calculates the weighted average value for each of the m alternatives as follows:

$$A_i = \sum_{j=1}^n w_j r_{ij}(x_{ij}), \quad i = 1, \dots, m, \quad 0 \leq A_i \leq 1, \quad (1)$$

where $r_{ij}(x_{ij})$ is the normalized value of the i^{th} alternative about the j^{th} attribute. The most preferred alternative, A^* , is determined by the equation below:

$$A^* = \{A_i | \max_i \sum_{j=1}^n w_j r_{ij}(x_{ij})\}. \quad (2)$$

Since SAW converts attributes measured using a ratio scale into normalized, dimensionless values, the method can account for qualitative as well as quantitative attributes so long as the qualitative attributes can be compared numerically. Though simplistic, SAW produces close approximations to more sophisticated non-linear forms (e.g. weighted product methods). In reality, however, attribute values are not necessarily additive or multiplicative. Decision makers often experience challenges with assigning consistent preferences, and may employ manipulation of weighting schemes to reinforce intuition. Moreover, SAW methods assume preference independence and utility independence. Important complementarities between the attributes are ignored by necessity, which may give misleading results. (Hwang & Yoon 1981) When assigning weights, decision makers must find a reasonable basis to reflect the importance of each attribute, which may require a high level of abstraction (e.g. comparing operational energy to schedule duration). Nonetheless, SAW is a popular technique within project organizations and in MADM literature. Hwang and Yoon (1995) recommend SAW and other scoring methods for “unsophisticated” (or inexperienced) decision makers.

Group Decision-Making

Group decisions are defined as “decisions where a group of two or more individuals must collectively select an alternative from a set of two or more alternatives that best satisfies the group's objectives.” (Keeney 2013) No single individual has veto power. This assumption may not hold in design and construction projects in which the client requires direct consultation on all decisions. In this context, the group of AEC professionals is selecting an alternative to recommend to the client, who ultimately decides whether or not it will be chosen. From the group's perspective, it is advantageous to suggest an alternative that they believe the client will approve. Individual preferences can and do differ from the group preferences, but group decision making is interactive – each stakeholder's anticipated actions affect the choices of others – so

there are interdependencies between the stakeholders. (Sebenius 2009) Moreover, building projects are comprised of not one but many decisions and AEC firms may be required to collaborate on future projects, so group recommendations and decisions may be characterized as stochastic repeated negotiations (of uncertain number). Although individuals may profit from taking advantage of others in the short-term (one decision), the group's loss of faith in that individual can set up loss for the group as a whole. (Luce & Raiffa 1957)

Instead, the group members should strive for consensus on the decision or recommendation. Consensus building is associated with a number of desirable outcomes: innovative strategies, new social, intellectual, and political capital, and high-quality agreements. Indirectly, consensus building may lead to the formation of new partnerships, implementation of agreements, and improved coordination and joint action. (Innes & Booher 1999) With multi-disciplinary, multi-objective, and multi-stakeholder decision problems, achieving absolute consensus among different stakeholders is often impossible. To develop a satisfactory level of support and realize the benefits of consensus building, the group must regard the decision process as “fair, open, inclusive, accountable, and otherwise legitimate.” (Innes & Booher 1999) MADM alone may not satisfy these criteria. Despite providing a structured framework and fair approach, MADM methods may not be seen as open and inclusive, especially if decision makers require training to be able to implement them.

Decision Problem Visualization

Decision visualization tools and models can play an important part in the transparency and accessibility of a decision process. Classic decision models include decision tables, decision trees, and influence diagrams. (French et al. 2009) Decision support systems may also be built on other graphical representations of data that are appropriate for more complex decision methods or decision problems with a larger set of alternatives, including 2-dimensional Pareto fronts, Level Graphs, and other multi-dimensional Pareto representations. (Blasco et al. 2008) According to Blasco et al. (2008), it is “widely accepted” that decision visualization tools are “valuable and provide decision-makers with a meaningful method to analyze the (Pareto) set and select good solutions.” However, few studies have been done that demonstrate the ability of decision visualization tools to enhance decision-making and consensus building, nor that examine the use of decision visualization tools in relation to MADM methods in a group decision setting.

RESEARCH METHODOLOGY

Four charrettes were conducted with 30 industry professionals and 59 graduate students in architecture and engineering as detailed in Table 1. The separate involvement of both experienced industry professionals and graduate students (*i.e.* AEC professional “novices”) was done to better assess the usefulness of the decision-making and visualization tools in each group. Participants were divided into teams of 3 to 5 individuals, each serving a unique AEC role on the team (*i.e.* owner, architect, *etc.*), and asked to solve a simple building design problem that minimized life cycle cost, capital cost, and construction schedule duration. Teams could alter six discrete design parameters, providing 144 unique design alternatives. Cost and schedule performance were available for each design. Teams were split into four experimental groups,

each of which received up to two tools to aid their decision-making. Note that teams with no Pareto front visualizations and no MADM method effectively serve as control groups. Both team and experimental group assignments were random to avoid as much bias as possible. The first tool used simple additive weighting (SAW) to provide a normalized score (0-1) for each alternative relative to the complete population of designs, thus allowing teams to view the score for each alternative in each of the three objective categories, as well as an overall score. The second tool graphically plotted design alternatives on two Pareto fronts: First Cost vs. Life-Cycle Cost and First Cost vs. Construction Schedule. Participants also completed surveys before and after the charrette to gather qualitative data related to satisfaction with the decision-making process and level of consensus around the team’s final recommendation.

Table 1: Design Charrette Experimental Set-Up

	<i>Date and Location</i>	<i>Number of Participants</i>	<i>Participant Type and Average Experience</i>	<i>Experimental Groups (Number of Teams)</i>
1	6/10/2013 Stanford, CA	30	All professionals (architects, structural engineers, construction managers, developers) with an average of 15 years of AEC experience	a) No MADM/No Pareto (1*) b) SAW/No Pareto (2) c) No MADM/Pareto (2) d) SAW/Pareto (2)
2	10/22/2013 Los Angeles, CA	24	All graduate students (civil engineering) with an average of less than 5 years of AEC experience	a) No MADM/No Pareto (1*) b) SAW/No Pareto (2) c) No MADM/Pareto (1) d) SAW/Pareto (1)
3	10/23/2013 Los Angeles, CA	8	All graduate students (architecture) with an average of less than 5 years of AEC experience	c) No MADM/Pareto (1) d) SAW/Pareto (1)
4	10/23/2013 Los Angeles, CA	27	Undergraduate and graduate students (architecture) with an average of less than 5 years of AEC experience	a) No MADM/No Pareto (1) b) SAW/No Pareto (2) c) No MADM/Pareto (1*) d) SAW/Pareto (1)

* Experimental groups that initially had two teams; however, data for one of the teams had to be discarded due to failure to submit complete information to the researchers or total disregard for the charrette instructions (e.g. maximizing instead of minimizing performance metrics).

Decision Problem

Teams were asked to develop a project of 1 to 2 building footprints to house 2,000 occupants with 50ft²/occupant (100,000ft² total). Each team was required to recommend a design alternative at the end of the charrette that best matched the owner’s objectives, which were all equally weighted. The three objectives of the design problem were to:

- Minimize the capital cost of the building.
- Minimize the life-cycle cost for the building’s operation.
- Minimize construction schedule duration.

Design teams had six design variables to consider, each with a prescribed set of possible values listed in Table 2. Given the number of possible values for each variable, design teams could select among 14 values to create a design alternative. A particular configuration of the variables represented a design alternative and the collection of all design alternatives represented the design space. Thus, as mentioned, the design space consisted of 144 design alternatives. The generation and analysis of a single design alternative represented one complete design iteration.

Table 2: Design Variables and Possible Values for the Building Decision Problem

<i>Design Variable</i>	<i>Possible Values</i>
Number of Buildings	1, 2
Number of Floors	5, 7, 9
Building Shape	Rectangle, L-Shaped
Glazing Percentage	50%, 70%
Orientation	0, 45, 90 degrees
Structure Type	Steel, Concrete

In order to simplify the design space, the researchers established four design constraints. For all designs, Total Gross Floor Area was 100,000ft², Floor-to-Floor Height was 13ft, and the Building Aspect Ratio (L1/W) was fixed at 2. For the L-shaped design, the L-shape Aspect Ratio (L1/L2) was set at 1. Dimension variables are indicated in Figure 1.

All teams were able to request performance information for a specific design alternative. To mimic project latency, teams could get information for only one alternative at a time but could explore as many alternatives as they liked within the charrette time constraint of 20 minutes. The cost performance metrics were generated by Beck Technology, an AEC firm, based on the Architectural Design and Performance Tool (ADAPT) created by researchers at Stanford University. (Basbagill et al. 2013) The construction schedule duration estimates came from the Space Constraint Method (SCM) developed at Stanford. (Morkos 2014)

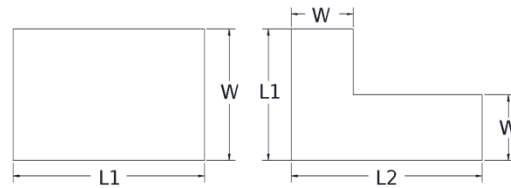


Figure 1: Rectangular and L-Shape Building Layouts for the Design Charrette with Dimensions

Multi-Attribute Decision-Making

Teams with MADM received a macro-enabled spreadsheet that implemented the SAW method to facilitate a formal decision-making process. The researchers predetermined the weights in accordance with the stated owner objectives, which meant that each metric was weighted equally, $\underline{w} = \{w_1, w_2, w_3\}, w_1 = w_2 = w_3 = w$. The weights were normalized such that $\sum_{j=1}^3 w_j = 1$, so $w = 1/3$ and $\underline{w} = \{1/3, 1/3, 1/3\}$. The score for the i^{th} alternative was calculated using a linear scale transformation to normalize performance metric values, r_{ij} ,

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^* - x_j^{\min}} \text{ where } x_j^* = \max_i x_{ij}, \quad 0 \leq r_{ij} \leq 1, \quad (3)$$

and a linear weighted average to obtain the total score across all performance metrics, A_i ,

$$A_i = \sum_{j=1}^3 w_j r_{ij}(x_{ij}), \quad i = 1, \dots, 144, \quad 0 \leq A_i \leq 1. \quad (4)$$

The overall design alternative scores were approximately normally distributed (Figure 2).

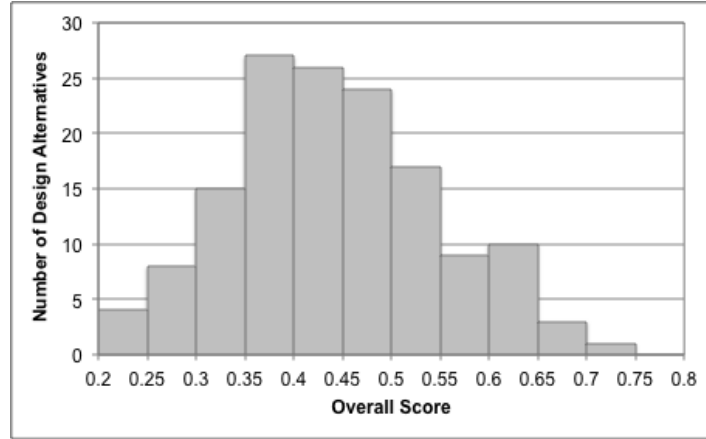


Figure 2: Histogram of Overall Owner Objective Scores, A_i , for All 144 Possible Design Alternatives Included Within the Design Charrette

Since the objective was to minimize performance metrics, a lower overall score represented a better alternative, with the most preferred alternative, A^* , computed as

$$A^* = \{A_i | \min_i \sum_{j=1}^n w_j r_{ij}(x_{ij})\}. \quad (5)$$

Teams were instructed to input the performance information for a particular design alternative into the spreadsheet, which then calculated the normalized rating for each performance metric for the alternative. Teams were shown the normalized rating for each performance metric of a particular design alternative (0-1) as well as the overall score for each design alternative (0-1) in the outputs tab. Teams could also compare the scores graphically as demonstrated in Figure 3.

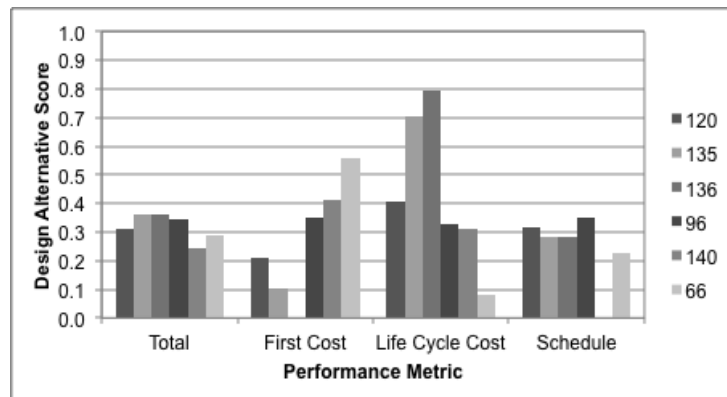


Figure 3: Sample Output of the SAW Spreadsheet Tool for Six Design Alternatives (Design Numbers 120, 135, 136, 96, 140, and 66) Showing Normalized Scores for Total Performance, First Cost, Life Cycle Cost, and Schedule Performance

Pareto Front Visualization

Teams with Pareto visualization received an Excel spreadsheet that mapped each design alternative explored in two scatter plots representing the overall design space. The two Pareto fronts were created using the performance metrics generated for every design from ADAPT (Basbagill et al. 2013) and SCM (Morkos 2014). Both graphs included the performance for all 144 designs to allow teams to view the performance of their alternatives in the context of the feasible design space as displayed in Figure 4.

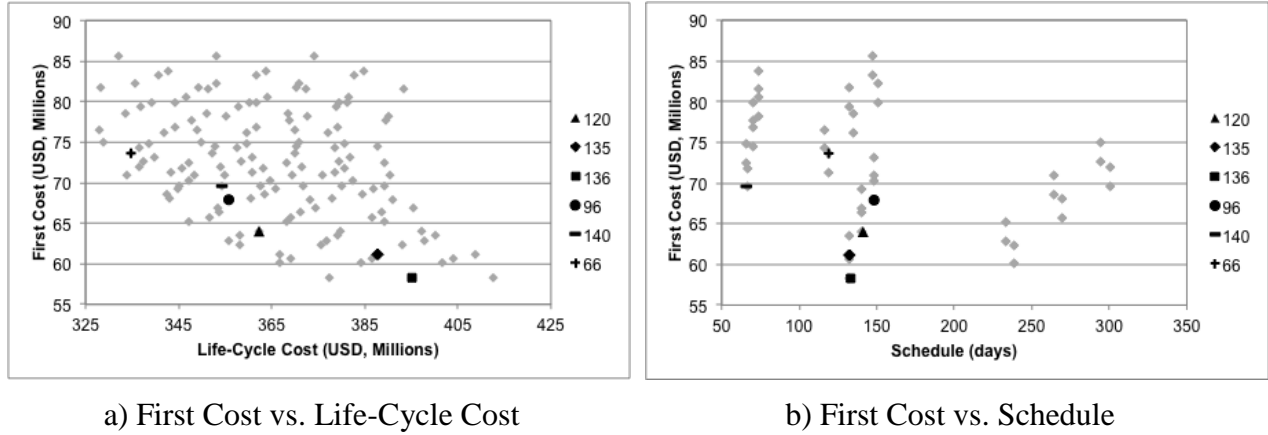


Figure 4: Sample Output of the Pareto Visualization Tool for Six Design Alternatives (Design Numbers 120, 135, 136, 96, 140, and 66) Showing the Relative Positions vis-à-vis (a) First Cost vs. Life Cycle Cost and (b) First Cost vs. Schedule

EMPIRICAL FINDINGS

Solution Quality

Solution quality, Q_i , was assessed by normalizing the overall score for design alternatives between 0 and 1,

$$Q_i = 1 - \frac{A^* - A_i}{A^* - A^{\max}} \quad \text{where} \quad A^{\max} = \{A_i | \max_i \sum_{j=1}^n w_j r_{ij}(x_{ij})\}, \quad 0 \leq Q_i \leq 1, \quad (6)$$

such that a normalized score of 0 represented the least-preferred design and a normalized score of 1 represented the most-preferred design. All figures that follow use normalized solution quality as the measure of overall design performance. The average score for each experimental group is shown in Figure 5.

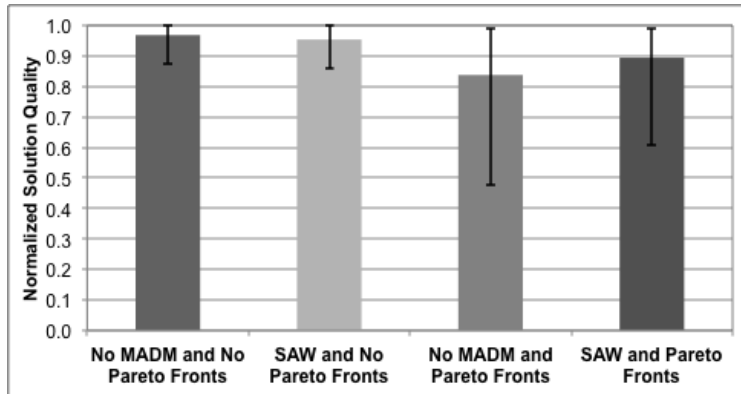


Figure 5: Final Normalized Solution Quality by Experimental Group over All Charrettes (Professional and Student). Error bars indicate range of design solution quality (*i.e.*, best and worst teams within the experimental group).

A couple of interesting trends emerge when comparing the final solution quality across the experimental and control teams. Teams provided with Pareto visualization but no MADM method tended to produce solutions of lower quality than teams with no Pareto visualization and no MADM method (control groups). This trend was supported by observations during the charrette and during post-charrette discussions with the participants, which suggested that the usefulness of added insight into the objective tradeoffs was diminished because of the small number of alternatives (*i.e.*, only 144 designs in the solution space) and familiarity with estimating cost and schedule performance (*i.e.*, past professional AEC experience). The combination of a small design space and professional familiarity allowed for successful solution by intuition in very few iterations. In fact, charrette participants with no encumbrance of decision-making tools or visualization support, on average, arrived at the best final solutions within the charrette time constraint. However, post-charrette discussions implied that this may not be the case with a much larger design space and additional design metrics.

The data also suggest that the unfamiliar representation of design performance in the graphical form increased the complexity of the problem, which made the fixed time constraint of the charrette an important factor. Teams with Pareto visualization but no MADM method had difficulty quickly making sense of the information they received: 60% of these teams were unable to identify the best alternative in the set they had explored and recommended a worse option (Figure 6). A structured approach to interpreting the tradeoffs – here a simple, quantitative decision method – was necessary to extract meaningful information from the Pareto visualizations, as teams with SAW and Pareto fronts recommended final solutions of higher quality. Regardless, all teams with SAW were all within one variable change of the best design alternative. Teams with both SAW and Pareto fronts recommended the best alternative in the set they had evaluated.

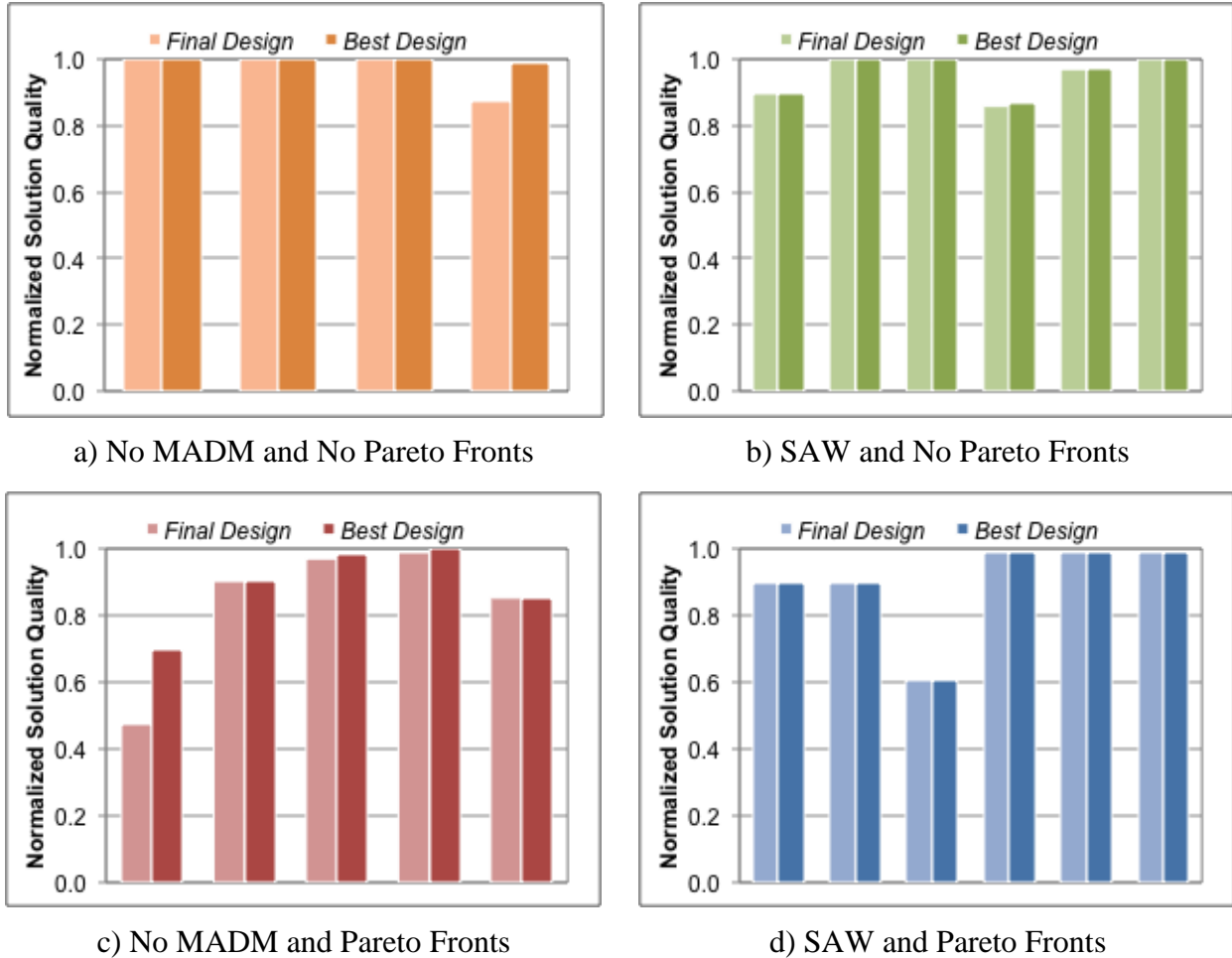


Figure 6: Final Design vs. Best Design by Experimental Groups. One team each in (a) and (b) and three teams in (c) failed to identify the highest quality solution in the set of designs explored.

Design Exploration

For the professional charrette specifically, teams with Pareto visualization but no MADM method actually had a negative average improvement in solution quality by iteration; that is, there was an average decrease in solution quality of 1.38% during the design process. In fact, teams with no Pareto visualization and no MADM method (*i.e.* control groups) performed better than their counterparts with Pareto fronts with an average improvement of 2.80%. Teams with SAW had a greater average improvement in solution quality by iteration than those teams without SAW, and teams with Pareto fronts and with SAW did the best on average. These results are shown in Figure 7a.

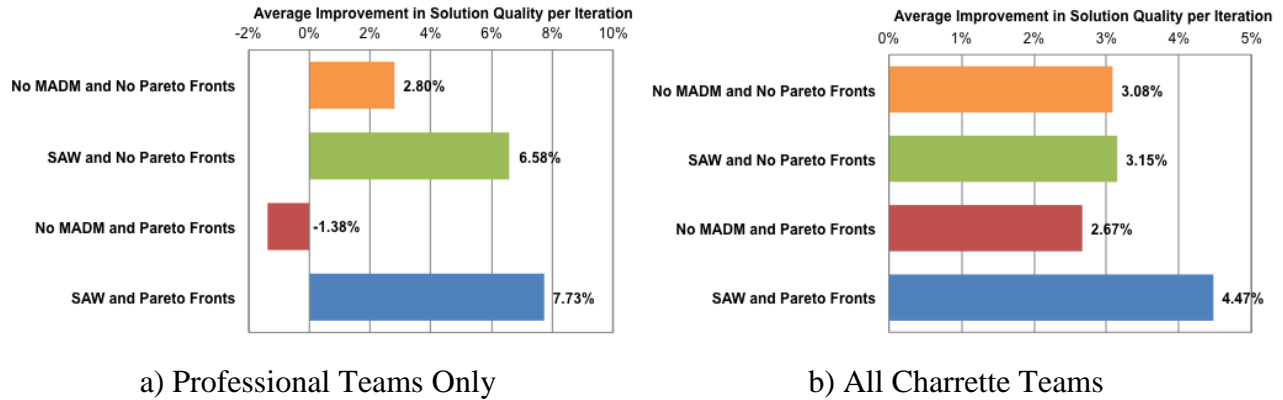


Figure 7: Average Improvement in Solution Quality by Iteration for (a) Professional AEC Charrette Participants and (b) All AEC Charrette Participants

When the graduate student charrette results were included in the analysis, the trend was the same. Again, teams with Pareto fronts and no MADM performed worse than teams with no Pareto fronts and no MADM (2.57% vs. 3.08% average improvement). Teams with SAW achieved greater average improvement in solution quality by iteration. Although these teams conducted fewer design iterations on average than teams without MADM, they were able to use iterations more effectively. In other words, teams were able to learn about the interdependencies between objectives and direct their search towards the non-dominated solution. Of all the experimental groups, teams with both Pareto visualization and the SAW method exhibited the greatest improvement in average solution quality by iteration at 4.47%. These teams performed the fewest number of iterations on average but were the most efficient at navigating the design space. The combined results for both professional and student teams are given in Figure 7b.

Values were calculated using solution quality data for all iterations. Figure 8 on the next page shows the normalized solution quality (scaled between 0 and 1 as part of the analysis) for each team and is graphed by experimental group.

Decision-Maker Consensus

Teams with SAW expressed the greatest satisfaction with the decision-making process and the highest confidence in the team’s final recommendation. For the design charrette including only professionals, 92% of participants applying the SAW method were confident in the quality of their team’s final design with 50% reporting very high confidence as seen in Figure 9. By contrast, only 58% of those with no MADM method were confident in their team’s design quality. Professional participants preferred MADM methods to routine practice and 67% reported that they felt more engaged in the decision process. Moreover, 78% believed MADM was a valuable tool for project management.

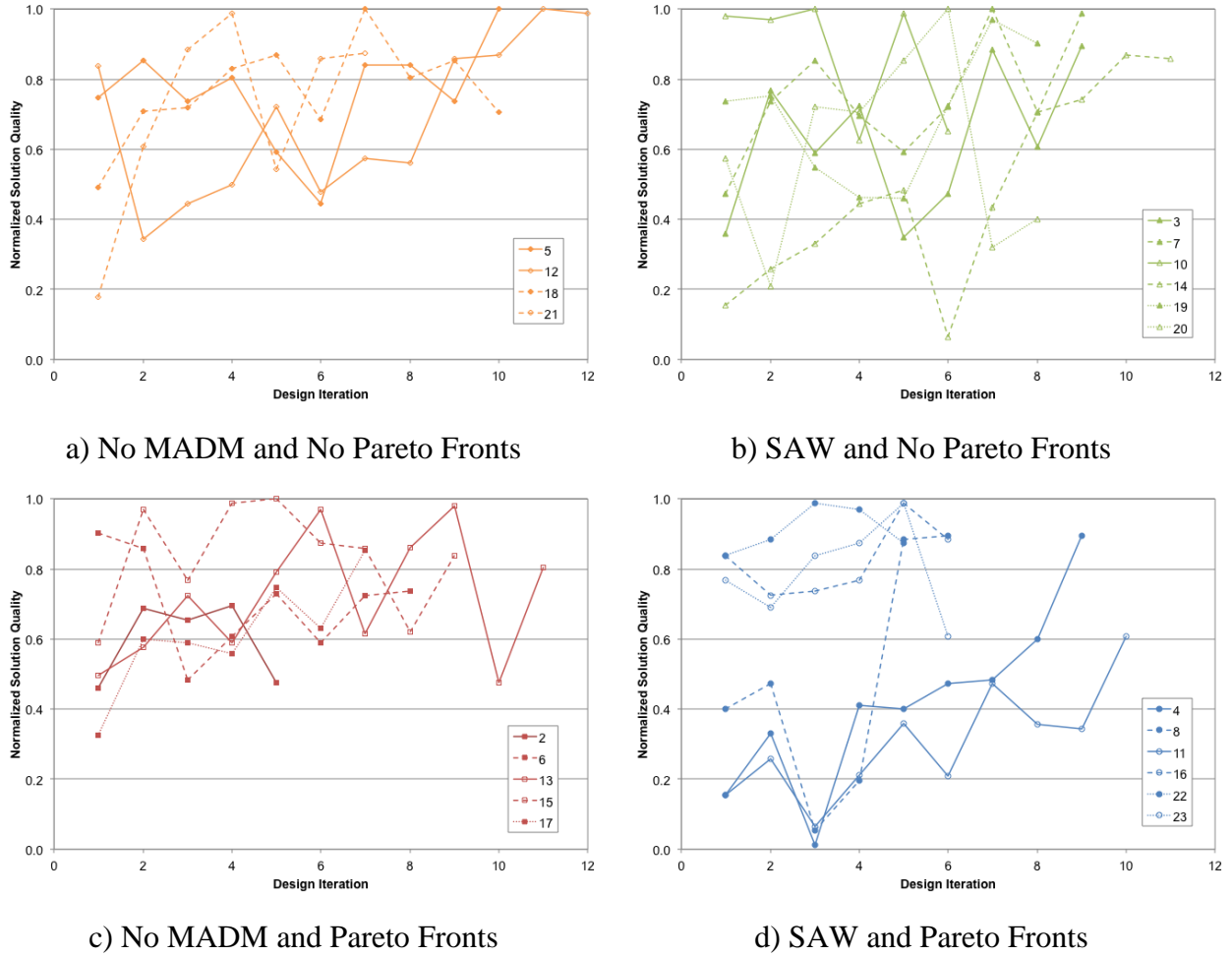


Figure 8: Normalized Solution Quality at Each Iteration of the Design Charrette for Teams with (a) No MADM and No Pareto Fronts (control group), (b) SAW and No Pareto Fronts, (c) No MADM and Pareto Fronts, and (d) SAW and Pareto Fronts

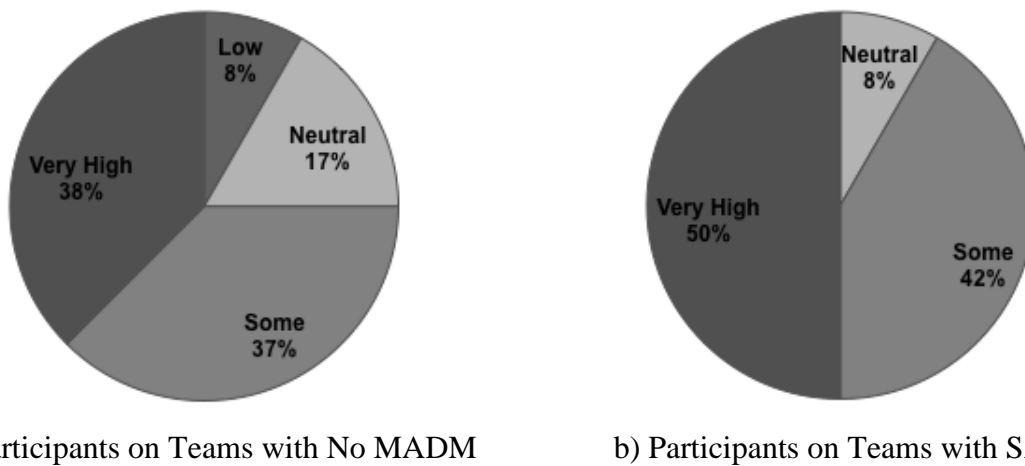


Figure 9: Professional Participants' Confidence in the Quality of their Team's Final Charrette Design for (a) Participants on Teams with No MADM and (b) Participants on Teams with SAW

DISCUSSION AND CONCLUSION

The experimental data supports the claim that some implementation of MADM methods can help guide decision-makers through a complex design space and build consensus within a group. The time-constrained format of the charrette, simplicity of the design space, and familiarity with the estimation of the objectives may account for the high final solution quality for those without decision support tools, particularly among those with more AEC industry experience. However, the more significant conclusions lie in the trends in solution quality over time. This is especially true for application to more realistic design decision problems with more relaxed timelines, a greater number of alternatives, and unfamiliar objectives (*e.g.* sustainability performance metrics). From this perspective, a formal, structured MADM method also enhances the value of Pareto visualizations and helps decision makers focus their search on better quality solutions. The ability to generate a large set of design possibilities is much more useful if decision-makers have a consistent way to interpret the design space. The use of Pareto visualizations and quantitative measures of design quality help design and construction professionals to better communicate to clients the motivation behind design decisions and can be directly related to environmental, economic, and social sustainability outcomes, ensuring that the client's objectives are carried through the design process in a transparent manner.

While the initial set of experiments does not lead to statistical significance due to the still small sample size, the data is descriptively valid and indicates the need for further development of the research to lead to improved visualization tools that will further the implementation of MADM in the AEC industry. One avenue for future work is the continued study of visualization techniques and graphic aids using charrettes to generate a larger statistical pool for further analysis. Additional approaches to test the validity in practice are necessary, and may include increasing design problem scale by adding more alternatives, examining later phases of building design and construction such as detailed design and pre-construction, and introducing new objectives like sustainability performance metrics.

One of the most important findings of this work is that simply adopting decision support tools does not strictly improve decision-making. Rather, a smart combination of tools to aid decision-making is required. Considering the performance of teams without MADM and with Pareto fronts, visualization tools without context and without quantitative decision support do not work. More research is necessary to find the right suite of tools to best enhance decision-making and consensus building on design and construction projects. There is also some small evidence that the use of tools allows experienced and neophyte practitioners to come to the same conclusions in a similar number of design iterations. This has implications for project staffing, organizational learning, *etc.*, and should be explored in the future.

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