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Using Discrete Choice Methodology to Explore the Impact of Patient Room Window Design on Hospital Choice

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Abstract

Evidence-based design has been fundamental to designing healthcare environments for patient outcomes and experience, yet few studies have studied how design factors drive patient choice. 652 patients who recently received care at hospitals across the United States were administered an online discrete choice survey to investigate the factors playing into their choice between hypothetical hospitals. Discrete choice models are widely used to model patient preferences among treatment alternatives, but few studies have utilized this approach to investigate healthcare design alternatives. In the current study, respondents were asked to choose between hypothetical hospitals that differed in patient room design, window features of the room, appointment availability, distance from home, insurance coverage, and HCAHPS ratings. The results demonstrate that patient room design that allowed unobscured access to daylight and views through windows, in-network insurance coverage, closer distance from home, and one-star higher patient experience rating increased the likelihood of a patient's hospital choice. The study broadly explores discrete choice model's applicability to healthcare design and its ability to quantify patient perceptions with a metric meaningful for hospital administrators.

Keywords

healthcare design, daylight, hospital environment, window, patient choice, discrete choice

Introduction

Access to daylight and views through windows has proven critical for fostering a therapeutic and supportive healing environment (1–4), ultimately manifesting in better patient outcomes such as shortened length of stay and reduced pain medication use (5–11). Although the relevance of these design factors from an experience and clinical quality perspective are clear, less is understood about how these factors make a hospital a more competitive choice for patients seeking care. Patients are now more likely to shop around, with a recent survey suggesting that 71% use online reviews to find a new doctor and 43% would go out-of-network for a provider with better reviews (12). Regarding the healthcare environment itself, hospitals have been likened to airlines, where the amenities that create a pleasant atmosphere factor into the perception of the overall quality of service provided (13). An analysis of fee-for-service patients with pneumonia in the greater Los Angeles area found that hospital amenities were a greater driver of patient choice than clinical quality, with one standard deviation increase in amenity scores raising a hospital's demand by 38% (14). Thus, hospital design elements and amenities present a large opportunity for capturing patient choice and ultimately the success of a healthcare facility.

Quantifying patient choice is challenging as there are several factors that come into play, such as provider referrals and accessibility of care. One widely adopted methodology to estimate choice while accounting for such factors is discrete choice modeling (DCM). Originating from mathematical psychology, DCM is rooted in the theory that when confronted with a discrete set of options, people choose the option of maximal benefit or utility to them. This approach

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has seen practical application in various disciplines as a better gauge of collecting hypothetical consumer choice (referred to as "stated preference") than direct survey questions such as, "Would you be willing to pay $X more for alternative A?." As such, DCM has become mainstream in marketing and economics to predict individual and collective choices in the absence of data on the actual choices consumers have made.

DCM has recently grown exponentially in healthcare, particularly in evaluating patient perceptions of treatment alternatives and developing priority setting frameworks based on those perceptions (15–17). de Bekker-Grob et al demonstrated the external validity and potential ability to predict real-world patient choices when DCMs are designed and implemented correctly (18).

Within healthcare, DCM has also been utilized to quantify patient choice as it relates to choosing hospital or healthcare providers. Previous research indicates that cost (19) and insurance coverage (20) are 2 fundamental factors that explain patient choice of hospital. Clinical quality as measured by patient outcomes has also been proven a large driver of patient choice (21), and more recently, hospital quality as measured by hospital reputation or patient satisfaction ratings has also been shown to influence patient choice (22,23). Accessibility of care is also a large driver of choice, with several studies pointing to patients choosing hospitals that are closer to home or have a shorter wait until the next available appointment (20–22, 24–26).

However, few studies have utilized DCM to quantify patient preference for healthcare design factors. In a survey of 406 respondents, Suess and Mody found that high-end material finishes strongly influenced patient choice, with less healthy patients reporting a willingness to pay 13% higher out-of-pocket expenses for hotel-like hospital rooms than more healthy patients (27). Cunningham et al used the DCM approach to survey 467 hospital staff and stakeholders in the design process of a children's health center and found that interactive design features were important factors to consider (28). More recently, van Oel et al used 3D design models within a DCM survey and found that both patients and staff consistently chose hospital rooms with high daylight access and an open door, suggesting the importance of features that allow patients to stay connected to the outside world (29). Although large, expansive windows are often designed into patient rooms with the intention of delivering natural light and connectivity, in practice, staff, visitors, and patients themselves often occlude the window with shades or blinds to control for heat, glare, or privacy (30,31). This necessitates a deeper understanding of this nuanced factor of window occlusion and how it impacts daylight access, view clarity (32), and ultimately patient preferences.

The aim of the current study is therefore 3-fold: (1) quantify choice as an outcome as it relates to windows and daylight, (2) hone in on view clarity as a factor beyond window access or size, and (3) explore the implementation of the discrete choice methodology in healthcare design research.

Methods

Survey Deployment

The DCM survey was distributed online to a national sample of patients who recently received care at hospitals across the United States. Inclusion criteria included being age 18+, having spent at least one night in a hospital inpatient unit in the past year, and residing in the United States. Data were screened for quality, which included removing duplicates, responses under the minimum duration threshold, and straight-lined or patterned responses for matrix questions. After filtering, a total of 652 patients who participated in the survey between November and December 2020 were included in the study. The sampling and data collection process for this IRB-approved study were conducted through Qualtrics panels, and all participants were compensated for their time. Information related to patients' demographics (age, gender, race, education) and clinical information (admission status and unit) were also obtained. The current manuscript is an extension of a broader research study, the details of which are outlined in Mihandoust et al (33).

Survey Design

The survey prompted patients with a hypothetical scenario of choosing a hospital based on 5 factors: insurance coverage, distance from home, appointment availability, hospital experience rating, and patient room design. These factors were chosen for their strong influence demonstrated in previous choice studies and their relevance to hospital facility design and operations.

To provide the necessary context, the following statement prefaced the question set: "Imagine you are seeking inpatient care for the same reason as your most recent inpatient stay. You will be asked to select a hospital for your care based on the five considerations listed below, assuming everything else is similar between the two hospitals." Definitions for the factors were provided as follows:

- *Patient room design*—This refers to the overall ambience and design of the patient room as represented in the image
- *Insurance coverage*—This refers to whether the hospital is listed as "in-network" or "out-of-network" by your health insurance provider
- *Distance from home*—This refers to the driving distance from your home to the hospital
- *Appointment availability*—This refers to the number of days until the next available appointment
- *Hospital experience rating*—This refers to overall patient experience at the hospital based on patient survey ratings, available publicly online from Medicare's Hospital Compare

The model employed a full factorial design, containing all possible combinations of factors and creating a balanced design that allows estimation of both main effects and interactions. To limit choice sets, each factor had 2 levels: insurance coverage was in-network or out-of-network, distance from home was 30 or 45 min, appointment availability was a 15-day or 30-day wait, hospital experience rating was 3- or 4-star (out of 5) ratings, and room design was a room with either the window unobstructed to allow daylight and views or with the window partially occluded by a shade. Three and 4-star hospital ratings were used as these ratings together account for approximately 74% of all hospitals in the Center for Medicare and Medicaid Services HCAHPS system (34). With 2 levels each for 5 factors, the full factorial design entailed $2^5 = 32$ choices, randomly paired into 16 choice sets. Respondents were prompted to assume that all other factors, including clinical care quality, were the same across choices.

The patient room design variable was represented by 2 pairs of images representing 2 different window conditions and levels of daylight and view access incurred by those conditions. Images were photographs of 2 actual single-bed patient rooms in the United States with electrochromic glass windows that are not occluded by shades, and those same rooms with traditional windows and shades partially drawn. Room 1 appears visually lighter in color, with white walls and bedding (top-left image, Figure 1); Room 2 appears bluer in color with blue-gray walls and blue bedding (top-right image, Figure 1). In the choice sets, these 2 rooms were alternated such that patients were choosing between, not within, the room pairs. In the analysis, these patient room elements (window condition and overall hospital room design, Room 1 and Room 2) were treated as separate choice variables.

Although validation studies suggest that respondents can be asked up to 20 choice tasks before data quality degrades (35), each participant was randomly assigned 4 of the 16 possible choice sets to minimize survey fatigue. Choice display order was randomized to reduce bias. An example of 2 of the choice sets is represented in Figure 1.

Analytical Approach

Patient choice was modeled as a function of the characteristics of the 5-choice factors using a conditional logit model. The conditional logit model is similar to logistic regression and estimates the effect of each model parameter on binary choice by seeking to maximize the likelihood function (36). It is described using Equation 1, where utility (η_{ij}) is modeled as a function of choice attributes (z'_j representing the vector of characteristics of the j-th alternative and $\boldsymbol{\gamma}$ representing choice-specific parameters). As this conditional logit model yielded poor model fit (McFadden $R^2 = 0.035$), it is not presented in the results.

$$\eta_{ij} = z_j'\gamma \tag{1}$$

As previous research indicates the importance of patient's individual (ie, demographic or clinical) attributes on choice behavior, choice was then modeled using a mixed multinomial conditional logit model. In this approach, underlying utility depends not only on the attributes of the choices but also on the attributes of the individual. The mixed model can be described by Equation 2, where utility (η_{ij}) is modeled as a function of choice attributes and individual characteristics ($\boldsymbol{x}'_i$, the characteristics of the individuals that remain constant; and $\mathbf{z}'_{ij}$, the characteristics of the individuals that vary across choices).

Backward selection identified the following demographic variables for inclusion in the mixed logit model: age, gender, race, education, and household income level. As the survey prompted patients to consider the hypothetical scenario of selecting a hospital for the same reason as their most recent inpatient stay, the model incorporated the patient's most recent visit classification (emergency, urgent, or elective) and was stratified by the hospital unit that the characterized the patient's most recent inpatient stay (ie, Labor and Delivery unit, ICU). Finally, based on evidence in the literature, income was modeled as interaction with binary categorization (<\$100 000/year vs ≥\$100 000/year), but otherwise with the same set of predictors (25).

$$\eta_{ij} = \boldsymbol{x}_i'\beta j + z_{ij}'\gamma \tag{2}$$

All statistical analyses were performed using R and discrete choice modeling using conditional and mixed logit models was performed using the statistical package mlogit (37).

Results

Respondent Demographics

Respondents were primarily age 50 or younger (n = 587, 90%), equally distributed by male or female gender, primarily white (n = 477, 73%), with an annual income above \$25,000 (n = 539, n = 83%). When asked to describe their most recent inpatient stay, approximately one-third of respondents categorized the nature of their visit as elective, urgent, and emergency; 44% reported inpatient stay of 1 to 2 days and 56% reported stays of 3 days or longer. Respondent demographics are detailed further in in the Supplemental Material (Table S1).

Effect estimates for gender ($n_{male} = 324$, $n_{female} = 322$), race ($n_{White} = 477$, $n_{Black} = 108$, and $n_{Other} = 67$), and age ($n_{30\ and\ under} = 213$, $n_{over\ 30} = 439$) yielded nonsignificant results across all models (odds ratios ranging from 0.71 to 1.26, $P >$ .1). As household income and educational level were found to be collinear when introduced into the model together, educational level was removed from the final analyses.

Mixed Multinomial Conditional Logit Model

The results of the mixed multinomial-conditional logit model are presented in Table 1. Controlling for patient demographic characteristics of age, gender, race, income, and nature of

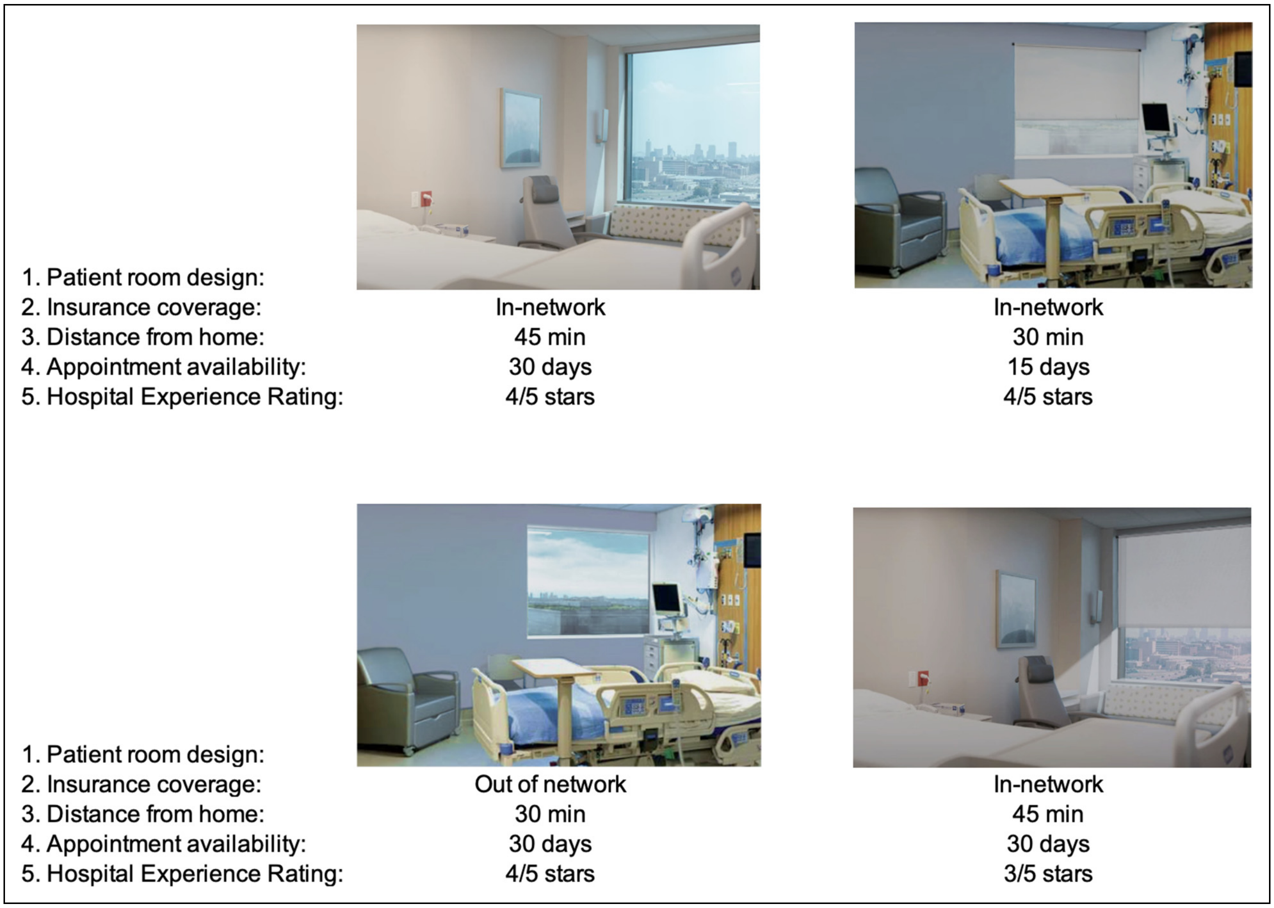

Figure 1. Example choice sets within the discrete choice survey design. The window condition (occluded by blinds versus not) and the overall patient room setting (Room 1, represented by the lighter colored room as pictured the top-left most image vs Room 2, represented by the darker (blue colored) room as pictured in the top-right most image), both elements of patient room design, were treated as separate variables in the analysis.

their most recent patient stay (elective, urgent, or urgent), the model suggests that patients were more likely to choose the hospital with an in-network provider (vs out-of-network, OR = 1.38, $P < .001$), closer to home (30 min away vs 45 min away, OR = 1.27, $P < .001$), and with a 4-star experience rating compared to 3-star rating (OR = 1.27, $P < .001$). When it came to patient room design represented in the images, patients were more likely to choose the room where the window was completely unobstructed by the blind (OR = 1.47, $P < .001$) and did not indicate a preference between the other design elements (Room 1's design with lighter colored features vs. Room 2's design with blue features). Appointment availability was not found to be a significant predictor of patient choice.

Mixed Multinomial Conditional Logit Model, Stratified by Hospital Unit

The results of the mixed model stratified by hospital unit are presented in Table 2. The models suggest that the window condition of the patient room design had a significant

Table 1. Results of the Mixed Multinomial-Conditional Logit Model.[a]

Choice characteristic	Patient choice odds ratio (OR)	*P* value
Hospital attributes		
Insurance Coverage *In-network versus out of network*	**1.38**	**<.001**
Distance from Home *30 min away versus 45 min away*	**1.27**	**<.001**
Hospital Experience Rating *4-star rating versus 3-star rating*	**1.27**	**<.001**
Appointment Availability *15 day wait versus 30 day wait*	1.02	.902
Patient room design attributes		
Overall Room Design *Room 1 versus Room 2*	1.08	.808
Window Condition *Unoccluded window versus partially occluded window*	**1.47**	**<.001**

[a]Model controls for respondent age, gender, race, income, and inpatient stay classification (elective, urgent, emergency). McFadden $R^2 = 0.065$.
The bold values signify model estimates with statistical significance ($P < 0.05$).

impact on patient choice across various hospital units. Patients reflecting on their recent intensive care unit stay (n = 98) reported that if they were to seek care again for a similar visit, they would be 56% more likely to choose a hospital with full access to patient room windows ($P < .001$), whereas the other factors were not found to impact choice. The model for medical surgical unit patients (n = 165) indicates a 40% higher likelihood of choosing the in-network hospital ($P = .012$) and 30% higher likelihood of choosing a hospital with unobscured patient room windows ($P = .002$). Among emergency department patients (n = 159), the model demonstrates a 39% higher likelihood of choosing an in-network hospital, 68% higher likelihood of choosing a hospital with a higher experience rating, and a 66% higher likelihood of choosing a hospital with unobscured patient room windows. Finally, among Labor and Delivery Unit patients (n = 75), the model suggests 70% higher likelihood of choosing the hospital closer to home and 47% higher likelihood of choosing the hospital with patient rooms with unobscured windows.

Mixed Multinomial Conditional Logit Model With Interaction Term for Income

The results of the mixed model incorporating an interaction term for insurance coverage and respondent income category (Table 3) revealed that the effect of in-network coverage and being in the lower-income category (<\$100,000 per year, n = 435) had the strongest effect on choice (OR = 1.54, $P = .008$), compared to the effect for those in the higher income category (≥\$100,000 per year, n = 217; OR = 1.31, $P = .031$). Distance from home, experience ratings, and the patient room window condition revealed similar effects estimates to the model without interaction term.

Discussion

This national survey of 652 recent inpatients revealed that patient preferences for a hospital are a function of several factors, both of the hospital itself and of the individual. Controlling for patient demographic and inpatient stay characteristics, patients were 47% more likely to choose the hospital with patient rooms with unobscured access to daylight and views, 38% more likely to choose the hospital with in-network care, a factor with greater influence among lower-income respondents; 27% more likely to choose the hospital that was 15 min closer to home; and 27% more likely to choose the hospital with a one-star higher patient experience rating. These results demonstrate the expected directionality and are aligned with previous research: van den Broek-Altenberg and Atherly found that patients were over twice as likely to choose an in-network provider, Smith et al estimated that patients were 70% to 80% more likely to choose a hospital closer to home, and Schwartz et al estimated that patients were willing to pay approximately \$3,000 more to receive care at a hospital with an additional star rating. Although previous studies indicate the role of appointment availability or wait time, this factor was not statistically significant in the current study.

The results indicate the strength, and therefore the opportunity, of patient room design for influencing patient choice. The results also highlight the demand for daylight and views across hospital unit types: patients with recent stays in the ICU, medical surgical, emergency department, and labor and delivery units all demonstrated a higher likelihood of choosing the hospital that provided full, unobscured access to patient room windows. Amongst those units, the strongest preference for unobscured windows was observed among ICU patients, who often have longer and more intensive stays, and the emergency department patients, who often have the least access to windows during a stay.

Preferences for patient rooms with unobscured windows reinforce the findings of van Oel et al which suggested overwhelming patient preference for rooms with more daylight access and connectivity to the outside world. The findings of the current study add additional insights for designing for daylight, as they demonstrate that it is not only important to design for daylight by providing access to windows in patient rooms, but that in practice, it is important to operate these windows in such a way that maintains access to daylight and views throughout the day. Deployment of blinds or shades helps to mitigate glare and thermal discomfort, but closing these blinds effectively removes the ability to access daylight and views. As evidenced in observational studies, shades, once deployed, often remain static and closed long after the need for glare or heat control passes (38,39)—a condition that is likely similar, if not exacerbated, in healthcare settings where patients are largely dependent on staff or visitors to adjust the shades for them.

Limitations

Although only studying one design factor, this exploratory study demonstrates the applicability of DCM in healthcare design more broadly. It is important to note the limitations of the approach as implemented in the current study. First, DCM measures stated preference (hypothetical choice) as opposed to revealed preference (consumer choices in reality); however, as revealed preference data are often unavailable, this is where the value of DCM lies. Second, its application in hospital choice necessitates the assumption that patients have full authority over choice, when in reality, their primary care physician may refer them to a specific hospital and patients do not have a choice in the specific hospital room they may be assigned to. Third, one must consider the importance of imagery or text used to describe the features of interest and balance experimental control with reality. For example, one must consider the realism of visual-based choice assessments and whether to use renders or photographs, 2-D or 3-D imagery. Furthermore, choice sets that combine choice variables as described by text and as

Table 2. Results of the Mixed Multinomial-Conditional Logit Model, Stratified by Hospital Unit.[a]

Choice characteristic	Intensive care unit (n = 98) Odds ratio (OR)	P value	Medical surgical unit (n = 165) OR	P value	Emergency department (n = 159) OR	P value	Labor and delivery unit (n = 75) OR	P value
Hospital attributes								
Insurance Coverage *In-network versus out of network*	1.27	.197	**1.40**	**.012**	**1.39**	**.035**	1.32	.243
Distance from Home *30 min away versus 45 min away*	1.13	.584	1.12	.471	1.28	.192	**1.70**	**.044**
Hospital Experience Rating *4-star rating versus 3-star rating*	0.93	.759	1.15	.443	**1.68**	**.015**	1.73	.077
Appointment Availability *15 day wait versus 30 day wait*	1.20	.337	1.07	.616	1.04	.817	0.91	.687
Patient room design attributes								
Overall Room Design *Room 1 versus Room 2*	1.21	.210	0.84	.793	0.58	.533	0.81	.512
Window Condition *Unoccluded window versus partially occluded window*	**1.56**	**<.001**	**1.30**	**.002**	**1.66**	**<.001**	**1.47**	**.005**
McFadden R^2	0.099		0.075		0.153		0.147	

[a]Model controls for respondent age, gender, race, income, and inpatient stay classification (elective, urgent, emergency). McFadden R^2 reported below each model result.
The bold values signify model estimates with statistical significance ($P < 0.05$).

Table 3. Results of the Mixed Multinomial-Conditional Logit Model With Interaction Term.[a]

Choice characteristic	Patient choice odds ratio (OR)	P value
Hospital attributes		
Insurance Coverage * Income (<$100,000 per year) *In-network versus out of network*	1.54	.008
Insurance Coverage * Income (≥$100,000 per year) *In-network versus out of network*	1.31	.031
Distance from Home *30 min away versus 45 min away*	1.30	.002
Hospital Experience Rating *4-star rating versus 3-star rating*	1.42	<.001
Appointment Availability *15 day wait versus 30 day wait*	1.08	.323
Patient room design attributes		
Overall Room Design *Room 1 versus Room 2*	−1.06	.846
Window Condition *Unoccluded window versus partially occluded window*	1.36	<.001

[a]Model controls for respondent age, gender, race, income, and inpatient stay classification (elective, urgent, emergency). McFadden $R^2 = 0.061$.

represented in images should consider potential biases, as noted in Liu et al (26). Finally, the survey was conducted online targeting a respondent pool who stayed a minimum of one night in a hospital within the past year, which present the following limitations: those with shorter stays may have differential perceptions of experience, and those who stayed in the hospital nearly a year ago may have greater recall bias than those who were at the hospital only one week prior to the survey. However, secondary analyses of the discrete choice survey indicated no significant differences across respondents categorized by length of stay or hospital stay timeline.

Conclusions

This exploratory study demonstrates the role patient room design can play on patient preference. Incorporating windows into the patient room is common sense and expected in modern hospital design, yet this research indicates the need for a nuanced consideration of *how* these windows are designed to maximize the benefits of daylight and views. Technologies that optimize for window access and clarity, such as automated shades or electrochromic windows, may provide such solution. The study also demonstrates the application of DCM in healthcare design. As hospitals seek to create facilities of excellence that attract new patients, the ability to utilize survey research to quantify not only patient experience but also patient *choice* can serve as a valuable tool for healthcare design professionals, hospital administrators, and stakeholders.

Authors' Note

Ethical approval to conduct this study was obtained from Institutional Review Board of Clemson University, Clemson, South Carolina, USA. All procedures in this study were conducted in accordance with the Clemson University Institutional Review Board's (IRB2020-363) approved protocols. Informed consent was obtained from the survey participants for their anonymized information to be published in this article.

Declaration of Conflicting Interests

MW and PM are employed by View, Inc., the sponsor of the research study. Their contributions to the study included conceptualization, data collection, data analysis, and writing.

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Supplemental Material

Supplemental material for this article is available online.

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