

Designers Lighting Forum

View Quality: Why and How to Measure?

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Questions related to specific materials, methods, and services will be addressed at the conclusion of this presentation.



Learning Objectives

At the end of this course, participants will be able to:

- 1. Understand the significance of view quality and the factors
- 2. Learn various image quality metrics related to indoor and window views
- 3. Identify the primary image quality metrics that can predict view quality
- 4. Discuss the integration of image quality metrics into the building and lighting design



Agenda

- 1. What is view quality?
- 2. Why does view quality matter?
- 3. How is view quality measured?
- 4. Can we improve it?
 - Indoor view quality
 - Window view quality
- 5. What is next?





Lighting and occupants









Indoor (view) quality and lighting











ther 3





Factor 4





Factor 7

Factor S

Factor 8

Scott, S. C. (1993). Visual attributes related to preference in interior environments. *Journal of interior design*, 18(1-2), 7-16.







Royer, M. P., Wilkerson, A., Wei, M., Houser, K., & Davis, R. (2017). Human perceptions of colour rendition vary with average fidelity, average gamut, and gamut shape. *Lighting Research & Technology*, *49*(8), 966-991.

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All low overhead: low track: low task: off		Overhead low overhead: low track: off task: off	
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Rockcastle, S., Danell, M., Calabrese, E., Sollom-Brotherton, G., Mahic, A., Van Den Wymelenberg, K., & Davis, R. J. L. R. (2021). Comparing perceptions of a dimmable LED lighting system between a real space and a virtual reality display.





Indoor (view) quality and lighting

- We know (with caveats) that...
- 1. People prefer natural light and spacious settings with plants.
- **1. Complexity is preferred to a certain extent.**
- 1. Light levels matter in dim conditions, but not so much at photopic levels.
- **1. Colorfulness is preferred to a certain extent.**
- 1. CCT is not a good preference measure, unlike color (especially red) saturation.



Views in the built environment

























Multiple benefits of views







What is the impact of having a window view?





Background

Source: Multisensory Cognition Lab.

- Vision and multi sensory system
- Visual perception may affect thermal perception



Source: Harry Cock, Designtrend.

Source: Tori Powers, SJExpress.



Ko, WH, et al. "The impact of a view from a window on thermal comfort, emotion, and cognitive performance", Building and Environment. 175 (2020) 106779. https://doi.org/10.1016/j.buildenv.2020.106779.



Methods

Thermally identical spaces with and without windows (28° C, slightly warm condition)



LEDUCATION. What is the impact of having a window view? Do people feel differently about the thermal environment when they have a window view? Trade Show and Conference

Results

Felt cooler



At slightly warm ambient condition,

- Approximately 1 °C lower thermal sensation
- 12 % more thermal comfort
- 8% in cooling energy and 6.5% of total HVAC energy reduction for a building in San Francisco, USA

Felt happier



- Increase in positive emotions
- Decrease in negative emotions

More focused



- 6% better working memory
- 5% better concentration



Ko, WH, et al. "The impact of a view from a window on thermal comfort, emotion, and cognitive performance", Building and Environment. 175 (2020) 106779. <u>https://doi.org/10.1016/j.buildenv.2020.106779</u>.

What determines the quality of a window view?



Where would you prefer to sit?



Method

Literature Review

Building Standards

- CIBSE
- EN
- ASHRAE
- IES...

Green certification systems

- LEED
- WELL
- BREEAM
- Green Globes
- Green Star...
- Scientific research papers
- Architecture
- Urban planning
- Landscape
- Environmental psychology
- Vision science

Window view assessment: Primary variables

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

1. View Content

High

Low

Definition

The sum of the visual features seen in a window view

Criteria

- Natural and urban features
- Horizontal stratification
- Content distance
- Dynamic features (movement)

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. https://doi.org/10.1080/15502724.2021.1965889

1. View Content Natural and urban features

Content distance

Distant view

Nearby view

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

Horizontal stratification

Ground layer

Landscape layer

Sky layer

Dynamic features (movements)

People and water feature(s)

2. View Access

High Low

Definition

 A metric quantifying how much of the window view(s) an occupant can see through from a particular location within a space

Criteria

View angle of a window

What determines the quality of a window view?

- Distance from a window and window-to-wall ratio (WWR)
- Spatial assessment of view access

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

2. View Access View angle of a window

Horizontal and vertical view angles, View Factor

Distance from a window and WWR

View

No view

The percentage of floor space that can provide visual contact with the window(s)

– Movable funiture

Simulations

Rays cast from one viewpoint in a 120 degree cone of vision (Turan et al. 2021)

3. View Clarity

High

Low

What determines the quality of a window view?

Definition

 A metric assessing how clearly the visual content in the view can be seen by the occupant

Criteria

- Window design
- Glazing and shading materials
- Temporal attributes of view clarity

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

3. View Clarity Window design

Window view

Horizontal mullion

Vertical mullion

Temporal attributes of view clarity

- Minimum acceptable levels
- The consideration of climate-based daylighting metrics

Glazing and shading materials

A building in Vancouver Image: https://thriveglobal.com/

Window view with different fabric shades, LBNL Window Testbeds

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

Symposium and position statement

Virtual Symposium: View Research and Design Practice

Critical Aspects of View Research

- View from the Classroom Window
- Influence of Window View Landscape Distance Effects on Visual Satisfaction
- View Clarity Towards Visual Satisfaction

2. Development of a View Index

- A Window View Assessment Framework
- Visualizing and Evaluating Views in Architectural Design Using Google Earth Studio
- Simulation-Based View Analysis

3. Integration of Research and Practice

- Fragmented Views: Solid Angle and the Search for Quantifiable View Metrics
- Integrating View Analysis in Practice: A Perspective from KieranTimberlake Research
- Views as a Driver for Real Estate Outcomes
- Define window view quality
- Reach a consensus on the primary components of window view quality
- Identify research gaps in current view assessment methods
- Develop a position statement 54 researchers and practitioners "signed on"

Hichael Kent PhD

Christopher Connock

Galen Burrel

Ko, W.H., Kent, M.G., Schiavon, S., Levitt, B., Betti, G., 2021. A window view quality assessment framework. LEUKOS - Journal of Illuminating Engineering Society of North America 40. <u>https://doi.org/10.1080/15502724.2021.1965889</u>

Where are we now?

Problem statement

Current view quality assessment methods

Primarily classification and prescriptive methods (LEED v4.1, WELL v2, EN17037, etc.)

- Presence of green and blue spaces (e.g., trees and rivers)
- Number of horizontal layers (sky, landscape, and ground)
- Content distance (close, medium, far)
- Movements (moving objects)

Nature vs. Man-made objects

Horizontal layers

Ground layer

Landscape layer

Problem statement

When the view is complex, it is difficult to determine its quality using existing methods.

Can other disciplines help us evaluate images systematically?

Inspiration from vision science

Spatial frequency: sinusoidal components (as determined by the Fourier transform) of an image repeated per unit distance.

Kauffmann, L., Ramanoël, S., & Peyrin, C. (2014). The neural bases of spatial frequency processing during scene perception. *Frontiers in integrative neuroscience*, *8*, 37.

A potential solution

Image quality assessment (IQA), a sub branch of computer science, offers computational (objective) tools.

Ravela, R. S. (2019). No Reference Image Quality Assessment. Thesis. University of Texas at Tyler.

Image quality metrics (IQMs)

General image quality metrics

- Energy: The rate of change in the color, brightness, or magnitude of the pixels over local areas.
- Euler: Total number of objects minus holes in those objects.
- Contour: Detect the structural outlines of objects in an image, which may then be used to determine the form of an object.
- Naturalness image quality evaluator (NIQE): Evaluate the overall quality of images by computing statistics of its gradient.
- Brightness: The average value of all pixel intensities in the image.

https://www.mathworks.com/help/images/workflow_niqe.png

Contrast metrics

- Edge-based contrast measure (EBCM): Assessing the quality of an image by comparing its edge contrast.
- Root mean square (RMS): The standard deviation of brightness levels in the stimulus.

Extraction of strong and weak edges from a sample image: a original image, b extracted edges

Choukali, M. A., Valizadeh, M., & Chehel Amirani, M. (2020). An efficient contrast enhancement method using repulsive force of edges. *Multidimensional Systems and Signal Processing*, *31*, 299-315.

Clarity metrics

- Maximum local variation (MLV): The overall clarity of an image in terms of focus and contrast.
- Blind/referenceless image spatial quality evaluator (BRISQUE): Possible losses of "naturalness" in the image using normalized luminance values.

Complexity metrics

- Detectability suprathreshold (*R*_{spt}): The number of detectable regions in an image over a threshold
- Entropy: The average uncertainty of the information source.
- Spatial Information (ITU SI): The spatial detail in an image.
- Fractal Dimension: A statistical index of complexity detail in a self-similar pattern.

Tanabe, N., Sato, S., Suki, B., & Hirai, T. (2020). Fractal analysis of lung structure in chronic obstructive pulmonary disease. *Frontiers in physiology*, *11*, 603197.

Color metrics

- Chroma (C*): CIE 1976 L*a*b* chroma
- Colorfulness (M): Overall colorfulness of images

Cortez, R., Luna-Vital, D. A., Margulis, D., & Gonzalez de Mejia, E. (2017). Natural pigments: stabilization methods of anthocyanins for food applications. *Comprehensive Reviews in Food Science and Food Safety*, *16*(1), 180-198.

Further considerations

Human subjective responses are often contextual and conditional.

A single metric is likely too simple to quantify occupants' overall mood.

https://imotions.com/wp-content/uploads/2024/03/Emotional-Reactions-scaled.webp

Is it possible to analyze granular subjective responses (go beyond good/bad)?

- 50 images
- 4 subjective ratings: preference, complexity, clarity, colorfulness
- **12 IQMs**

Residential spaces

Retail Spaces

Museums

Houses of

worship

Gyms

Offices

Industrial spaces

Health Centers

Educational spaces

Wang, Y., & Durmus, D. (2022). Image quality metrics, personality traits, and subjective evaluation of indoor environment images. Buildings, 12(12), 2086.

Some of metrics predicted subjective evaluations, but none could predict preference.

Metric	Preference	Complexity	Clarity	Colorfulness
MIV	r _s = -0.030	r _s = 0.363	r _s = 0.222	r _s = 0.262
Ter La	p = 0.839	p = 0.010	p = 0.121	p = 0.066
BRISOUE	r _s = -0.060	r _s = -0.318	r _s = -0.075	r _s = -0.152
Dhibqor	p = 0.679	p = 0.024	p = 0.603	p = 0.293
Burr	r _s = -0.116	r _s = 0.153	r _s = -0.191	r _s = 0.096
34x	p = 0.424	p = 0.288	p = 0.184	p = 0.509
si	r _s = -0.080	r _s = 0.388	r _s = 0.337	r _s =0.288
	p = 0.579	p = 0.005	p = 0.017	p = 0.042
Spa. freg. slope	r _s = -0.067	r _s = 0.217	r _s = -0.168	r _s = 0.190
	p = 0.642	p = 0.129	p = 0.245	p = 0.186
Entropy (S)	r _s = 0.144	r _s = 0.249	r _s = 0.304	r _s =0.371
	p = 0.318	p = 0.081	p = 0.032	p = 0.008
Colorfulness (M)	r _s = 0.083	r _s = 0.268	r _s = -0.034	r _s =0.727
	p = 0.564	p = 0.060	p = 0.815	p < 0.001
RMS contrast	r _s = 0.040	r _s = 0.044	r _s = 0.088	r _s =0.163
	p = 0.784	p = 0.764	p = 0.543	p = 0.258
Euler	r _s = -0.117	r _s = 0.295	r _s = -0.149	r _s =0.256
	p = 0.420	p = 0.038	p = 0.300	p = 0.073
Energy (E)	r _s = -0.002	r _s = -0.201	r,=-0.007	r _s = -0.356
- 07 1-7	p = 0.990	p = 0.163	p = 0.964	p = 0.011
Contour	r _s = 0.072	r _s = 0.419	r, = 0.191	r _s =0.389
	p = 0.620	p = 0.002	p = 0.184	p = 0.005
Fractal dimension	r _s = 0.172	r _s = -0.275	r _s = -0.103	r _s = -0.356
	p = 0.233	p = 0.053	p = 0.176	p = 0.011

- 12 images
- 5 subjective ratings: preference, complexity, clarity, colorfulness, interest
- 2 display x 4 illuminance levels
- 17 IQMs + lighting metrics

Display	Horizontal	Target luminance (cd/m ²)		Background luminance (cd/m ²)					
luminance	mummance (ix)	White	Gray	Dark	Left wall	Right Wall	Opposite Wall	Ceiling	Light Source
Low (50 cd/m ²)	50	50	23	1	4	4	5	3	930
	150	51	24	1	14	13	11	9	3322
	450	51	24	1	40	46	26	26	10130
	900	52	24	1	82	84	80	57	12160
High (250 cd/m ²)	50	255	96	3	5	4	4	3	973
	150	258	110	3	12	12	14	9	3189
	450	259	117	3	39	41	34	27	10100
	900	263	120	4	83	82	65	59	12340

Wang, Y., & Durmus, D. (2025). Effect of display luminance and ambient illuminance on the perceived quality of indoor environment images. *Journal of the Society for Information Display*.

Lighting conditions were secondary to IQMs.

That is, neither display nor ambient lighting impacted subjective evaluations.

Wang, Y., & Durmus, D. (2025). Effect of display luminance and ambient illuminance on the perceived quality of indoor environment images. *Journal of the Society for Information Display*.

We found correlations between subjective ratings.

Colorfulness increased interest, and interest increase preference.

Wang, Y., & Durmus, D. (2025). Effect of display luminance and ambient illuminance on the perceived quality of indoor environment images. Journal of the Society for Information Display.

LEDucation. Trade Show and Conference Study 2

Some of the metrics showed accurate predictions for subjective ratings, including preference.

However, correlations were not always very strong.

*0.05 **0.01

Metrics	Complexity	Preference	Clarity	Colorfulness	Interest
MLV	0.404**	0.01	0.026	0.496**	0.184**
BRISQUE	-0.098**	-0.016	-0.042**	-0.060**	-0.054**
$R_{\rm spt}$	0.176**	0.016	-0.123**	0.195**	0.017
SI	0.435**	-0.059**	0.012	0.479**	0.115**
α	0.234**	-0.051**	-0.116**	0.247**	0.018
S	0.101**	-0.009	0.126**	-0.022	0.024
М	0.136**	0.059**	-0.037*	0.399**	0.094**
RMS	0.215**	0.053**	-0.068**	0.203**	0.103**
Euler	0.367**	-0.205**	-0.108**	0.288**	0.004
Energy	-0.216**	0.017	0.093**	-0.247**	-0.131**
Contour	0.311**	0.060**	0.154**	0.241**	0.158**
FD	-0.439**	0.153**	0.001	-0.434**	-0.081**
NIQE	-0.269**	0.058**	0.046**	-0.305**	-0.068**
C_{ab}^*	0.333**	-0.098**	-0.005	0.356**	0.056**
EBCM	-0.216**	0.017	0.092**	-0.247**	-0.131**
Brightness	-0.193**	-0.082**	0.110**	-0.364**	-0.172**
L_{ab}^{*}	-0.284**	-0.003	0.129**	-0.377**	-0.140**
Lv, display set	-0.01	-0.037*	-0.018	0.031*	-0.022
$L_{ m v,\ display}$	-0.151**	-0.036*	0.049**	-0.162**	-0.091**
Ebackground	0.006	-0.035*	0.014	-0.016	-0.031
$E_{ m v,~eye}$	0.022	-0.073**	0.035*	0.050**	-0.037*

Wang, Y., & Durmus, D. (2025). Effect of display luminance and ambient illuminance on the perceived quality of indoor environment images. *Journal of the Society for Information Display*.

Can IQMs accurately assess window view quality?

Experiment data collected from a VR study

- 30 images representing different window view conditions.
- A typical open-plan office window views.
- Window view quality rating from 40 participants

16 Image quality metrics

LEDucation. Trade Show and Conference Study 3

30 VR images depicting various views of a typical open-plan office workstation

Satisfaction with view access (window distance: 2m)

Study 3 Data analysis

- Principal Component Analysis (PCA)
 - Interpretation of numerous variables
 - Condense 16 IQMs into a smaller set of composite variables
- Cumulative Linear Mixed Model (CLMM)
 - Assessment of the significance of each image metric
 - Estimate the predictive power for of each metric for view quality

Predictor variable (x)

Harrison, X. A., Donaldson, L., Correa-Cano, M. E., Evans, J., Fisher, D. N., Goodwin, C. E. D., Robinson, B. S., Hodgson, D. J., & Inger, R. (2018). A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ, 6, e4794. https://doi.org/10.7717/peerj.4794

https://towardsdatascience.com/understanding-principal-component-analysis-ddaf350a363a

LEDucation Trade Show and Conference Study 3

Principal component analysis (PCA)

- Correlation matrix of 16 IQMs
- RC1 and RC2 represent the two principal components and their relative orders.
- The higher the value, the most positively correlated the two variables are.
- The closer the value to -1, the most negatively correlated they are.

LEDucation. Trade Show and Conference Study 3

Cumulative Linear Mixed Model: Comparison of performance for each image quality metric

Metrics	β	SE	р		R ² _C	R ² _M
Chroma	2.09	0.09	< .001	***	0.65	0.60
ITU SI	1.34	0.06	< .001	***	0.41	0.36
NIQE	-1.12	0.05	< .001	***	0.40	0.35
Colourfulness (M)	1.21	0.06	< .001	***	0.36	0.31
R _{spt}	1.32	0.07	< .001	***	0.34	0.29
RMS contrast	0.78	0.04	< .001	***	0.28	0.24
Euler	-0.98	0.07	< .001	***	0.21	0.17
Sharpness	0.47	0.04	< .001	***	0.14	0.10
Contour	0.57	0.05	< .001	***	0.13	0.09
Entropy	0.40	0.04	< .001	***	0.11	0.08
BRISQUE	-0.32	0.05	< .001	***	0.07	0.04
F slope (α)	0.24	0.04	< .001	***	0.06	0.03
Brightness	0.16	0.04	< .001	***	0.04	0.01
Fractal dimension	0.16	0.05	0.0027	*	0.04	0.01

Energy, EBCM: Not significant

Cumulative Linear Mixed Model

The final model

Metrics	β	SE	р	
Intercept	0.49	0.70		
Chroma	2.41	0.15	< .001	* * *
ITU SI	-0.74	0.13	< .001	* * *
NIQE	-0.51	0.08	< .001	* * *
R ² _C	0.69			
R ² _M	0.64			

- IQA metrics can offer an alternative method, that is quantifiable, repeatable, and automated.
- Color saturation, spatial information and naturalness are the primary dimensions of IQA.
- This alternative method can help designers in building design process.
- IQA-based view quality assessment can help autonomous (intelligent) building systems balance energy and occupant needs.

https://www.buildings.com/smart-buildings/article/33018134/smart-building-products-forhvac-and-communications

Study limitations

Based on a limited dataset of images:

- Number of images tested (30)
- Type of images (VR image only)
- Sample size (view quality ratings from 40 participants)

Future Studies

Enhance the model's accuracy and generalizability by incorporating additional image datasets:

- Diverse view conditions (varying content and room settings)
- Various view image formats (e.g., screen images and physical spaces)
- Integration of computer vision analysis

Develop a view quality assessment framework through image quality metrics

- Subjective ratings can be contextual and widely varied.
- Some IQMs (and sometimes people too) assume there is a reference (optimal) condition.
- Rather than finding "the optimum," we should aim for "acceptability" or "detectability" ranges.

Nutrient, dietary content, or daily intake

Pagan, J. D. (2009). Nutrient requirements: applying the science. Advances in Equine Nutrition IV, 1.

- **Questions?**
- Won Hee Ko (<u>wonhee.ko@njit.edu</u>)
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This concludes The American Institute of Architects Continuing Education Systems Course

Thank you for attending!

Please scan the QR code to rate it and leave feedback.

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