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RESEARCH ARTICLE

Instantaneous lighting quality within higher educational classrooms in Singapore

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Abstract This paper presents a field study that explores lighting qualities within higher educational classrooms in Singapore. Eight classrooms of three types—computer labs, collaborative learning spaces and lecture halls—are studied. Lighting simulation models are calibrated and validated by measurements taken onsite and utilized to generate both instantaneous and annual physical lighting data. A questionnaire survey is distributed to 333 participants to gather subjective responses to current lighting perception. The results show that electrically lit lecture halls present more uniform distributions of lighting environments, while daylit computer labs and daylit collaborative learning spaces present relatively lower daylighting conditions. For daylit computer labs, horizontal illuminance is an effective predictor in terms of controlling lighting levels; For electrically lit lecture halls, the mean luminance of the horizontal 40° band is an effective predictor in terms of subjective lighting comfort.

1. Introduction

Given that students spend a considerable amount of time within classrooms to learn knowledge, generate new thoughts and ideas to increase their abilities towards affective learning, Indoor Environmental Quality (IEQ) of classrooms plays an important role in their learning process (Leder et al., 2015; van Duijnhoven et al., 2019). Of four IEQ parameters—thermal comfort, indoor air quality, visual comfort and acoustic comfort—lighting has an important impact on learning performance and well-being (Ricciardi and Buratti, 2018). The fundamental and paramount function of lighting environments is to support students' visual tasks and academic performance. (Korsavi et al., 2016). Moreover, lighting environments influence students' non-visual aspects, including their sleepiness, alertness and circadian rhythms (souman et al.,2018; Yan et al., 2012). Given the importance of lighting factor within classrooms,

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this paper concentrates on lighting quality within higher educational buildings under tropical skies, a climate zone where insufficient field studies have been conducted compared to other climate zones.

This paper presents a field study that comprehensively explores lighting quality and visual comfort within higher educational classrooms in Singapore. Daylighting or electric lighting data within eight classrooms are measured or created using rigorously validated simulation models. Three-hundred and thirty-three higher education students evaluate their current lighting experience. The objectives of this study are threefold: (1) to evaluate objective and subjective instantaneous lighting quality; (2) to explore research factors that influence subjective lighting perception; and (3) to seek relationships between lighting predictors and subjective lighting assessments. This Post-Occupancy Evaluation (POE) study provides new information on daylight quality in higher educational buildings under tropical skies.

2. Research background

2.1. Lighting studies in higher educational buildings

Based on literature review, three types of research have involved lighting quality within higher educational classrooms: research on IEQ that includes lighting as one factor, research on specific topics that utilizes classrooms as a lab for conducting experiments, and direct research on lighting quality. The first type has explored comprehensive IEQ and concluded the significant influence of lighting on students' satisfaction and course evaluations. Hill and Epps (2010) found that lighting environments play an important role in students' evaluations of upgraded classrooms. In seeking relationships between students' learning performance and IEQ, Lee et al. (2012) found that thermal comfort, indoor air quality and lighting environment are of comparable importance. Ricciardi and Buratti (2018) pointed out that average measured illuminance values are strongly correlated with perceived visual comfort within seven classrooms. Studies concerning IEQ of higher educational classrooms are carried out in field and focus on the influence of IEQ by collecting subjective feedback and/or physical environmental quantities. Simple lighting predictors, like horizontal and vertical illuminance, are widely employed (Trivedi and Badarla, 2019). However, in order to cover comprehensive environmental factors, this type of studies presents field data with limited lighting predictors and subjective assessments. Detailed studies that include more types of lighting predictors and aspects of subjective lighting perception can provide specific information.

The second type uses classrooms as a laboratory to explore specific research questions, including both electric lighting and daylighting performance. Yan et al. (2012) explored the effects electric lighting colour temperature and luminance levels on students' learning efficiency, asthenopia and brain fatigue. Bian and Ma (2018) used classrooms to explore the relationship between human perception of discomfort and glare as exposure time increases. Reinhart et al. (2014) compared simulated Daylight Autonomy results to subjective evaluations of daylit area from students at 11 architecture schools to propose the thresholds of climate-based daylight metrics. Researchers have utilized classrooms as an experimental lab to investigate specific research questions. Subjective evaluations and physical lighting data are designed accordingly. Hence, lighting quality within classrooms is not the subject of the research.

Finally, the third type of studies focuses on lighting quality within higher educational classrooms. Obeidat and Al-Share (2012) found that lighting is the most important feature that influenced the teaching and learning process in design-studios. Chiou et al. (2020) explored visual comfort within four classrooms where a projector and white board were utilized and concluded that Unified Glare Rating (UGR) outperform Daylight Glare Probability (DGP) in terms of identifying glare across all four classrooms. Yildiz et al. (2018) investigated visual comfort in 16 classrooms at a university by simulating lighting quantities and collecting students' assessments. Castilla et al. (2018) had spent four years to collect 427 university students' previous opinions towards fluorescent and LED. The number of this type of studies is limited, especially the ones that cover different types of classroom and involve both illuminance-based and luminance-based lighting predictors.

2.2. Assessment criteria of lighting performance

Commonly used static lighting design metrics include illuminance-based and luminance-based ones. Illuminance-based metrics include illuminance on a horizontal working plane and vertical eye illuminance. Horizontal illuminance and vertical illuminance have been widely proposed and applied in design handbooks (DiLaura, 2011). Previous studies have also proposed horizontal and vertical illuminance as effective lighting metrics for predicting subjective lighting perception in the context of Singapore (Jakubiec et al., 2020; Kong and Jakubiec, 2019; Kong and Jakubiec, 2021). On the other hand, there are various luminance-based lighting predictors derived from predetermined regions. For example, mean luminance of an entire scene or the horizontal 40° band are representative values of scene-independent regions, while the maximum luminance or 90th percentile of luminance within a window or lateral wall areas are representative values of scene-dependent regions (Van Den Wymelenberg and Inanici, 2016). In other words, window areas and lateral wall-based measures will vary according to different scenes, necessitating a geometrically specific analysis for each occupant location and view direction. Luminance values within the horizontal 40° band have been proposed as effective lighting predictors for explaining subjective lighting perception since the horizontal 40° band is the focus area of visual performance (Van Den Wymelenberg, 2012). Since luminance-based lighting predictors outperform horizontal illuminance in terms of explaining subjective lighting perception, they have been gradually applied in studies and design projects (Van Den Wymelenberg and Inanici, 2016). As one objective of this research is to seek relationships between lighting predictors and subjective assessments, both illuminance-based and luminance-based lighting predictors will be explored.

3. Method

3.1. Studied classrooms

Three types of classrooms—computer labs, collaborative learning spaces and lecture halls at the Singapore University of Technology and Design (SUTD)—were investigated. The campus has two seven-storey-high buildings on campus. As shown by Fig. 1, each building has a layout of with two courtyards forming a figure-eight shape (indicated by the four blue zones in Fig. 1). Each courtyard is bordered by classrooms or offices. Table 1 lists detailed information of the eight studied classrooms. Fig. 2 presents the layout of all eight classrooms including room dimensions, spatial configurations and orientation. Lecture halls seven and eight have identical layouts but on different floors. Two computer labs and three collaborative learning spaces have windows on opposite sides with window to wall ratios (WWR) varying between 48% and 73% and visible light transmittance of the glazing materials varying between 42% and 84%. These five classrooms have exterior overhangs and circulation spaces varying between 2.1 m and 2.5 m, which effectively block direct sunlight. None of the five classrooms have daylight-linked control system for electric lights. As shown by Fig. 1, the north-east façades of collaborative learning spaces 3 and 5 are facing towards the city without surrounding building obstruction. The remaining three classrooms are all located at the centre of building blocks, meaning that both window sides are facing towards opposite courtyard facades. On the other hand, three lecture halls have no exterior windows or access to daylight but only recessed ceiling fluorescent luminaires. Therefore, daylighting performance within computer labs and collaborative learning spaces was explored, separately from electric lighting performance within lecture halls.

In the two computer labs, monitors were arranged parallel to the windows, meaning that students were facing towards one side of the windows and away from the other. Students took screen-based lectures and worked on screen-based assignment individually or in groups in these labs. In the three collaborative learning spaces, table arrangements were flexible according to lecturers' requirements. Students' positions related to windows in each course might varied. Students took lectures and worked on individual or collaborative assignments. In the three lecture halls, seating positions were fixed, and students merely attended lectures there.

3.2. Data collection overview

Fig. 3 shows the data collection processes, which were different for the daylit and electrically lit classrooms. For daylit computer labs and collaborative learning spaces, High dynamic range (HDR) images were taken at representative calibration points, and five daylighting simulation models were built and calibrated in advance. In order to minimize disturbance in class, students only completed a 5-min survey during the end of a class period. All surveys within one classroom were collected simultaneously using an online platform which records the start and end time. Participants self-reported their seating locations based on a presented classroom layout. Instantaneous daylighting predictors associated with participants' daylighting assessments were simulated according to the time and seating positions recorded by the questionnaires. For electrically lit lecture halls, HDR images and illuminance values at participants' reported seating positions were recorded after the survey was conducted.

3.3. Measurements and model calibrations

To minimize disturbance in class, physical lighting data was collected outside of class time. For the two daylit computer labs and three daylit collaborative learning spaces, HDR

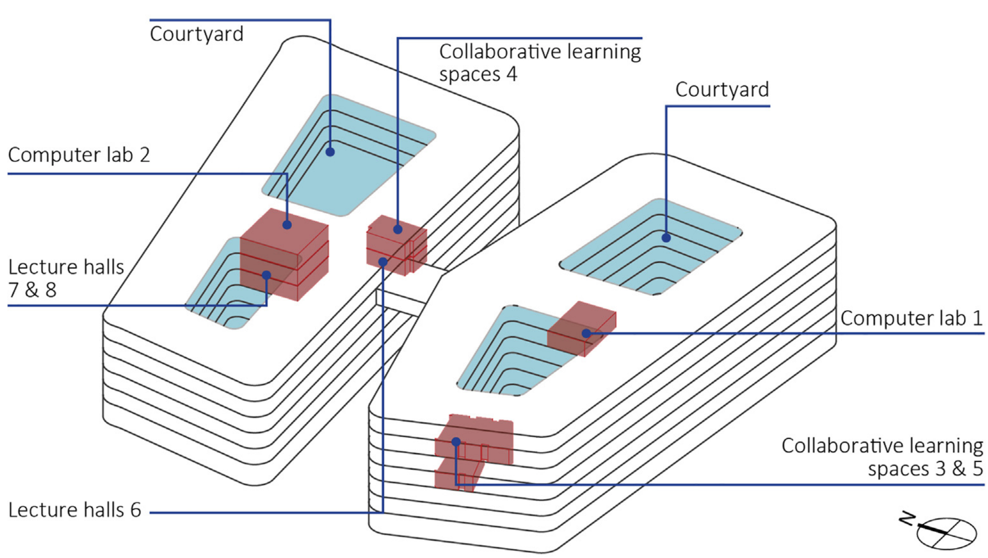

Fig. 1 Locations of the eight classrooms within the SUTD campus.

Table 1 The detailed information of eight classrooms.

Classroom Type	No.	Room Dimensions (m)	Façade Orientation	WWR	Glazing visible transmittance	No. Of seats	Floor
Computer labs	1	15.5 × 10.3	East and West	48% and 59%	84%	40	6th
	2	15.6 × 15.3	East and West	54%	84%	50	6th
Collaborative learning spaces	3	12.5 × 17	Northeast and Southwest	51% and 57%	62%	128	6th
	4	12.6 × 8.6	North and South	73%	62%	30	4th
	5	12.5 × 8.5	Northeast and Southwest	54% and 59%	64%	64	4th
Lecture halls	6	10.7 × 15.0	–	–	–	60	3rd
	7	12.7 × 13.7	–	–	–	145	4th
	8	12.7 × 13.7	–	–	–	145	5th

images at three to six seating positions were taken by a Canon COS 5D Mark III with a SIGMA f/3.5 fisheye lens. The procedure and settings of taking HDR images followed the instruction pointed out by Inanici (2010) and Jakubiec et al. (J. Alstan Jakubiec et al., 2016; J Alstan Jakubiec, Reinhart and van Den Wymelenberg, 2015). A FARO 3D scanner was used to record the geometric information of interior spaces and exterior surrounding environments. A portable

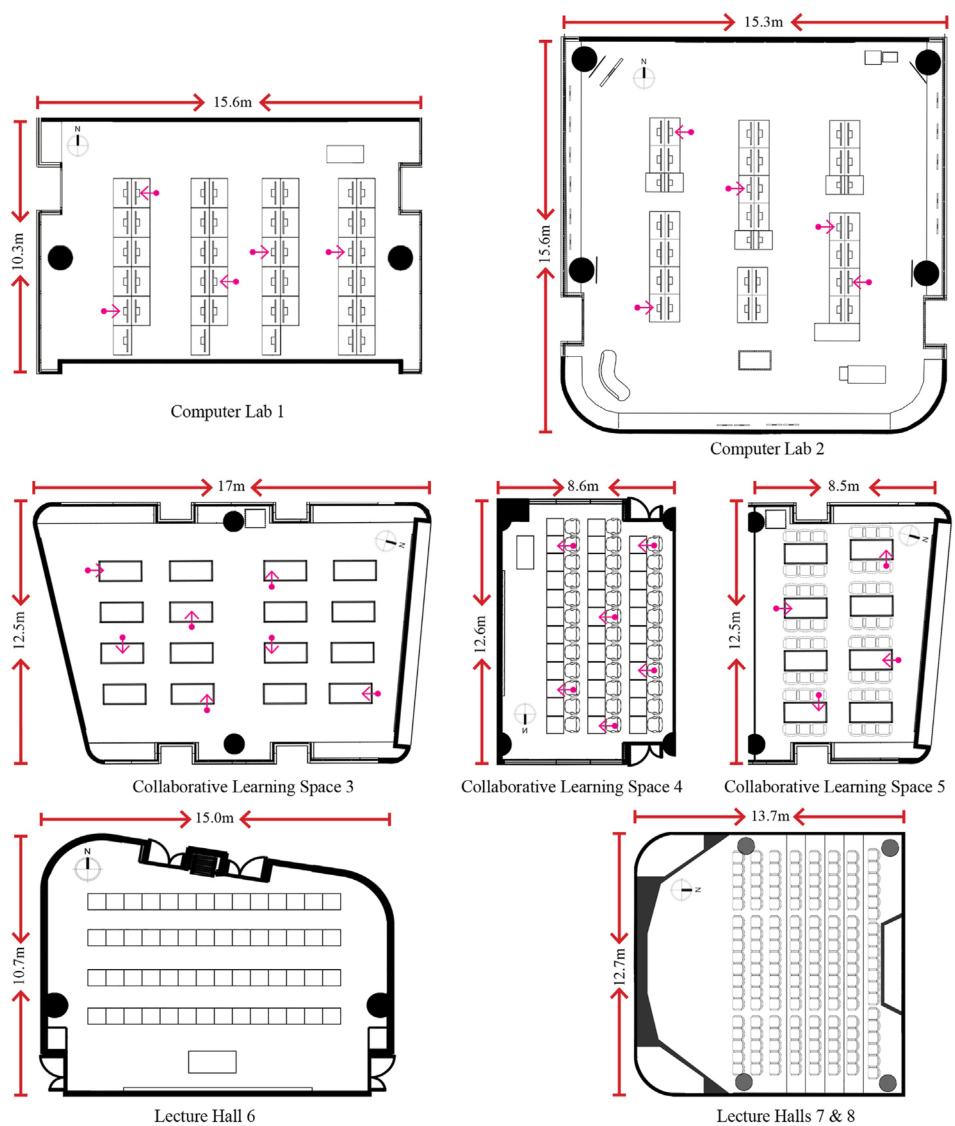

Fig. 2 Layouts of eight classrooms.

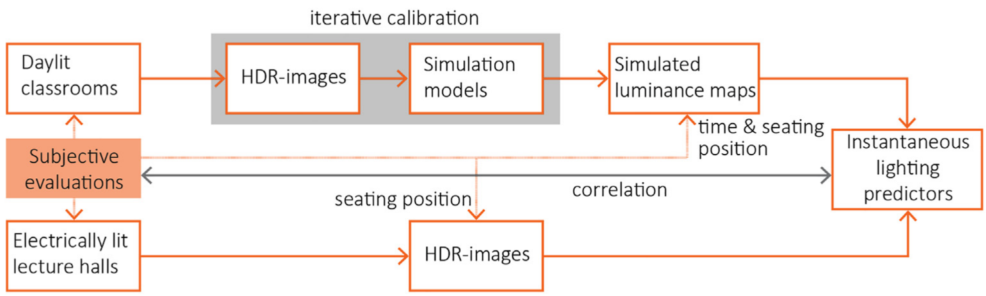

Fig. 3 Data collection process.

reflectance spectrophotometer was used to measure interior and exterior material reflective properties (J. A. Jakubiec, 2016). Glazing transmittances were measured onsite by taking multiple paired illuminance measurements in front of and behind the glazing and are presented in Table 1. A weather station located on the roof of SUTD continuously logged global horizontal solar irradiance when taking HDR images and collecting survey data. For lecture halls where electric lighting ensured a constant lighting environment, HDR images, horizontal and vertical illuminance were recorded at the seating positions filled by participants. Horizontal illuminance on the desktop surface was measured by a Konica Minolta Illuminance Meter T-10 A, and the vertical illuminance was taken at the camera lens by a Konica Minolta LS-100. Electric lights were adjusted to full power during the survey conduction and HDR-image capture. Fig. 4 presents example HDR images taken onsite and the associated falsecolor images.

The 3D models of two computer labs and three collaborative learning spaces were built in Rhinoceros 3D (Associates, 2019) and then exported to ClimateStudio (Solemma, 2020), which integrates Radiance (Ward and Shakespeare, 1998) for lighting simulations. For daylit computer labs, a typical monitor model was employed, consisting of a plastic monitor case, a grid of high (62 cd/m^2) and low (7.4 cd/m^2) glowing pixels, and a translucent screen that enabled reflections from daylight in the space (Jones and Reinhart, 2017).

Table 2 lists measured properties of important surfaces within eight classrooms—total visible reflectance (R_{vis}) and their Radiance-format definitions. All eight classrooms have similar interior materials as they are on the same campus. Two computer labs, three collaborative learning spaces and lecture hall 6 have the same white walls, white columns, white suspended ceilings and the black ceilings above. Lecture halls 7 and 8 have purple walls and ceilings, as well as black chairs; however, their lighting conditions were directly measured, not simulated. Moreover, the two computer labs and three collaborative learning spaces bordered by exterior open-air hallways are composed of concrete floors and white walls, with either purple or green segments. In order to generate Perez All-Weather skies (Perez et al., 1993) for model calibrations, measured global horizontal solar irradiance from the weather station located on the rooftop of SUTD was converted to direct normal and diffuse horizontal irradiance using the Reindl

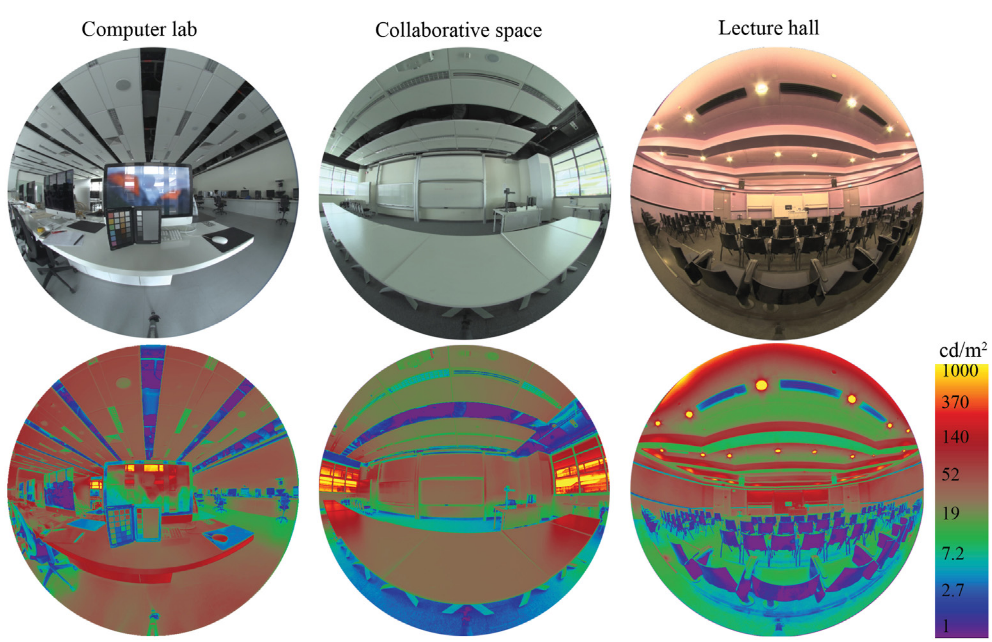

Fig. 4 HDR images and associated falsecolor images representations of a computer lab, collaborative learning space and lecture hall.

Table 2 Radiance material definitions of important classroom surfaces.

	Material	R_{vis}	Radiance definition					Classrooms
			Red	Green	Blue	Specularity	Roughness	
Interior surfaces	Column	85%	0.8689	0.8462	0.7308	0	0.01	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5, Lecture hall 6
	White wall	85%	0.8715	0.8484	0.7313	0	0	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5, Lecture hall 6
	Black ceiling	12%	0.1116	0.1085	0.0938	0	0.1	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5, Lecture hall 6
	White suspending ceiling	85%	0.8544	0.8406	0.783	0.0047	0.01	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5, Lecture hall 6
	Ceiling grid	82%	0.845	0.8165	0.717	0.0137	0	Collaborative learning spaces 3 & 5
	Partition	74%	0.7464	0.7412	0.6929	0.0442	0	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5
	Floor	37%	0.3636	0.3689	0.359	0.0102	0	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5, Lecture hall 6
	Window frame	21%	0.2181	0.2116	0.1925	0.03	0	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5
	Purple wall and ceiling	31%	0.304	0.245	0.298	0	0.05	Lecture halls 7 & 8
Interior furniture	Cabinet door	85%	0.8525	0.8597	0.8151	0.009	0	Collaborative learning spaces 3, 4 & 5
	Cabinet top	86%	0.8553	0.8614	0.8141	0.0105	0	Collaborative learning spaces 3, 4 & 5
	White table	25%	0.385	0.201	0.0826	0.06	0.04	Computer labs 1 & 2, Collaborative space 4
	Wooden table	24%	0.3849	0.2013	0.0826	0.06	0.04	Collaborative learning spaces 3 & 5
	Monitor plastic	47%	0.464	0.47	0.452	0.078	0	Computer labs 1 & 2
	Black chairs	9.8%	0.096	0.098	0.0938	0	0.1	Lecture halls 7 & 8
Exterior surfaces	Green wall	38%	0.3343	0.4298	0.0535	0	0.01	Collaborative learning spaces 3 & 5
	Concrete floor	34%	0.3265	0.3005	0.2423	0	0.1	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5
	White wall	85%	0.8153	0.81	0.781	0	0.05	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5
	Overhang frame	19%	0.189	0.1825	0.166	0.015	0.01	Computer labs 1 & 2, Collaborative learning spaces 3, 4 & 5
	Purple wall	28%	0.294	0.2556	0.286	0	0.05	Computer labs 1 & 2, Collaborative learning spaces 4

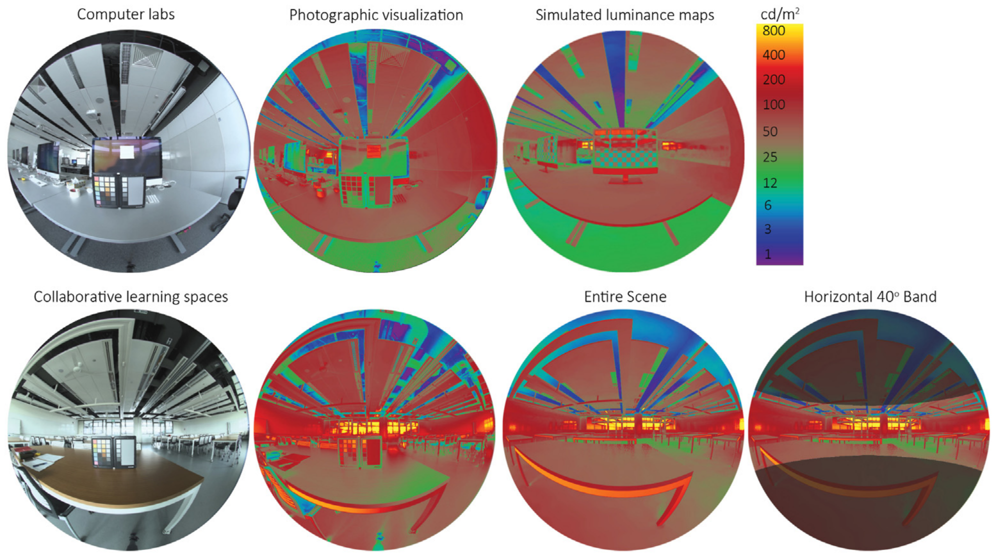

Fig. 5 Comparison of luminance distributions between HDR photographs and simulated luminance maps for computer labs and collaborative learning spaces.

method (Reindl et al., 1990). Then, Perez skies were generated by selecting site location, time, direct normal and diffuse horizontal irradiance in gendaylit (Delaunay, 2016).

Five models were calibrated using visual comparisons of luminance distributions between HDR photos and renderings as well as statistical comparisons of vertical illuminance (Quek and Jakubiec, 2019). Fig. 5 compares the luminance distributions of example HDR photographs and simulated luminance maps for computer labs and collaborative learning spaces. Simulations show comparable luminance distributions between the HDR photographs and simulated luminance maps. Furthermore, simulated vertical illuminance (E_v) was compared to the average of measured E_v before and after taking an HDR image. Within the five daylit classrooms, four to seven groups of comparison between HDR images and simulated luminance maps were made, which resulted in a total of 27 groups (the purple arrows in Fig. 1 of five classroom layouts). As shown by Fig. 6, 27 groups of E_v comparison resulted in a relative mean bias error (MBE_{rel}) of 3.11% and a relative root mean square error ($RMSE_{rel}$) of 16.8%. As illustrated by Fig. 6 and 24 of 27 measured E_v values varied between 50 lx and 300 lx, which agrees with the ranges of daylighting predictors presented in the result section. The simulated E_v falling within 20% relative error demonstrates the accuracy of the calibrated simulation models for five classrooms in terms of representing real lighting environments (Jones and Reinhart, 2017; Kong et al., 2018a; Makaremi et al., 2018).

3.4. Subjective survey

The questionnaire was comprised of demographic characteristics and subjective lighting assessments. The latter asked participants to evaluate their instantaneous and long-term lighting experience. Due to the limit of paper

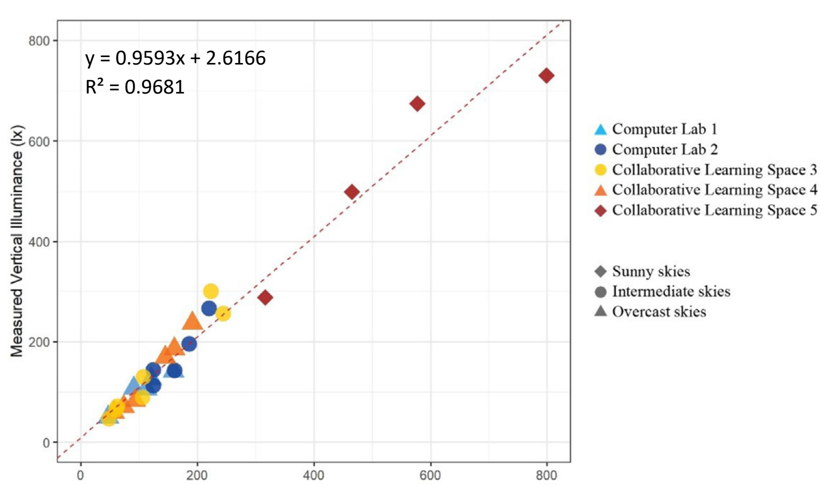

Fig. 6 Scatter plots between simulated E_v and measured E_v.

Table 3 Survey questions for evaluating current lighting environments and assigned values to the associated choices.

Assessment of current lighting quality			
Topic	Question	Choices and assigned values	
Lighting sufficiency	1. Right now, assess the amount of light in this space.	Too dark (+1), Inadequate (+2), Adequate (+3), Too bright (+4)	
Lighting comfort	2. Assuming you must conduct your daily work under the current conditions, do you feel that the lighting is	Clearly uncomfortable (+1), Uncomfortable (+2), Just uncomfortable (+3), Neutral (+4), Just comfortable (+5), Comfortable (+6), Clearly comfortable (+7)	
Lighting adjustment	3. How would you adjust lighting levels in this space to improve the current lighting environment?	Daylit classrooms	Lower the shades entirely (+1), Lower the shades a lot (+2), Lower the shades a little (+3), Do not change the lighting (+4), Increase electric lighting a little (+5), Increase electric lighting a lot (+6)
		Electrically lit classrooms	Turn electric lighting off (+1), Reduce electric lighting a lot (+2), Reduce electric lighting a little (+3), Do not change the lighting (+4), Increase electric lighting a little (+5), Increase electric lighting a lot (+6)
Glare sensation	4. Glare is physical discomfort caused by excessive light, bright reflections or contrast. While completing this survey, please mark the degree of glare you experienced.	Imperceptible (No glare) (+1), Noticeable (Little glare) (+2), Disturbing (Significant glare) (+3), Intolerable (Extreme glare) (+4)	
Glare sources	5. If you are experiencing glare or visual discomfort, please indicate the cause(s) or source(s). Select all that apply.	Reflections in computer screen, Windows, Shading device, Electric lighting, Projector screen, Other (please specify)	

length, this paper only presents the results associated with participants' instantaneous evaluations. The questionnaire was designed based on the UC Berkeley CBE survey (Zagreus et al., 2004), Wienold and Christoffersen's Daylight Glare Probability (DGP) study (2006), Van Den Wymelenberg's work (2010), along with Jakubiec and Reinhart's study (2015). As shown by Table 3, five questions that explored occupants' current lighting perception include lighting sufficiency, lighting comfort, lighting adjustment, glare sensation and glare sources. Only Question 5—glare sensation—was designed as a multiple-choice response, and the remaining eight questions was designed as Likert-scale responses. Questions and responses were adjusted according to lighting sources. For example, the choices of lowering shades to different positions of Question 3 were provided for both daylit computer labs and daylit collaborative learning spaces, while the choices of reducing electric lighting levels to different degrees were provided for lecture halls. Each survey included the layout of the corresponding classroom with numbered seating positions; and participants located their current sitting positions while filling out the survey.

Faculty members at Architecture and Sustainable Design were randomly contacted first to ask if a lighting survey could be conducted by the end of their class. Once the permission was given, the authors observed students' way of occupying the class several times and prepared a layout of seating positions. Survey conductions were carried out during the second half of each semester, when students were familiar with lighting environments in classrooms. By the end of a class, the researchers briefly introduced the purpose of this study and invited students to participate in this 5-min survey. Students who agreed to undertake this anonymous survey assigned the formal consent first and then fill the survey by using their phones or computers. Both the consent and survey were provided through Survey Monkey (Monkey, 1999—2020). For the daylit computer labs and daylit collaborative learning spaces, all shades were fully retracted, and electric lights were turned off before introducing the survey, similar to the daylighting conditions when the HDR photographs were taken at calibration points. For the three electrically lit lecture halls, lights were adjusted to the full power before introducing the survey, the same lighting conditions when the HDR photographs were taken after.

Within the two computer labs, surveys were conducted at four different times with different groups of students—once under overcast skies and three times under intermediate skies. The average time to complete a survey was 5.8 min, and the count of valid responses varied between 19 and 63. Within the three collaborative learning spaces, surveys were conducted at seven different times with different groups of students—one under clear sky conditions, two under intermediate sky conditions and four under overcast sky conditions. The average time to complete a survey was 5.28 min, and the count of valid responses varied between 16 and 26. Finally, within the three lecture halls, surveys were conducted at four different times with different groups of students. The average time to complete a survey was 4.67 min, and the count of valid responses varied between 16 and 28. Given that two questions specific to long-term daylighting conditions were excluded for LH-E, it was reasonable that the time expended on surveys for participants in the three lecture halls was shorter. During the time when each survey was being completed within the computer labs and collaborative learning spaces, no dynamic variations of daylighting conditions occurred during the survey conduction. The collection of survey responses began in March 2017 and ended in November 2018.

3.5. Participant demographics

Subjective responses were grouped according to the three types of classrooms: daylit computer labs (CL-D), daylit collaborative learning spaces (CS-D) and electrically lit lecture halls (LH-E). Incomplete survey responses were excluded. Survey responses with a duration longer than 15 min were also excluded. For CL-D, 152 participants initiated the survey, and 122 responses were valid; for CS-D, 167 participants initiated the survey, and 132 responses were valid; for LH-E, 101 participants initiated the survey, and 79 responses were valid.

Table 4 shows all participants' demographic information. Given that the study was conducted at higher educational buildings, over 98% of the participants were between 18 and 30 years of age. Females roughly outnumbered males at a 2:1 ratio. Around a quarter of participants did not wear either contacts or glasses while taking the survey.

3.6. Lighting metrics generation

For CL-D and CS-D, four instantaneous daylighting predictors—horizontal illuminance (E_h), vertical illuminance (E_v), mean luminance within an entire hemispherical HDR capture of a view (All_{mean}) and mean luminance within a horizontal 40° band ($Band_{mean}$)—were generated by using the five calibrated simulation models. Sky models were generated using the Perez sky based on the midpoint between the started and end survey filling time of each participant. E_h was simulated by setting calculation points on tables facing upwards. An instantaneous luminance map was simulated by setting a camera according to a participant's seating position and direction. Radiance simulation parameters were set at a high quality (-aa .1 -ar 512 -ab 5 -ad 2000 -as 1024 -lw 1.0e-5) for both the calibration and simulations of instantaneous daylighting predictors, the results of which can be seen in Fig. 5. E_v, All_{mean} and $Band_{mean}$ were extracted from simulated luminance maps using evalglare, a software to calculate glare index and representative luminance ratios based on HDR images (Wienold and Christoffersen, 2006). $Band_{mean}$ was calculated by applying the option −B angle option, which analyses the luminance distribution of a horizontal band. An entire scene and a horizontal 40° band are illustrated by the simulated luminance map within CS-D on the second row of Fig. 5. Both analysis areas are scene-independent, unlike window areas which varied according to the composition of each scene. For LH-E, HDR images, E_h and E_v were recorded according to participants' seating positions after adjusting the electric lighting to full power.

4. Results

4.1. Distributions of lighting predictors

Table 5 provides a statistical summary of E_h, E_v, All_{mean} and $Band_{mean}$ across the three types of classrooms. Fig. 7 shows the boxplots of E_h, E_v, All_{mean} and $Band_{mean}$ across the three types of classrooms. CL-D presented a more dispersed distribution of E_h with greater mean of 128.6 lx and a narrower distribution of E_v with lower mean of 120.4 lx, while CS-D presented inverted distribution in terms of E_h and E_v. There were outliers of E_h and E_v for both CL-D and CS-D caused by side windows, where the maximum E_v reached 1390.3 lx. Most E_v within the five daylit classrooms were insufficient to trigger glare in accordance with DGP, which has been developed under more brightly illuminated spaces (Wienold and Christoffersen, 2006). On the other hand, mean E_h of 372.2 lx was greater than mean E_v of 187.2 lx for LH-E, where recessed ceiling fluorescents flushed more on horizontal rather than vertical planes.

Furthermore, All_{mean} presented a lower mean and a narrower distribution than those of $Band_{mean}$ for both CL-D and CS-D. Several outliers of All_{mean} and $Band_{mean}$, including the maximum value $Band_{mean}$ of 740 lx, were caused by the sight of side-view windows. However, under constant electric lighting environments, LH-E presented a reverse distribution with a greater mean and wider distribution of All_{mean} than those of $Band_{mean}$. Given that LH-E were composed of purple walls and black chairs (as shown by Fig. 4 and Table 2), the horizontal 40°-band that mostly excluded recessed ceiling fluorescents of great luminance values resulted in low distributions.

Table 4 Demographic information of all participants across eight classrooms.

	Age		Gender		Eyewear	
CL-D	18—20	7.8%	Male	29.5%	Contacts	14.8%
	21—30	91.4%	Female	70.5%	Glasses	64.7%
	31—40	0.8%			None	20.5%
CS-D	18—20	17.6%	Male	35.6%	Contacts	10.1%
	21—30	82.4%	Female	64.4%	Glasses	66.9%
	31—40	0%			None	23.0%
LH-E	18—20	12.6%	Male	32.9%	Contacts	12.7%
	21—30	86.1%	Female	67.1%	Glasses	60.7%
	31—40	1.3%			None	26.6%

4.2. Subjective lighting assessments

4.2.1. Distributions of subjective lighting assessments

Fig. 8 presents the distributions of subjective responses to the five survey questions regarding instantaneous lighting evaluations. The count of participants selecting each choice was marked on the corresponding block. For lighting sufficiency (Fig.8(a)), over 60% of participants reported "adequate" lighting environments across the three groups of data, and 26.6% of participants considered lighting environments "too bright" within LH-E. For lighting comfort (Fig. 8(b)), around a quarter of participants reported "neutral" levels of lighting comfort. Both CL-D and CS-D presented 40% of participants considering lighting environment comfortable, while the percentage within LH-E was 48.1%. For lighting adjustment (Fig. 8(c)), around a third of participants within both CL-D and CS-D desired to either increase or decrease lighting levels. However, 55.7% of participants within LH-E desired to decrease lighting levels, and only 8.9% of participants desired to increase lighting levels. For glare sensation (Fig. 8(d)), the percent of participants reporting disturbing or intolerable glare within CL-D, CS-D and LH-E were 24.6%, 15.2% and 15.2%, respectively. No participant reported intolerable glare within CS-D. For glare sources (Fig. 8(e)), reflections in monitors was the top glare source reported by 87 participants (71.3%) within CL-D. Given that monitors were parallel to windows, window luminances were easily reflected in glossy monitor screens. Within CS-D where participants were flexible to select seating positions and adjust their laptops to avoid reflections, the top glare source reported by 77 participants (58.3%) was windows. For LH-E without exterior windows, luminaires were the top glare source reported by 45 participants (57%).

4.2.2. Individual attributes on lighting assessments

A one-sample Kolmogorov-Smirnov test was used to assess if subjective evaluations across three types of classrooms followed a standard normal distribution. A p-value lower than 0.05 is able to reject the null hypothesis and confirm a normal distribution of subjective evaluations. However, as all p-values of a Kolmogorov-Smirnov test for all subjective questions within each classroom type were greater than 0.05, non-parametric tests were applied to reveal differences among subjective evaluations due to gender and eyewear. To minimize biases caused by classroom types and sky conditions, subjective responses for both CL-D and CS-D were combined together for analysis.

A nonparametric statistical test, a Mann-Whitney *U* test, was applied to test subjective evaluation differences caused by gender. A p-value (significant level) lower than 0.05 indicates that two tested groups have statistically significant differences, and a large difference of mean rank between two groups indicates the diversity of data distributions. Given that participants evaluated daylighting environments within both CL-D and CS-D, subjective responses within these two types of classrooms were combined for the gender analysis. As shown by Table 6, males (mean = 4.48) reported higher levels of daylighting comfort than females (mean = 3.84) did (*U* test = 5231.50, p-value = 0.001). Given that no statistically significant difference among E_h (*U* test = 7,010, p-value = 0.875), E_v (*U* test = 6,047, p-value = 0.065), All_{mean} (*U* test = 6,986, p-value = 0.841) or $Band_{mean}$ (*U* test = 7,150, p-value = 0.922) was illustrated between genders, male and female participants experienced similar lighting environments while filling the survey. Males were more likely to report neutral or comfortable attitudes than females under the same daylighting environment.

Additionally, there were statistically significant differences between male and female participants' responses to lighting sufficiency (*U* test = 467, p-value = 0.004), lighting adjustment (*U* test = 502, p-value = 0.033) and glare sensation (*U* test = 459, p-value = 0.008) within LH-E (Table 6). Male participants rated these questions greater than female participants did. More specifically, males (mean = 3.46) considered electric lighting environments brighter than females (mean = 3.11) did; Males (mean = 3.85) were more likely to maintain current electric lighting levels than females (mean = 3.43) who preferred to decrease lighting levels in higher probability; Males (mean = 2.12) rated glare sensation more noticeable than females (mean = 1.70) did. A Mann-Whitney *U* test revealed no statistically significant differences of E_h (*U* test = 757.5, p-value = 0.475), E_v (*U* test = 757.5, p-value = 0.475), All_{mean} (*U* test = 596, p-value = 0.332) or $Band_{mean}$ (*U* test = 830.5, p-value = 0.14) caused by gender, meaning that males and females experienced similar electric lighting conditions. Hence, male

Table 5 Mean, maximum, minimum, and S.D. of E_h, E_v, All_{mean} and $Band_{mean}$ of all collected data across three types of classrooms.

	Mean	Min.	Max.	S.D.	Mean	Min.	Max.	S.D.
	E_h (lx)				**E_v (lx)**			
CL-D	128.6	27.1	689.4	123.9	120.4	53.4	342.9	55.5
CS-D	110.1	4.0	919.4	107.6	184.2	0.97	1390.3	195.1
LH-E	372.2	141.2	550	89.5	187.2	94	347	65.3
	All_{mean} (cd/m^2)				**$Band_{mean}$ (cd/m^2)**			
CL-D	31.3	13.2	86.7	14	54.67	25.1	164	25.8
CS-D	51	0.4	267.6	42.9	125.55	0.9	740	115.3
LH-E	62.7	25.8	115.2	22.2	49.97	19.8	85.9	20.5

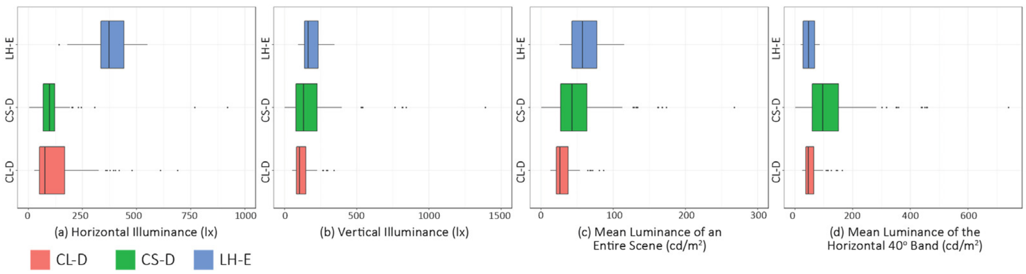

Fig. 7 Boxplots of E_h, E_v, All_{mean} and $Band_{mean}$ across three types of classrooms.

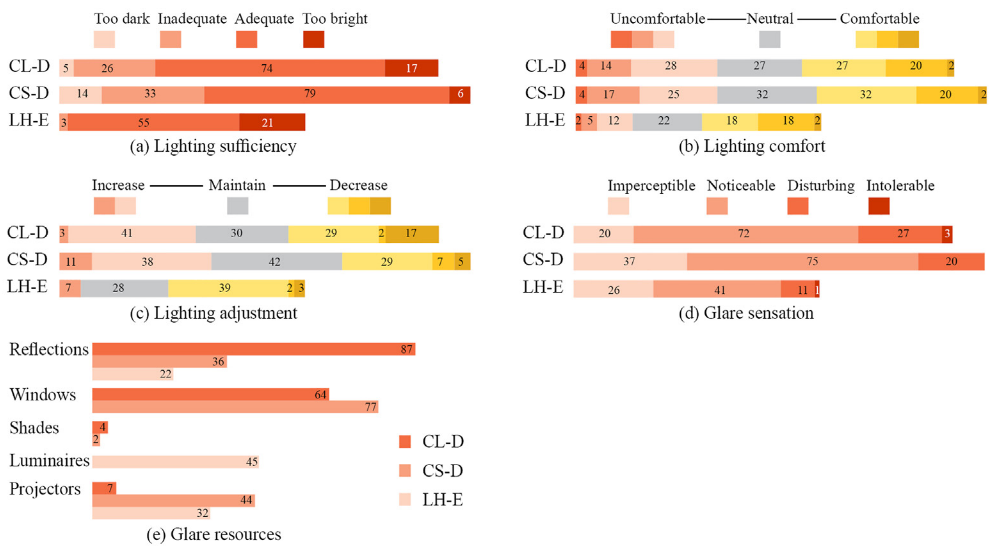

Fig. 8 Distributions of subjective responses to five survey questions of lighting environments across three types of classrooms.

participants were more sensitive than females in terms of evaluating electric lighting environments.

4.3. Relationships between lighting predictors and subjective assessments

4.3.1. Correlations between lighting predictors and subjective assessments

Given the subjective responses were ordinal variables, a Spearman analysis was used to seek correlations between lighting predictors and subjective assessments. Given that the four lighting predictors (E_h, E_v, All_{mean} and $Band_{mean}$) were tested against one subjective question, the likelihood of incorrectly rejecting a null hypothesis was increased. Hence, the Bonferroni correction (Cabin and Mitchell, 2000) was applied to the Spearman correlation p-values. Table 7 presents the Spearman ρ correlation coefficient and Bonferroni corrected p-values between lighting predictors and subjective assessments. Grey cells indicate the correlations with Bonferroni corrected p-values greater than 0.1; White cells indicate the correlations with the Bonferroni p-values lower than 0.1; and white cells with bold numbers indicate the correlations with the corrected p-values lower than 0.05.

Table 6 The Mann-Whitney *U* test of subjective assessments due to gender differences across three types of classrooms.

Lighting comfort for both CL-D and CS-D					Lighting sufficiency for LH-E				
	Mean rank	U-value	Sig.	Mean	LH-E	Mean rank	U-value	Sig.	Mean
Male ($n = 83$)	149.97	5231.5	0.001**	4.48	Male ($n = 26$)	48.54	467	0.004**	3.46
Female ($n = 171$)	116.59			3.84	Female ($n = 53$)	35.81			3.11
Lighting adjustment for LH-E					**Glare sensation for LH-E**				
	Mean rank	U-value	Sig.	Mean		Mean rank	U-value	Sig.	Mean
Male ($n = 26$)	47.19	502	0.033*	3.85	Male ($n = 26$)	48.85	459	0.008**	2.12
Female ($n = 53$)	36.47			3.43	Female ($n = 53$)	35.66			1.70

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

For CL-D, E_h was positively correlated with lighting sufficiency ($\rho = 0.224$, Corrected p-value $= 0.052$) and negatively correlated with lighting adjustment ($\rho = -0.282$, Corrected p-value $= 0.008$). It was reasonable given that higher levels of E_h resulted in higher probability of participants who considered lighting levels bright and higher probability of participants who desired to decrease lighting levels. For CS-D, E_h was positively correlated with glare sensation ($\rho = 0.212$, Corrected p-value $= 0.06$). For LH-E, lighting comfort was positively correlated with E_h ($\rho = 0.255$, Corrected p-value $= 0.092$), E_v ($\rho = 0.259$, Corrected p-value $= 0.084$) and $Band_{mean}$ ($\rho = 0.345$, Corrected p-value $= 0.008$). Although two of the correlations presented corrected p-values greater than 0.05, these three correlations suggest that greater E_h, E_v and $Band_{mean}$ values resulted in higher probability of participants comfortable with electric lighting environments.

4.3.2. Ordinal logistic regression models

Since the spearman test reveals the correlations between lighting predictors and subjective assessments, the next step was to test how they were correlated. One commonly applied way is to extract linear regression equations between grouped data based on lighting predictors (Hirning et al., 2017; Mangkuto et al., 2017; Wienold and Christoffersen, 2006). However, this method results in great ρ values and increases the probability of Type I errors. Therefore, this paper utilized an ordinal logistic regression model to extract equations between individual data. The procedure of this data analysis has been used in previous studies (Jakubiec et al., 2020; Rockcastle et al., 2016). Based on Table 7, the correlations with the corrected p-values close to or lower than 0.05 were selected for logistic regression analysis, which explores probability of subjective assessments associated with lighting levels. Four correlations were further explored: the correlation between lighting sufficiency and E_h as well as the correlation between lighting adjustment and E_h for CL-D, the correlation between glare sensation and E_h for CS-D, along with the correlation between lighting comfort and $Band_{mean}$ for LH-E.

For CL-D, the responses to the question of lighting sufficiency were grouped into three categories: reporting "too dark" or "inadequate" (31 responses), reporting "adequate" (74 responses) and reporting "too bright" (17 responses). Fig. 9 (top left) shows the ordinal logistic regression model (the red dashed line) between lighting sufficiency and E_h ($X^2 = 6.5$, $p = 0.15$). Despite the p-value greater than 0.05, the boxplot (Fig. 9 top right) demonstrates the trend that greater E_h resulted in higher probability of subjective reports of "adequate" or "too bright" lighting levels.

Furthermore, the responses to the question of lighting adjustment were grouped into three categories: desire for increasing lighting levels (44 responses), desire for maintaining lighting levels (30 participants) and desire for decreasing lighting levels (48 participants). Fig. 9 (bottom left) shows the ordinal logistic regression model between lighting adjustment and E_h ($X^2 = 12.17$, $p < 0.001$), where the "increase group", "maintain group" and "decrease group" were assigned values of 0, 0.5 and 1.0, respectively. The red dashed curve in Fig. 9 (bottom left) indicates the predicted probability of the subjective lighting adjustment. Based on the logistic regression model, Eq. (1) was proposed and converted to Eq. (2). Eq. (3) includes the probability of both occupants desiring to increase or maintain lighting levels. And $P_{decrease}$ was equal to one minus $P_{increase\&maintain}$. For each $\log_{10}$ unit increase of E_h, there was a predicted increase of 5.6 in the odds of a participant's desire from increase to maintain or decrease lighting levels, along with from increase or maintain to decrease lighting levels.

$$\mathrm{logit}\frac{P_{increase}}{1 - P_{increase}} = 2.76 + 1.725 * \log_{10}(E_h) \quad (1)$$

$$P_{increase} = \frac{1}{1 + e^{2.76 + 1.725 * \log_{10}(E_h)}} \quad (2)$$

$$P_{increasemaintain} = \frac{1}{1 + e^{3.852 + 1.725 * \log_{10}(E_h)}} \quad (3)$$

Table 7 Results of a Spearman test between CBDMs and subjective assessments for CL-D.

		Lighting sufficiency		Lighting comfort		Lighting adjustment		Glare sensation	
		ρ	Corrected p-value	ρ	Corrected p-value	ρ	Corrected p-value	ρ	Corrected p-value
CL-D	E_h	0.224	0.052	−0.080	1.0	**−0.282****	**0.008**	0.101	1.0
	E_v	−0.122	0.716	0.102	1.0	−0.114	0.836	0.006	1.0
	L_{mean}	−0.122	0.728	0.073	1.0	−0.126	0.672	−0.002	1.0
	$Band_{mean}$	−0.133	0.584	0.124	0.688	−0.084	1.0	0.004	1.0
CS-D	E_h	0.174	0.188	0.127	0.596	−0.175	0.184	0.212	0.06
	E_v	−0.152	0.324	0.040	1.0	−0.146	0.384	−0.052	1.0
	L_{mean}	−0.126	0.592	0.019	1.0	−0.099	1.0	−0.015	1.0
	$Band_{mean}$	−0.141	0.428	0.025	1.0	−0.113	0.784	−0.031	1.0
LH-E	E_h	−0.021	1.0	0.255	0.092	0.124	1.0	0.122	1.0
	E_v	−0.062	1.0	0.259	0.084	0.077	1.0	0.217	0.216
	L_{mean}	0.110	1.0	0.164	0.596	0.002	1.0	0.09	1.0
	$Band_{mean}$	0.235	0.148	**0.345***	**0.008**	0.236	0.144	0.16	0.64

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

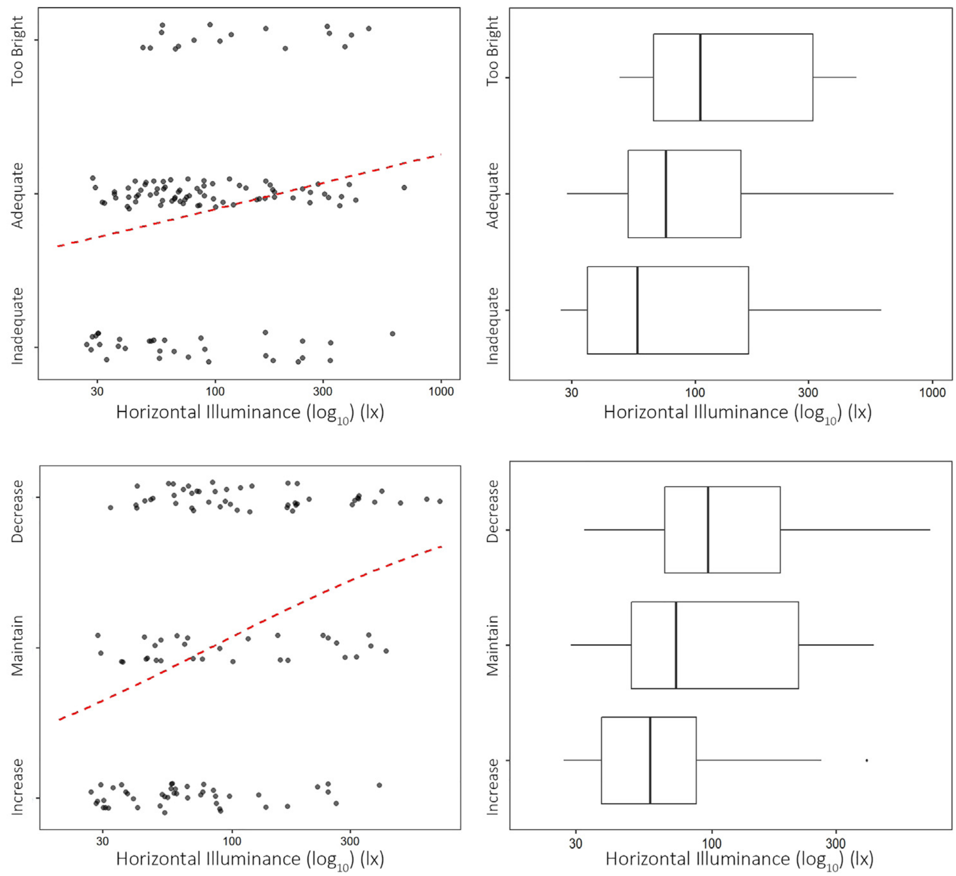

Fig. 9 Logistic regression model between lighting sufficiency and E_h (top left) and the associated boxplots (top right), along with the logistic regression model between lighting adjustment and E_h (bottom left) and the associated boxplots (bottom right) for CL-D.

For CS-D, the responses to the question of glare sensation were grouped into three categories: imperceptible glare (37 responses), perceptible glare (75 responses) and disturbing glare (20 responses). The ordinal logistic regression model between glare sensation and E_h presented an X^2 of 0.986 and p-value of 0.32, meaning that E_h was not a significant predictor of glare sensation.

For LH-E, the responses to the question of lighting comfort were grouped into three categories: comfortable (38 responses), neutral (22 responses) and uncomfortable (19 responses). The "uncomfortable group", "neutral group" and "comfortable group" were assigned values of 0, 0.5 and 1.0, respectively. Fig. 10 shows the ordinal logistic regression model (the red dashed line) between lighting comfort and $Band_{mean}$ ($X^2 = 12.11$, $p = 0.001$). Following the same method, Eqs. (4) and (5) that describe the relationship between $Band_{mean}$ and the probability of an occupant's lighting comfort were proposed below. For each $\log_{10}$ unit increase of $Band_{mean}$, there was a predicted increase of 43.3 in the odds of a participant's attitude from lighting discomfort to neutral attitude or lighting comfort, along with from lighting discomfort or neutral attitude to lighting comfort.

$$P_{discomfort} = \frac{1}{1 + e^{5+3.768 * \log_{10}(Band_{mean})}} \quad (4)$$

$$P_{discomfortneutral} = \frac{1}{1 + e^{6.385+3.768 * \log_{10}(Band_{mean})}} \quad (5)$$

5. Discussion

5.1. Gender influence on lighting assessments

Data analysis demonstrated that gender has influence on subjective lighting assessments. Female participants' lighting comfort levels were lower than males within daylit classrooms, while male participants were more sensitive than females within electrically lit classrooms. This finding agrees with previous studies. Giulia et al. (2012) found that gender influences subjective evaluations of environmental factors, including lighting factor. Kim et al. (2013) found that female occupants' satisfaction levels were consistently lower than male occupants, including their satisfaction with lighting environments. This result suggests that compared to male participants, female participants accept lower lighting levels and may be more satisfied in less-lit classrooms.

5.2. Performance of lighting predictors

This research revealed limited correlations between commonly used lighting predictors (E_h, E_v, All_{mean} and

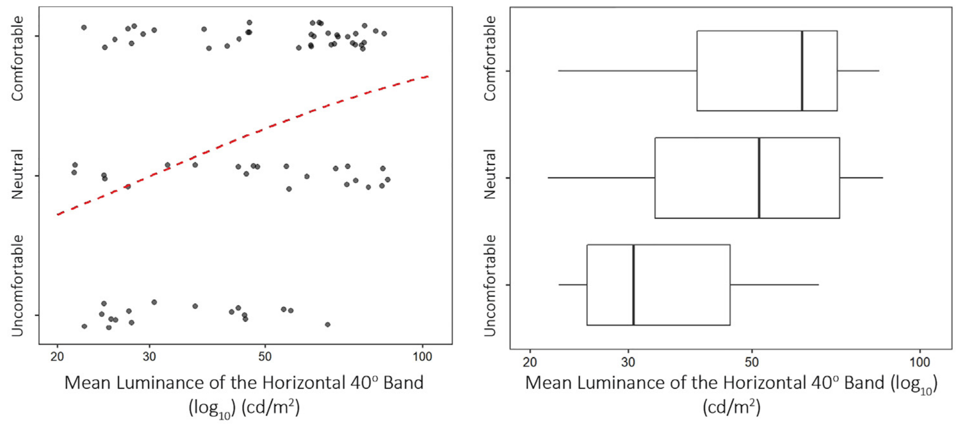

Fig. 10 Logistic regression model between lighting comfort and $Band_{mean}$ (left) and the associated boxplots (right) for LH-E.

$Band_{mean}$) and subjective assessments for both CL-D and CS-D, which was mainly caused by low daylighting quantities typical of tropical architecture designed for minimal solar penetration. For example, Bian et al.'s study in China presented measured and simulated E_v levels greater than over 6000 lx (Bian and Ma, 2018). Van Den Wymelenberg et al.'s study in America presented maximum values of E_h at 21,224 lx and E_v at 3783 lx (Van Den Wymelenberg, Inanici and Johnson, 2010). Low daylighting quantities under tropical skies have been demonstrated by previous studies. Compared to Wienold's thresholds (Wienold and Christoffersen, 2006), Mangkuto et al. (2017) suggested much lower Daylight Glare Probability (DGP) thresholds for defining glare thresholds in Indonesia. Hiring et al. (2017) proposed the ratio of window to background luminance (a pure contrast measure) as a more sensitive measure of occupant discomfort under tropical skies. Further analysis focusing on contrast-based metrics rather than absolute illuminance or luminance ratios will be carried out.

There were two main reasons that led to low daylighting quantities: sky conditions during the survey conduction and well-protected classrooms in terms of daylighting design. First, five survey conductions were assessed under overcast sky conditions, five were under intermediate sky conditions, and only one under a sunny sky condition. Given that Singapore has high sky coverage range with the monthly mean value varying between 81% and 89%, the sky conditions during the survey conductions represented the weather conditions in Singapore to a certain extent. Second, classrooms at SUTD are well-protected from direct sunlight. Both CL-D and CS-D have exterior hallways varying between 2.1 m and 2.2.m and 1 m-wide overhangs, the combination of which effectively prevent direct sunlight from entering the classrooms. Additionally, Daylight Factor across five daylit classrooms were simulated as a reference. The two CL-D had a mean DF of 0.5%, and three CS-D had mean DF of 0.4%, 0.3% and 0.7%, respectively. In other words, double-sided hallways and overhangs not only block direct sunlight but also present the classrooms from harvesting diffuse skylight.

The low Spearman ρ values revealed in this paper were -0.282 and 0.345. A Spearman ρ of 0.2 indicates a practical effect size, and 0.5 indicates a moderate effect (Ferguson, 2009). The ρ values in this paper fall within the range of previous field studies (Hirning et al., 2017; Mahić et al., 2017; Van Den Wymelenberg et al., 2010), which also achieved practical effect sizes. Two ordinal logistic regression models, one between lighting adjustment and E_h for CL-D and the other between lighting comfort and $Band_{mean}$ for LH-E, were presented. Nonetheless, these models were specific to the context of university classrooms under tropical skies.

6. Conclusions

In this paper, we assessed subjective and objective lighting quality across eight classrooms: two daylit computer labs, three daylit collaborative learning spaces and three electrically lit lecture halls in Singapore. Detailed measured lighting and spatial data as well as calibrated daylight models were collected or created. Responses to survey were collected from 333 participants. Based on the data analysis, the following conclusions were made.

- Daylit computer labs presented low daylighting distributions with the mean horizontal illuminance and mean vertical illuminance of 128.6 lx and 120.4 lx, respectively. Under this daylighting condition, 60% of occupants considered daylighting environments adequate, 38% of occupants considered daylighting environments uncomfortable, 36% of occupants desired to increase lighting levels, and 24.6% of occupants experienced disturbing or intolerable glare. However, as monitors were parallel to double-sided windows, reflections in monitors was the top glare source reported by 71.3% of occupants. Rearranging the monitors perpendicular to windows could effectively reduce reflection glare.
- Without monitors blocking daylight penetration, daylit collaborative learning spaces presented slightly greater daylighting distributions with the mean horizontal illuminance and mean vertical illuminance of 110.1 lx and 184.2 lx, respectively. Under this daylighting condition, 60% of occupants considered daylighting environments adequate, 37% of occupants considered daylighting environments uncomfortable, and 37% of occupants desired to increase lighting levels. Given that students

were able to rearrange desks and chairs in class, only 15.2% of occupants experienced disturbing glare. Windows was the top glare source reported by 58.3% of occupants. Since both computer labs and collaborative learning spaces have similar spatial configurations, material properties and daylighting designs, they presented similar daylighting performance and subjective assessments.
- Lecture halls presented constant electric lighting environments with the mean horizontal illuminance and mean vertical illuminance of 372.2 lx and 187.2 lx, respectively. Under this electric lighting condition, 26.6% of occupants considered lighting environments "too bright", 24% of participants considered lighting environments uncomfortable, 55.7% of occupants desired to decrease lighting levels, and 15.2% of occupants experienced disturbing or intolerable glare. Moreover, 57% of occupants reported luminaires as the top glare source. For the purpose of comfortable lighting environments and energy conservation, electric lights within lecture halls could be slightly decreased to lower the percentage of occupants considering lighting environments "too bright" or reporting disturbing or intolerable glare.
- Finally, two logistic regression models, isolated based on spearman correlations, were extracted: one between lighting adjustment and horizontal illuminance within daylit computer labs and the other between lighting comfort and mean luminance of the horizontal 40° band within electrically lit lecture halls. The former model implies the effectiveness of utilizing horizontal illuminance to control shading devices or optimize electric lights dimming systems; the latter implies the effectiveness of utilizing mean luminance of the horizontal 40° band to tune the brightness of projector screens and background luminance levels.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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