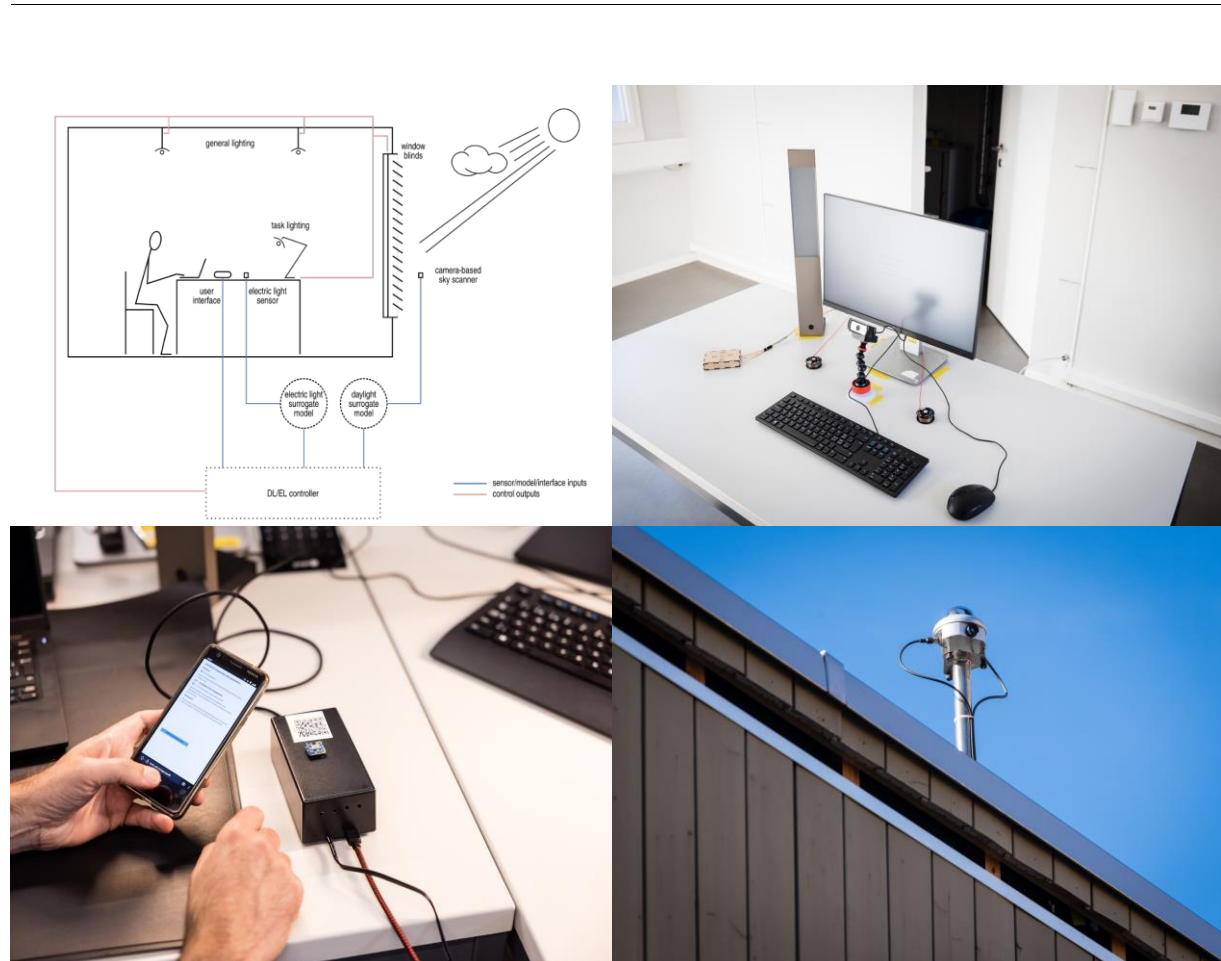




Final report dated 31st May 2023

LUCIDELES

Leveraging User-Centric Intelligent Daylight and Electric Lighting for Energy Saving



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The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.



Zusammenfassung

Die zunehmende Automatisierung in Gebäuden, um die elektrische Beleuchtung (EL) zu verringern und aus Gesundheits-, Komfort- und Energiespargründen um mehr Tageslicht (DL) zu benutzen, leidet unter einer negativen Benutzerwahrnehmung. Das vorgeschlagene Projekt zielt darauf ab, das Potenzial eines gezielten Zusammenspiels zwischen einem benutzerzentrierten Interface-Design und einer intelligenten Tageslicht- und elektrischen Lichtsteuerung zu untersuchen, um den Komfort zu optimieren, die Benutzerakzeptanz zu fördern und letztlich elektrische Energie zu sparen.

Der vorliegende Bericht stellt die Endergebnisse dieses Projekts vor, in dessen Verlauf ein Prototypsystem hergestellt und durch Benutzerexperimente (1) in einer kontrollierten Umgebung und (2) in bestehenden Büroumgebungen in den Räumlichkeiten von Smart Living Lab (Freiburg) und Idiap (Martigny) getestet wurde. Dieser Prototyp bringt eine Arbeitsleuchte mit der allgemeinen Beleuchtung des Gebäudes und den Jalousien zusammen, um eine energieoptimierte Beleuchtungsstärke zu erzeugen, ohne eine Blendung für den Nutzer zu erzeugen. Diese Optimierung wird durch ein Ersatzmodell erreicht, das auf maschinellem Lernen (ML) basiert und anhand von detaillierten Raytracing-Analysesimulationen trainiert wurde. Die entwickelte Systemarchitektur ist hochgradig modular und hat ihre Anpassungsfähigkeit an die verschiedenen Studienbedingungen bewiesen, insbesondere die Steuerung nur der Tisch-/Allgemeinbeleuchtung im Smart Living Lab, während die Tisch-/Allgemeinbeleuchtung und die Jalousien in Idiap gesteuert werden. Die Ergebnisse der Tests mit 60 Nutzern in einer kontrollierten Umgebung haben gezeigt, dass die Nutzer mit dem System zufrieden sind, ohne dass es einen Produktivitätsunterschied zwischen dem automatisierten und dem manuellen Zustand gibt, obwohl das System im automatisierten Zustand deutlich weniger Energie verbraucht. Die Ergebnisse von Längsschnittstudien bestätigen die Zufriedenheit der Nutzer mit ähnlichen Leistungssteigerungen während eine längere Nutzung des Systems über mehrere Wochen. Weitere Analysen der gesammelten Daten werden den Einfluss von Änderungen an der Farbtemperatur (CCT) auf die Zufriedenheit der Nutzer und die Akzeptanz des Systems untersuchen.

Résumé

L'augmentation de l'automatisation des bâtiments afin de diminuer l'éclairage électrique (EL) et d'augmenter l'exposition à la lumière du jour (DL) à des fins de santé, de confort et d'économie d'énergie souffre de la perception négative des utilisateurs. Ce projet vise à étudier le potentiel d'une interaction ciblée entre une conception d'interface centrée sur l'utilisateur et un contrôle intelligent de la lumière du jour et de l'éclairage électrique, afin d'optimiser le confort, de promouvoir son acceptation par l'utilisateur et, en définitive, d'économiser l'énergie électrique.

Le présent rapport présente les résultats finaux de ce projet au cours duquel un système prototype a été produit et testé par des utilisateurs (1) dans un environnement contrôlé, (2) dans des bureaux existants dans les locaux du Smart Living Lab (Fribourg) et de l'Idiap (Martigny). Ce prototype met en interaction une lampe de travail avec l'éclairage général du bâtiment et les stores pour produire un niveau d'éclairement optimisé sur le plan énergétique, sans générer d'éblouissement pour l'utilisateur. Cette optimisation est obtenue grâce à un modèle machine learning (ML) de substitution entraîné à partir de simulations détaillées d'analyse par lancer de rayon. L'architecture du système développé est très modulaire et a démontré son adaptabilité aux différentes conditions d'étude, en particulier en contrôlant uniquement l'éclairage général et de travail au Smart Living Lab, et l'éclairage général/de travail et les stores à l'Idiap. Les expérimentations du système avec 60 utilisateurs dans un environnement contrôlé ont démontré le confort des utilisateurs sans différence de productivité entre la condition automatisée ou manuelle, bien que le système ait utilisé beaucoup moins d'énergie dans la condition automatisée. Les résultats des études longitudinales confirment la satisfaction des utilisateurs avec des gains de performance similaires lors de l'utilisation du système sur une période de plusieurs semaines. Une analyse plus approfondie des données recueillies permettra d'évaluer l'influence des modifications de la température de couleur (CCT) sur la satisfaction des utilisateurs et l'acceptation du système.



Summary

The increase of automation in buildings in order to diminish electric lighting (EL) and increase daylight (DL) exposure for health, comfort and energy saving purposes suffers from negative user perception. This project aims at studying the potential of a purposeful interplay between a user-centric interface design and an intelligent daylight and electric lighting control, in order to optimize comfort, promote its user acceptance and, in definitive, save electric energy.

The present report presents the final results of this project during which a prototype system has been produced and tested through users' experiments (1) in a controlled environment, (2) in existing office settings in the premises of Smart Living Lab (Fribourg) and Idiap (Martigny). This prototype puts in interplay a task light with the building's general lighting and blinds to produce an energy optimized illuminance level, without generating glare for the user. This optimization is achieved through a surrogate model based on Machine Learning (ML) trained from detailed ray-tracing analysis simulations. The system architecture developed is highly modular and has demonstrated its adaptability to the different study conditions, in particular controlling only desktop/general lighting at the Smart Living Lab, while controlling desktop/ general lighting and blinds at Idiap. Results of testing the system with 60 users in a controlled environment demonstrated users' comfort without difference of productivity between automated or manual condition, although the system used significantly less energy in the automated condition. Results from longitudinal studies confirm users' satisfaction with similar performance gains when using the system over several weeks. Further analysis of the data gathered will assess the influence of correlated color temperature (CCT) changes over users' satisfaction and system acceptance.

Main findings

- A study conducted in a controlled environment allowed to assess different kinds of desktop luminaires in terms of user preferences in an office task, unveiling a relationship between light characteristics (illuminance, colour temperature), power consumption and user satisfaction.
- A developed intelligent control prototype was tested in three different environments (controlled and real settings) and showed significant energy usage reduction - between 49% and 68 % - compared to normative usage of the same luminaires. The energy consumption of the computational infrastructure involved was taken into account in the calculation.
- The performance of the Intelligent control scheme achieves energy reduction performance without impairing comfort, keeping real office users satisfied for prolonged testing periods.
- The implemented infrastructure framework was demonstrated to function in real time, thanks to the help of surrogate models. It involved open source software/hardware and displayed prolonged stability despite its prototypical nature.



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Abbreviations

ML - Machine Learning

DL - Daylight

EL - Electric Light

WPI - Work Plane Illuminance

DGP - Daylight Glare Potential

KPI - Key Performance Indicator

CCT - Correlated Color Temperature

SLL - Smart Living Lab (Fribourg)



1 Introduction

1.1 Background information and current situation

Lighting accounts for approximately 19% of the global electric energy consumption (IEA SHC Task 50). Research and development in the field of energy efficient lighting techniques encompassing daylighting, electric lighting and lighting controls can significantly contribute to reducing this demand. Nonetheless, growing economies, higher user demands for quality lighting and rebound effects as a result of low priced and more versatile electric lighting – “more for less” – lead to an absolute increase of worldwide lighting energy consumption [Gillingham et al, 2016]. More light is used, less consciously. The lighting as well as the facade market have seen significant technological developments and strong growth in the past decade, nevertheless both market sectors still act mainly independently of each other, leaving out opportunities for better user centered and at the same time energy efficient systems. Research and developments towards energy efficient lighting techniques that integrate daylighting, electric lighting and lighting controls is thus needed, with the ultimate goal to bring this integrated approach to the market in order to significantly reduce the electricity consumption.

Even though highly glazed buildings increase the daylight penetration and - with appropriate planning - may reduce the heating loads in winter while preserving the view outwards, an excessive daylight provision in buildings leads to an increase of thermal discomfort in summer. Likewise, the visual comfort may be impaired by strong luminance gradients between indoors and outdoors in the field of view of the occupants. Either discomfort leads most of the disturbed occupants to maintain the shading systems closed relying mainly on electric lighting. As a result, (1) the building's energy consumption increases compared to the intended design (performance gap), (2) the occupants do not benefit fully from the healthy effects of daylight. To overcome that barrier, multiple shading and electric lighting automation systems have been proposed and investigated by practitioners and researchers over the past decades [Andersen, 2015; D'Oca et al, 2018]. But they suffer from either simplistic control and interface design or limited budget, resulting in occupants perceiving negatively the automatic system behavior [Bellia et al, 2016; Day & O'Brien, 2017; Gilani & O'Brien, 2018].

The project particularly focuses on the proposed system's impact on energy usage for lighting. The International Energy Agency (IEA) Task 61 was focusing on the aforementioned problematic by investigating “Integrated Solutions for Daylighting and Electric Lighting: From component to user centered system efficiency”. To give some numbers, the Task D.1 (IEA 61) was looking at evaluating the potential energy savings: an example from literature state that, in a 7-months long study comparing various control techniques in a San Francisco office building, controls yielded 23% savings for bi-level switching, 45% savings for occupant sensing with task tuning, 40% savings with occupant sensing and manual dimming, and 44% savings for occupant sensing and automatic dimming [Jennings et al, 2000]. Indeed, energy savings cannot be realized in daylight buildings unless the electric light sources are dimmed or switched in response to the available daylight. The magnitude of potential energy savings which can be achieved with daylight-responsive lighting controls depends on the daylight climate, the sophistication of the selected control system, and the size of the control zones. The electricity demand for lighting can be lowered by at least 50% by using existing efficient technologies [Dubois et al, 2015]. Additionally, integration schemes with daylighting can save up to 60% compared to traditional installations [Ihm et al, 2009], with lighting retrofit being one of the most cost-efficient energy conservation measure in buildings [Enkvist et al, 2010]. However, human behavior highly impacts the actual building energy performance, including lighting [Menezes et al, 2012]. It is thought to have a potential energy saving of 5-30% in non-residential buildings [Zhang et al 2018], while even efficient technologies may achieve little savings. By focusing on the behavioral aspect, the project strives to provide an approach achieving such levels of performance.

Two project's participants were member of Task 61: J. Nembrini at UniFR to showcase the future developments of the SmartLivingLab (SLL) in Fribourg, a joint research and development center between EPFL, HEIA-FR and UniFR to achieve energy efficiency, digital transformation and the well-being of its users. The SLL studies the development of a state-of-the-art building that should be representative of our buildings in 2050. This future development has been selected within the SubTask D for its methodology to illustrate a best user-



centric integration design of day and electric lighting. In the meantime, J. Kämpf at Idiap focused on software solutions in SubTask C for the optimal user-centric control of day and electric lighting.

1.2 Purpose of the project

To address current shortcomings of daylight shading systems, the project focuses on the relationship between comfort and energy saving by encompassing the interplay between daylight and electric light with a user-centered approach. The proposal is:

- (1) to adapt state-of-the-art research on intelligent shading systems and electric light control [Alaa et al, 2019; Nguyen & Aiello, 2013],
- (2) to integrate such techniques into a controller interfaced with a dedicated user interface [Hakkulinen et al, 2013; Mennicken et al, 2016; Petrushevski, 2012], and
- (3) to study the usage and acceptance of the system by building occupants, through user experiments in a controlled environment and in real office settings [Oh et al, 2014, Keyvanfar et al, 2014].

The project thus aims at investigating the energy saving potential of user-centric intelligent DL/EL balancing. By taking advantage of the monitoring infrastructure, it allows to evaluate the energy saving potential of different automatic control strategies in interplay with user intervention and behavior. Typically, the aim is to assess the magnitude of sub-optimal user interventions on the final energy balance. Precedence is given to algorithms and interaction strategies that show robustness to energy intensive user behavior.

1.3 Objectives

The general research objectives of the project are to study the following themes:

- The energy savings potential for DL/EL user-centric intelligent control in recent case-study buildings (SLL & Idiap),
- The user's acceptance of machine-learning DL/EL control in an office environment,
- The appropriate degree of automation vs user-level control with respect to DL/EL and impact on energy saving potential,
- compromise on user comfort and wishes between different occupants of a shared-space environment.

During project development, the involvement of the industrial partner has brought additional sub-objectives, through a dedicated luminaire and questioning the relative importance of luminaire design:

- impact of purposeful CCT control over automation acceptance,
- user perception of the luminaire devices and environment.

The corresponding hypotheses that were tested are the following:

1. Automatic daylight strategy allows to save energy without compromising occupant's comfort.
2. Specific CCT adaptation increases automation acceptance.
3. Allowing users to set their preferred illuminance (or lux) level increases acceptance and is more energy efficient.
4. There is high correlation between automation acceptance and positive perception of task luminaire design.

These hypotheses were firstly tested in a short pilot study in December 2020, then in a 1-hour long controlled user study which took place between August and October 2021. Finally, two longitudinal user studies took place at the Smart Living Lab and at the Idiap Research Institute in single and shared offices. At SLL, the study



ran between Monday 18th October 2021 and Wednesday 2nd February 2022 (see Figure 1) and at the Idiap Research Institute between Monday 7th March to Friday 15th April 2022 (see Figure 2).

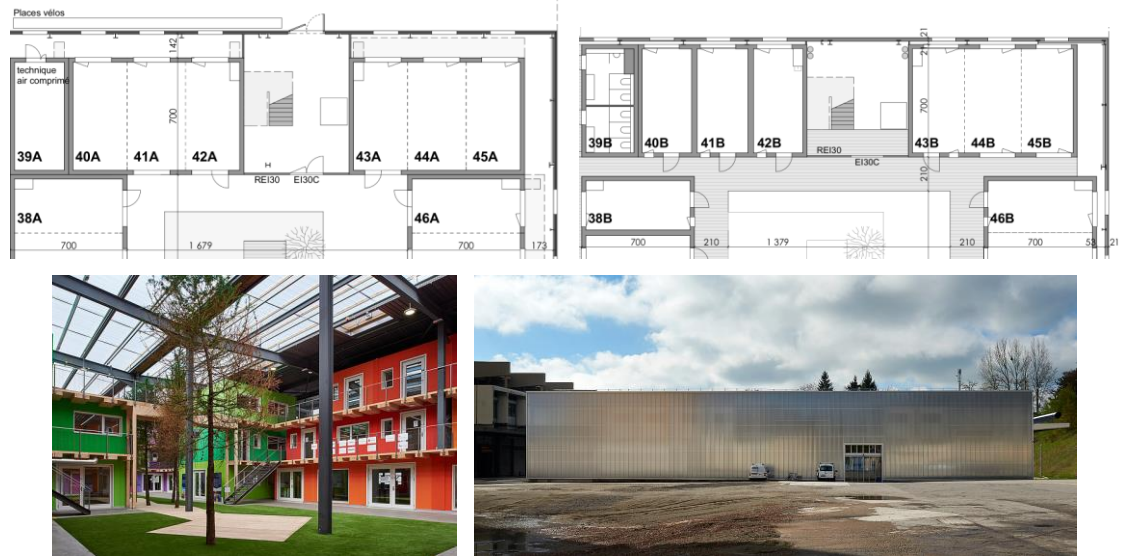


Figure 1: Two rooms tested at SLL, one single (41B) and one shared space (40A/41A/42A) with eleven occupants, both located on the south-east side of the BlueHall building, with the single office located on the first floor above the shared one. The BlueHall building is constituted of office boxes built within an industrial translucent outer shell.



Figure 2: Two rooms analysed at the Idiap Research Institute, one single and one shared space with seven occupants, both located on the same floor at the middle and extreme east wing side respectively of the building.

2 Description of facilities

The system developed combines three components:

1. an intelligent daylighting control using a sky pyranometer feeding a surrogate predictor and controller able to maximize Work Plane Illuminance (WPI) while minimizing glare (DGP),
2. an intelligent electric lighting control calibrated using workplane sensors with machine-learning control to reach set WPI,
3. an interface to input user requirements.

The computing speed of the daylight controller is enhanced using a machine-learning (ML) surrogate model trained by a physically realistic illuminance and glare dataset simulated with RADIANCE under measured sky models. The electric lighting controller further bases its lighting level predictions on an ML surrogate model



that is trained using a light response function (the workplane illuminance) inferred by purposefully controlling electric lights over a short period of time (at night or during the day with closed blinds). The user interface allows users to input their requirements and record their preferred settings in an intuitive manner. It is based on web technologies for rapid prototyping.



Figure 3: Schematic view of the proposed system (left) and implementation view of the controlled experimental setup (right), with desktop luminaire, desktop lux sensors, control interface and camera for eye tracking (camera only used for user analysis)

The intelligent DL/EL controller takes input from all three components to output commands to the shading and lighting actuators. In order to pursue the overarching aim to explore the relationship between energy savings goals and the degree of (intelligent) automation that users feel comfortable with, the design of the intelligent DL/EL controller allows to set the level of precedence of user inputs relative to automatic control. Aiming at testing the system in multi-user settings, the project considers from the onset multiple - possibly contradicting - user inputs and system acceptance. For the longitudinal experiment, the general lighting has been set to two different minimum (150 and 300 lux) to assess the influence of this value while letting users choose the level of compensation they prefer with the task light.

The facilities to monitor energy consumption, and to control blinds and electric lighting fixtures are available at the SLL and were installed for the project at Idiap. The approach follows a two-staged methodology:

I. A controlled environment at the SLL with two identical test modules in which DL and EL, as well as user tasks, can be assessed and monitored (Figure 4). This facility allows to develop, test and adapt interface/algorithm prototypes with a specific focus on the performance of control solutions evaluated by the users themselves.

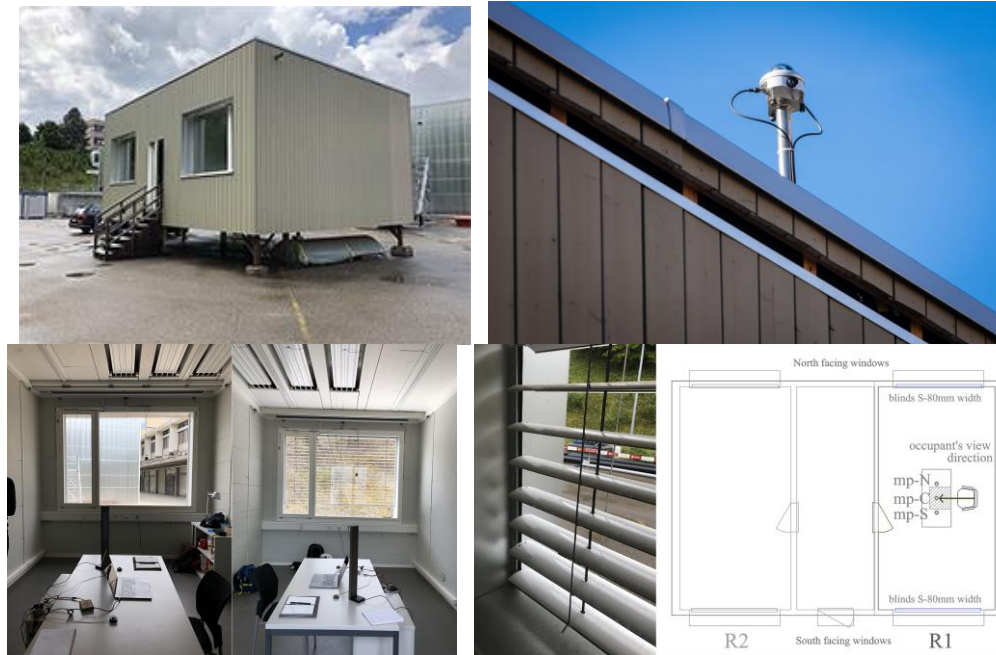


Figure 3: CELLS experimental facility at the Smart Living Lab (above, left) SPN-1 pyranometer on the roof of CELLS (above, right, Picture Guillaume Perret, Lundi 13), inside north and south views (below, left), blind type (below, middle) and floor plan (below, right)

II. Uncontrolled environments in an office building in which users are exposed to a mature prototype while carrying on their normal activities. Two case studies were tested:

A. At the BlueHall of the actual (and temporary) SLL building representing a specifically difficult environment (Figure 1 and 4) as it combines: a) the lack of DL control by the absence of blinds, and b) an open-space type of working environment leading to compromises between different users' preferences. In this case study, DL availability is scarce due to the offices being located within an industrial hall with mainly translucent façades, leading to quasi absence of glare situations.



Figure 4: Blue Hall's open space office (left), with its typical translucid double façade with limited direct view through the windows (right and below), which hosts the Smart Living Lab research institute



B. At the Idiap Research Institute, two offices located in the Centre du Parc in Martigny (Figures 2 and 5), which combines: a) a fully automated blinds system with a basic control algorithm (actually two automated movements per day), and b) two different work space configurations: single person and open spaces. The window, identical in both rooms, is divided in three sections: the upper and lower sections have translucent glazing of 31% Tvis, while the central section with transparent glazing is 73% Tvis. The electric lighting was retrofitted in both rooms for energy savings purposes, where fluorescent tubes T8 of 58 W were replaced by LED linear lamps with dimmable features. The properties of interior materials were measured as common to both rooms with an 8% reflectance for the floor, 24% for the ceiling concrete material, 34% for the concrete wall, and 70% for the white wall.



Figure 5: Idiap Research Institute's individual office (left) and the open space office (right) at the Centre du Parc in Martigny

3 Procedures and methodology

3.1 General methodology

As mentioned previously, the project adopted a two-stage methodology by firstly conducting a controlled user study and secondly two longitudinal in-the-wild studies. Both studies involved the same system design with some adaptations to the multi-user context of the longitudinal studies. More details regarding the precise methodology followed for each user study can be found in 3.2.1 for the controlled study and longitudinal studies.

In terms of interface design, the project meant to adopt a user-centric methodology by conducting focus groups involving neutral users, prior to defining the experimental prototypes. However, the COVID crisis prevented from organizing such focus groups, firstly by delaying the work and secondly by making potential users unavailable through home-office. As a result, a simple tangible interface was developed for the controlled lab study in the form of physical buttons to control the task light. For the longitudinal study, it was decided to rely on the existing task light button with the complement of a web app to let user announce their presence.

For results analysis, the set of materials gathered during the user studies were analyzed through a data driven approach in order to consequently study user behavior and unveil specific usage patterns.

3.2 Coordination and collaboration procedures

3.2.1 Meetings

During the course of the project, there has been 48 coordination meetings involving all partners, with additional bilateral meetings according to research needs. During the first part of 2021, coordination meetings have happened online because of COVID regulations. There has been a minority of co-presence meetings, with recurrent meetings mainly happening online.

3.2.2 Research agreement



A research agreement has been coordinated by UniFR and signed by the participating institutions. This agreement details the rights and duties of all project parties in the framework of the LUCIDELES project about IP rights, confidentiality, publication and communication.

3.2.3 Methodological collaboration

The different research dimensions and the corresponding experimental protocols have been concertedly elaborated through shared documents. This setup has allowed to discuss the potentially differing participants' needs. The project has been organized in different Work Packages (WPs):

- **WP1 Test rooms prototype:** development of prototype system applicable to the case studies
- **WP2 Surrogate (day)lighting models:** development and assessment of ML models trained on data produced by calibrated simulation models
- **WP3 Controlled user experiments:** setup and conduct of short user tests with controlled environment and user task
- **WP4 longitudinal user experiments:** set-up and conduct of mid-term users tests within normal office settings with users performing their usual tasks
- **WP5 Analysis and reporting** testing data analysis, publication and reporting

More details on the work packages can be found on the Table 1 below.



Table 1: Work packages summary

WP	Challenges	Methods	Partners involved
WP 1 – Test rooms prototype @ SLL (CELLS) Test rooms setup and control scheme integration	Integration of digitally controlled sensors and actuators Energy monitoring Usability, intuitivity and efficacy of the interface	Sky pyranometer sensor WPI sensors Existing KNX bus, Embedded control server, REST API for rapid prototyping Web-based technologies for rapid prototyping, exhaustive pre-testing	UniFR: expertise in experimental setup and controller development, experience in user-centred interface design for lighting control Idiap: experience in sky measurements Regent: expertise in lighting design and robust user interfaces
WP 2 – Surrogate (day)lighting models	Accurate and computationally tractable simplification of model-predictive control	Machine-learning based modeling, Consistent comparison between physical and surrogate models	Idiap: expertise in machine-learning and light prediction (physically-based RADIANCE simulations)
WP 3 – Controlled lab experiments @ SLL (CELLS) Studies setup, management and analysis	Test users' recruitment, dependent/independent variables control,	Strict experimental protocol, user agreement approved by ethical commission, comprehensive experimental logging, Usability, intuitivity and efficacy of the interface	UniFR: expertise in experimental setup, and management Regent: expertise in gathering customer experience
WP 4 – Longitudinal user studies Studies setup and management	Infrastructure long term robustness and maintenance, users' involvement	User agreement approved by ethical commission, maximal use of existing infrastructure	UniFR: direct and privileged access to the BlueHall case study facilities. Idiap: direct access to the Idiap case study
WP 5 – Analysis and reporting	big data statistical analysis reporting coordination	data-driven analysis	UniFR: expertise in experimental data analysis, project management



3.2.4 Technical collaboration

Technical collaboration has happened through exchanges of methods and devices. Models developed have been integrated in the final system setup resulting in extensive exchange of knowledge and coordination needs. The necessity to address needs from all experimental facilities have increased the need for facilitated information exchange.

The contributions of the different project partners are detailed as follows:

Human-IST

- Prototype system and control scheme implementation,
- User testing methodologies initial proposal and refinement
- Study results data analysis.
- Controlled experiment setup and conduction
- Organization and conduction of SLL longitudinal study
- Control system monitoring during both longitudinal studies
- Overall project coordination

Idiap Research Institute

- Modeling and calibration of case studies offices (SLL and Idiap)
- Data production of multiple ray-tracing simulations
- Development, implementation and analysis of ML surrogate models
- Discussion of user testing methodologies
- Organization and conduction of Idiap longitudinal study
- Project co-coordination

Regent lighting

- Provision of desktop lighting infrastructure and technical help for interfacing
- Participation to research questions definition
- Discussion of user testing methodologies

All project partners contributed to the publications.

3.2.5 Impact of COVID on project

Initially planned to last for two years, the project has seen significant time extension to reach its intended results. Nevertheless, the outcomes of the project are significant and have been achieved without additional support from SFOE. More particularly, the impact of COVID-19 on the project has been multiple:

1. The first confinement phase has obliged to work on the project in a very abstract manner instead of experiencing the space and the lighting situations.
2. The international travel situation has made post-docs less mobile professionally, which made the intended hiring of a post-doc almost impossible.
3. The encouraged home-office work policy has literally emptied the intended workspace, impacting users' presence for the longitudinal studies.
4. Finding participants for the controlled experiment proved more difficult than expected.



Due to the COVID situation it has been highly difficult to plan research with reliability. The research plan has been subject to many changes during the project, especially because of changes in working habits due to the development of home office.

3.3 Research methods

3.3.1 Daylighting control scheme

Surrogate (day)lighting models

As the objective is to perform an optimal and dynamic control of blinds and electric lighting, with the ultimate goal of maintaining visual comfort for the occupants with a reduced use of electricity for lighting, fast models are necessary to evaluate key performance indicators (KPIs). For the latter, the work plane illuminance (WPI) was selected as first KPI to determine the required amount of light on the desk to perform specific tasks. Secondly, the Daylight Glare Probability (DGP) was employed to identify particular situations in which the level of discomfort glare would represent a potential risk for performing working activities. Ray-tracing techniques are a typical way to compute the above mentioned KPIs as for instance by the use of advanced simulation tools such as the RADIANCE lighting simulation software. However, due to the very nature of the stochastic ray-tracing, the computations are intensive and require considerable amount of time to be completed, and therefore are not suitable to be embarked on a small computer, such as the one employed for the control of building parameters.

The same workflow for producing accurate Daylight (DL) and Electric Lighting (EL) predictor models has been applied to the case-studies into consideration:

1. At the CELLS for the controlled experiment,
2. At the BlueHall for the first longitudinal study,
3. At the Idiap Research Institute for the second longitudinal study.

The DL predictor model (D2.1), is derived from a database built from year-round simulations, which were carried-out with the use of the RADIANCE matrix multiplication methods (Geisler-Moroder D., 2017). From those, hourly work plane illuminance (WPI), was obtained, as well as HDR fisheye 180 degrees images, from which the risk of glare was estimated using the daylight glare probability index (DGP) (Wienold, 2009). The WPI as well as the DGP were estimated taking into account the working area dedicated to each participant and their view direction for each of the three case-studies. Each office room's geometric features as well as material properties were replicated in a virtual model that was later used for the simulations. In order to do that, the reflectance, transmittance and other physical properties of the interior materials were measured with specialized photometric equipment, such as a Chromameter (Minolta CR-200b) and a Glossmeter (GM-060). The correspondence of on-site illuminance measurements with those obtained with the use of RADIANCE simulations, were evaluated to validate the representativity of the office room by the virtual model.

Several machine learning models were tested in order to fit the dataset generated from the RADIANCE software for each case-study. Such set of data, corresponds to an entire year, distributed in hourly timesteps and contains the estimated WPI as well as the DGP predicted from the occupant's view position. The dataset is useful to describe the relation that exists for a specific case-study between the input: a particular weather condition, the date and time, the blind tilt angles; and the output: indoor daylight conditions described by WPI and the DGP. In details, the content of the dataset is allocated in 6 columns as input: 1 Boolean indicator which is true only if the blinds are fully open, 5 floating-point variables representing blind angle, direct and diffuse irradiance, and the sun position indicated as altitude and azimuth. Two additional columns contain the output data: average WPI and DGP. Figure 6 presents the process involved on the training of the surrogate model.

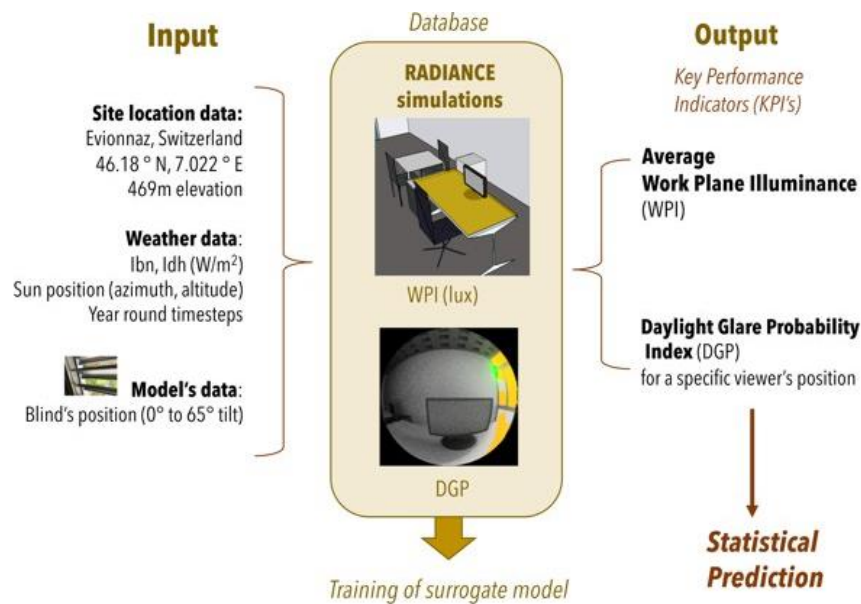


Figure 1: Graphical description of the process involved on the training of the surrogate model, illustration for the daylight performance prediction at Idiap Research Institute

The EL predictor model (D2.2), is much simpler than the DL predictor model and do not necessitate complex machine learning methods. Indeed, the WPI is a simple monotonous increasing function with the light dimming pre-set. For each case-study, WPI monitoring was realized at night increasing the dimming state of the luminaires between 0 and 100% by regular adaptive steps.

Both DL and EL predictor models were integrated in the control system: a small embedded 32-bits Raspberry Pi. Thanks to the light superposition principle, the results from both models for WPI were added to provide the combined illuminance on the users' desk, while the glare considered only potentially comes from the outdoor lighting conditions (daylight).

Control system setup

To find a good tradeoff between energy consumption and occupants' comfort, the chosen KPIs (DGP and WPI) are optimized by means of an intelligent control system. This is based on simulations of the resulting DGP and WPI depending on the outdoor lighting conditions, measured by means of a sun pyranometer, with different blinds and electric (general and task) lighting conditions by employing the developed surrogate (day)lighting models. To reduce energy consumption, the system follows the heuristics that office spaces should be illuminated in a way maximizing the use of daylight while preserving visual and thermal comfort of the occupants.

To implement this, the adopted control strategy performs predictions via the surrogate models at regular intervals of time to find the position of blinds that provides the highest possible WPI with an "imperceptible" DGP (≤ 0.35) (Wienhold, 2009) and a low incident solar radiation ($\leq 150 \text{ W/m}^2$) (Basurto-Davila and Kämpf, 2020). Next, aiming to compensate for an insufficient daylight provision, the minimum intensity of the general lighting necessary to reach the general illuminance threshold is determined with the electric lighting predictor model for general lighting. The same is then done to determine the minimum intensity setting of the task lighting to provide the desired WPI to each user. Finally, the determined optimal parameters are set in the physical room by means of a KNX controller. In a setup with multiple occupants in the same room (longitudinal



experiments), the control strategy considers keeping a low DGP for all present users and provide the minimum amount of lighting to reach the WPI threshold for all occupants.

The system envisioned at the time of proposal writing has seen little adjustments during its development. The current design is robust and versatile, as its application both to the controlled and longitudinal experiments demonstrated. The open-source software technologies chosen allow for replication and adaptation to differing contexts. Its modular design enables rapid knowledge transfer between project partners. The need to propose a stable system for the longitudinal study participants, as well as to allow for remote control of two concurrent experimental sites fostered the development of specific software systems able to remotely debug/update/restart. Such development can be considered as an output of the project since software technologies and solutions will be used in further projects.

After extensive discussion among partners during the COVID confinement period, the lighting environment has been defined using task luminaires able to control CCT and luminous intensity. The test room building is located at the SLL and is equipped with a KNX system allowing for control of general lighting, blinds and window opening (see Figure 3, left).

The prototype system (D1.1) is implemented on a Raspberry Pi which connects to:

1. A sky pyranometer SPN-1 situated on the CELLS roof (see Figure 3, right). The pyranometer has been preferred to a camera-based sky sensor because of its availability both at Idiap and SLL (from other projects) and for added system reliability.
2. A WPI sensor through I2C bus. An embedded sensor has been preferred to smartphone sensors given the difficulty to control mobile phone position (Figure 7 (c)).
3. Surrogate DL and EL models implemented in python, calibrated through the use of high quality lux sensors (Figure 7 (a,b))
4. KNX-IP bus to control general lighting, blinds position and gather energy data.
5. MODBUS for Joker task lighting control (CCT and intensity)
6. A 5-button interface (Figure 7(c))
7. A high-resolution webcam for participant eye-tracking.

The main control is based on node-red event-based visual programming (similar to LabView). The relationship between system components is made with simple REST APIs implemented in separated docker containers (micro-services). A dashboard allows for rapid component testing. A complete experimental interface including camera-based eye-tracking and the task performance recording is implemented using web technologies (html + JavaScript) (Task 1.4 and deliverable D1.2). The previous idea to compare between two luminaires using the IKEA Tradfri for task lighting control (CCT and intensity) was abandoned for stability reasons.

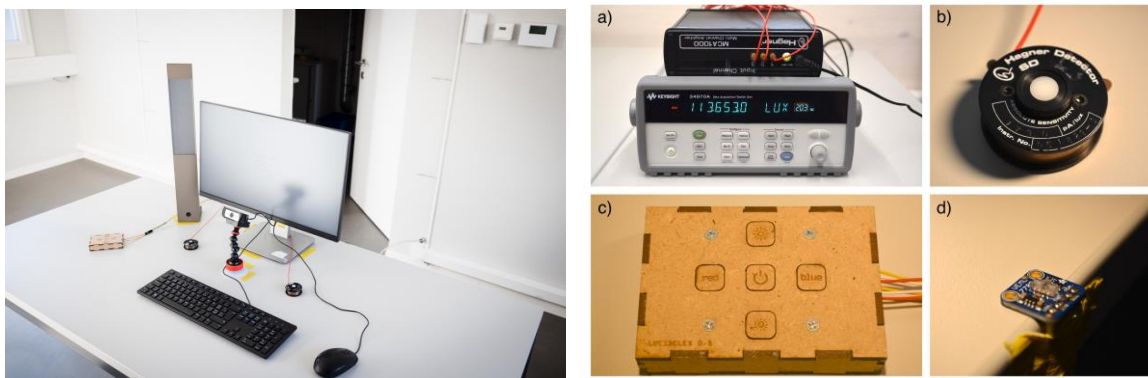


Figure 7: Controlled experiment setup (left, picture Guillaume Perret, Lundi 13), sensors (luxmeters a,b,d) and user interface (c)

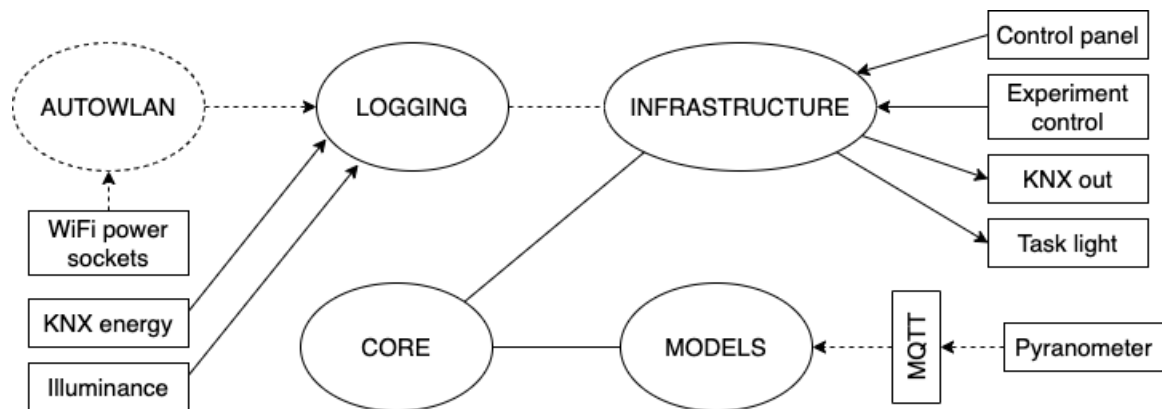


Figure 8: Software system schematic description

Hardware setup

The hardware setup for the automatic lighting system consists of several components to retrieve data useful for the estimation of the best lighting conditions, processing this data, physically changing the room's conditions, and sensing different parameters to analyse the quality of the automation system. Some components of the hardware setup can be found in Figure 7.

The outdoor daylight conditions are obtained with a Delta-T SPN-1 pyranometer located on the roof of the building, which returns every 3 seconds the direct and diffuse radiation and the presence or absence of bright sunshine on the office premises. The data from this sensor is collected by a Raspberry Pi 3B via RS232 serial interface and published to an MQTT broker.

The MQTT broker serves the pyranometer data to the central actor (master) of the optimisation process, a low-energy Raspberry Pi 3B, where it is used to find the room settings that provide the optimal lighting conditions. Once the optimal conditions are found, these values can be applied to the physical room. This is done for the blinds height, position and general lighting through a KNX architecture installed in the office. The intensity and CCT of the used lamp for the task lighting (Regent Lighting Joker) are controlled through a USB-C breakout board connected to the master Raspberry Pi 3B using the Modbus protocol.

To allow manual control of some parameters of the system (e.g., task lighting's CCT and minimum WPI threshold in the user input automation), a control panel with 5 buttons (intensity up/down, CCT up/down and ON/OFF) was implemented and connected via GPIO to the master Raspberry Pi 3B. This control panel was added on the basis of the pilot study showing the difficulty of rapid user appropriation of the single-button interface available on the task luminaire [4].

To check the quality of the proposed automation system, several sensors are used to collect information about illuminance and energy consumption. High quality illuminance sensors (Hagner SD2 with Hagner MCA1000 amplifier) are placed on the experiment's desk to analyse WPI. This data is processed by the Agilent 34970A data acquisition unit, from where the master Raspberry Pi 3B regularly collects the data via an RS232 serial interface and stores them locally for future analysis.

Energy consumption of the automation system includes the energy used by the general lighting, the blinds, the task lighting, and the optimisation system. Energy used by general lighting and blinds is available through the KNX interface, whereas to retrieve that of the task lighting and the optimisation system, two smart WiFi power sockets NETIO PowerCable REST 101J are used. A WiFi access point has to be set up on the master Raspberry Pi 3B to exchange data between these two devices with REST APIs using the JSON protocol.

Software setup

The software allowing to interface the physical world with the automatic lighting control is structured in modules with different purposes. The overall software architecture is depicted in Figure 8. In practice, each of these independent modules is a separate Docker container for consistency, mobility, scalability, and modularity reasons. Information is exchanged within different modules with REST API interfaces.



The central module that is handling all the others is the CORE. Here, the control algorithm is defined. The optimisation system consists in finding the optimal values for blinds, general and task lighting, such that while preserving the comfort of the occupants, the least possible energy is used.

In the CORE, the results from the models are used. These are handled in the software by the MODELS module. This component retrieves from the external MQTT broker the values of the pyranometer on the roof of the office and then uses this in combination with the blinds and lighting conditions given by the CORE to provide an estimation of the WPI and DGP.

When the optimisation process is completed by the CORE, the INFRASTRUCTURE module takes care of updating the physical room by sending out KNX telegrams and Modbus messages. In this component, the input from the control panel and the experiment parameters are also handled.

In the LOGGING module, all data and events to be logged are collected and stored locally.

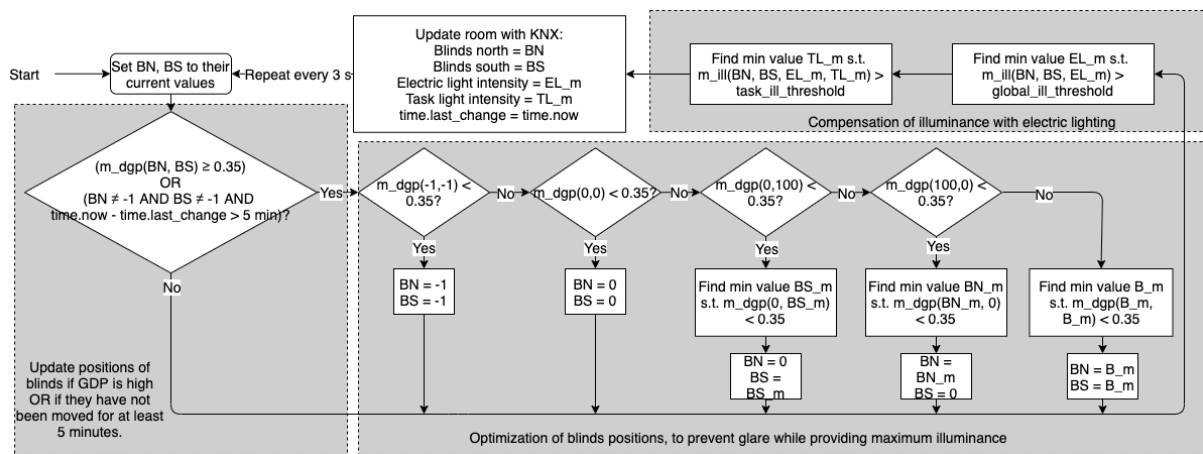


Figure 9: Automatic lighting control strategy. EL m and TL m represent the intensity of general and task lighting.

Automatic lighting control strategy

In this system, the daylight and electric light models are used to optimise the room settings (blinds positions, general lighting intensity and task lighting intensity) by continuously running estimations of WPI and DGP on a low energy 32-bit computer (Raspberry Pi 3B), based on measures of direct and diffuse horizontal irradiance from the Delta-T SPN-1 located on the roof of the premises. Once an optimal solution to the problem is found, the physical system is updated using the infrastructure.

The overall strategy for reducing energy consumption consists of providing the highest possible levels of daylight that still are in a comfortable range for the occupants (i.e., 'imperceptible' glare, $DGP \leq 0.35$). In case that the illuminance provided by daylight alone is not sufficient to reach the minimum WPI threshold, electric lighting is used for compensation (Figure 9). To further lower energy consumption, a reduced amount of lighting is provided for the background and walking area by the ceiling lights (100 lx threshold), while a more focused but higher intensity task lighting is supplied by a desk lamp (500 lx threshold), in compliance with the ISO 8995-1:2002 and EN12464-1:2011 workplace lighting standards.

The proposed lighting optimisation process consists in repeating the following procedure every 3 seconds.

1. Estimating DGP with the current north and south blinds (BN and BS) and sky conditions using m dgp, the DGP prediction model;
2. Using m dgp and increments in steps of 5% in the blinds angles, select the blinds position that provides the highest illuminance in combination with adequate lighting comfort ($DGP \leq 0.35$).
3. With the found optimal blinds positions, estimate the WPI from daylight alone using m ill, the WPI prediction model;



4. Using the electric general lighting model, find the minimum intensity 379 which provides at least 100 lx when summed to the estimated daylight WPI (the general light is off if the daylight WPI is higher than global ill threshold = 100 lx);
5. Using the electric task lighting model, find the minimum intensity which provides at least 500 lx when summed to the estimated global light WPI (the task light is off if the daylight and general light WPI is higher than task ill threshold, which is 500 lx in automatic mode, and variable starting at 500 lx in the user input automation).

As a further measure to improve user comfort, the blind positions are instantly adapted only in case $DGP > 0.35$ with the current conditions; otherwise, a time interval of at least five minutes is considered between each blind movement. This way of operating the system represents a good trade-off to avoid discomfort glare between comfort (both acoustic and visual) and the frequency of disturbances due to blind motions.

In the controlled experiment, an automatic and a user input control strategy are being investigated. The difference between these two modes consists in the fact that in the automatic mode, the threshold of the illuminance provided by the combination of daylight, general lighting and task lighting is fixed at 500 lx, according to the minimum suggested by the ISO 8995-1 standard, whereas in the user input automation this starts at 500 lx but can be increased or decreased manually by the user using the controls in Figure 7c.

In the user input automation, the maximum value for the WPI threshold is set to the indicative value of 4000 lx. However, for any WPI threshold higher than the maximum illuminance provided by the task light (~640 lx) and ceiling lights (100 lx) combination, one cannot ensure that the WPI will always be higher than the threshold, as this depends on the amount of available daylight. The only difference in setting a threshold higher than 740 lx, is the amount of daylight necessary to reduce the electric lighting intensity.

In both control modes, the threshold of the minimum total illuminance of daylight and general lighting is fixed at 100 lx.

Moreover, in both control modes, the Correlated Colour Temperature (CCT) of the task luminaire was controlled to follow a circadian curve to accommodate user preferences, adapting the colour temperature based on the sun's altitude in the sky relative to the minimum and maximum altitude during the day. In the automatic mode, this curve is fixed, with values spacing between 3100 K during the night and 5250 K at solar noon (Figure 10), in the user input automation, the whole curve can be moved up or down of a certain amount of Kelvin, with the minimum values ranging between 2700 K and 3500 K at night, and 4000 K and 6500 K at solar noon (Figure 10, right). These values were defined based on the colour temperature produced by the sun at sunrise and sunset (2500 K - 3500 K) and at solar noon (4000 K - 7000 K), adapted to the temperatures that the used task lamp could achieve.

3.3.2 Longitudinal studies setup

The setup of the longitudinal experiments involved:

- the selection of the spaces with agreement on occupants' participation (agreement at management level, individuals always be able to opt out),
- calibrated modeling of the spaces in RADIANCE,
- the involvement of >24 Joker luminaires from Regent Lighting the design of the second-generation system prototype, including production of >24 units and their deployment on-site,
- the adaptation of both buildings' infrastructure to allow for the control of general lights and blinds,
- the agreement among all project partners on the longitudinal study protocol (D4.1).

The prototype system used in the longitudinal experiment differs from the controlled study by presenting a master-slave architecture, in which slaves represent desktop controllers each attached to a task luminaire and distributed over the office desks (implemented using Raspberry Pis Zero W), while a master per office room provides a local Wi-Fi network and is responsible for running the ML models (implemented using Raspberry Pis 4B). This ensures simpler deployment and further reduces the energy expenditure of slaves. Both systems can be monitored and updated remotely given the distance between Martigny and Fribourg.



At Idiap, on top of the infrastructure upgrade (D1.3) carried out by:

- the installation on the roof of Idiap of a sky sensor (BF5) monitoring direct normal and diffuse horizontal irradiance every 10 seconds and providing the values through a MQTT server,
- the installation of a Raspberry Pi, an Ethernet to KNX bridge, KNX blinds actuators, a KNX to DALI bridge, and finally dimmable DALI luminaires with LEDs,
- the installation of energy meters to monitor the electricity consumption by the electric lighting,
- the installation of the Node-RED flow developed by UniFR in the Raspberry Pi to control the blinds and the new general lighting dimmable LED luminaires. APIs were provided to control the blinds and general lighting from the external “Master” Raspberry Pi controlling also the Task Lights (named Jokers),

the sky scanner MQTT server and KNX control of blinds and lights were integrated for the two offices 103 and 107 in the developed prototype. As the objective was to have the same controlling code for the two longitudinal experiments, the following elements were achieved:

- an equivalence between the KNX control command for the blinds and the actual tilt angle of the blinds measured in degrees,
- an equivalence between the KNX control command for the electric lighting dimming intensity and the WPI measured on the desk(s) using a professional instrument,
- unified messages between all case-studies from the sky scanner’s MQTT server to provide the current beam normal and diffuse horizontal irradiance values.
- the installation of the prototype of master control provided by UniFR to centralize and make the link between the users, the automation and the experimenters at UniFR.

Specifically for the Idiap case-study, a solar protection mode was developed and integrated in the controller to avoid direct sunlight in the room during the summer causing overheating and therefore thermal discomfort for the occupants. Furthermore, a night mode when no user is present was integrated to reduce the heating needs in winter by fully closing the blinds, and to increase night cooling in summer by fully retracting the blinds.

At SLL, despite the availability of a KNX system at the time of proposal writing, the installed system was found to be malfunctioning at the start of 2021. As a result, a consequent adaptation work had to be conducted, thanks to the help of the SLL Building 2050 group. The following adaptations were made:

- The data stream of the Delta-T SPN-1 on the CELLS building had to be made available site-wide,
- The KNX sensor data stream was restored in August 2021 and the corresponding energy meter interfaced with the system,

the KNX actuation needed for controlling the lights (Task 4.1) was achieved with a virtual machine connected to an external MQTT server because of network restrictions (SLL is made of EPFL/UniFR/HEIA:FR networks which adds a level of complexity).

For both locations, the proximal work environment of each participant included a task light with tunable system parameters, such as a target illuminance at the desk level and the CCT scheme (see Figure 10). The participants had the ability to interact with the task light in two distinct ways: the first method involved using a physical button (Figure 10, left), which allowed them to adjust the light’s intensity and CCT (depending on the chosen CCT scheme); the second method involved accessing a web application with a QR code located on the device (Figure 10, middle), which enabled them to choose the desired CCT scheme and indicate their presence to the system.

Two types of CCT schemes were proposed for the task light. The first is a standard CCT scheme that remains fixed over time (hereafter referred to as fixCCT). The second one provides a dynamic change of CCT throughout the day with a colder light in the midday and a warmer light in the morning and evening, with values computed based on the sun’s height in the sky (hereafter referred to as dynCCT).

Participants could tune both schemes using the task light’s button; in fixCCT, any value between 2690 and 6470 K could be selected and remained constant until changed again. In contrast, in dynCCT, a percentage of the range between the minimum and maximum curves allowed at a given time of day could be set (Figure 10,



right). The dynCCT scheme was the default pattern; participants could change the scheme at any time from the web app. Additionally, the participants had to set their presence when arriving in the office and unset it when leaving, through the web app or a physical sensor. This allowed to activate the automation system - including the CCT control - only when they were present at their desk.

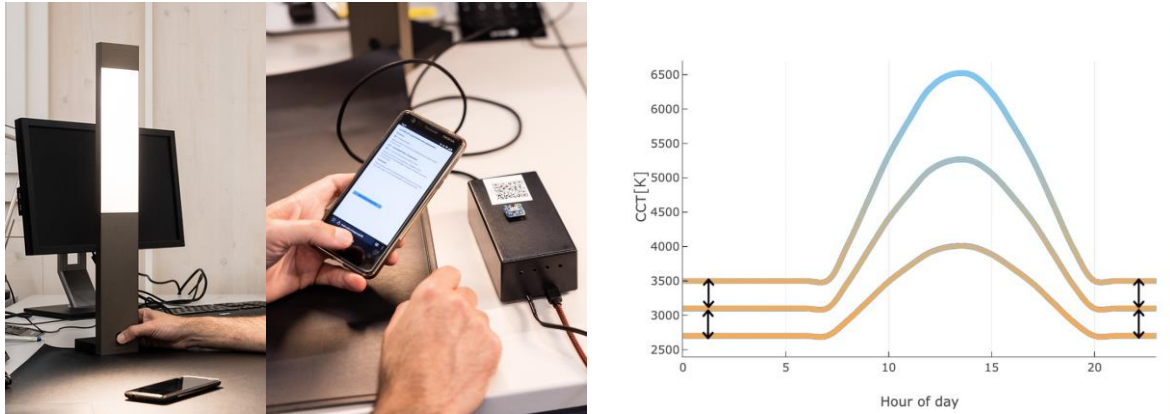


Figure 10: Luminaire used for the project with a signal button interaction (left), users could set their presence and choose between CCT scheme through a web app (middle), for dynamic CCT control (dynCCT) a family of curves evolving over the day was used (right), for automatic control, the curve in the middle is used, for the user input automation, the user can move the curve up or down of a certain percentage between the minimum and maximum CCT.

3.3.3 Testing methods

Three testing phases were conducted as follows:

1. **Pilot study:** within group comparative short term testing of different task luminaires available on the market allowing CCT and intensity control. Study duration of 20-30 minutes with 13 participants, conducted in December 2020.
2. **Controlled study:** between group comparative study of the prototype system involving different control conditions (CCT automated and/or control over automation). Study duration of 1.5 hours involving 60 participants, conducted in August-October 2021.
3. **Longitudinal studies** in real office settings, conducted:
 - a. At SLL during 15 weeks between November 2021 and February 2022 involving 11 participants.
 - b. At Idiap during 6 weeks between March-April 2022, involving 8 participants.

Pilot study methodology

The pilot experiment evaluated participants' task light usage patterns and their characteristic preferences from a user-centered perspective. The aim was to provide guidelines in terms of luminaires characteristics. 13 participants evaluated three different task lights in both paper and computer conditions. The task was to set preferred light environment using the 3 luminaires provided and answer a comparison questionnaire at the end. The pilot experiment additionally allowed to test a new methodology to record participants' emotions through the circumplex model of affects. This methodology was used in the subsequent controlled experiment. 13 participants - 6 females; 11 right-handed (age $M=31.69$, $SD=10.44$) - took part in the study. All participants gave informed consent to participate in the study and were informed that they could withdraw their data by the end of the study.

Procedure

Participants first completed a short questionnaire designed to gather socio-demographical data. Then, participants were presented each luminaire in a random order, with which they had to set lighting conditions



as comfortable as possible for reading tasks on computer and paper (order randomized). Desktop illuminance and color temperature of these conditions were then recorded. Participants also answered a questionnaire including the selection of adjectives among a list for the circumplex method of affects. After all luminaires testing, participants answered an additional questionnaire comparing the luminaires preference. The study duration was about half an hour.

Materials

For the pilot user study the following materials have been collected:

- Desktop illuminance and CCT for both computer and paper task (2 readings per luminaire).
- Questionnaire for each luminaire, including circumplex adjectives.
- Entry and exit questionnaire for demographics and luminaire comparison.
- Picture of preferred setup for both computer and paper task (2 pictures per luminaire, Figure 13).

Controlled study methodology

The experimental protocol for the controlled lab studies (Deliverable 3.1) includes CCT adaptation and automation control as independent variables. It was originally thought to test in parallel two different luminaires taking advantage of the CELLS twin layout. However, lack of stability of the IKEA Tradfri control through the raspberry PI prevented it, given the stability requirements to run tests for dozens of participants. The final experimental setup is depicted in Figure 7 (left).

In order to test the CELLS setup of WP1, the controlled experiment was set up aiming at testing the performance both in terms of comfort and energy saving of different automation strategies: (1) automated setup (AUTOMATED), (2) automated with user being able to operate changes in CCT curve (USER INPUT), and (3) operated entirely manually by the user (MANUAL). The specificity of the CELLS building having large windows on both north and south sides was compensated by testing with blinds fully open or closed on one side or the other. 60 participants -- 53 females; 54 right-handed (aged from 18 to 51 years old; $M=22.57$, $SD=5.80$) -- took part in the study. All participants gave informed consent to participate in the study and were informed that they could withdraw their data.

Procedure

Participants were randomly assigned to an automation condition and went through all modalities of the blind condition (both opened, north closed and south closed). Before the experiment start, participants answered a questionnaire to assess locus of control and provide socio-demographical data. For each blind position, participants had the possibility to adjust visual conditions using the blinds (in manual setup only), the general light (in manual setup only), and the task light (intensity: in manual setup and CCT: in both manual and user input setup). The task was to copy and correct a text with mistakes. At the end of the experiment, participants filled in a questionnaire to assess automation acceptance. The experiment lasted about 1 hour and 30 minutes.

Materials

For the controlled user study the following materials have been collected:

- user comfort subjective appreciation and automation perception (entry and exit questionnaires, plus blind condition questionnaires),
- lighting energy consumption,
- WPI measurements,
- user performance on achieving a task,
- user interaction with the interface,
- user's physiological markers such as eye movements.

All materials are gathered during or at the end of each blind condition block (each lasting 20 to 25 minutes), apart from the entry and exit questionnaires.



The Levenson locus of control scale] was used to evaluate the locus of control through Powerful others, chance and internal construct. This scale was favoured over classical scales reporting internal and external locus as those two constructs seem to tap different beliefs. We adapted the scale by removing items that performed poorly.

After each trial, we used the Office Lighting Survey (OLS) with a likert scale from strongly disagree to strongly agree to evaluate light quality and the Karolinska Sleepiness Scale to evaluate the sleepiness. To analyse participant sentiment toward their emotion and the light after each trial and the object perception at the end of the experiment, we asked participants to tick adjectives within a list following the circumplex method of affects. We inferred those three circumplexes from a previous crowd-sourced online questionnaire with more than 100 participants, which will be described in a subsequent publication.

Regarding the assessment of automation acceptance, we selected several models in the literature and extracted meaningful constructs for our goal. We ended with eight constructs, *i.e.*, perceived control (3 items), perceived system reliability (3 items), compatibility (3 items), perceived ease of use (3 items), perceived usefulness (4 items), attitude (3 items), intention to use (3 items) and trust (3 items). All the items were assessed on a Likert scale from strongly agree to strongly disagree.

The task selected was a typing task of texts containing errors. This task appeared to have the right balance between ecology and control. Six texts of 796.17 words on average ($SD=20.53$) were extracted from the well-known book Harry Potter and The Philosopher's Stone. Typing errors — letter replaced by a letter in the surround according to a QWERTZ keyboard layout, letter inversion, or phoneme errors — letters replaced by other letters reading the same sound, *e.g.*, "é" and "et" in french — were randomly inserted every 20 words following a Poisson distribution with $\lambda = 20$.

Data Analysis

Data was analysed using R, and charts were plotted using Python. All data collected was averaged across trials, while questionnaires data was averaged across constructs. The locus of control was computed according to the methodology described in this study.

To evaluate the impact of the automation and blind condition, we set up (generalised) linear mixed models (with appropriate distribution, when both conditions were present) and (generalised) linear models (with appropriate distribution, when only the automation condition was considered), with participants as a random factor. We used the Anova function in the car packages in R to generate p-values using Wald Chi-square test. The Bayes factor was computed using the Bayesian information criterion (BIC) of the null model as compared to the model including a factor, both factors or the full model with an interaction effect. This computation allowed us to ensure that the automation condition did not impact on certain variables.

Regarding the circumplexes analysis, Rayleigh tests assessed whether the selected adjectives indicated a direction around the circumplex space. When at least two groups exhibited a direction, a CM test assessed the significance of the difference in directions.

Longitudinal studies methodology

The experimental protocol for the longitudinal studies (D4.1) is derived from the protocol of the controlled experiment (D3.1). It involves entry and exit questionnaires, as well as short daily questionnaires¹.

The longitudinal study with users started at Idiap (D4.3) on October 25 2021, and 2 weeks later at SLL (D4.2), and was foreseen to last until the Christmas break. After several discussions within the project members, for a first period of time the general lighting was brought to a maximal value of 300 lx on the work plane, as required by the norms. A second period of time, completely symmetrical with sun positions, was foreseen from Christmas to February 16 to bring the general lighting to a maximal value of 150 lx on the work plane, thus reinforcing the need of the task light (Joker) to achieve a sufficient light flux depending on the users'

¹ <https://www.idiap.ch/~jkaempf/AllQuestionnaires.pdf>



preferences. These levels were inverted at SLL for protocol symmetry purposes. The task light (Joker) could be used to increase the amount to 500 lx or beyond depending on users' preferences. This first longitudinal study was perturbed by COVID home office regulations with less user occupancy than anticipated.

Due to technical problems, the 6 weeks of longitudinal experiment were postponed to March-April 2022 at Idiap. After this second period of time, an analysis and comparison of the results was carried out.

Control system specific to longitudinal study @ SLL

The automatic lighting control strategy presented in 3.2.1. was adapted to the use case of the SLL to consider the peculiarities of the studied office spaces. These spaces were not equipped with blinds, so the control strategy predicts the WPI from daylighting and compensates it with general lighting to reach the general illuminance threshold for all the occupied desks in the room. Then, the task lights are used to provide the extra lighting necessary to satisfy the preferences specified by each user.

As the optimization of the lighting is dependent on the presence of people at a certain location, the system provides a way to register a user's presence, by means of a switch in a web application accessible by scanning a QR code at the occupied table, or by covering the illuminance sensor on the desk with the hand.

In the web application, users can also set their preferences regarding the CCT control method (fixed or mimicking the sun's temperature variations) and provide textual feedback to the experimenters.

For further personalization of the task lighting, people can set their preferred WPI and CCT by interacting directly with the task light, which then acts to constantly keep the WPI over the set threshold and the CCT to the set value (in case of fixed CCT) or at the same ratio compared to the CCT of sunlight at any given time.

Procedure

Given the dependency to the general lighting affecting all users in the room, care is put in involving all occupants of the rooms under test. At SLL, two rooms are participating with 11 users and 1 user respectively. Given the different presence patterns, the study was not started simultaneously for each participant, but the functioning of the light control system was introduced gradually during a one-week period.

Each participant received a short introduction on how the system works and has access to the web application controlling the preferences through a QR code displayed on the system. Due to the changed office presence patterns with facilitated home office infrastructure, patterns of participants' presence of participants are very dynamic and individual.

All participants signed an informed consent form, all data is collected anonymously.

Materials

For the longitudinal studies only the following materials can be collected as we cannot expect users to follow strictly defined tasks or wear physiological recording apparatus for the whole study duration (between 6 to 15 weeks).

- user comfort subjective appreciation and automation perception (daily questionnaires, plus entry and exit questionnaires),
- lighting energy consumption (sample rate 5 minutes),
- WPI (sample rate 5 minutes),
- user interaction with the interface (each interaction logged).

Control system specific to longitudinal study @ Idiap

At Idiap, the same control system as the one of the SLL was employed. However, due to the building features, glare and overheating would represent an issue in this location. Therefore, in order to take advantage of the installed exterior blinds, an automatic blind control strategy presented in Section 3.4.1 was implemented, in addition to the system proposed for the SLL. This integration allows to maximize the amount of daylighting



while preventing visual discomfort (glare) and thermal discomfort (overheating of the room as a consequence of high solar radiation through the windows).

Procedure

The procedure is identical to the one used at SLL. while for the individual and open-space office, 7 and 1 users participated in the experiment respectively.

Materials

The collected data is identical to the SLL case study.



4 Results and discussion

4.1 Surrogate (day)lighting models

Amongst the tested Machine Learning surrogate models on the Idiap Research Institute's case study, it was observed, that the two 'tree-based learning algorithms', the 'Random Forest' (RF) and the 'Gradient Boosting Machine' (GBM), were the ones that achieved a highest accuracy prediction compared to the other models tested in this study. From those, the GBM achieved the highest degree of accuracy with both predictions of the performance indicators, WPI and DGP slightly below 100%. The 'RF' and 'multi-layer perceptron neural network' (MLP), both achieved an accuracy close to 100% for DGP and 97% and 96% respectively for WPI. In the case of the 'Linear model', the results for WPI were far below of what would be considered a good candidate; however, such a model may be suitable for the classification of glare comfort levels. For the GBM model, the discrepancies between the predictions and the true values were analysed in order to assess their meaningfulness for the objective of our application (blinds and electric lighting control). In the case of DGP, 6 out of 7884 predictions in the test set were misclassified, as illustrated in Figure 11.

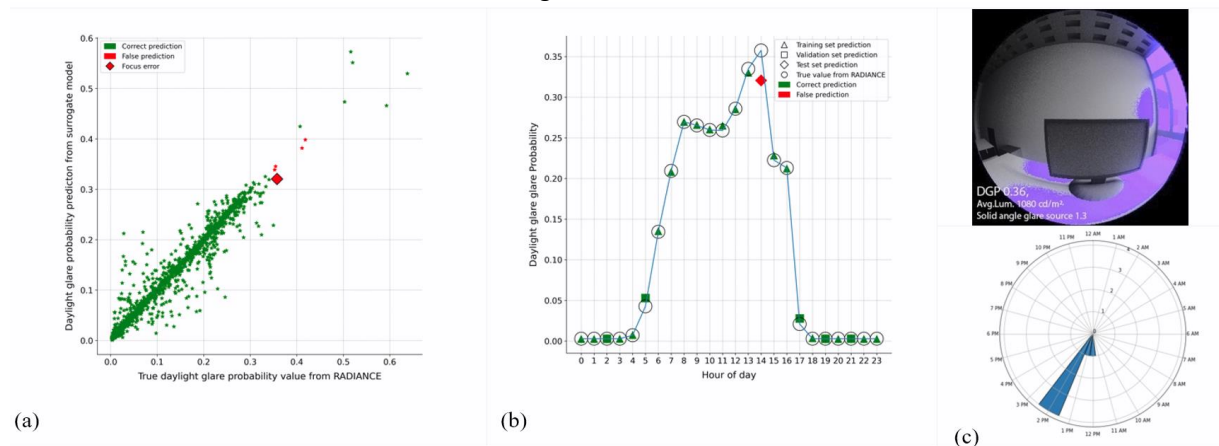


Figure 11: Scatter plot of ML model predictions against true values for glare probability (a), the false prediction highlighted in red displayed in a 24 hours' time-sequence (b). The HDR image illustrating the false prediction glare situation (c-above), and the histogram showing the frequency of the false DGP predictions (c-below).

First, the entire test set of ML model predictions vs the true values is shown in the segment 'a' of the graph, in which, a single false prediction is highlighted in red. The false prediction is then displayed in a 24 hours' time-sequence where the extent of the inaccuracy of 'prediction vs the true value' is shown in detail (segment 'b'). In this particular case, the graph illustrates in segment "c top" the glare situation on August 28th at 14:00 with the blinds in a retracted position. The HDR image shows the spread of the glare source from the occupant's point of view. For that specific time a DGP of 0.36 was obtained from the RADIANCE simulations, while the ML model resulted in an underpredicted value of 0.32. The colour in the picture illustrates the large extent of the glare source, which is due to the contrast between the window and the background area. The *evalglare* reports an average luminance of 1080 cd/m² and a solid angle of 1.3 sr, indicating a very large source of glare with a luminance of about 4 times the luminance of the computer screen. This situation may slightly be uncomfortable for the user according to the average population used in the study to build the DGP categories. However, depending on the individual, itself, it may be perfectly tolerated, showing the importance of a user feed-back loop in the automation to minimize the unwanted glary situations. The distribution and frequency of the DGP false predictions with respect to time is shown in the histogram (Fig. 7c-below). It shows, that all the false predictions occur in the afternoon from 12:00 to 14:00, while most of them take place at the latter hour, all showing an under prediction of the ML model vs the true value. This would signify that during those rare moments, the blinds would be kept in a retracted (fully open) position leading to a higher risk of glare for the average occupant.



The tested and chosen machine learning model for the CELLS was LightGBM, a lighter implementation of the GBM, to be integrated in the Raspberry Pi. The performance of the LightGBM was assessed by comparing the WPI model estimations with monitored data obtained for this specific purpose in two new sessions in Spring 2021. In such case, a MAE of 36 lx and MAPE of 19.28% was reported for module-R1, while 97 lx and 19.4% respectively, were reported for module-R2. An illustration of the discrepancies between the WPI model predictions and the true values is shown in Figure 12.

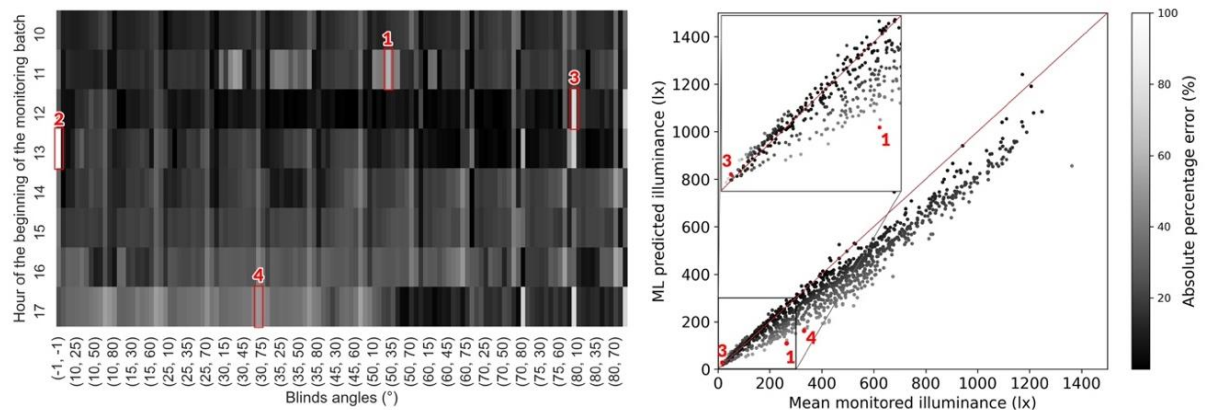


Figure 12: ML predictions against true values for WPI in module-R2, displayed in a heatmap (left) and scatter plot (right). Four false predictions are highlighted in red and numbered to be identified in the map according to time and blind setting. The combinations of North and South blind positions are indicated as x-axis in the heatmap (left).

The entire data set is shown as a heatmap (Figure 12 left), showing the absolute percentage error as a function of blinds positions and time of day. Interestingly, regular patterns for cases with increased errors appear, from which four selected situations are highlighted in red. In cases 1 and 4, which correspond to the relevant range of 300 lx for our application, an average underprediction of 54% by the ML model was observed, which would signify an overestimation of the electric lighting needs, resulting in less energy savings. In case 2, for a true value of 2730 lx the ML model overpredicts by 109%, while in case 3 for a true value below 20 lx, it overpredicts by 75%. In both cases 2 and 3, the errors are not impacting the outcomes of our algorithm regarding both the visual comfort and the required illuminance on the workplane.

A limited portion of the data set below 1500 lx is shown as a scatter plot (Figure 12 right), while the illuminance threshold representing the relevant range for our application (300 lx) is shown in a zoomed display. We notice that in both scatter plots, an underprediction of the ML model can be observed for close to 100% of the dataset analyzed in this study. The overpredictions on the relevant range, correspond to an average of 10 lx, which is negligible. The latter would signify a small increase on energy consumption, yet, not having an impact on visual comfort, as the requirements of the norms for minimum WPI can always be guaranteed.

The models for the SLL BlueHall present exactly the same kind of results but are much simpler due to the absence of blinds. Finally, for the EL predictor model, different polynomial models were tested as candidates, considering degrees 1 to 6. A polynomial regression model of degree 5 was selected as it achieved a good accuracy for all case-studies.

As a summary, two conference papers [1] and [2] were published on the surrogate model for daylighting, while the electric lighting one was just mentioned as too simplistic for scientific conferences. Moreover, a journal paper presenting all results for the single and shared offices at Idiap was also published in Solar Energy Advances [5].



4.2 Case studies results

4.2.1 Pilot study

Setup

All participants moved the three task lights, except one participant who moved only the task light C. The main reasons to move the luminaires were, according to participants' comments, to avoid glare or change light direction to illuminate the working area properly. Participants place luminaires in idiosyncratic ways, directing light toward or away from them, close or far from the paperwork (see Figure 13).

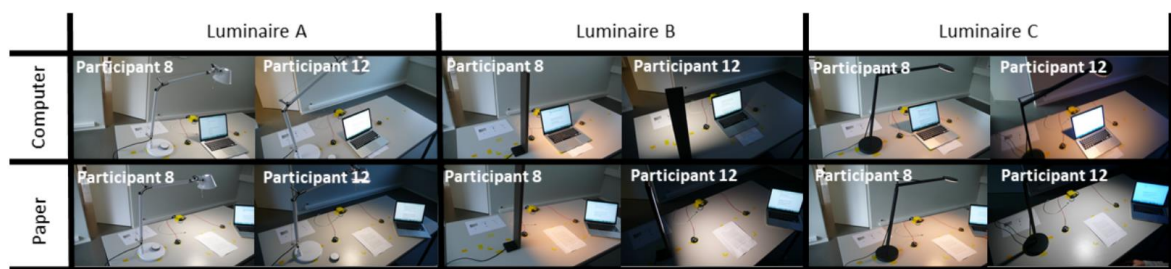


Figure 13: Pictures showing the position of each task light of two participants before either the computer or paper task.

Questionnaires

Every participant noticed the ability to control task lights' intensity with the three luminaires. However, the CCT control ability of task light C was not clear to participants as eleven participants did not have the impression they were able to change CCT. The interaction effect between task lights and the ability to change CCT revealed a significantly greater number of participants that did not perceive the change in CCT with luminaire C, whereas the two other luminaires exhibited a higher number of participants that perceived CCT changes (see Table 2).

Questions	Luminaire	Descriptives	Statistics	Comparison
Notice a change in (choice between yes, no and not sure):				
CCT	A	yes: n=12, no: n=1 not sure: n=0	$\chi^2(4) = 24.96, p < .001$	-
	B	yes: n=11, no: n=1 not sure: n=1		-
	C	yes: n=1, no: n=11 not sure: n=1		-
Ranking (scale from 1 the worst to 5 the best):				
Ease of use	A	$Mdn = 5.00, CI_{95} = [2.60, 5.00]$	$\chi^2_F(2) = 7.30, p = .026$	A vs B: p=.03
	B	$Mdn = 3.00, CI_{95} = [1.00, 5.00]$		A vs C: N.S.
	C	$Mdn = 4.00, CI_{95} = [2.00, 5.00]$		B vs C: N.S.
Ease of understanding	A	$Mdn = 5.00, CI_{95} = [4.00, 5.00]$	$\chi^2_F(2) = 13.41, p = .001$	A vs B: p=.008
	B	$Mdn = 2.00, CI_{95} = [1.00, 5.00]$		A vs C: N.S.
	C	$Mdn = 5.00, CI_{95} = [2.00, 5.00]$		B vs C: N.S.
Preference (choice)				
Luminaire	A	n=8	$\chi^2(2) = 7.15, p = .028$	-
	B	n=3		-
	C	n=2		-
Interface	Button	n=8	$\chi^2(2) = 7.15, p = .028$	-
	Application	n=3		-
	Not sure	n=2		-

Table 2: Pilot study questionnaire results

The task lights differed significantly in the rating of ease to use and understand to use with luminaire A having higher ratings than luminaire B, whereas the luminaire C did not differ significantly from the two others. There was no significant difference between task light rated comfort (see Table 2).

Regarding the light's ranking, there were no significant differences across preference, interface, working and comfort ranking.



There were significantly more participants preferring task light A over the two other task lights. Moreover, participants would rather interact with a task light through a button than an application (see Table 2).

Circumplex evaluation of emotion, object, and light

No significant differences were found between luminaires' emotional perception within the three circumplexes spaces.

Regarding the circumplexes analysis between the preferred and not-preferred luminaire, the circumplex for emotion revealed that only the preferred luminaire indicates a specific direction toward *pleasant*. Interestingly, in the circumplex for object, the preferred luminaire points toward *common*, whereas the not-preferred luminaire point between *common* and *artificial* and this difference was statistically significant (see Table 3 and Figure 14). Finally, regarding the circumplex for light, both preferred and not-preferred task lights indicated a common direction toward *relaxing*.

Circumplex type	Luminaire	Direction	Comparison of directions
Emotion	Preferred	toward pleasant ($S = 4.31, p = .011$)	Not Evaluated
	Not-preferred	Uniformly distributed	
Object	Preferred	toward common ($S = 9.97, p < .001$)	$P = 3.85, p = .049$
	Not-preferred	between common and artificial ($S = 3.49, p = .027$)	
Light	Preferred	toward relaxing ($S = 4.84, p = .006$)	N.S.
	Not-preferred	toward relaxing ($S = 5.45, p = .003$)	

Table 3: Pilot study results of Circumplexes method of affects

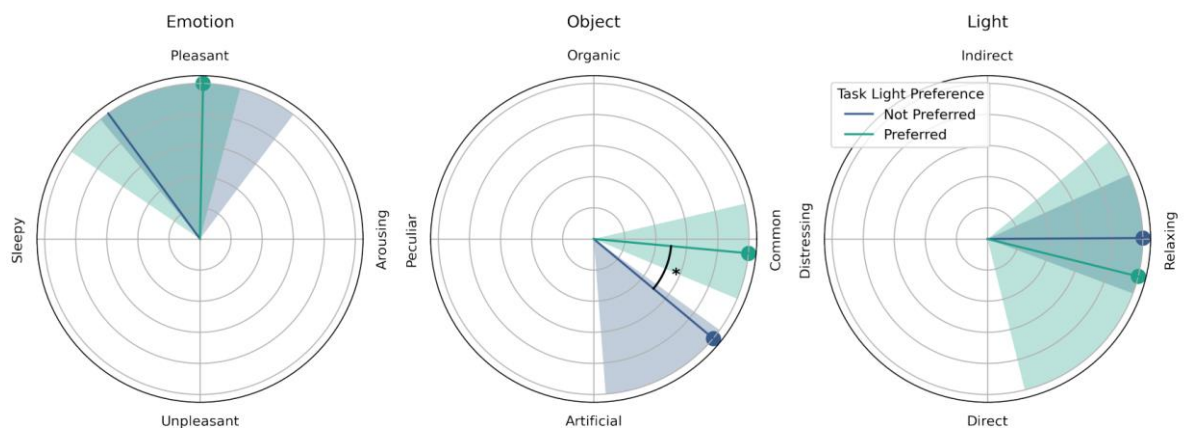


Figure 14: Pilot study results differences between preferred and not-preferred task lights within the three circumplexes space.

Light usage across luminaires and tasks

Results from Table 4 and Figure 15 reveal that both the luminaire and the task conditions impact significantly on the illuminance. The principal effect of the task light condition reveals that overall, the luminaire C was dispatching a significantly higher illuminance than the two other luminaires. Regarding the task condition, participants increased the illuminance significantly from the starting condition in both the paper and computer task. Interestingly, the illuminance set during the paper task was significantly higher than the computer task. Finally, the interaction effect indicates that the difference between starting illuminance, the computer, and the paper task were the biggest for luminaire C and the smallest for luminaire A (see Table 4 and Figure 15).



The luminaire and the task condition also impacted significantly on the CCT level. Specifically, post-hoc tests show that luminaire C was dispatching a significantly warmer light than luminaire A and B. Additionally, participants set a significantly warmer light than from the starting condition in both the paper and computer task. Finally, the interaction effect indicates that the difference between the starting condition and the computer and paper task differed more for luminaire C than the two other luminaires (see Table 4 and Figure 15).

	Condition	Descriptive		Effect		Post-hoc	
		M	SD	Principal	Interaction	Comparison	P-value
Lux	Luminaire	A	475.28	343.49	$F(1.13, 11.26) = 8.57$, $p = .012$, $\eta^2 = .10$	A vs B	N.S.
		B	613.31	441.69		A vs C	.002
		C	996.82	1203.62		B vs C	.021
	Task	Start	137.08	36.31	$F(1.34, 13.35) = 32.53$, $p < .001$, $\eta^2 = .39$	Start vs Paper	<.001
		Paper	1278.92	1023.46		Start vs Computer	.003
		Computer	669.41	439.11		Paper vs Computer	.001
CCT	Luminaire	A	4435.79	1080.21	$F(2, 20) = 10.27$, $p < .001$, $\eta^2 = .06$	A vs B	N.S.
		B	4449.92	987.12		A vs C	.004
		C	3861.77	1231.17		B vs C	.002
	Task	Start	5553.00	314.10	$F(4, 40) = 6.22$, $p < .001$, $\eta^2 = .03$	Start vs Paper	<.001
		Paper	3512.00	576.52		Start vs Computer	<.001
		Computer	3682.49	908.36		Paper vs Computer	N.S.

Table 4: Pilot study results of light usage across luminaires and task

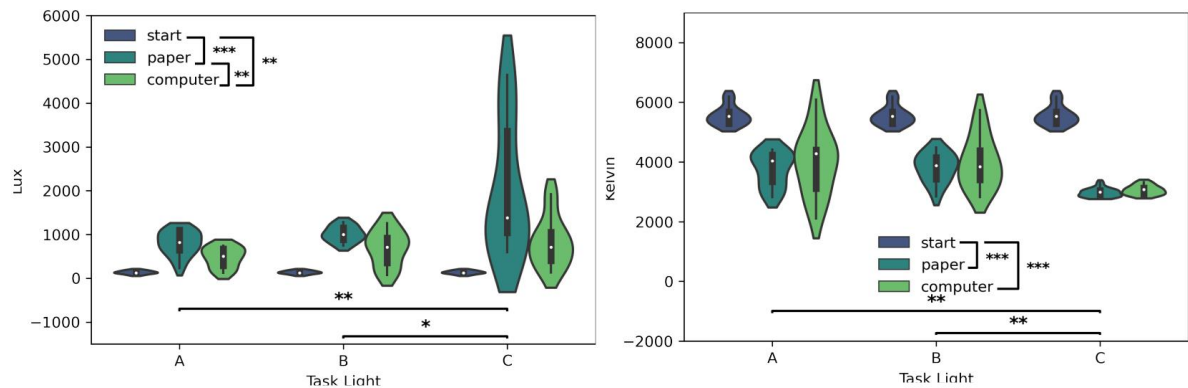


Figure 15: Pilot study results using violin plots of the color and illuminance levels within each task conditions and for each task light. Notes: * $p < .05$, ** $p < .01$ and *** $p < .001$.

The results of the pilot study show that users' preferences are very heterogeneous (Figure 16) and that they tend to prefer a luminaire that allows them to set these different preferences easily.

These results have been published at the CISBAT conference 2021 [3].

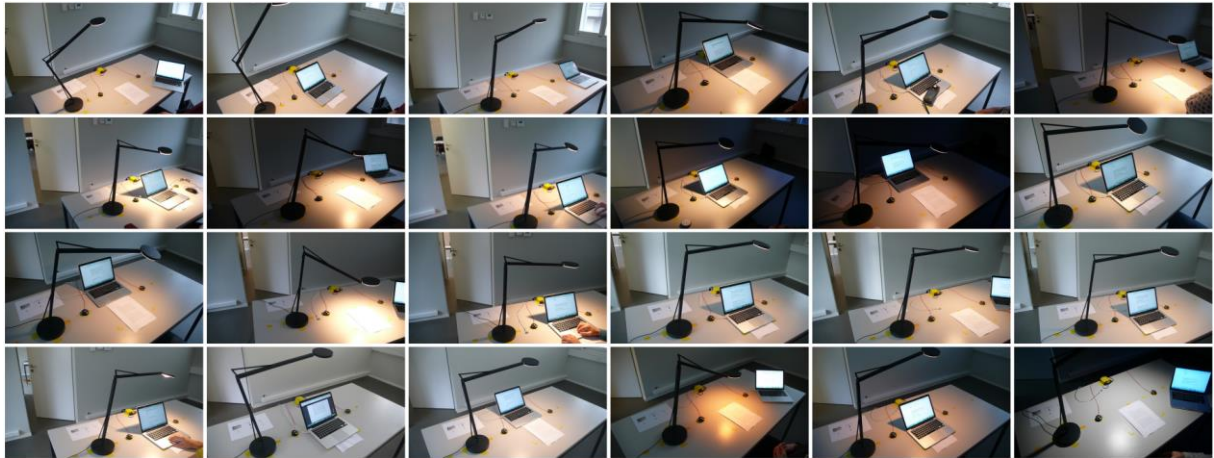


Figure 16: Different light conditions set up by the pilot study participants

4.2.2 Controlled study

Physical modelling

Virtual model calibration: on-site monitoring vs RADIANCE simulations. On-site monitored and simulated WPI were first compared to assess the representability of the existing situation by the virtual model. A resulting R^2 of 5260.96 was observed, while a MAE of 19 lx and MAPE of 24% were obtained for module in which the experiment was conducted.

Statistical modeling

ML model verification: ML predictions vs RADIANCE simulations. In order to evaluate the performance of the two statistical models on approximating the RADIANCE simulations on the specific case study, a set of unseen samples has to be used. For this reason, 5% of the data was set aside before training the models.

The WPI model achieved a MAE of 2.28 lx and a R^2 of 0.99, while the DGP model achieved a MAE of 0.00058 and a R^2 of 0.99. Furthermore, while situations of high DGP were not common in the considered setting, the DGP model achieved a MAE of 0.0021 and a R^2 of 0.96 on the subset of test samples with a ground truth value higher than 0.20. These results can be observed in Figure 17, where the distances between the models' predictions and the actual test values are presented. In general, the models' predictions are very close to the target values as simulated with RADIANCE. Few outliers can be seen in the plots, mainly in the WPI predictions for true values above 400 lx. Only in two cases, the predicted WPI is well below the actual values, which would lead the system to provide more light than needed. Despite causing an unnecessary increase in energy use, this behaviour is acceptable as it still guarantees the minimum required illuminance on the workplane. Out of the test samples where the target illuminance was between 200 and 400 lx, in 1.23% of the cases the model predicted a WPI of more than 300 lx when the ground truth was below this threshold. This subset of test samples is particularly relevant as 300 lx is the minimum value that needs to be guaranteed according to the current laws. In such cases, the mean absolute prediction error was 11 lx, with a peak of 111 lx. Concerning the DGP, an important threshold is at 0.35, which is the limit to guarantee visual comfort. While only few test cases were available with a target DGP around this value (43 samples where the simulated DGP was between 0.25 and 0.45), none of them was estimated by the model to be below the threshold when it was not.

ML model verification: on-site monitoring vs ML prediction. In order to assess the performance of the predictor model, the WPI results produced by the LightGBM model estimations were compared to on-site monitored data obtained during Spring 2021. As a result, a MAE of 36 lx and a MAPE of 19.28% were reported for module-R1.

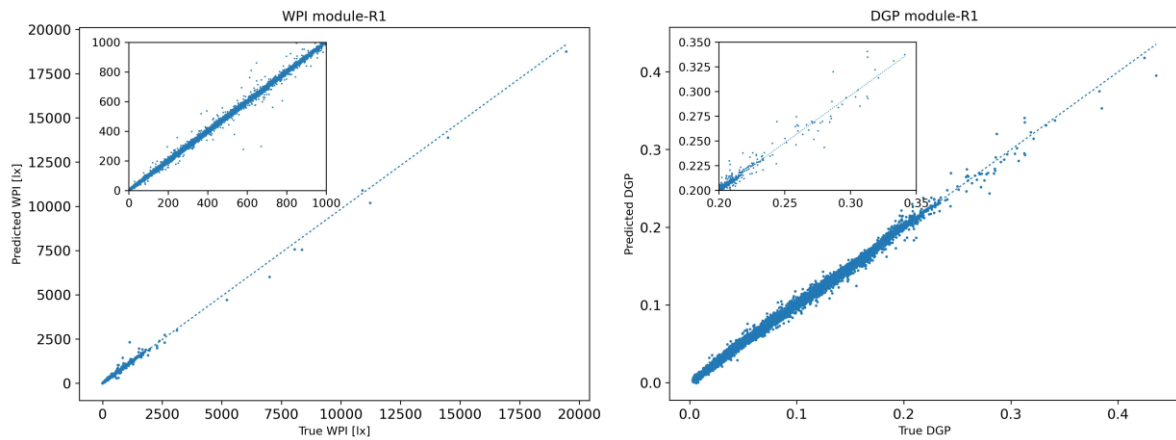


Figure 17: Scatterplots comparing the statistical models' predictions with the actual values on the test sets for module-R1: WPI (left, with a zoom in the range 0-1000 lx) and DGP (right, with a zoom in the range 0.20-0.35).

User Fatigue and Visual Comfort

The automation condition had no impact on the rating of the light. This was confirmed by Bayesian analysis showing decisive evidence for no effect ($BF_{10} < 1/100$). This suggests that the automation condition did not have an impact on light ratings. The blind condition reveals a significant impact on the rating of light, $\chi^2(2) = 19.79$, $p < .001$, $BF_{10} = 2.52$. Specifically, both blind opened elicited a better rating of lighting conditions ($M = 1.08$, $SD = 1.00$) than when north blind was closed ($M = 0.61$, $SD = 0.98$, $p < .001$) or when south blind was closed ($M = 0.87$, $SD = 1.14$, $p < .05$, see Figure 18). No interaction effect was found. In short, the condition with both opened blinds positively impacts light ratings, whereas the automation condition did not have any impact on ratings.

The automation did not have an impact on the reported fatigue with decisive evidence ($BF_{10} < 1/100$). Regarding the blind condition, it had no impact on the fatigue reported with decisive evidence ($BF_{10} < 1/100$) as illustrated in Figure 18. On overall, neither the automation nor the blind condition impact on the fatigue, preserving participants' arousal.

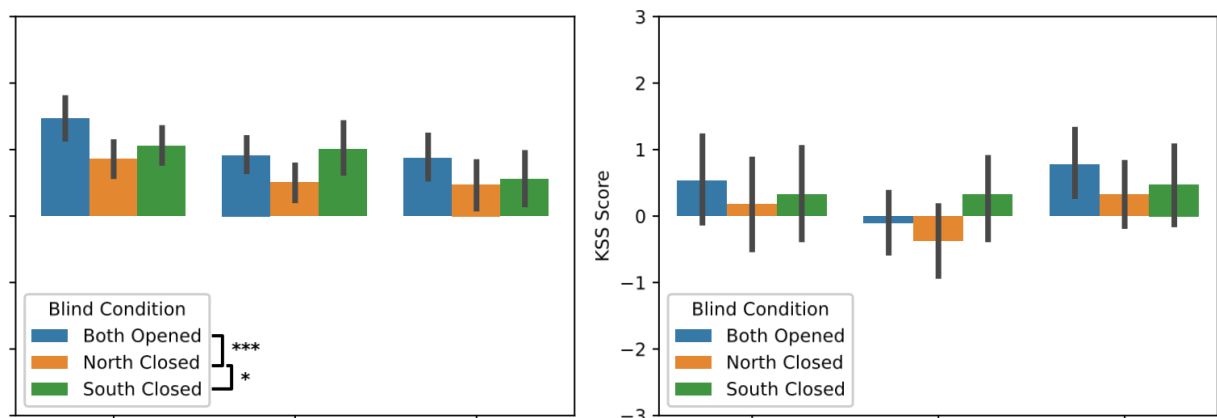


Figure 18: Violin plots depicting the impact of the automation condition and the blind condition on both OLS and KSS scales. On the left: the OLS averaged score evaluating comfortable lighting conditions, ranging from -3 (Strongly disagree) to 3 (Strongly agree). On the right, the KSS averaged score ranging from -4 (Extremely sleepy) to 4 (Extremely alert). The y axis was truncated to -3 and 3 for readability. Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.



User Performance

The blind conditions had a significant impact on the number of errors, $\chi^2(2) = 8.56$, $p < .05$. When the south blind was closed, participants made about 1 mistake less ($M = 10.58$, $SD = 6.64$) than when both blinds were closed ($M = 11.78$, $SD = 7.62$, $p < .05$). On the contrary, Bayes Factor indicated no effect with moderate evidence ($BF_{10} = 1/4$). The automation condition did not impact the performance in terms of number of errors with extreme evidence ($BF_{10} = 1/260$). Both conditions did not impact on the typing speed with substantial and decisive evidence ($BF_{10} = 1/4$ and $BF_{10} < 1/100$, respectively). In other words, the automated system or the blind configuration preserve overall the performance of participants, suggesting that participants managed to work efficiently with the proposed automation system.

Light

The automation had no impact on the amount of light. However, the Bayes factor revealed an effect of automation on the amount of light with decisive evidence ($BF_{10} > 100$). Suggesting, that the automated setup provided more light (1427.11 lux on average, $SD = 1639.06$) than the manual setup ($M = 823.79$, $SD = 1197.44$). Regarding the blind condition, it had a significant impact on the amount of light in the room ($\chi^2(2) = 8.77$, $p < .05$) with decisive evidence ($BF_{10} > 100$). More specifically, both blind closed eliciting a higher amount of light in the room ($M = 1328.98$, $SD = 1531.32$) than when the north blind was closed ($M = 952.91$, $SD = 1215.15$, $p < .05$) or when the south blind was closed ($M = 984.44$, $SD = 1308.75$, $p < .05$, see Figure 19). In summary, the blind condition allow more light to enter the room when both blinds were open. However, this possibility is a particularity of our test space that had two windows on each side of the working space. Importantly, while the automation did not impact on the amount of light, the automated setup provided with twice as much light than the manual setup.

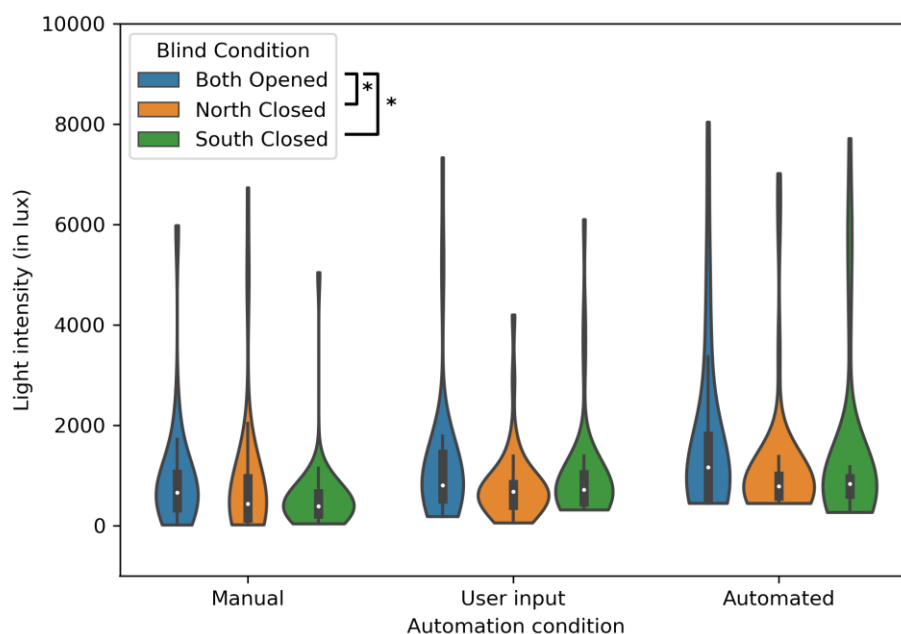


Figure 19: Violin plots depicting the impact of the automation condition and the blind condition on the quantity of light. Note: *: $p < .05$



Energy consumption

The automated and the user input setup consume more energy for task light ($\chi^2(2) = 6.24, p < .01$), and less energy for the general lighting ($\chi^2(2) = 8.13, p < .001$) than the manual setup. More particularly, the manual conditions consumed less task light energy (about 2.00 Wh on average, $SD = 2.08$) than user input setup ($M = 5.07, SD = 3.81, p < .01$); but consumed more energy from the general lighting ($M = 48.21, SD = 61.95$) than automated ($M = 6.14, SD = 11.87, p < .01$) and than user input setup ($M = 7.79, SD = 14.57, p < .01$). An example of the general lighting intensity control with automated and manual modes is depicted in Figure 20, where a higher general lighting energy consumption for the manual control, due to the fact that the high majority of users set the desired intensity at the beginning of the experiment and did not change it, despite the changes in external lighting conditions.

The automation condition did not reveal any significant impact on the energy consumption of the raspberry pi with strong evidence ($BF_{10} = 1/20$). Altogether, the automation significantly decreased the total energy demand ($\chi^2(2) = 6.67, p < .01$) with substantial evidence ($BF_{10} = 9$). More specifically, the manual setup had a higher energy demand ($M = 53.72, SD = 63.50$) than both the user input automation ($M = 16.37, SD = 17.27, p < .01$) and the automated setup ($M = 13.61, SD = 13.57, p < .01$), with this last condition saving the most energy for lighting. Overall, the automated setup saved on average about 63440.11 Wh and the user input saved 37.35 Wh (see Figure 20). Following the Swiss SIA 2024:2015 Norm, an open space office in an energy efficient design should target 1290 hours of lighting on. For a 60 minutes-long experiment and a 20.12 m² room area, 40 Wh extrapolates to an annual reduction of 63851.6 kWh or 2.56 kWh/m². This reduction is valid for a single workplace (in the experiment) in a room where at least 4 workplaces can take place, adding up the savings through the possibility of sharing general lighting.

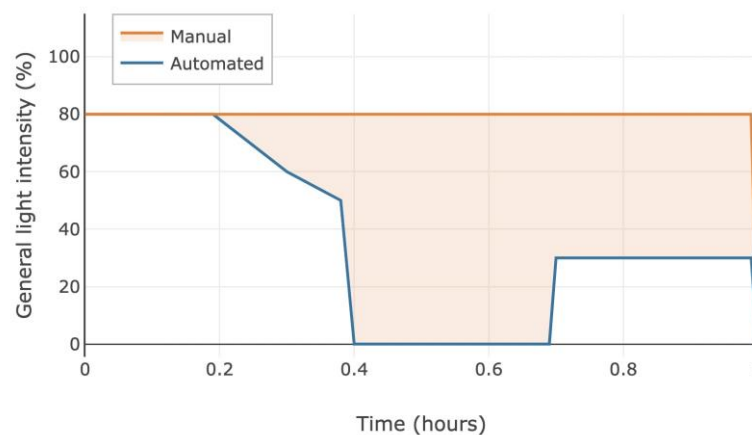


Figure 20: Example of general lighting intensity with different controls during the experiment. In this example, the experiment started with no daylight. Any change in the daylight availability was compensated by the automated control. In the manual control, participants were observed to set the general lighting at the beginning of the experiment and not modify it until the end. This caused an energy consumption overhead in the automatic mode, shown by the difference between the two curves. User input automation corresponds to the automated curve, as the general lighting threshold is fixed.

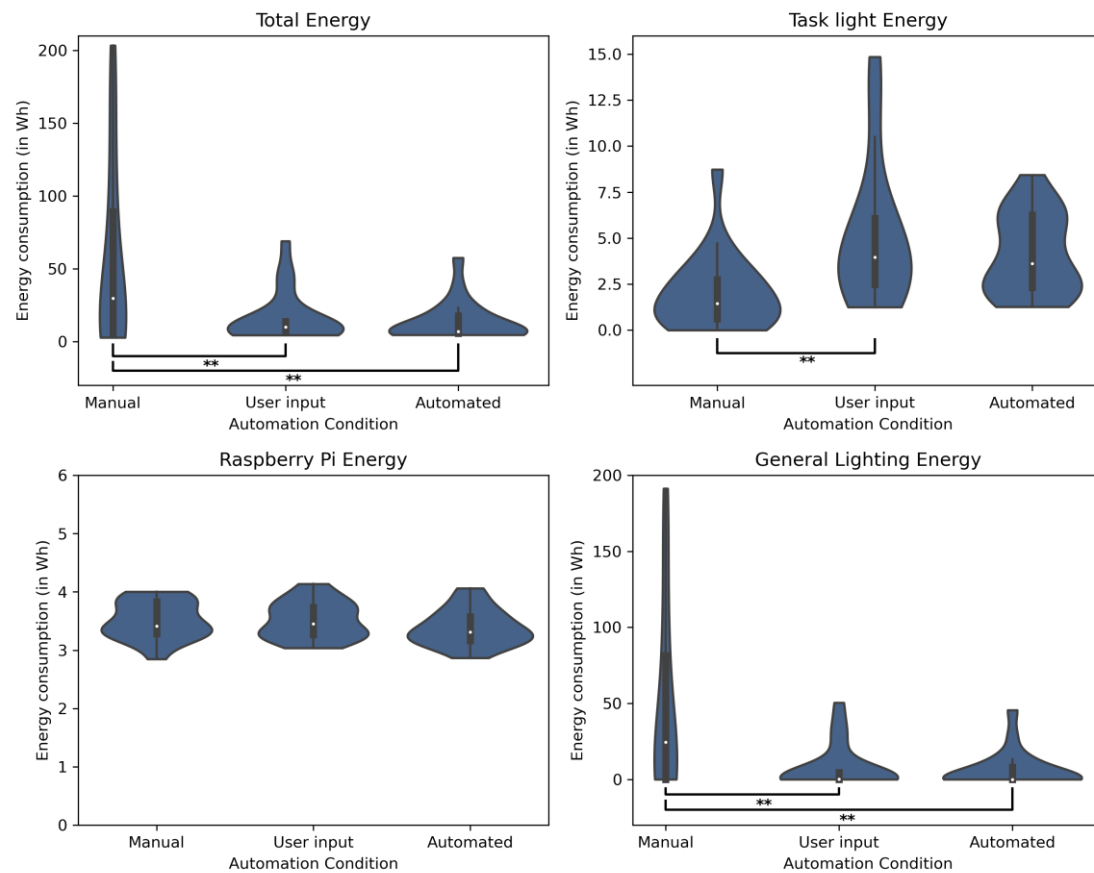


Figure 21: Violin plots depicting the impact of the automation condition and the blind condition on energy consumption. The total energy consumption, the energy used for the task light, the general lighting and the raspberry pi used for the automation are depicted. Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.

Circumplexes for emotion, light and object

The circumplex for emotion did not reveal any direction from the automation condition, indicating that the emotion was too uniformly distributed around the circumplex for each automation setup. Regarding the circumplex for emotion, the blind condition did not reveal any direction. Regarding the circumplex for light, the automation revealed a direction for all setup: automated and manual setups indicated a direction between relaxing and indirect ($S = 15.21$, $p < .001$ and $S = 4.99$, $p < .01$, respectively), whereas the user setup indicated a direction close to indirect ($S = 3.18$, $p < .05$). For the blind condition, the circumplex for light revealed that both opened blinds and north closed indicated the same direction between relaxing and indirect ($S = 13.22$, $p < .001$ and $S = 4.88$, $p < .01$, respectively), whereas when the south blind was closed the light was felt as more indirect ($S = 3.06$, $p < .05$).

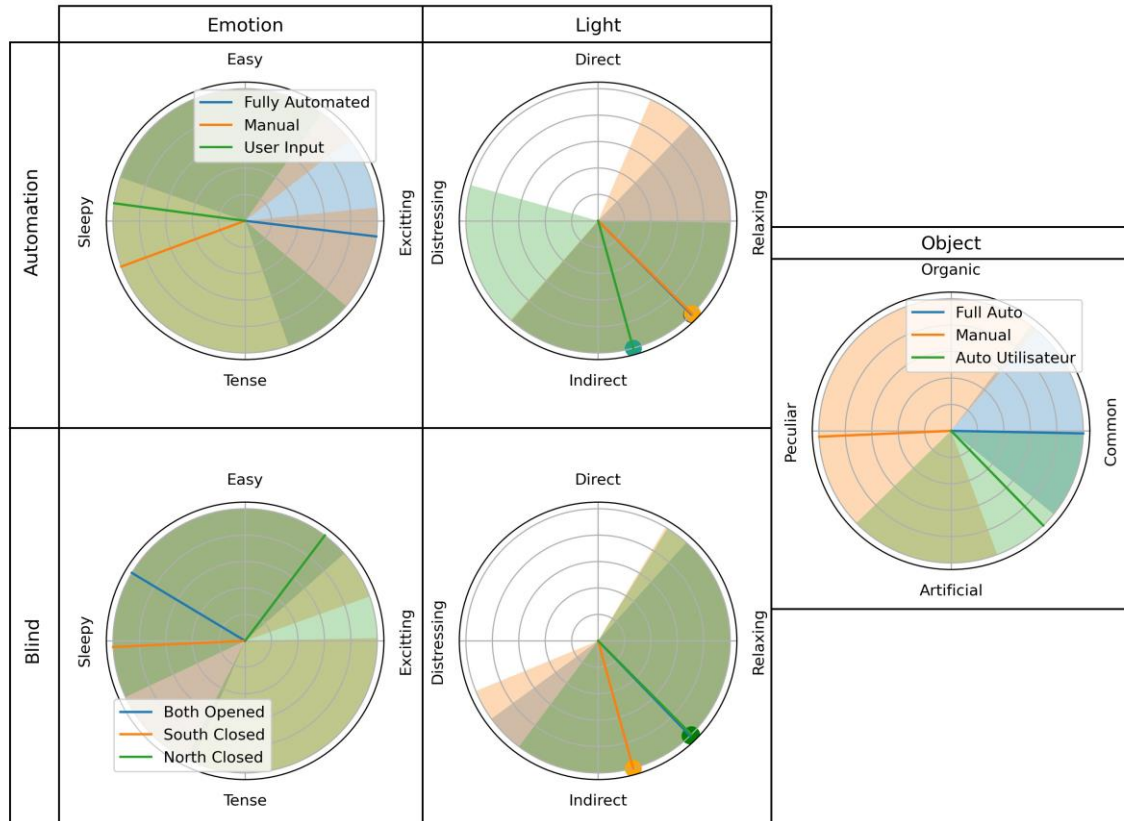


Figure 22: Circumplexes for emotion light and object. Columns represent the type of circumplex and row the condition (either automation or blind). The rightmost circumplex is the circumplex for objects and was evaluated for the automation condition only. A filled circle represents a significant direction spotted by the Rayleigh test. When there is nothing at the end of the line, the distribution was found to be uniform around the circumplex. The shaded areas represent the 95% confidence interval of the identified direction.

Automation Acceptance

For clarity, Table 5 reports all the significant results from the acceptance questionnaire. In short, the manual setup was evaluated as letting participants have more control, was perceived as more reliable and compatible with persons' life as compared to both user input and automated setup. There was no difference across automation conditions regarding, the usefulness, the attitude, the intention to use and the trust toward the systems.



Table 5: Results from the acceptance questionnaire.

		Mean (SD)	F value (df=(2,57))	p-value	BF ₁₀	Post Hoc tests (Tukey's correction)
Control	Manual:	1.62 (0.85)	1.62 (0.85)	<.01	12	Manual-Automated <.01
	User input:	0.72 (1.11)				
	Automated:	0.10 (1.75)				
System Reliability	Manual:	1.53 (1.06)	5.72	<.01	4	Manual-User input: <.01 Manual-Automated: <.05
	User input:	0.43 (1.08)				
	Automated:	0.68 (1.10)				
Compatibility	Manual:	1.70 (0.92)	9.26	<.001	77	Manual-User input: <.01 Manual-Automated: <.01
	User input:	0.33 (1.19)				
	Automated:	0.36 (1.29)				
Ease to Use	Manual:	2.12 (0.50)	3.63	<.05	1/2	Manual-Automated: <.05
	User input:	1.57 (0.88)				
	Automated:	1.42 (1.11)				

Note: ns: not significant

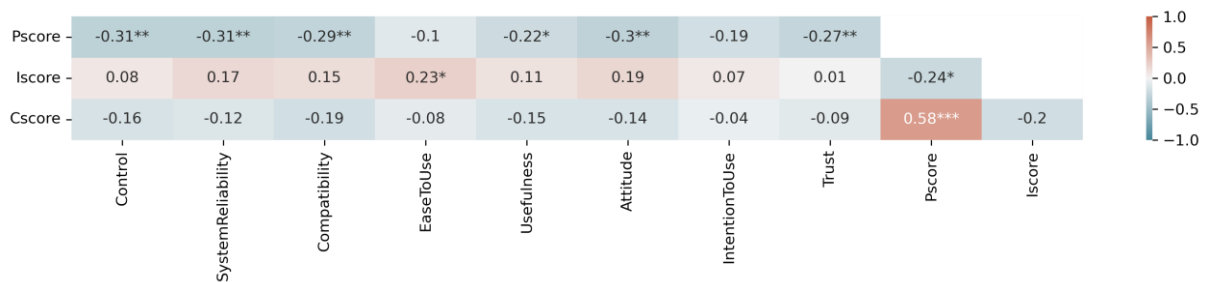


Figure 23: Heatmap exhibiting the correlation between the locus of control constructs and acceptance constructs (see the appendix in Section 6 for more information about the items used for each construct). Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.

As Figure 23 shows, overall, acceptance constructs were mainly related to powerful others construct. This was the case for control, system reliability, compatibility, usefulness, attitude and trust that had a significant negative correlation with the powerful others' score. On the opposite, the ease to use construct increases with the internal attribution ($r = .23$, $p < .05$). The intention to use the system was not related to the locus of control.

Interestingly, separating automation conditions revealed that compatibility had a strong negative and significant correlation with the powerful others construct. In contrast, other acceptance construct did not have any link with the locus of control. The user input setup revealed that the powerful others construct correlated negatively and significantly with the perceived control, system reliability, ease to use and attitude towards the user input system. Finally, the manual setup did not reveal any link with the locus of control.

These results have been published in [4].

4.2.3 Longitudinal study

Energy consumption @Idiap

The reduction in general light illuminance (150 lx vs 300 lx) was compensated by the task light. Moreover, a larger provision of daylight signified a diminished use of the general light, which was compensated with task lighting. Those insights were confirmed by a descriptive analysis of the aggregation of all sources of light in Figure 25. In general, we observed a compensation of the reduction of general light by task light. Moreover, the different provision of daylight between the weeks at 150 lx and the weeks at 300 lx were compensated by task lighting as particularly exhibited in the room #103 at 150 lx with almost no general light (see Figure 25 middle graph).

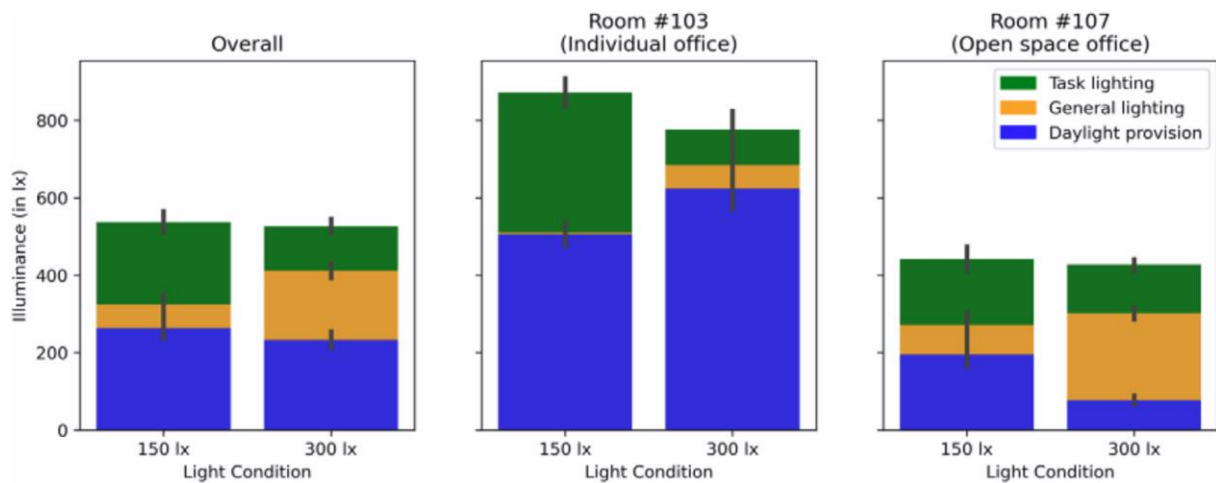


Figure 25: Stacked bar plot representing the light compensation from daylight and electrical lighting changing according to light condition. From left to right: overall, office #103, office #107. Black lines represent the 95% confidence intervals

Over the course of the experiment, the two offices consumed together 59.90 Wh in the 150 lx light condition and 92.86 Wh in the 300 lx light condition. The reduction of the intensity of the general lighting, signified energy savings of 32.96 Wh over the experiment's period, hence 35.45%. When considering the usual operation of the building before the implementation of the control system (general light at 100%, during occupied hours), the consumption would have averaged to 182.24 Wh, which represents energy savings of:

- 122.34 Wh or 67.13% at 150 lx,
- 89.38 Wh or 49.05% at 300 lx.

The latter, represent a double achievement, by the reduction of the energy consumption without disrupting the occupant's comfort.

Number of CCT scheme selection

Most participants operated at least one CCT scheme selection during the experiment (11 of 14 participants representing 78.57%). One participant alternated between both schemes and switched, after one week, from dynCCT to fixCCT. A more frequent selection of the dynCCT was found in both buildings, with the dynCCT being selected over the fixCCT equally often in the two buildings (65.83% and 67.50% of the time, respectively). Interestingly, occupants of individual offices selected exclusively dynCCT and occupants in open-space offices switched hence more often to a fixCCT (40.91% of the time) than individual office users (see Table 6). Indeed, the difference was of 7.41 on average, and the null difference was outside the highest density intervals ($HDI=[2.02,13.85]$), indicating statistical significance.

Table 6. Number of scheme selections for each building and office type

	Idiap		SLL Blue Hall	
	Individual	Open-space	Individual	Open-space
fixCCT	0	13	0	41
dynCCT	5	22	23	56



CCT of the different schemes during the day

Overall, dynCCT produced a significantly whiter light, with an average CCT of 714.98 K more than fixCCT (HDI=[618.72,808.71]). Figure 23 shows that the significant difference in Kelvin between dynCCT and fixCCT occurred from 9 am to 3 pm, with the dynCCT providing a whiter light than the fixCCT, and in the afternoon from 5 pm to 7 pm, with the fixCCT providing a whiter CCT. The highest significant difference occurred at noon, with dynCCT delivering an average CCT of 1854.53 K whiter than fixCCT (HDI=[1651.44,2083.15]). There were no differences at 4 pm and in the evening from 8 pm. While dynCCT constrained the occupants' CCT choice within a limited range of values depending on the hour of the day (see the shaded area in Figure 26), fixCCT allowed occupants to set CCT more freely within a range from 2690 to 6470 K during the day. This freedom exhibits an interesting pattern along the day, as shown in Figure 23 below. A crucial observation is that occupants in the fixCCT scheme were unable to adjust the CCT according to the time of day as effectively as with the dynCCT. Furthermore, they often chose a CCT that could potentially disrupt their circadian rhythms. Specifically, in the morning, occupants tended to select a warmer CCT than the average (~3600 K). In the evening, they frequently opted for a cooler CCT until both the dynCCT and the fixCCT appeared to have similar light color in the late evening.

Link between CCT scheme and both personality and acceptance

To determine whether there was a relationship between personality traits and the selection of the CCT scheme, a Bayesian linear mixed model was used. This model employed a distribution of the Bernoulli family and included all the personality sub-scales as regressors. Specifically, the OCEAN personality sub-scales, the locus of control sub-scales, and the chronotype sub-scales were analyzed. The results of the analysis showed that all of the sub-scales included zero in their HDI, indicating that personality traits did not have a significant effect on the selection of the CCT scheme.

However, the selected CCT scheme played a significant role in the acceptance of the automated system. Specifically, the dynCCT was associated with higher acceptance rates in seven out of eight sub-scales of the acceptance scale. Selecting dynCCT decreased the "compatibility with occupants' life" sub-scale of the acceptance scale, which comprises three items (refer to Appendix A of [10] for more details on items of sub-scales). The impact of the building where the user study was executed on the level of acceptance of the system was mixed, with Idiap building increasing acceptance in two sub-scales, and Blue Hall building increasing acceptance in three sub-scales. Furthermore, working in an open-space office was found to increase acceptance in five out of eight sub-scales. In summary, the acceptance level of the automated system was significantly influenced by the CCT scheme and the type of office, whereas the impact of the building was comparatively minor.

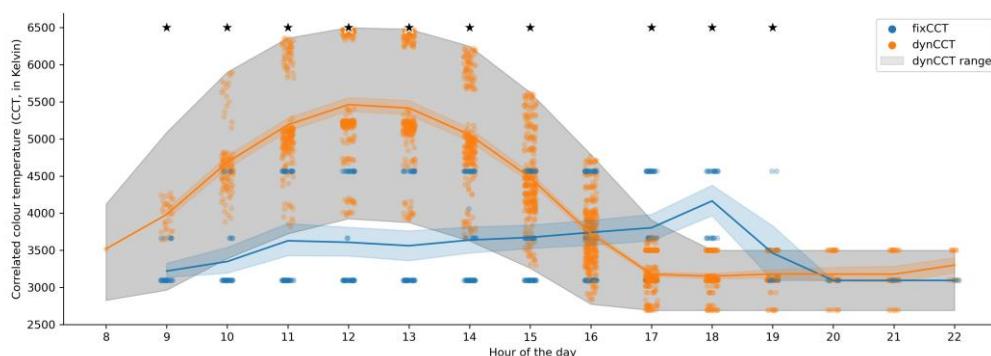


Figure 26. Correlated colour of temperature across the hours of the day for fixed CCT and dynamic CCT. The dots represent a record of CCT and the solid line represent the average with a coloured shaded area representing the 95% confidence intervals. The gray shaded area indicates the range of possible values for the dynamic CCT. Note: The stars highlight significant differences.



Visual comfort provided by CCT schemes

Possibly due to different architectural qualities, the visual environment was significantly more comfortable during both sunny ($M=1.21$, $HDI=[0.54, 1.84]$) and cloudy ($M=1.10$, $HDI=[0.38, 1.80]$) conditions in Idiap building than in Blue Hall. In open-space offices, the appreciation of light homogeneity was significantly lower compared to individual offices ($M=-3.21$, $HDI=[-3.92, -2.49]$). Regarding the CCT scheme, occupants using fixCCT reported higher comfort than occupants with dynCCT during sunny days ($M=2.97$, $HDI=[2.21, 3.68]$) and cloudy days ($M=3.20$, $HDI=[2.45, 3.99]$). Moreover, fixCCT users also reported a higher homogeneity of the lighting ($M=3.20$, $HDI=[2.66, 3.78]$). This observation aligns with the fact that fixCCT remained constant throughout the day.

SLL longitudinal study results

The data collected from the 12 participants to the longitudinal study in the SLL has not yet been analyzed extensively, as the priority was given to the analysis of the Idiap data, which allowed to provide more direct results.

The results from the SLL longitudinal study will be presented in a future publication, which will focus on the analysis of the reduction in energy consumption obtained by implementing the presented intelligent lighting control strategy with different thresholds (150 lux and 300 lux), compared to the traditional automatic lighting control strategy implemented in the SLL rooms, using recorded data. Additionally, the perceptions of the occupants in terms of visual and thermal comfort and acceptance of the proposed system will be examined.



4.3 Discussion

4.3.1 Control system

The energy gains reported here are reachable specifically through joint control of systems that are typically disjointed in current planning practices, e.g. blinds and desktop luminaires. In terms of industrial applications, the process described is built on several requirements:

1. The parametrization of the ML surrogate models requires availability of data mapping outdoor sky conditions to inside KPI values. This data was produced with calibrated simulation models, whose development requires expert knowledge.
2. The control algorithm requires accurate real-time outdoor sky condition data, that are currently only produced with high price range, high quality sensors.
3. The building's general lighting and blind infrastructure needs to be digitally controllable, which is not necessarily the case, even in new or recently retrofitted infrastructure. Furthermore, with actual A/C motors, the control of the tilt angle of the blinds is based on a timing of the motor's rotation, which lead to some inaccuracies in the tilt position that our system had to cope with. An interesting improved would be the use of D/C stepper motors with which we could control precisely the tilt angle.
4. Desktop luminaires also need to be digitally controllable, while at the same time offering proximal and haptic user control.

These requirements are not often to be found in current installations. However, the questions of controllability (4) and availability of high quality sensing data (2) appear solvable and represent more a question of integrating such requirements in the lighting planing process, or in the luminaire design process. The parametrization of the surrogate models instead can be more problematic, as it requires accurate surroundings, building and space information, as well as dedicated expert knowledge. It remains an open question how easily this can be implemented in practice and if less accurate models are able to deliver similar energy and comfort performance.

4.3.2 Usage of illuminance levels and CCT

Pilot Study

The results of the pilot study show that users' preferences are very heterogeneous (Figure 16) and that they tend to prefer a luminaire that allows them to set these different preferences easily. Previous findings regarding the difference of needs in terms of WPI when working on a computer were confirmed. These results emphasize the role of the luminaire's form factor, interface and lighting control characteristics, providing general recommendations on luminaire design.

This pilot study allowed to define and test a methodology to assess emotions towards lighting using the circumplex method of affects. This approach applied to desktop luminaires allowed to capture the preferences of users for a pleasant, relaxing light, emitted by a common object, instead of a peculiar one.

The pilot experiment has shown significant interest from users for the possibility to set illuminance and CCT levels on a local basis. In the longitudinal studies, the experimental condition that explicitly lowered general lighting triggered local compensation by users, without creating notable discomfort.

On the dimension of light CCT, users mentioned the added value provided by a luminaire allowing complete control over it. On the other hand, limited user intervention on the CCT happened during experiments. The default condition, which dynamically changed CCT according to time of day, was generally accepted. In other words, the automatic system apparently managed to select the same level of CCT that people would have selected. The correlation of lower illuminance levels with warmer light was the only effect unveiled up to now by the experiments. Further analysis needs to be done on this topic, which will be published in the coming months.



This interest of users for local control of both illuminance and CCT requires appropriate interface modalities, which have been solved differently by desktop luminaires manufacturers. Typically the use of smart phone applications appears to be a trend, probably for its development costs. However, users tend to loose interest in using apps and value haptic and simple interfaces, which should be at least included for future designs.

Controlled study

Results of the controlled study show that the system, while requiring a greater amount of task light energy, reduced general lighting energy. On overall, the total energy demand was greater in the manual setup as compared to when the system was operating the blinds, the general lighting and the task light. The magnitude of energy saving was 37 Wh during the one and a half hour experiment (taking into account the model processing energy), which resulted in a 68% energy saving compared to the manual control [4]. Although being preliminary and relevant to the specific conditions of the controlled study, such results are very promising in terms of lighting automation design.

There was no impacts of the blinds' position and the automation on the CCT level, which means that as compared to the fully automated system, participants did not select a different CCT level than the automation no matter the blind conditions. In other words, our automation was able to adapt the CCT level within the participant range of preferences, or at least not outside enough to trigger reaction.

Longitudinal study

The comparison of energy usage during the experiment leads to a decrease of consumption of 67% (150 lux condition) and 49% (300 lux condition) compared to the baseline which implies always on general lighting when users are present. According to the occupants, the visual and thermal environment was maintained within a comfortable range, while the uniformity of the interior lighting distribution was given a rather positive impression, regardless of the condition assessed.

In this experiment, the room (individual vs. collective office) and the indoor light level (150 lx vs. 300 lx) had a significant impact on the level of CCT. In particular, in the individual room, users set the CCT higher (~5000 K) than in the collective room (~4800 K). Regarding the level of light, a low light required a warmer CCT (~4500 K) and a light at 300 lx a cooler CCT (~5000 K). However, in terms of visual comfort there is no difference in any condition. We can therefore conclude that the CCT is chosen differently depending on the room and the amount of light without having an impact on visual comfort.

In a more detailed analysis, the two participants chose a different level (about 4500 K and 5000 K). There was no significant differences in terms of perceived visual comfort. It should be noted, however, that the Bayes Factor (comprised between 0 and 3) does not clearly indicate a lack of difference. It can be concluded that the CCT depends on the participants' preferences, but that they manage to achieve sufficient comfort.

Although the type of room seems to impact on the level of CCT selected, the position of the blinds does not seem to impact it. Furthermore, it can be concluded that CCT is a subjective choice and is highly dependent on the amount of light inside (warm and low light and strong and cold light).

Overall, our results revealed that the dynCCT was more frequently selected no matter the building or type of office. While the dynCCT delivered a physiologically adequate light colour throughout the day, especially in the morning and evening, it was perceived as less comfortable and homogeneous than fixCCT. Still, choosing the dynCCT improved the acceptance of the proposed automatic lighting system. Crucially, we demonstrated how light settings could interfere with the relationship between personality and acceptance of an automated system.

One hypothesis possibly explaining the different scheme choices in individual and shared offices may be related to potential coworker disturbance. In open-space offices, occupants may have been more likely to select the fixCCT option because their selection of dynCCT could have affected their coworkers' visual conditions. On the



other hand, occupants in individual offices may have felt more comfortable experimenting with the system since they were not concerned about disturbing or drawing attention to themselves. This may explain why no fixCCT selections were made in individual offices, while more interactions involving the fixCCT were observed in open-space offices.

An interesting pattern appeared when fixCCT was in use. Occupants coming early morning set a warm CCT using fixCCT, whereas occupants using the fixCCT and staying late set a cold CCT. Although those patterns seem more comfortable, as self-reported by occupants, such warm CCT in the morning might decrease arousal, respectively the cold CCT in the evening might maintain high arousal. While high arousal might be desired to work in the evening, it could be detrimental to sleep and circadian rhythms, as mentioned in the introduction. Dynamic control over the CCT might thus be more suitable for delivering adequate light when required, although having been reported by participants as less comfortable than the fixCCT.

The increased overall acceptance of the automated lighting optimization system reported by participants mainly using the dynCCT scheme might be related to the fact that the changes in the CCT with this pattern serve as an additional visual cue of the running system and provide an impression of control.

Psychological aspects measured in this study did not impact the CCT scheme selection. However, in the present study and a previous one [11], personality was found to relate to acceptance. As the CCT scheme also relates to acceptance, a more complex situation than both CCT schemes and personality traits increasing acceptance might be underlying. To control for this, analyses of the possible mediation of the CCT scheme on relationships between personality sub-scales and acceptance sub-scales were conducted, disclosing the significant mediation of the CCT scheme. Importantly, this implies that environmental factors such as the CCT of daylight could interact with the relationship between psychological aspects or ratings. This highlights the importance of firmly controlling or/and measuring such characteristics in user experiments within an uncontrolled built environment. Future studies should evaluate more precisely how psychological aspects and acceptance of automated systems relate to CCT.

To conclude, we shed some light on the impact of the HCL CCT scheme on visual comfort and their role with personality in the acceptance of an automated system. We highlighted the need to conduct controlled user experiments and to use appropriate statistical methods. This methodology allowed us to discover that, to improve the acceptance of an automated lighting system, and thus the commitment of people to use an energy-efficient automated lighting strategy, the role of CCT is fundamental. More precisely, it is suggested to have dynamic control of the CCT on the desk level to improve the acceptance of the system. This finding remains valid, even if the specific tunable dynamic scheme proposed in this study based on observations of HCL related to the circadian rhythm of people - was considered less comfortable than the fixed CCT scheme. Finally, we emphasize the need for further study on the relationship between CCT and the psychological aspects of building occupants, as the demonstrated impact of CCT does not appear to be mirrored in the number of scientific publications addressing this question.

Further details can be found in [5] and [6].

4.3.3 Findings relevant to lighting industry

The automation of providing sufficient light intensity on the work-plane without causing glare resulted in a reduction of energy usage. This is realised by balancing the operation of daylight, general light and task light through the automated system in an optimal way. In terms of operational relevance, this reduction of energy usage supports the building operator in saving money and fulfilling his environmental goals. Further on, the automation system provides a greater amount of daylight without glare as if the user is operating the blinds manually. This gives the building occupants the comfort of better lighting conditions.

The strategies for potentially reaching those values were twofold. On the one hand to use a machine learning system which is controlling the window shades considering the local sun and weather situation on each specific site. On the other hand, to incorporate a specific new task luminaire. The first strategy involves limited manual investment in the commissioning phase, provided the machine learning step can be to a certain extent automated and the preparation of the virtual model of the space simplified. This would be the subject of



further research both on the simplification of the commissioning phase using simplified virtual models of the space and generalisable machine learning models.

The second strategy, the use of a specific task luminaire provides added degrees of freedom, enabling occupants to personalise their environment by controlling locally the horizontal illuminance level both in light intensity and light spectra with variable colour temperatures between 2700 and 6500 K.

The task luminaire is mobile on the table and can be adapted to personal preferences regarding its position and light direction, and thanks to its visible but glare-free light-emitting surface, the user may potentially experience the colour of light in an even more emotional way. These attributes bear the potential to address the identified problem of lower user acceptance caused by a lower feeling of control, allowing the building operator to partially compensate for the disadvantage in occupants' satisfaction caused by the automated system.

Through further validation of these strategies, resulting in highly tailored but lighting situations during the user input automation, a higher value for the market could be created, leading to higher visual comfort, better mood, and higher acceptance of automated light situations. Thus, ensuring lower operational energy consumption and at the same time providing a highly personal light quality for the users. Creating a better-balanced solution with higher overall value, fulfilling the needs of the user and the building operator in a holistic way.

With regards to the feasibility of transferring the present method to different building situations, some considerations have to be made. The use of ML models as alternative for daylight prediction in buildings, implies the creation of an extensive database for the training of the surrogate model, representing an important investment in terms of time and computing resources. The method presented here to create such database involves a lengthy preliminary work in order to characterize the building's features in a virtual model, making the application of the present method, impractical for the prediction of daylight in highly complex and large environments. Furthermore, a considerable number of simulations need to be carried out in order to take into account the evolution of daylight conditions over the entire year. This number can significantly grow if the considered room has multiple windows that can be controlled separately, as the contribution of each window has to be modeled separately. However, certain steps of the method presented here can be simplified or automatized, reducing the manual workload needed to generate the necessary data. For instance, the simulation process can be automatized by means of scripting, for which only few initial steps for the creation of the scene descriptive files would be required. In addition, certain building features can be standardized in the virtual model, such as geometric shapes and dimensions, as well as including a selection of typical windows and interior materials. This would greatly reduce the time needed to prepare the virtual model, which is the step that requires most manual work.

Finally, it is also worth mentioning that the energy savings for lighting can be extended to the energy savings for heating and cooling. In another case-study (Basurto and Kämpf, 2020), we have used EnergyPlus to compute the heating and cooling loads' offset by taking into account the heat gains provided by the daylight penetration in the building, the presence and activity of the occupants, and the electricity consumed by the electric lighting and appliances. The combination of Radiance and EnergyPlus simulations allowed us to broaden the spectrum of our conclusions in the mentioned paper to the heating and cooling loads, with the expense of an additional virtual model for the thermal behaviour of the space under study.

4.3.4 Energy savings and comfort

The results presented in this report confirm that the control strategy implemented in this study allows a reduced energy use for lighting, while creating an interior environment that does not represent discomfort for the occupants. The use of a carefully tuned automatic control is able to achieve at the same time significant energy savings without triggering typical users' rejections of inappropriate control decisions. It is to be noted that users from the longitudinal studies are - because of its generalization - accustomed to presence-based automatic lighting controls and reported having sometimes difficulties with control decisions made by such systems.



Despite its prototypical nature, the project thus demonstrates that significant progress can be made on the dimension of energy for lighting and that problems raised by simplistic automatic lighting control can be circumvented. The proposed solution completely relies on the availability of individual desktop luminaires, which are more than often not taken into account in office lighting planing. Industrial manufacturers should thus strive to go beyond current practices to develop and propose solutions that are able to achieve similar performance.



5 Conclusions

With regards to its initial aims, the project has achieved the successful development of a prototype system and its several variants adapted to three different case studies settings. This system was subsequently put under thorough testing in user studies of differing purposes and length. As initially hypothesized, the implemented infrastructure framework was demonstrated to function in real time, thanks to the help of surrogate models. It involved open-source software/hardware and displayed prolonged stability despite its prototypical nature.

The first study conducted (pilot) allowed to assess different kinds of desktop luminaires in terms of user preferences in an office task, unveiling a relationship between light characteristics (illuminance, CCT), power consumption and user satisfaction. The importance of a simple and tangible interface was also highlighted. This first study allowed to define and test a methodology able to capture emotions related to lighting using the circumplex method of affects. This methodology was also used in the subsequent longitudinal studies.

The subsequent user studies conducted in three different environments (controlled and real settings) tested the developed intelligent control prototypes and showed significant energy usage reduction - between 49% and 68% - compared to normative usage of the same luminaires, even taking into account the energy consumption of the computational infrastructure involved. Furthermore, this energy performance is achieved without impairing comfort, keeping real office users satisfied for prolonged testing periods.

These results allow us to declare the project as successful, despite limited financial support with regard to its technical and methodological endeavours. This assertion is further confirmed by the project's high scientific output - with 3 journal and 2 conference articles already published.

6 Outlook and next steps

The energy results demonstrated during the project calls for additional R&D efforts to materialize the innovative opportunities unveiled. These opportunities are:

- The development of approaches that allow to integrate the proposed intelligent lighting and blind control approach in the building design and planning processes.
- The development of computational methods simplifying the setup of accurate ML surrogate models.
- The integration at the industrial level of open, stable and efficient sensing and digital control of desktop luminaires, as such capabilities have been identified as the most critical difficulty and point of failure when using current off-the-shelf products.
- The development of intuitive tangible, proximal desktop lighting control integrating at least tunable illuminance and CCT.
- These R&D opportunities appear sufficiently defined to qualify for innovation project support such as Innosuisse or similar.

In terms of scientific research, further developments on the surrogate model approach for additional dimensions of intelligent building control is believed to lead to similar successful results. In terms of user interaction, further study on the impact of CCT control on users' comfort and well-being should be investigated with purposeful user experiments.



7 National and international cooperation

7.1 IEA-SHC Task 61

Both Dr Jérôme Kämpf and Dr Julien Nembrini participated to the IEA-SHC Task 61. Dr Kämpf to subtask C and Dr Nembrini to subtask D. This participation has taken the following form:

1. Participation to two expert meetings (online)
2. Development of a case study analysis protocol
3. Participation to the Technical Report of IEA SHC Task 61 / EBC Annex 77 T61.C.1 C1: Workflows and software for the design of integrated lighting solutions

The SLL BlueHall was planned to be included as a case study in Subtask D. However, the lack of building occupants as a consequence of the home office policy made it difficult to gather meaningful results.

A follow-up activity of the Task 61 was announced as IEA SHC Task 70 “Low Carbon, High Comfort Integrated Lighting” starting in January 2023, for which a strong interest was raised by Dr Kämpf and Dr Nembrini.

8 Communication

For the 30th anniversary of the Idiap Research Institute in 2021, two days of communication of its activities to the public were achieved. The first day was dedicated to industries (Industry Day), while the second day was dedicated to the largest public (Open Doors). A poster presentation of the project was prepared, and a live demonstration of the automated control of blinds and general lighting as a function of the monitoring of the weather was performed. With over 700 visitors for the Open Doors, a large public was informed about our current activities within the project LUCIDELES.

Communication dedicated to the scientific community was achieved at the CISBAT and the 17th IBPSA Conferences in Lausanne and Bruges, Belgium respectively (both in September 2021), and at the EuroSun Conference in Kassel, Germany in September 2022. At CISBAT, for about 300 participants on-site and 150 online participants, our activities were presented by the way of two oral presentations and their corresponding conference proceedings. In both conferences, a strong interest was raised by the use of Machine Learning algorithms in the prediction of Daylight in Buildings. A paper has been submitted to CISBAT 2023 and has been selected for an oral presentation.

The Smart Living Lab has selected the project to appear as a “research story” which will be communicated in English/French and German through the SLL website and in printed material. Professional photographer and journalist interviewed Julien Nembrini and Michael Papinutto in October 2021. The web page is available at the following address: <https://www.smartlivinglab.ch/en/bringing-human-centred-design-to-smart-light-control-systems/>

An event involving researchers from the LUCIDELES project, as well as representant of the industry, is planned at Idiap in 2023. It will focus on Perspectives on AI for Energy purposes.

These communication activities have been and are conducted in agreement with the research agreement detailing the necessary steps to followed to agree on the content of any communication (especially relevant not to interfere with the commercial communication of Regent Lighting).



9 Publications

The surrogate models and their associated results (WP2) on the pilot experiment were published as a first CISBAT conference paper [1]. While the experimental data analysis for the pilot experiment (WP3) delivered its first data, published as a second CISBAT conference paper [3]. A deeper and unified presentation of the complete methodology and results analysis was published as a journal paper in *Energy and Buildings* for a Special Issue dedicated to the IEA Task 61 [4]. Finally, the longitudinal study at Idiap happening in the single office was published as a EuroSun conference paper [6], while the study involving both single and shared offices was published as a journal paper in *Solar Energy Advances* [5], as well as in a recent conference paper submitted to CISBAT 2023. Regular workshops were carried out with the industrial partner to integrate his vision and analysis where relevant in the aforementioned papers.

A journal paper is foreseen to be submitted in 2023 about the methodology and the results obtained for the longitudinal studies at the SLL BlueHall.

All publications are available in open access, which allows us to include them as appendix in the present report.

[1] Machine learning techniques for the daylight and electric lighting performance predictions, Chantal Basurto, Oliver Paul and Jérôme Kämpf, in: *Proceedings of the 17th IBPSA Conference*, , 1-3 September, Bruges, Belgium, 2021. <https://doi.org/10.268668/25222708.2021.30387>

[2] Implementation of machine learning techniques for the quasi real-time blind and electric lighting optimization in a controlled experimental facility, Chantal Basurto, Roberto Boghetti, Moreno Colombo, Michael Pappinutto, Julien Nembrini and Jérôme Kämpf, in: *Journal of Physics: Conference Series*, IOP Publishing, 2021. doi:10.1088/1742-6596/2042/1/012112

[3] Towards the integration of personal task-lighting in an optimised balance between electric lighting and daylighting: A user-centred study of emotion, visual comfort, interaction and form-factor of task lights., Papinutto, M., Colombo, M., Golsouzidou, M., Reutter, K., Lalanne, D., & Nembrini, J. (2021). *Journal of Physics: Conference Series*, 2042(1), 012115. <https://doi.org/10.1088/1742-6596/2042/1/012115>

[4] Papinutto, M., Boghetti, R., Colombo, M., Basurto, C., Reutter, K., Lalanne, D., Kämpf, J. H., & Nembrini, J. (2022). Saving energy by maximising daylight and minimising the impact on occupants: An automatic lighting system approach. *Energy and Buildings*, 268, 112176. <https://doi.org/10.1016/j.enbuild.2022.112176>

[5] Integrating daylight with general and task lighting: A longitudinal in-the-wild study in individual and open space working areas, Chantal Basurto, Michael Papinutto, Moreno Colombo, Roberto Boghetti, Kornelius Reutter, Julien Nembrini, Jérôme Kämpf, *Solar Energy Advances* 2 (2022). <https://doi.org/10.1016/j.seja.2022.100027>

[6] An exploratory interplay between daylight, general and task lighting for visual comfort and electricity savings in a personal office space, Chantal Basurto, Michael Papinutto, Moreno Colombo, Roberto Boghetti, Kornelius Reutter, Julien Nembrini, Jérôme Kämpf, *Eurosun2022 Conference*, 25-29 September 2022, Kassel Germany

[7] Enhancing user acceptance in automated systems with human-centric lighting: the role of visual comfort, personality, and preference, Michael Papinutto, Moreno Colombo, Roberto Boghetti, Chantal Basurto, Kornelius Reutter, Denis Lalanne, Jérôme Kämpf and Julien Nembrini, submitted to CISBAT 2023



Prior related research whose results/methodologies are used in the project has been published by the project partners in:

Papinutto, M., Nembrini, J., & Lalanne, D. (2020). "Working in the dark?" investigation of physiological and psychological indices and prediction of back-lit screen users' reactions to light dimming. *Building and Environment*, 186, 107356. [open access link](#)

Basurto, C., Kämpf H. Jérôme (2020). "An Integrated and strategic evaluation of automatic blind controls to achieve energy and occupant's comfort objectives". *Proceedings of the Building Simulation and Optimization Conference BSO-V-2020*, September 21st and 22nd, Loughborough University, UK.



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11 Appendix

Machine learning techniques for the daylight and electric lighting performance predictions

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Abstract

The use of external blinds is a common strategy for the design of energy efficient buildings, its performance evaluation in this study involves an integrated assessment of daylight, electric lighting and blinds controls. Nowadays, such evaluations are mostly performed with the use of computer simulations, which, due to the complexity of the issue, are still highly demanding in terms of computing time and performance capabilities. In order to improve the response time of daylight and electric lighting performance-predictions, machine learning techniques are employed in this study as surrogate models. The workflow for producing daylight surrogate models from RADIANCE simulations was validated for an individual office room, and the obtained accuracy for predicting daylight performance resulted in 98.91% for work-plane illuminance (WPI) and 99.92% for daylight glare probability (DGP).

Key Innovations

- The study is based on an existing monitored room and its corresponding calibrated virtual model
- The evaluation involves the use of advanced simulation techniques: RADIANCE matrix multiplication methods
- The Machine Learning (ML) models aim to predict external blinds and electric lighting control performance
- The selection of the appropriate ML models involved the analysis of four possible candidates.

Practical Implications

This study implements the performance prediction of daylight and electric lighting, considering occupant's visual comfort and energy savings by the control of exterior horizontal blinds as well as electric lighting. The latter, is achieved at a reduced simulation cost in terms of computing time with a satisfactory prediction accuracy.

Introduction

The use of exterior blinds for solar protection is a common practice in the design of energy efficient buildings. However, due to their multiple effects in different aspects of the building performance, their adequate operation requires to address distinct challenges. An example of such a challenge is achieving a correct balance between

an increased daylight admission for the reduction of heating and lighting loads in winter, while minimising the risk of glare for the occupants. Providing an adequate solar protection while achieving a sufficient daylight provision at task area is a similar quest for summer time. The use of blinds and electric lighting controls represents a step forward in achieving an efficient operation of external blinds, since it involves the application of a performance strategy that considers relevant aspects related to their performance. In order to perform an adequate assessment of their impact, the implementation of an integrated evaluation is recommended, where ideally, aspects related to the occupant's comfort as well as to the energy consumption are considered. However, the implementation of such assessment usually signifies a laborious task, since it implies evaluating the effects of multiple blind positions, considering year-round weather conditions. While such an assessment is usually simplified with the use of computer simulations, the tools that are able to perform the most accurate predictions are expensive in terms of computing time as well as post-process evaluation, due to the human-hours invested on the interaction with distinctive tools and interfaces.

As related to this study, the RADIANCE matrix multiplication methods are a validated method for the prediction of daylight (Geisler-Moroder et al., 2017), representing a highly accurate alternative for the prediction of blinds and complex fenestration systems (CFS) performance, as it allows the use of their BSDF data (Andersen and Boer, 2006). However, with such methods, the creation of HDR images for the evaluation of the risk of glare, implies the execution of several steps that signify the generation of thousands of images. If the implementation of climate-based simulations at hourly or shorter time-steps is considered, it implies high costs in terms of computing time and performance, as well as for the procurement of sufficient storage capacity.

Machine Learning techniques have been effectively employed for the prediction of daylight performance in recent years. In most research studies, the main objective has focused on estimating the indoor interior illuminance as an absolute value (Kazanasmasz et al., 2009; Ngarambe et al., 2020), or in the form of performance metrics, such as: Daylight Factor (DF), Daylight Autonomy (DA), Useful Daylight Illuminance (UDI) or Daylight Glare Probability (DGP) (Lorenz et al., 2018; Lorenz and Jabi, 2017; Radziszewski and Waczynska, 2018). The prediction of daylight performance by the use of predictive models is primarily based on the variation of

two main input parameters: external (climate, temporal settings, exterior obstructions), and internal (building physical features, openings and shading systems, occupancy and sensor data) (Ayoub, 2020). As Ayoub reports, 61% of studies are based on the variation of internal parameters, from which the building physical features (external obstructions, building orientation, building materials), is the most recurrent (30%). While, only 22% have focused on variations relative to the use of shading systems or blinds, and few are found that have considered the use of Artificial neural networks (ANN) for blind control performance predictions (Hu and Olvina, 2011).

This study explores the use of Machine Learning Techniques as a surrogate model to improve the response time of daylight and electric lighting performance predictions. In order to achieve an optimal control of blinds and electric lighting, a predictor model is employed to evaluate the impact of a certain blind's position on the work-plane illuminance (WPI), and of glare in the occupant's eye. Simulation cost is a relevant feature of this work, since, due to the longer time that RADIANCE simulations require to complete, the predictor model is rather based on statistical surrogate models such as ANNs. Ubiquity is another feature of this work, since the predictor model is derived from year-round simulations generated by the RADIANCE based matrix multiplication methods, where all possible blinds positions and weather conditions are considered. The ultimate goal is to include the predictor model in a Model Predictive Control (MPC), aiming to obtain a quasi-real-time optimization of the building parameters, to provide visual comfort to the user with less electric lighting.

Methods

Room Description

The evaluated room is located in the first floor of the Idiap Research Institute, in the city of Martigny Switzerland (Lat. 46.10° N, Long. 7.08° E, 471 m above sea level). The building dimensions are approximate 60 m long by 50 m width, with an orientation of 56° due to the South West (Figure 1). The evaluated office room is located on the first floor, it has a rectangular shape with an area of 23 m² and dimensions approximately 7.05 m deep by 3.05 m width and 3.06 m height, while the Window to Wall Ratio (WWR) is 60% (Figure 2).



Figure 1. Exterior view of the Idiap Research Institute.

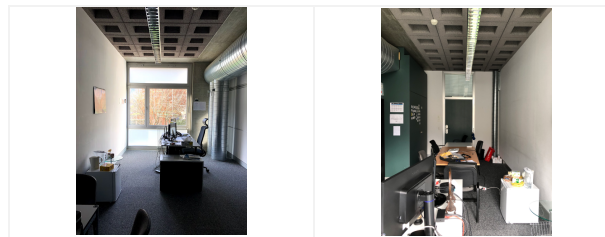


Figure 2. The evaluated office room from the back towards the window (left) and from the window towards the back of the room (right).

In order to create a virtual model that would be later used for the simulations, the photometric properties of surface materials were measured using a Chromameter (Minolta CR-220), which was employed to measure the visual reflectance of walls, ceiling and floor as well as the exterior blinds. The specularity of materials was measured using a glossmeter (Minolta GM-060) characterized at 60° incident angle.

The surfaces reflectance was then determined from the room monitoring: floor grey carpet (8%), concrete ceiling (24%), concrete wall (34%) and white wall (70%). The window is divided in three sections, an upper and lower section with a translucent glass of 31% transmittance, and double clear glazing at the centre unit with 73% transmittance, those were measured with a digital Lux meter (Gossen Mavo-Lux 5032-B). The window is equipped with metal exterior blinds of a halved hexagonal shape with approximate dimensions of 9.0 by 3.0 cm, of a clear grey matte colour and 30% reflectance (Figure 3). In regards of electric lighting, the office room is equipped with three fluorescent tubes of 58 W, which are suspended from the ceiling and placed at the central axis along the room.

As shown in Figure 4, the room geometric features were then reproduced in a virtual model using the program Sketch-up, where the collected data was used to adapt the model characteristics to match as closely as possible to the existing situation.

Virtual Model Calibration

The representativeness of the existing room by the virtual model was assessed by comparing the correspondence of WPI measured on-site with those obtained with the use of RADIANCE simulations. The calibration of the virtual model reported an R^2 of 0.93, which indicated a good correspondence between the monitoring and simulation.



Figure 3. Close view of the exterior blinds with halved hexagonal shape.

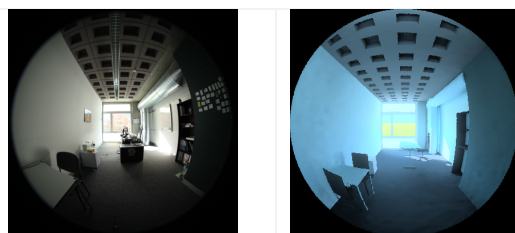


Figure 4. Comparison of a fisheye view image of the existing vs the simulated office room on November 9th at 14:00 pm.

Data acquisition: simulation methods and key performance indicators (KPI)

As a first step, a database was produced to be employed for the training of the surrogate (or predictor) model. Its input parameters are the weather data (direct and diffuse solar irradiance), hourly sun position (related to the site location), as well as exterior blinds position. The predictor model is derived from year-round simulations, which were carried-out with the use of the RADIANCE matrix multiplication methods (Geisler-Moroder D., 2017). Local weather data such as beam normal and diffuse horizontal irradiance (W/m^2), are required to reproduce the sky luminance distribution in the simulations.

However, since the building is not yet equipped with a local weather station, the simulations were carried out using data obtained from a meteorological station located in the city of Evionnaz at approximately 8 km from the location of the studied room. In order to create the testing cases scenarios, the features of the exterior horizontal blinds were reproduced in a virtual model as well, where eight variants of the blind's positions were created from an open (horizontal, zero tilt) to a closed position (tilt 65°) in steps of 10° . In total, nine feasible positions of the exterior blinds were tested: retracted and deployed considering 8 tilting variants (Table 1).

Table 1. Description of the 'testing cases' that were evaluated in this study.

RC (reference case)	Exterior horizontal blinds							
	Slats horizontal (open)	Tilting variations						'Eyb tilt 65°+ Slats vertical (closed)
Double glazing translucent and clear.	0°	10°	20°	30°	40°	50°	60°	65°

Their BSDF data (Andersen and Boer, 2006) was generated with the use of the software LBNL-Window v.7.4 (Lawrence Berkeley National Laboratory, 2019)(McNeil, 2015). With the use of the virtual model, annual WPI at hourly time-steps were estimated at the height of the work plane area corresponding to a 0.6 by 0.6 m surface (0.36 m^2).

Then, the estimation of the risk of glare was based on the use of the DGP index which is based on the vertical eye illuminance, while its criteria is built on the probability of glare disturbance as perceived by the occupants under a certain daylight condition (Wienold, 2009; Wienold and Christoffersen, 2005).

In order to perform such an evaluation, HDR fisheye images of 180° were generated from the occupant's view field (See Figure 5), for every time step using the RADIANCE matrix multiplication methods as well, while the glare prediction was performed with the use of the program *evalglare*. As a result, a vast amount of data was created representing the interior daylight situation in the office room as characterized by the two KPI's (WPI and DGP).

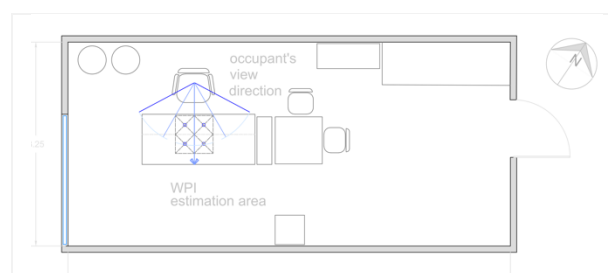


Figure 5. Floor plan view of the analysed room indicating the WPI estimated area and view direction for the HDRI generation.

As a final step, an approximation function was derived from the relationship between data inputs and outputs, represented by the two KPI's for a specific user (as graphically explained in Figure 6). In order to do so, four machine learning models were evaluated and tested to determine the one that: 1) would yield satisfactory accuracy for both WPI and DGP, and 2) that would be more suitable to the problem. The latter is explained in detail in the following section.

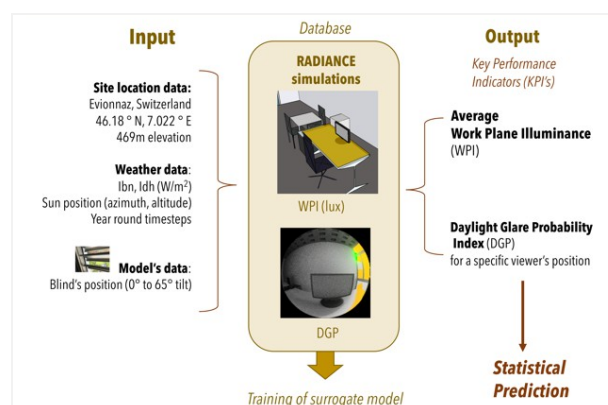


Figure 6. Graphical description of the process involved on the training of the surrogate model, for the daylight performance prediction.

Surrogate Model for the predictions of Daylighting Machine Learning Models

The “no free lunch theorem”, is a common concept in machine learning which states that for any two learning algorithms (considering an infinite set of situations or problems), there are just as many situations where algorithm 1 outperforms algorithm 2, and vice-versa (Wolpert, 2001). Therefore, the suitability of a particular model or architecture to a specific problem should not be assumed without prior experimentation and benchmarking between models (leading to the “almost-no free lunch theorem”).

In order to find the most suitable model for the problem described by this study, four diverse statistical and algorithmic approaches were tested. These included: a linear model (which is equivalent to linear regression), a ‘multilayer-perceptron neural network’ (MLP) and two ‘tree-based learning algorithms’ – a ‘random forest’ (Breiman, 2001) and ‘gradient boosting machine’ (GBM) (Friedman, 2001).

Some of the main features and strengths of these models are explained as following. While linear models are highly interpretable, they show certain performance flaws when the function mapping between the inputs and outputs is not linear. In the context of this study, linear regression is used as a baseline model, providing a performance reference for more complex and computationally expensive algorithms. By establishing such a baseline, one can determine whether increasing modelling complexity is justified given the potential performance gains.

Random forests and GBM algorithms, have empirically shown strong performance on small to medium sized tabular data problems, such as the one formulated in this study. In addition, they are relatively efficient on datasets of this scale and allow for iterative experimentation without the need for large-scale computing resources.

Finally, deep neural networks are considered ‘state of the art’ across a number of applications. They typically outperform traditional machine learning algorithms when the relationship between input features and target variables is complex, and where the dataset size is very large. The dataset considered in this study may not be of the scale the applications where neural networks are being shown to excel. However, if their suitability is proven with a room characterized by a single window and a desk, then their use would be justified in future work on significantly larger and more complex daylight performance datasets.

Due to the aforementioned reasons, random forest, GBM and MLP algorithms were chosen as suitable candidates to find a function mapping between the input/output data considered in this study. Random forest algorithms were implemented using Python’s SKLearn library. The GBM implementation used in this study is XGboost. Both linear regression and MLP models are built using PyTorch version 1.7.0.

Input Features and Data Pre-processing

The features describing the input data used for training the models are summarized in Table 2, while the target variables are described in Table 3.

Table 2. Description of the Input features available for model training.

Name	Type	Description
Blind angle	Integer	Angular position of blinds. Feature takes a discrete choice of values within {0, 10, 20, 30, 40, 50, 60 and 65}.
RC	Boolean	Reference case – true or false. True if data point belongs to reference case with no blinds and clear windows.
Ibn	Float	Normal solar beam radiation measured by weather station. W/m ² .
Idh	Float	Diffuse horizontal solar radiation measured by weather station. W/m ² .
Altitude	Float – angular	Solar inclination in degrees referenced to the horizon - range [0,90].
Azimuth	Float – angular	Solar azimuth in degrees – range [0, 360].

Table 3. Target variables predicted by models tested in this study.

Name	Type	Description
WPI	Float	Work plane illuminance. Float averaged from 4 measurement points.
DGP	Float	Daylight Glare probability. Float representing the glare in eye. Variable has a range of [0.2, 1.0].

It should be noted that, ‘altitude’ and ‘azimuth’ are time features which are directly related to the ‘time of day’ and ‘day of year’, therefore, for data corresponding to a full calendar, the temporal aspect can be learned from these features alone; hence, date-time specifications are not necessary. Typically, such angular, or cyclic features can pose a challenge for machine learning algorithms, due to difficulties in learning the relation between two given values; as for instance, the fact that 1 and 360 angular values are close to each other.

In order to address this issue, the original ‘azimuth’ feature was dropped from the dataset and two new features were engineered: Sin azimuth and Cosine azimuth. The exact computation involves taking the sin and cosine of each angle, normalised by the maximum angular value in the feature.

In order to determine whether such a transformation was indeed useful, a shallow gradient boosting model was trained on a fixed number of boosting rounds on datasets with and without the transformation. The transformed dataset showed a small increase in performance, indicating that such a transformation will indeed increase performance, reduce training time, or both.

The dataset was split into training, validation and test sets representing splits of 70, 20 and 10% respectively. Since the validation set is used for the validation of hyperparameters and early stopping, its use adds bias to the training process. It is therefore important to create a test set which is held out throughout the training process, representing “unseen data”. Prior to performing such a split, the data was randomly shuffled to ensure that training, validation and test sets remain independent and identically distributed (IID).

Neural networks are highly sensitive to feature scaling. While, scaling or feature normalisation has no impact on the performance of tree-based estimators, all models were trained and evaluated on normalised data for the sake of continuity. In order to avoid data leakage, only training set statistics were used for the normalisation of all three datasets (training, validation and test). Normalisation resulted in all features having a mean of zero, with a standard deviation of one. It should be noted that sin and cosine azimuth features were not normalised, since their values had a range of $[-1,1]$ and hence already a mean value close to zero. Similarly, the categorical RC feature was not normalised.

Hyperparameter Selection

It was observed that all models, in particular, the GBM model, were highly sensitive to hyperparameter tuning - the optimum hyperparameters found for the GBM model yielded a 65% improvement in performance when compared to default parameters. For the random forest and GBM models, the procedure to find optimal hyperparameters was identical.

A search space of all possible hyperparameter candidates was pre-defined, grid search was then used to train and evaluate the models with all possible combinations of these parameters. This procedure involved the use of K-folds cross validation with 5 folds on the training set. K-folds splits the training data into 5 equally sized sections. For fixed hyperparameters, 4 of these folds are used to train the model, and the fifth is used to produce an evaluation score. A new set of folds are then used for training and prediction until 5 performance scores are obtained, which are averaged to produce an evaluation score for a given set of hyperparameters. This process is repeated in a loop until evaluation scores are obtained for all possible combinations of hyperparameters defined in our search space.

An optimal neural network architecture was also found using K-folds with an optimal learning rate found using learning rate scheduling (Smith, 2017). A summary of the optimal hyperparameters for each model used in this study is shown in Table 4. It should be noted that, in the case of

the XGboost, multi-output regression is not implemented, therefore, an independent model is trained for each target variable respectively.

Table 4. Summary of hyperparameters chosen for the training of ML models.

Model	Hyperparameters
Neural Network	Number of hidden layers: 2, Number of neurons hidden layer 1: 1000, Number of neurons hidden layer 2: 1000, Optimiser: ‘Adam’, Learning rate: 0.0004, L2 regularisation/weight decay: 0.000008
Random Forest	Number of decision trees: 500, Minimum samples leaf: 1, Minimum samples split: 2
GBM - WTI	Maximum depth per tree: 10, Minimum child weight: 1, Subsample: 0.9, Colsample: 1, eta/learning rate: 0.05
GBM - DGP	Maximum depth per tree: 12, Minimum child weight: 1, Subsample: 0.9, Colsample: 1, eta/learning rate: 0.03

Model Training and Validation Strategy

For all gradient based models (linear regression, MLP, GBM), mean squared error (MSE) was used as a loss function. The advantage of using MSE is that the function is smooth (differentiable and continuous) with zero gradient where $y == \hat{y}$, which implies small errors are penalised with less magnitude than large errors, often improving convergence when compared to loss functions such as mean absolute error (MAE).

With respect to the random forest model, MSE was used as a metric to find the optimum split threshold for each node in each tree. A disadvantage of MSE is that a single outlier can cause MSE values to swell, making the metric less interpretable. For this reason, the performance of each model is presented and evaluated using MAE. To obtain the accuracy of model predictions for the dedicated task of blinds and electric lighting control, custom metrics were defined for WPI and DGP. These metrics take into account known tolerances in measuring illuminance, and known classifications in daylight glare comfort (Wienold, 2009).

The computation to determine a correct WPI classification is described as follows. If a true value y_i is greater than 300 lx then a prediction is correct if the absolute percentage error between y_i and $\hat{y}_i$ is less than 20%. If the true value y_i is between 100 lx and 300 lx then a prediction is correct if the absolute percentage error between y_i and $\hat{y}_i$ is less than 10%. Below 100 lx, a prediction is correct if the absolute difference between y_i and $\hat{y}_i$ is less than 10 lx. For DGP a prediction is considered correct if both the true value and the prediction fall within the same classification for daylight glare comfort. These classifications are Imperceptible glare: $DGP < 35\%$, Perceptible glare: $35\% \leq DGP < 40\%$, Disturbing glare: $40\% \leq DGP \leq 45\%$ and Intolerable glare $DGP \geq 45\%$.

For the MLP model, the validation set was used for early stopping to avoid overfitting. Training was ended when the validation loss failed to improve after 6 epochs. Similarly, for GBM models, boosting rounds were increased until validation loss failed to improve after 10 rounds. The test set was held out throughout the entire process, and used to evaluate performance after training. Feature normalization was reversed before computing the evaluation statistics presented later in this paper.

Electric Lighting Performance Prediction

The purpose of this study is to rely on a unified energy efficient scheme, therefore the use of a dimming system is considered in order to achieve a reduction of the electric lighting consumption in the office room. Therefore, the electric lighting dimming position would be estimated as a compensation of the WPI provided by daylight, using a minimum threshold of 300 lx at every time step. In order to do this, two possible forthcoming approaches are being considered: 1) The estimation of the electric lighting power is first obtained with the use of a simple polynomial regression based on measured illuminance, then the compensation of WPI to reach 300 lx will be determined from the daylight predictor model. 2) The estimation of electric lighting to achieve 300 lx of WPI will be estimated as a result of real-time monitoring with the use of a Lux-meter installed on the office occupant's desk.

Results and Discussion

The MSE, MAE and accuracy for each model for a single room at Idiap is summarized in Table 5. It was observed, that the two 'tree-based learning algorithms', the 'Random Forest' (RF) and the 'Gradient Boosting Machine' (GBM), were the ones that achieved a highest accuracy prediction compared to the other models tested in this study. From those, the GBM achieved the highest degree of accuracy with both predictions of the performance indicators, WPI and DGP slightly below 100%. The 'RF' and 'multi-layer perceptron neural network' (MLP), both achieved an accuracy close to 100% for DGP and 97% and 96% respectively for WPI.

In the case of the 'Linear model', the results for WPI were far below of what would be considered a good candidate, however, such a model may be suitable for the classification of glare comfort levels.

Whilst the MLP model was outperformed by the tree-based models in terms of both accuracy and MAE, it should be noted that in some cases, the MLP model yielded a lower MSE score than the tree-based models. Since MSE is more susceptible to outliers than MAE, this implies that the MLP model may have a greater capacity to generalize to outliers in the dataset than the tree-based models. This has significant implications for further work and model choice when the complexity of the problem is scaled.

For the GBM model, the discrepancies between the predictions and the true values were analysed in order to assess their meaningfulness for the objective of our application (blinds and electric lighting control). In the case of DGP, 6 out of 7884 predictions in the test set were misclassified, as illustrated in Figure 7. First, the entire test set of ML model predictions vs the true values is shown in the segment 'a' of the graph, in which, a single false prediction is highlighted in red. The false prediction is then displayed in a 24 hours' time-sequence where the extent of the inaccuracy of 'prediction vs the true value' is shown in detail (segment 'b'). In this particular case, the graph illustrates in segment "c top" the glare situation on August 28th at 14:00 with the blinds in a retracted position. The HDR image shows the spread of the glare source from the occupant's point of view. For that specific time a DGP of 0.36 was obtained from the RADIANCE simulations, while the ML model resulted in an underpredicted value of 0.32. The colour in the picture illustrates the large extent of the glare source, which is due to the contrast between the window and the background area. The *evalglare* reports an average luminance of 1080 cd/m² and a solid angle of 1.3 sr, indicating a very large source of glare with a luminance of about 4 times the luminance of the computer screen. This situation may slightly be uncomfortable for the user according to the average population used in the study to build the DGP categories.

Table 5. Summary of results for validation and test sets.

Model / target	Validation MAE	Test MAE	Validation MSE	Test MSE	Validation accuracy	Test accuracy
Linear - WPI	98.43	98.77	79930.37	89887.85	11.53 %	11.73 %
Linear - DGP	0.0354	0.0353	0.0021	0.0021	99.87 %	99.85 %
MLP - WPI	7.12	7.16	1101.94	1281.51	95.61 %	95.41 %
MLP - DGP	0.00358	0.00357	0.000123	0.000122	99.87 %	99.91 %
RF - WPI	5.61	5.59	1493.19	1691.98	96.77 %	96.78 %
RF - DGP	0.00254	0.00258	0.000110	0.000120	99.89 %	99.92 %
GBM - WPI	4.19	3.99	1164.09	1021.63	98.67 %	98.91 %
GBM - DGP	0.00229	0.00229	0.000109	0.000104	99.91 %	99.92 %

However, depending on the individual, itself, it may be perfectly tolerated, showing the importance of a user feedback loop in the automation to minimize the unwanted glary situations. The distribution and frequency of the DGP false predictions with respect to time is shown in the histogram (Fig. 7c-below). It shows, that all the false predictions occur in the afternoon from 12:00 to 14:00, while most of them take place at the latter hour, all showing an under prediction of the ML model vs the true value. This would signify that during those rare moments, the blinds would be kept in a retracted (fully open) position leading to a higher risk of glare for the average occupant.

In the case of WPI, 71 out of 7884 predictions were labelled as misplaced within a range equal or below 300 lx. This range is of specific interest for our application as we target to complement daylight with electric lighting to always keep a minimum of 300 lx as a spatial average on the work-plane satisfying the norms. The WPI analysis is shown in Figure 8, where the entire set of predictions is shown as scatter plot (segment 'a'), while the illuminance threshold representing the relevant range for our application [0, 300 lx] is shown in a zoomed display. The

focus of a single false prediction corresponding to a zero tilt blinds position in March 23th at 16:00 is shown in a 24 hours' time-sequence (b). It indicates for that case an overprediction of the ML model vs the RADIANCE simulation, since the true value averages 102 lx while the ML model estimated 200 lx. This overprediction of daylight provision would lead to an underprediction of electric lighting needs, which might result in a deficit of 98 lx on the work plane. Again, we count on user-feedback to further investigate if this is a major drawback of our surrogate model in which case we need to improve it further. The distribution and frequency of the false WPI predictions is shown in a histogram on the segment 'c' of the graph, showing that most of the predictions labelled as wrong are found in the afternoon about 16:00. From those, about ten were located outside working hours, making them irrelevant for the purposes of our study. Regarding the proportion of false predictions, the analysis showed that 63% of the time the ML model produced overpredicted values (like in our illustrated example), while 37% were underpredictions. Underpredictions would signify a waste of electricity for lighting, however insignificant on the final energy balance due to their low occurrences.

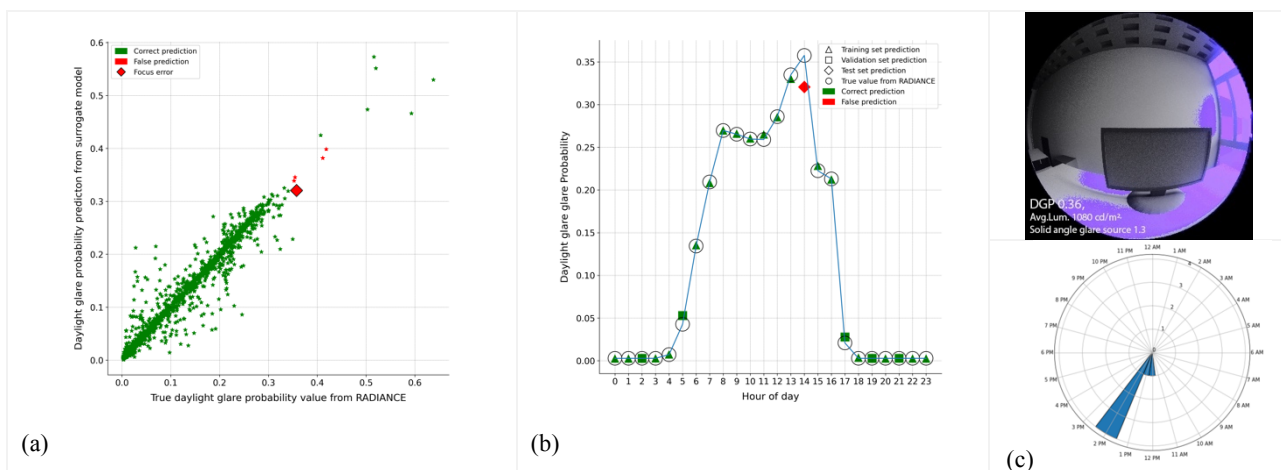


Figure 7. Scatter plot of ML model predictions against true values for glare probability (a), the false prediction highlighted in red displayed in a 24 hours' time-sequence (b). The HDR image illustrating the false prediction glare situation (c-above), and the histogram showing the frequency of the false DGP predictions (c-below).

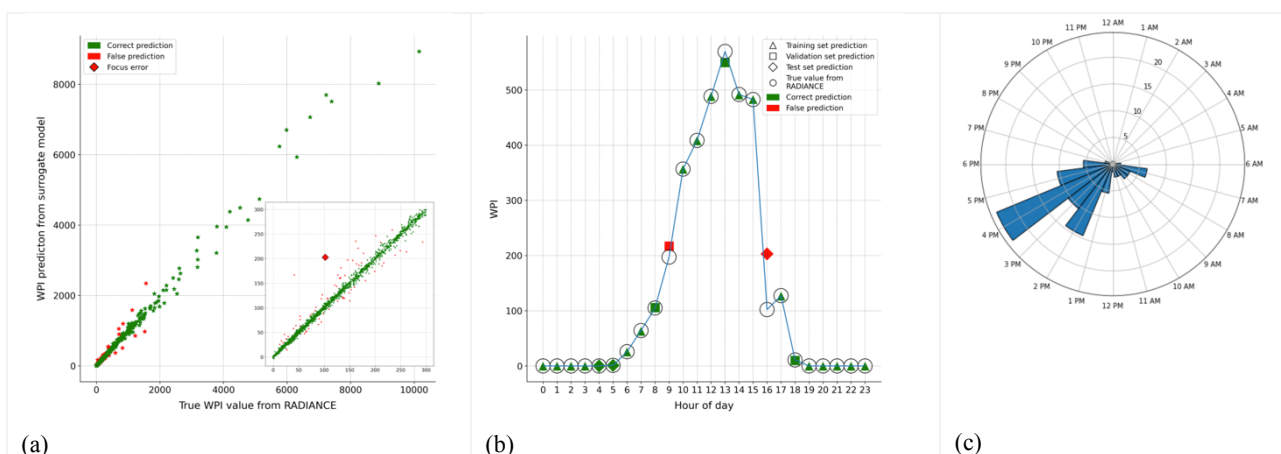


Figure 8. Scatter plot of ML model predictions against true values for WPI (a), the false prediction highlighted in red displayed in a 24 hours' time sequence (b), the histogram showing the frequency of the false predictions (c).

Conclusions

This study aimed to investigate the impact of external blinds on the occupant's visual comfort as well as on the energy use for electric lighting. The main objective was to improve the response time of daylight performance predictions by the use of ML. Different algorithms were explored as an alternative to computer simulations for daylight prediction, which are commonly very expensive in terms of computing time and performance capabilities.

The results showed, that all the 'non-linear models' explored in this study are able to estimate WPI and DGP to a satisfactory degree of accuracy, implying that such models could provide an alternative to offline physically based simulations. The GBM models showed to be the most reliable option since the test accuracy for DGP and WPI was the closest to 100%.

In this study, the use of ML techniques has proved to be a solid alternative for the prediction of daylight performance at a low-cost computing expense. Its use can be confidently implemented for quasi real-time embedded low-power blind control systems, aiming to achieve a bifold performance for glare reduction and a satisfactory daylight distribution indoors. Further work will explore the robustness and performance of the developed models with the feed-back of users in an increasing complexity of environments, such as, indoor spaces with multiple occupant positions and/or multiple windows or façade orientations.

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Implementation of machine learning techniques for the quasi real-time blind and electric lighting optimization in a controlled experimental facility

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Abstract Machine Learning techniques have been recently investigated as an alternative to the use of physical simulations, aiming to improve the response time of daylight and electric lighting performance-predictions. In this study, daylight and electric lighting predictor models are derived from daylighting RADIANCE simulations, aiming to provide visual comfort to office room occupants, with a reduced use of electric lighting. The aim is to integrate an intelligent control scheme, that, implemented on a small embedded 32-bit computer (Raspberry Pi), interfaces a KNX system for a quasi-real-time optimization of the building parameters. The present research constitutes a step towards the broader goal of achieving a unified approach, in which the daylight and electric lighting predictor models would be integrated in a Model Predictive Control. A verification of the ML performance is carried-out by comparing the model predictions to data obtained in monitoring sessions in autumn, winter and spring 2020-2021, resulting in an average MAPE of 19.3%.

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1. Introduction

The use of shading and electric lighting automation systems is considered as an energy efficient strategy to optimize the building performance, both for energy savings and an improved occupant's comfort. An adequate regulation of the daylit interior environment implicates an in-sync adjustment of the blinds position according to outdoor sky conditions. The latter should be ideally performed in regards to occupants' comfort and energy performance, using Key Performance Indicators (KPIs) such as the work-plane illuminance (WPI) as well as the daylight glare probability (DGP) [1]. However, the efficiency of an automated control system not only depends on implementing an integrated approach by considering energy and occupants comfort aspects [2], but also in terms of the technical aspects integration. As for instance, the use of HDR imaging techniques has been recently investigated for blinds control [3], [4]. However, its implementation implies the use of invasive devices where privacy and space issues are involved. Such research, preceded the development of a more sophisticated concealed device, featuring a dual function as sky luminance sensor as well as blinds controller [5]. The optimal shading position for daylight provision and glare risk, is determined by performing a lighting simulation according to outdoor sky conditions, its accurate estimation of the indoor WPI, indicates the device's reliability for daylight control [6]. However, due to the time required to perform the lighting computation, the process involved on the blind's adjustment can take up to 10 minutes. The latter, represents a disadvantage for an adequate synchronization of the blinds in regards to outdoor conditions, especially on situations of dynamic sky conditions variations. On the other hand, due to their characteristic noise, a constant adjustment of automatic blind's might cause



distractions or disturb the occupants. In this study, machine learning techniques (ML) based on daylighting RADIANCE simulations [7], are employed as surrogate models to assess the impact of blind positions on WPI and glare on the occupant's eye. A control strategy is implemented in an experimental office setting [8], using a system prototype based on a small embedded 32-bit computer (Raspberry Pi), which interfaces a KNX system to control electric light dimming and blinds position according to current outdoor sky conditions. The strategy presented aims to achieve a quasi-real time optimization of the building parameters, in a time-interval that can be tolerable for the occupants. Hence, a decision could be taken forthwith in the case of glare protection, or every five minutes in the case of daylight sufficiency. This paper further presents a verification of the ML model to predict one specific KPI in a real office setting: the WPI.

2. Methods

2.1 Room Description

The case study is located in the city of Fribourg, Switzerland (Lat. 46.8° N, Long. 7.16° E, 610 m above sea level). It consists of two experimental modules of identical characteristics, with dimensions of 6.23 m long by 3.23 m front, and 3.11 m height each. Both modules count with south and north facing windows, and a proportion window to wall ratio (WWR) of 46% (Figure 1 and 2). The 3D model of the modules in Sketchup format was employed to perform the simulations in which this study is based. The properties of interior materials were measured on-site using special equipment, and were later assigned to the virtual model aiming to achieve the most accurate representation of the existing situation. A Chromameter Minolta CR-2020 was employed to measure the reflectance properties of walls, floor and ceiling, while a glossmeter Minolta GM-060 (characterized at 60° incident angle), was used to measure the specularity of interior materials. The measured surfaces reflectance: floor 16%, white ceiling 80%, white wall at module-R1 (62%), white and light-beige walls at module-R2 (58% and 51% respectively). The glazing transmittance (75%), was determined using a CRI illuminance meter Minolta CL-70F. In regards to the electric lighting, two box-cases containing three ceiling recessed linear LED lamps of 24 W are installed at both sides of each module. The windows are equipped with two distinct horizontal blinds, which properties were also measured using the equipment previously described (Figure 3). Both windows of module-R1 and south of R2, are equipped with curved white venetian blinds of 80 mm width (S-80), and 69% reflectance. The north window of module-R2, is equipped with metallic blinds of a sinuous profile design, 90 mm width and 23% reflectance (L-90). Their geometry was also virtually reproduced in order to generate their BSDF data using the RADIANCE program genBSDF [9].



Figure 1. Exterior view of the CELLS modules, perspective from the south facade.

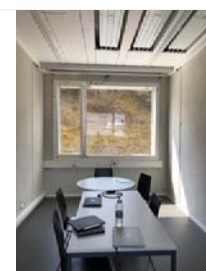


Figure 2. Interior views of CELLS modules R1 (left) and R2 (right), from the back of the room towards the south window.

Due to the characteristic dual window opening of the modules, the evaluation included the combination of all possible blind positions at both north and south facades. In order to do that, twelve positions of each blind's variant were created from an open (zero tilt) to a fully closed position (80°). In addition, four reference cases were considered: 1) both windows with blinds fully retracted, 2) both windows with blinds deployed (0° tilt, horizontal position), plus two cases where the north and south blinds are alternatively set in an open or closed position (See Section 2.5).

2.2 On-site monitoring and virtual model calibration

The correspondence between the measured work plane illuminance (WPI), and that obtained by the way of simulations was compared in order to assess the representability of the existing situation by the virtual model (Section 3.1). In order to do that, WPI measurements were obtained using two Hagner detectors (SD2, V-Lambda spectral response), which were placed at the center of the room at 0.80 m height (See Figure 4). Several sets of data were obtained in monitoring sessions carried out in Autumn, Winter and Spring between 2020 and 2021, in both modules. The monitoring process was executed automatically using a KNX system, for which all the different blind combinations were measured in routines that lasted about 10 minutes. In each session, north and south blinds positions were combined, one was set to a fix position while the other was progressively adjusted, from retracted (fully open), to deployed (from 0° tilt to fully closed 80°); while the WPI was simultaneously measured and recorded. The global and diffuse horizontal irradiance (W/m^2), were recorded using a Delta-T, SPN1 pyranometer installed on the top of the facilities, which was later used to reproduce the existing luminous situation in the simulations.

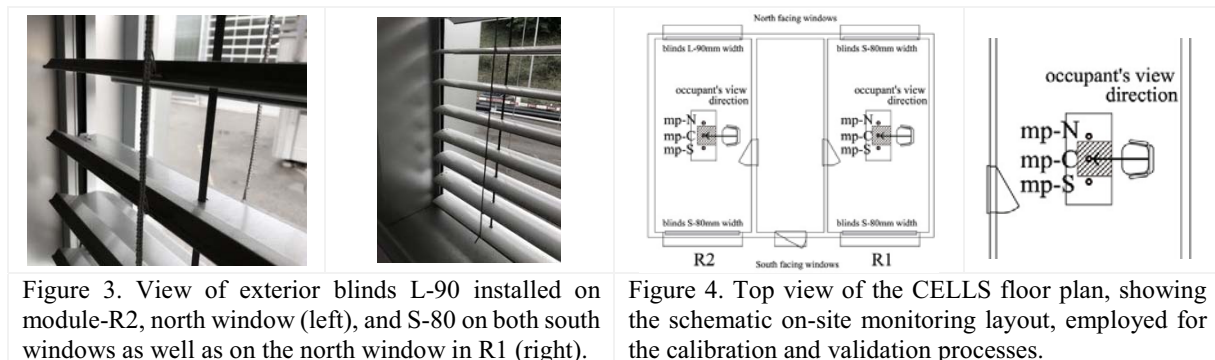


Figure 3. View of exterior blinds L-90 installed on module-R2, north window (left), and S-80 on both south windows as well as on the north window in R1 (right).

Figure 4. Top view of the CELLS floor plan, showing the schematic on-site monitoring layout, employed for the calibration and validation processes.

2.3 Data acquisition: simulation methods and key performance indicators (KPIs)

A database was first produced for the training of the predictor model, for which two KPI's were considered in order to assess the daylight performance inside the modules. First, the WPI, was obtained as a base for the estimation of the electric lighting requirements, which would be compensated from the daylight provision using a minimum threshold of 300 lx. The predictor model is derived from year-round simulations obtained with the use of the RADIANCE matrix multiplication methods [10]. In order to do that, measurement points were placed at the height of a table desk (0.80 m), covering an area of 36 dm² (0.6 by 0.6 m), corresponding to the occupant's working area. Then the estimation of the risk of glare was based on the daylight glare probability index (DGP), which indicates the probability that the room occupants would experience discomfort glare situations issued from daylight [1]. In order to do that, HDR 180° fisheye images were generated in a straight view direction from the sitting position of the occupant (Figure 4), while the glare prediction was obtained using the RADIANCE program *evalglare*. The main simulation parameters are: -ab 6, -ad 16384, -lw 1e-4; -pj 0.7, -dc 1, -dt 0, -st 1, -ss 0. The definition of the sky model was generated according to the Reinhart sky subdivision in 5185 sky patches (MF:6).

2.4 Machine Learning models for the daylighting performance prediction

Following a previous study [7], where four diverse statistical and algorithmic approaches were tested in order to find the most suitable model for a similar case study, 'gradient boosting machine' was chosen as function approximator. As the XGBoost, implementation of gradient boosting used in the previous study resulted in an excessive RAM usage for a Raspberry Pi, a lighter implementation, namely LightGBM [11], was used instead. Two models – one for WPI and one for DGP - were created using the same workflow. The model's inputs were equivalent to those used in the previous work: blind angle given in degrees, solar radiation data in W/m^2 , altitude, Sin and Cosine azimuth of the sun position; and Boolean values to indicate blinds deployment. The models were trained on 95% of the data, while the remaining 5% was held out as a test set. In order to find the best hyperparameters, an adapted version of stratified K-fold was used, where

the target values were grouped in 20 bins – a number chosen according to Sturge's rule [12]. The list of hyperparameters is given as follows, with the values ordered as WPI and DGP for module-R1, and WPI and DGP for module-R2: maximum depth of {10, 12, -1 (no limit), 11}; number of leaves of {60, 90, 140, 50}; learning rate of {0.09, 0.06, 0.06, 0.09}. In all the models, the minimum data in leaf was set to 20, and bagging and feature fractions to 1. With regards to module-R1 and R2, the WPI models had a mean absolute error (MAE) on the test set of 2.28 lx and 1.60 lx respectively, while the MAEs of the DGP models were 0.00058 and 0.00067. In all considered cases, the R^2 was 0.99.

2.4.1 Electric Lighting performance prediction. A dimming system is employed in this study aiming to achieve a reduction of the electric lighting consumption in the modules. The dimming position was estimated as a compensation of the WPI provided by the daylight, using a minimum threshold of 300 lx. The estimation of the electric lighting was based on on-site illuminance measurements obtained in module-R1 in dark outdoor conditions (illuminance with electric lights off ≈ 0 lx), using three photometric sensors placed on a desk (Figure 4). Then the prediction of the electric lighting power for a certain dimming position was obtained using a simple polynomial regression based on the measured illuminance. The necessary electric light compensation of WPI to reach 300 lx is determined from the daylight predictor model.

2.5 Implementation of an intelligent control system

Aiming to provide an adequate interior visual environment with a reduced lighting energy consumption, an intelligent lighting control strategy is implemented in the office setting, which scheme is shown in Figure 5. The daylight and electric lighting predictor models are used to optimize the room settings (blind position and electric lighting intensity), by a continuous estimation of the KPIs (WPI and DGP), based on monitored sky conditions. New specifications of the room settings are then provided, which are physically applied to the office environment through a KNX system. Such process is run on a small embedded 32-bit computer (Raspberry Pi 3B), in order to reduce the amount of energy required to optimize the room setup. The strategy of the optimization process consists on maintaining an adequate visual comfort with a reduced risk of glare for the occupants (≤ 0.35 DGP, 'imperceptible') [1], while maximizing the daylight provision indoors. If the WPI resulting from such optimization is still lower than the established 300 lx threshold, the latter would be achieved by the compensation from electric lighting. The electric lighting predictor model is then employed to find the minimum intensity of electric lighting required to reach the illuminance threshold. The blinds position would be instantaneously adjusted, only when necessary to prevent the DGP from exceeding the 0.35 limit, otherwise a time interval of five minutes is considered between every adjustment. Such interval represents a balance choice for blinds operation in office environments, in order to achieve an efficient performance as well as to avoid the blinds constant movement which could cause distraction to the occupants. In the schema describing the control strategy (Figure 5), the denotation **BN** and **BS** refers to

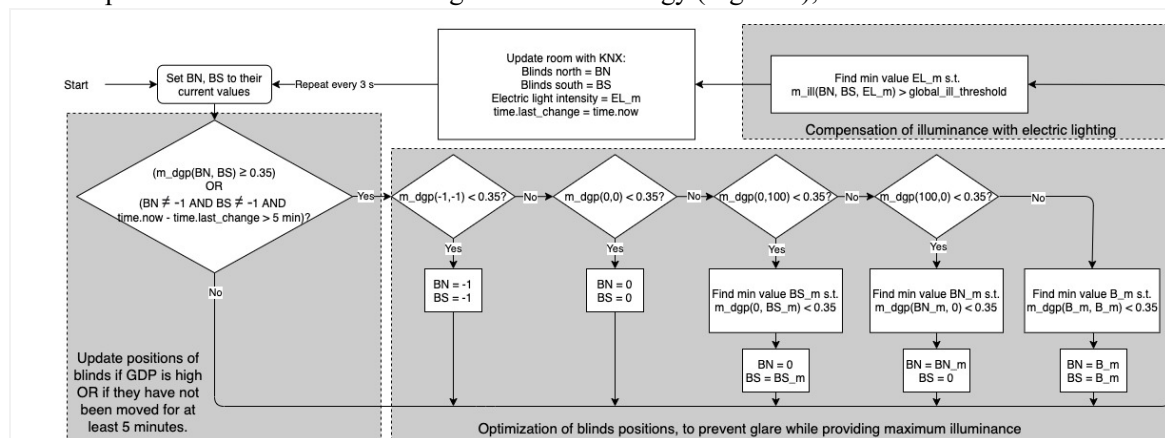


Figure 5. Intelligent control scheme for a quasi-real time optimization of building parameters to achieve visual comfort and a reduced use of electric lighting.

a deployed position of north and south blinds respectively. The '0' value represents the minimum tilt angle of the slats (horizontal position, 0°), while a value of 100 indicates the maximum (fully closed, approximately 80° from horizontal position), a value of -1 indicates the blinds completely retracted (fully open). The **m_dgp (BN, BS)**, indicates the implementation of the predictor model to compute the DGP based on the opening angle of north and south blinds (BN, BS), as well as on the sky conditions obtained from the SPN1 pyranometer. Then, **m_ill (BN, BS, EL)** computes the WPI based on the positioning of the blinds (BN and BS), as well as on the intensity of the 'electric lighting' (EL). Due to the unavailability of appropriate equipment to verify the glare KPI (a.k.a. the DGP), this paper focuses on the verification of ML predictions vs on-site measurements for WPI. DGP verification is considered as future work.

3. Results and Discussion

3.1 Virtual Model calibration: on-site monitoring vs RADIANCE simulations

As described in Section 2.2, the representability of the existing situation by the virtual model was assessed by comparing monitored and simulated WPI. A resulting R^2 of 0.96 was reported for both modules R1 and R2. Regarding the inaccuracy's analysis, a MAE of 19 lx and MAPE of 24% was reported for module-R1, as well as a MAE of 64 lx and 23% MAPE for module-R2.

3.2 Machine Learning model verification: on-site monitoring vs ML prediction

In a second step, the monitored WPI obtained during the sessions described in Section 2.2 were compared to ML predictions generated for the exact date and blind conditions as the monitored ones. As a result, a MAE of 35 lx, and 44% MAPE was reported for module-R1; while for module-R2, 142 lx and 41% was reported for MAE and MAPE respectively.

3.3 Machine Learning model verification: on-site monitoring vs ML prediction

The performance of the LightGBM was assessed by comparing the WPI model estimations with monitored data obtained for this specific purpose in two new sessions in Spring 2021. In such case, a MAE of 36 lx and MAPE of 19.28% was reported for module-R1, while 97 lx and 19.4% respectively, were reported for module-R2. An illustration of the discrepancies between the WPI model predictions and the true values is shown in Figure 6. The entire data set is shown as a heatmap (Figure 6 left), showing the absolute percentage error as a function of blinds positions and time of day. Interestingly, regular patterns for cases with increased errors appear, from which four selected situations are highlighted in red. In cases 1 and 4, which correspond to the relevant range of 300 lx for our application, an average underprediction of 54% by the ML model was observed, which would signify an overestimation of the electric lighting needs, resulting in less energy savings. In case 2, for a true value of 2730 lx the ML model overpredicts by 109%, while in case 3 for a

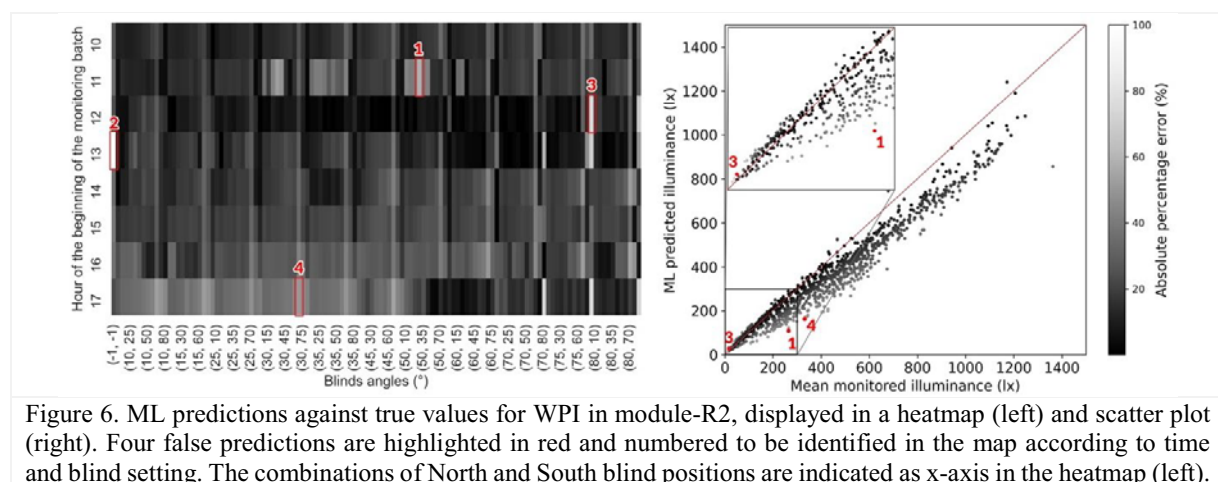


Figure 6. ML predictions against true values for WPI in module-R2, displayed in a heatmap (left) and scatter plot (right). Four false predictions are highlighted in red and numbered to be identified in the map according to time and blind setting. The combinations of North and South blind positions are indicated as x-axis in the heatmap (left).

true value below 20 lx, it overpredicts by 75%. In both cases 2 and 3, the errors are not impacting the outcomes of our algorithm regarding both the visual comfort and the required illuminance on the workplane. A limited portion of the data set below 1500 lx is shown as a scatter plot (Figure 6 right), while the illuminance threshold representing the relevant range for our application (300 lx) is shown in a zoomed display. We notice that in both scatter plots, an underprediction of the ML model can be observed for close to 100% of the dataset analyzed in this study. The overpredictions on the relevant range, correspond to an average of 10 lx, which is negligible. The latter would signify a small increase on energy consumption, yet, not having an impact on visual comfort, as the requirements of the norms for minimum WPI can always be guaranteed.

4. Conclusions

In this study, Machine Learning techniques were employed as surrogate models in order to achieve a quasi-real time optimization of the building parameters. A control strategy was implemented in a small embedded 32-bit computer that interfaces a KNX system to control blinds and electric lighting according to outdoor sky conditions. The ML model performance was assessed by comparing the WPI predictions with on-site measurements obtained in different monitoring sessions. The results report an average MAPE of 19.3%, indicating that the selected model LightGBM can estimate WPI to a satisfactory level of accuracy for our application. Therefore, daylight and electric lighting predictor models can be confidently employed in real environments, selecting the best blinds and dimming lighting settings to provide visual comfort with a reasonable reduction in the use of electric lighting while guaranteeing satisfaction of illuminance norms.

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Towards the integration of personal task-lighting in an optimised balance between electric lighting and daylighting: A user-centred study of emotion, visual comfort, interaction and form-factor of task lights

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Abstract. Task-lighting is a well-known strategy to save energy by bringing light where it is most needed, providing adaptable localised light conditions of special interest in the current home-office context. Despite these benefits and in addition to negatively impacting biological rhythms, the generalization of backlit screens has made task lights less demanded, with screen users tending to accept significantly lower amounts of the illuminance standards. In parallel, the advantages of task-lighting may contradict the energy benefits of presence-driven lighting or blinds automation. This pilot experiment aims at evaluating the task light usage patterns and characteristic preferences for both paper and computer work from a user-centered perspective to provide guidelines in terms of luminaires characteristics. Thirteen participants evaluated three different task lights in both paper and computer conditions. Our results emphasize the role of the luminaire's form factor, interface and lighting control characteristics, providing general recommendations on luminaire design.

1. Introduction

Given that the energy consumption of lighting loads represents, worldwide, almost 20% of the building energy demand of office buildings [1], lighting in buildings offers promising energy-saving potential [2]. Numerous research efforts pursuing this aim focused on developing adaptive systems according to the standards [3, 4], for instance by increasing the daylighting share [5]. An alternative and promising pathway could lie in fostering a user-centered approach to challenge the normative framework [6] and reach beyond standards to maximize occupants' visual comfort and minimize energy consumption. In this regard, task-lighting is a well-known energy-saving strategy, bringing light where it is the most needed while remaining in the occupants' control.

Recently, the generalization of backlit screens emitting direct light in the users' eyes has notably reduced the use of task lights in office buildings [7]. In addition to harmful impacts on biological rhythms [8, 9], we recently showed that such screens as the sole lighting source in the proximal working environment causes users to select a significantly lower amount of light



than recommended by existing standards ([10]). In such cases, the poor ratio brought by backlit screens between screen luminance and global illuminance leads to sore eyes, among others [11].

A strategy to counteract the adverse effects of backlit screens aims at increasing desk illuminance through the reintroduction of task lights. Indeed, task-lighting competes with the screen illuminance, involving lower energy expenses than general lighting [12], while enabling to personalize the proximal environment [13, 14]. This strategy is well suited to the current home office context, providing adaptable localised light conditions to support occupants' satisfaction [12]. However, some studies highlight the need to use task lights with caution, as their prolonged use without general lighting cause visual fatigue [15].

Task-lighting, being user-controlled, may also contradict the benefits of presence-driven lighting or blind automation. The present study is part of the LUCIDELES research project aiming to study the potential for an energy-efficient user-centered light automation preserving the advantages of task-lighting while overcoming the disadvantages of backlit screens. This pilot experiment was set up to evaluate the task light usage patterns and characteristic preferences for paper and computer work from a user-centered perspective. This approach aims at providing task luminaires guidelines regarding form-factors, interface characteristics, and lighting controls.

2. Method

2.1. Participants

13 participants – 6 females; 11 right-handed (age $M = 31.69$, $SD = 10.44$) – took part in this study. All participants were used to office work. Before the experiment, most participants were in a good mood, calm, and comfortable. They all gave informed consent to participate in this study and were informed that they could withdraw their data by the end of the study.

2.2. Room, Task lights characteristics and Measurements

The experimental space was rectangular, with a table at the centre facing the entrance door and two large windows fitted with blinds on both the north and south sides. The space had dimmable LED beams for general lighting. The three luminaires used in this user study were¹: **Luminaire A:** a luminaire with a smart bulb allowing both intensity and correlated colour temperature (CCT) control. **Luminaire B:** a luminaire allowing both intensity and CCT control independently. **Luminaire C:** a luminaire with intensity and CCT control combined. Figure 1 represents pictures of the luminaires and two users' chosen setup before each task. The room was also provisioned with global electrical lighting and daylight contribution. The initial light conditions were set by manipulating general lighting and daylight through the blinds. The amount of desktop illuminance was set to probe action from participants ($M = 142.00$, $SD = 33.52$) and a CCT of 5500 Kelvin ($M = 5553.00$, $SD = 314.19$). Two Hagners SD2 illuminance meters, placed on each side of the laptop, were dedicated to illuminance measurement. The laptop was plugged to power, and the screen brightness was kept fixed for the whole experiment duration at a brightness level of $120\text{cd}/\text{m}^2$ as recommended by ISO 3664:2009 [16].

2.3. Procedure

Participants first completed a short questionnaire designed to gather socio-demographical data as well as their feeling and comfort before the experiment. Then, participants were presented with each luminaire in a random order, with the experimenter explaining the luminaire's functionalities. After a short testing period, participants had to set lighting conditions as comfortable as possible to conduct two short reading tasks on computer and paper (order randomized). Task performance was not recorded as tasks provided tangible artefacts mimicking

¹ A: Tolomeo (Artemide) with Trådfri bulb and interface (IKEA); B: Joker (Regent); C: John (Tobias Grau)

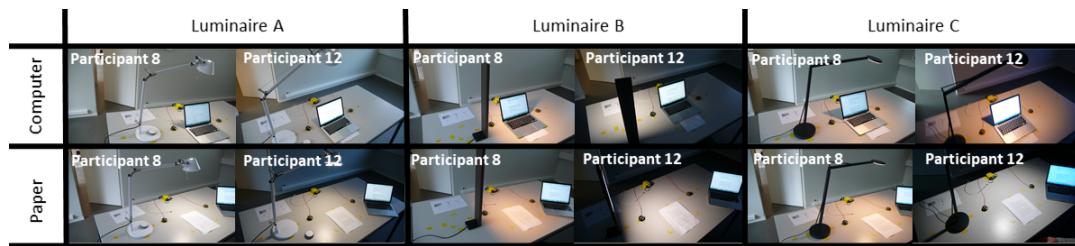


Figure 1. Pictures depicting the position of each task light of two participants before either the computer or paper task.

ecological working conditions. Upon optimal light conditions found by the participant, desktop illuminance and colour temperature were recorded. After each luminaire testing, participants answered a questionnaire, including the selection of adjectives among a list to map participant's sentiment using the circumplex method of affects [17] (see Section 2.4). After luminaires testing, participants answered an additional questionnaire comparing the luminaires preference. The study duration was about half an hour.

2.4. Data Analysis

Luminaire questionnaire data was collected for each task light after task completion. To compare the task lights with each other, Friedman tests compared the difference in luminaire's ratings, with Wilcoxon tests Bonferroni-corrected for multiple comparisons. Furthermore, task lights were separated in two groups: the "preferred" and the "not-preferred" (median score of the two not-preferred luminaires), with differences between them assessed using Wilcoxon tests.

To analyse participant sentiment toward their emotion, the aspect of the luminaire itself and the light provided by the luminaire, we used the circumplex method of affects [17]. We inferred three circumplexes (for emotion, object and light), using the method described in [18], which will be described in a subsequent publication. Adjectives selected by the participants in the questionnaires were mapped within each circumplex space. Rayleigh tests assessed whether the selected adjectives indicated a direction or resulted in a uniform distribution around the circumplex space. When at least two groups exhibited a direction, a CM test assessed the significance of the difference in directions. Again, we here divided the circumplexes data into preferred and not-preferred task lights.

Finally, the illuminance and the CCT were compared across luminaires and task conditions with repeated measures ANOVAs. To meet the ANOVAs assumption of normality, data were visually inspected and outliers winsorised. When the sphericity assumption was violated, the Greenhouse-Geisser correction was applied. Differences between task lights were assessed through Bonferroni-corrected post-hoc tests. One participant was excluded from this analysis for having wrong sensor readings. The data was analysed in python and JASP [19].

3. Results

3.1. Setup

All participants moved the three task lights, except one participant who moved only the task light C. The main reasons to move the luminaires were, according to participants' comments, to avoid glare or change light direction to illuminate the working area properly. Participants place luminaires in idiosyncratic ways, directing light toward or away from them, close or far from the paperwork (see Figure 1).

3.2. Questionnaires

Every participant noticed the ability to control task lights' intensity with the three luminaires. However, the CCT control ability of task light C was not clear to participants as eleven participants did not have the impression they were able to change CCT. The interaction effect between task lights and the ability to change CCT revealed a significantly greater number of participants that did not perceive the change in CCT with luminaire C, whereas the two other luminaires exhibited a higher number of participants that perceived CCT changes (see Table 1).

Questions	Luminaire	Descriptives	Statistics	Comparison
Notice a change in (choice between yes, no and not sure):				
CCT	A	yes: n=12, no: n=1 not sure: n=0	$\chi^2(4) = 24.96, p < .001$	-
	B	yes: n=11, no: n=1 not sure: n=1		-
	C	yes: n=1, no: n=11 not sure: n=1		-
Ranking (scale from 1 the worst to 5 the best):				
Ease of use	A	$Mdn = 5.00, CI_{95} = [2.60, 5.00]$	$\chi^2_F(2) = 7.30, p = .026$	A vs B: p=.03
	B	$Mdn = 3.00, CI_{95} = [1.00, 5.00]$		A vs C: N.S.
	C	$Mdn = 4.00, CI_{95} = [2.00, 5.00]$		B vs C: N.S.
Ease of understanding	A	$Mdn = 5.00, CI_{95} = [4.00, 5.00]$	$\chi^2_F(2) = 13.41, p = .001$	A vs B: p=.008
	B	$Mdn = 2.00, CI_{95} = [1.00, 5.00]$		A vs C: N.S.
	C	$Mdn = 5.00, CI_{95} = [2.00, 5.00]$		B vs C: N.S.
Preference (choice)				
Luminaire	A	n=8	$\chi^2(2) = 7.15, p = .028$	-
	B	n=3		-
	C	n=2		-
Interface	Button	n=8	$\chi^2(2) = 7.15, p = .028$	-
	Application	n=3		-
	Not sure	n=2		-

Table 1. Results of questionnaires

The task lights differed significantly in the rating of ease to use and understand to use with luminaire A having higher ratings than luminaire B, whereas the luminaire C did not differ significantly from the two others. There was no significant difference between task light rated comfort (see Table 1).

Regarding the light's ranking, there were no significant differences across preference, interface, working and comfort ranking.

There were significantly more participants preferring task light A over the two other task lights. Moreover, participants would rather interact with a task light through a button than an application (see Table 1).

3.3. Circumplex evaluation of emotion, object, and light

No significant differences were found between luminaires' emotional perception within the three circumplexes spaces.

Regarding the circumplexes analysis between the preferred and not-preferred luminaire, the circumplex for emotion revealed that only the preferred luminaire indicates a specific direction toward *pleasant*. Interestingly, in the circumplex for object, the preferred luminaire point toward *common*, whereas the not-preferred luminaire point between *common* and *artificial* and this difference was statistically significant (see Table 2 and Figure 2). Finally, regarding the circumplex for light, both preferred and not-preferred task lights indicated a common direction toward *relaxing*.

3.3.1. Light usage across luminaires and tasks Results from Table 3 and Figure 3 reveal that both the luminaire and the task conditions impact significantly on the illuminance. The principal effect of the task light condition reveals that overall, the luminaire C was dispatching a significantly higher illuminance than the two other luminaires. Regarding the task condition, participants increased the illuminance significantly from the starting condition in both the paper and computer task. Interestingly, the illuminance set during the paper task was significantly

Circumplex type	Luminaire	Direction	Comparison of directions
Emotion	Preferred	toward pleasant ($S = 4.31, p = .011$)	Not Evaluated
	Not-preferred	Uniformly distributed	
Object	Preferred	toward common ($S = 9.97, p < .001$)	$P = 3.85, p = .049$
	Not-preferred	between common and artificial ($S = 3.49, p = .027$)	
Light	Preferred	toward relaxing ($S = 4.84, p = .006$)	N.S.
	Not-preferred	toward relaxing ($S = 5.45, p = .003$)	

Table 2. Results of Circumplexes method of affects

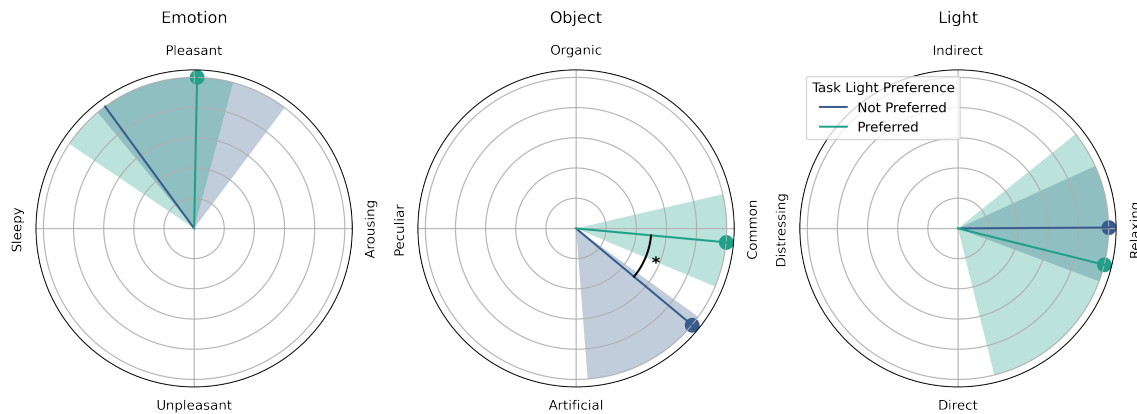


Figure 2. Depiction of differences between preferred and not-preferred task lights within the three circumplexes space.

			Descriptive		Effect		Post-hoc	
Condition			M	SD	Principal	Interaction	Comparison	P-value
Lux	Luminaire	A	475.28	343.49	F(1.13,11.26)=8.57, p=.012, η^2 =.10	F(1.36,13.57)=7.52, p=.011, η^2 =.11	A vs B	N.S.
		B	613.31	441.69			A vs C	.002
		C	996.82	1203.62			B vs C	.021
	Task	Start	137.08	36.31	F(1.34,13.35)=32.53, p<.001, η^2 =.39		Start vs Paper	<.001
		Paper	1278.92	1023.46			Start vs Computer	.003
		Computer	669.41	439.11			Paper vs Computer	.001
CCT	Luminaire	A	4435.79	1080.21	F(2,20)=10.27, p<.001, η^2 =.06	p<.001, η^2 =.03	A vs B	N.S.
		B	4449.92	987.12			A vs C	.004
		C	3861.77	1231.17			B vs C	.002
	Task	Start	5553.00	314.10	F(2,20)=119.84, p<.001, η^2 =.73		Start vs Paper	<.001
		Paper	3512.00	576.52			Start vs Computer	<.001
		Computer	3682.49	908.36			Paper vs Computer	N.S.

Table 3. Results of light usage across luminaires and task

higher than the computer task. Finally, the interaction effect indicates that the difference between starting illuminance, the computer, and the paper task were the biggest for luminaire C and the smallest for luminaire A (see Table 3 and Figure 3).

The luminaire and the task condition also impacted significantly on the CCT level. Specifically, post-hoc tests show that luminaire C was dispatching a significantly warmer light than luminaire A and B. Additionally, participants set a significantly warmer light than from the starting condition in both the paper and computer task. Finally, the interaction effect indicates that the difference between the starting condition and the computer and paper task differed more for luminaire C than the two other luminaires (see Table 3 and Figure 3).

4. Discussion and conclusion

Overall, most participants preferred the classic luminaire with a smart bulb (the luminaire A), while not scoring the highest either in terms of visual comfort or amount of light. Participants'

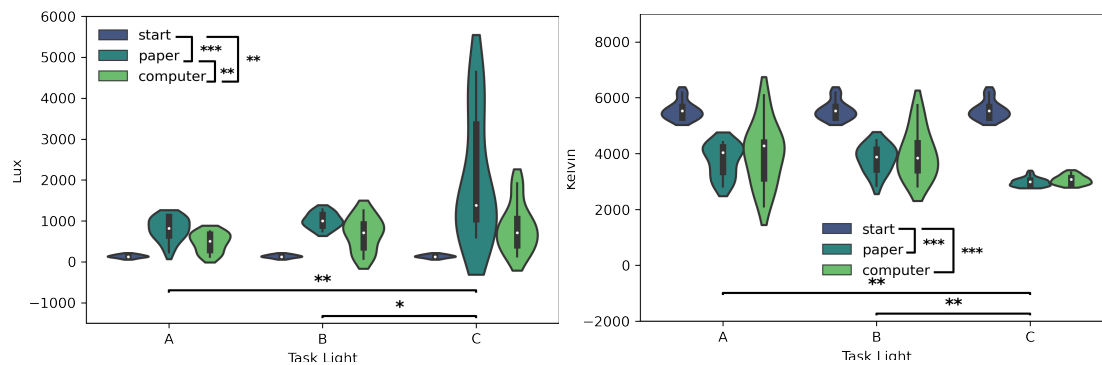


Figure 3. Violin plots of the color and illuminance levels within each task conditions and for each task light. Notes: * $p < .05$, ** $p < .01$ and *** $p < .001$.

reasons for preference lie in usage and interface simplicity. In terms of interface, participants would rather use a button over an application for task-lighting but would consider an application for general electric lighting control.

The luminaire A allows independence in CCT and illuminance control, which appears to be crucial as CCT control remained ignored from participants when CCT and illuminance were bound (Luminaire C), this even though luminaire C was set to provide a warmer light than the two others. Altogether, the binding of those light characteristics restrict participants' degree of freedom to achieve optimal visual comfort and conceal their impact on light.

The circumplex analyses revealed that the preferred luminaire brought on average a “pleasant” emotion, a “relaxing” and “direct” light, and was felt as “common”. This result reflects the preference of participant for a classic and straightforward luminaire providing a slightly warm and well focused light.

In terms of light characteristics, the participants needed less light when reading on a computer screen than on paper, while CCT appeared the same between these conditions. This confirms our previous results [10] and additionally reveals that solely the amount of illuminance appears to be affected by backlit screen luminance.

The study provides the following recommendations for task luminaires: The luminaire should be easy to use and understand, with a simple and common form factor. It should have the ability to be moved and provide a relaxing light avoiding either too gloomy or exciting atmospheres; with the ability to adapt both CCT and intensity independently through tangible buttons.

Our results should be appraised taking into account the variation of daylight throughout the experiment, hence modifying light quantity and quality during the tasks. While meant to preserve an ecological value, this could have led to different light settings across participants. However, we assumed that the variation in daylight was marginal, since the blinds were, in most cases, closed to reach the starting conditions (2 participants with both blinds closed; 4 with one blind close completely and the other partially, 5 with both blinds partially close and 3 with blinds open). Another limitation could arise from the use of a laptop computer. Indeed, prolonged laptop usage was found to lead to postural issue and consequently neck, back or wrist pains [20, 21]. However, in the current experiment, the laptop was mainly for the participant to set up the lighting when using a backlit screen for a short period of time. Consequently, we do not think using a desktop computer with screens, keyboard and mouse would have substantially changed our results.

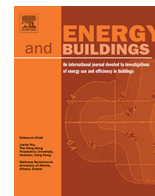
Future studies should complement the presented pilot experiment in evaluating other task light designs with focus on the interplay of desktop illuminance with backlit screens usage and including daylighting. The overall goal is to provide energy saving recommendations for the use of task lighting next to backlit displays without compromising occupant comfort.

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Saving energy by maximising daylight and minimising the impact on occupants: An automatic lighting system approach



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ABSTRACT

Electric lighting energy expenses has gained importance in the last decades representing a large part of the global energy expense worldwide. The increase of the proportion of glazed building facades is an incomplete solution raising other problems regarding thermal and visual comfort, while rebound effects in terms of lighting usage lowered the energetic benefits of LED technology. Another strategy to address the issue of energy is the well-known strategy of the re-introduction of task lights. The current study presents a system arbitrating the contribution of daylight with general and task electric lighting from the prediction of key performance indicators (work plane illuminance and daylight glare probability) by a machine learning model. It aims at reducing energy consumption while minimizing the impact on occupants' comfort and productivity. This system was validated by the mean of a controlled user experiment with 60 participants. Altogether, our data revealed that RADIANCE simulations model accurately predicts on-site monitoring ($R^2 = .96$) and that the machine learning model accurately predicts RADIANCE simulations for both work plane illuminance ($R^2 = .99$) and daylight glare probability ($R^2 = .99$) allowing to operate the automated system. Data from the user experiment shows that our system successfully saves 35 Wh on average compared to manual operation of the room by users, by making prior use of daylight and task lighting. This represents more than halving the energy demand. Importantly, the automation impacted neither users' comfort or task performance. System acceptance constructs such as system reliability or trust in the system were found to be linked with an attribution of the locus of control to powerful others. This result suggests that the key towards high user acceptance might lie in purposefully addressing this dimension. Altogether, the presented results support the potential for energy saving through the development of user-centred lighting automation.

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1. Introduction

Lighting energy expenses have gained attention in the last decade, firstly for their 19% approximate share of the global electric energy consumption [1], but also because recent progress in building thermal envelope efficiency increases the share of lighting on the overall building energy expenditure. Typically, presence-

based and daylight-availability lighting controls contribute to reduce this demand, demonstrating the positive impact of energy efficient techniques encompassing daylighting (DL), electric lighting (EL) and blind control. Nonetheless, growing economies, the emergence of LEDs, higher user demands for quality lighting and rebound effects as a result of low priced and more versatile electric lighting – “more for less”, lead to an absolute increase of worldwide lighting energy consumption [2]. In brief, more lighting is used, less consciously.

Increasing the proportion of glazing in building facades is only part of the answer: highly glazed buildings indeed increase daylight penetration, reduce heating loads in winter, and offer pre-

Abbreviations: CCT, Correlated Color Temperature; DGP, Daylight Glare Probability; DL, Daylighting; EL, Electric Lighting; KPIs, Key Performance Indicators; ML, Machine Learning; WPI, Work Plane Illuminance.

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cious views outwards. However, they also cause excessive daylight provision leading to an increase in thermal discomfort in summer [3], and impairing visual comfort by the strong luminance gradients between indoors and outdoors within the occupants' field of view – the *glare*. Either of these discomforts, would lead the most sensitive occupants to maintain the shading systems closed on sunny days, relying mainly on EL. As a result, (1) the building's energy consumption would increase compared to the intended design (performance gap), (2) the occupants do not benefit fully from the benefits of daylight. To overcome this problem, multiple shading and electric lighting automation systems have been proposed and investigated by practitioners and researchers over the past decades [4,5]. However, they often suffer from simplistic control or interface design, resulting in occupants perceiving negatively the automation system behavior [6–8]. Actually, if the EL and the facade market have seen significant developments in the last decade, the fact that they mainly act independently to each other leaves out opportunities for better user-centred and energy-efficient systems [9].

In the context of office lighting, high visual comfort is needed, providing the right illuminance in intensity and spectra while avoiding glare. For comfort and productivity reasons, it is crucial to reach high user acceptance of the lighting situation and to provide the ability to control it [7]. Simultaneously, energy consumption needs to be lowered, leading to a contradicting situation. Efficient and balanced strategies both fulfilling building occupants' and operator's needs are thus required, such as the well-known strategy of task lighting, which reduces energy-intensive general lighting usage by providing light where and when it is most needed, with the advantage of meeting users' personal needs [10,11]. The present research aims to evaluate and discuss the potential of automatic control able to arbitrate the contribution of DL with general and task EL. It focuses on the relationship between comfort and energy saving by encompassing the DL/EL interplay with a user-centred approach. To this end, a lightweight control system able to control (1) the general lighting, (2) a desktop lamp, and (3) the shading system, based on the estimation of resulting daylight conditions performed by a machine learning (ML) model, is proposed and evaluated in a controlled experiment. This paper particularly focuses on the proposed system's impact on energy usage for lighting. Evaluating the consumption of different levels of automatic control in interplay with user intervention and behaviour allowed us to assess the magnitude of sub-optimal user interventions on the final energy balance.

1.1. Related work

The field of lighting automation is extensive, and it would be too large a task to review it here. We refer the reader to existing reviews, such as [12]. We concentrate on presenting relevant examples of intelligent lighting automation and related examples of user experiments involving lighting. Encompassing reviews of the integration of lighting and shading control can be found in the context of intelligent building [13] and smart home controls [14].

Model-based predictive control for DL. The challenge of achieving balanced energy and comfort goals calls for an integrated approach involving blinds and lighting controls, in which discomfort glare and overheating risks are mitigated through the controlled admission of solar rays, with EL complementing DL availability. This approach requires three implementation steps [15]: a real-time estimation of sky conditions, a model to estimate indoor DL according to sky conditions, and performance-based control criteria. Key Performance Indicators (KPIs) such as work plane illuminance (WPI), and daylight glare probability (DGP) are relevant to

ensure adequate regulation of the daylight environment [16]. However, while the accuracy of the KPIs estimation is appropriate, the control response celerity to adjust blinds and lights according to outdoor conditions is decisive. Conventional methods employed for blinds and light automation control have mostly relied on interior mounted photo-sensors and digital cameras [17,18], requiring intricate calibration procedure and raising privacy concern, as well as on computer simulations [19], typically resulting in high computation resources, especially for the precision needed for DGP estimation (orders of magnitude higher than WPI). Even with further innovations integrating a digital camera and sky sensor [20], the prediction-control loop tend to be prolonged, especially in the case of solar protection for glare, leading to time delays that may jeopardise the occupant's visual comfort, and especially increasing the risk for glare in situations of dynamic sky conditions.

Surrogate models. ML techniques represent an alternative method for daylight performance predictions. They have been employed to model indoor illuminance as an absolute value to predict daylight performance metrics [21,22]. The potential and suitability of ML algorithms for daylight prediction have been explored by considering varying model parameters and input data, demonstrating its potential for high accuracy predictions [23,24]. More recent studies have also relied on ML surrogate models for dynamic predictive control, representing several advantages with regards to conventional methods [25–27], e.g. to rely on the use of non-invasive methods, adding simplification to the commissioning process. In this regard, the use of ML techniques represents a time-saving approach, with demonstrated performance prediction accuracy. As an all-encompassing approach, the use of ML surrogate predictor models for EL and DL as part of a model-based predictive control would allow more efficient regulation of the indoor environment due to its quasi-real-time optimisation of the building parameters in accordance with outdoor conditions.

Potential for energy-saving. The extent of electricity savings through light automation obviously varies depending on the context [9]. Lighting automation has been proven to strongly contribute to the reduction of energy consumption in office spaces [28,29]. As an example, a 7-months long study comparing various control techniques in a San Francisco office building, controls yielded 23% savings for bi-level switching, 45% savings for occupant sensing with task tuning, 40% savings with occupant sensing and manual dimming, and 44% savings for occupant sensing and automatic dimming [30]. The magnitude of potential energy savings that can be achieved with daylight-responsive lighting controls depends on the daylight climate, the sophistication of the selected control system, and the size of the control zones [9]. While electricity demand for lighting can be lowered by at least 50% by using existing efficient technologies [9], schemes integrating DL can save up to 60% compared to traditional installations [31], making lighting retrofit one of the most cost-efficient energy conservation measure in buildings [1]. On the other hand, human behaviour highly impacts the actual building energy performance – including lighting [32] – showing a potential energy saving of 5–30% in non-residential buildings [33]. The same occupant behaviour may actually have detrimental effects on the potential savings of automated control strategies [7].

User experiments with lighting. There are several examples of user experiments testing the effect of lighting ranging from the study of system usage and acceptance in a controlled environment [34], the inclusion of dynamic lighting [35], the assessment of cultural influences [36] to the importance of emotions [37]. Most relevant of the office lighting context, the recent generalized usage of backlit screens appears to delay the reaction towards light dimming and to reduce the amount of light required at the workplace [38,39].

Regarding emotions, light colour and intensity have been found to impact on productivity, mood and room perception [40,41], with daylight showing a positive impact due to its dynamic nature positively influencing mood and arousal [42,43]. Occupants seem however to prefer the completion of daylight input with artificial lighting [44]. The recent field of human-centric lighting (see, e.g., [45,46]) sets out to fulfill the needs for dynamic lighting and completion of daylight with artificial lighting following daylight correlated colour temperature (CCT). Altogether, the cited studies suggest that a provision of both DL and EL sources remains necessary in the building space.

The impact of dynamic lighting conditions on emotion calls for evaluating emotions in the context of dynamic DL/EL control. The use of the circumplex model of affects [47] for assessing emotions related to lighting seems appropriate to grasp the complexity of affects' interactions [37,38]. Other emotional aspects such as personality traits [39] or internal/external attribution of control over life outcomes, known as the *Locus of Control* [48,49] appear to be intertwined with light acceptance and satisfaction.

A review of user satisfaction with regards to lighting can be found in [50]. Such experiments evaluating new lighting control strategies are less frequent than evaluation focusing on energy savings [51], despite the low acceptance of currently installed controls [7] and the acknowledged rebound effects from less conscious usage [2].

Comfort and personalisation. As a result of current research mainly focusing on energy savings, the majority of automation techniques do not allow for personalisation and result uncomfortable for users, which adopt strategies to bypass the automation [52]. This relates to the notion of *technology acceptance*, which has to be maximised for a system to last over time (see [53] for a review on the topic). However, automatic systems often encounter users' reluctance, possibly due to novelty, or to control surrendering to an automated process. Two models were found to represent users' acceptance accurately, called the Technology Acceptance Model (TAM, [54,55]) and the Unified Theory of Acceptance and Use of Technology (UTAUT, [56]), which benefited from several upgrades recently [57–59]. While both models assess acceptance, they focus on different aspects and TAM can be considered as a part of the UTAUT model. Recently, these models were adapted to fit the specific needs for building automation and smart homes [60].

To obviate the acceptance problem and improve occupants' comfort, different levels of lighting personalisation combined with the automation system are proposed in the literature. In the simplest cases, the personalisation consists of manually overriding the automation system [28]. Other sources define more elaborate strategies, such as handling personalisation conflicts in a shared office space [61], finding the best balance between general and task lighting in a open plan office with personalised WPI [62], or learning to balance users' preferred lighting conditions provided by blinds and ceiling lights with the energy consumption of the system through reinforcement learning [63].

In the current study, the satisfaction of users interacting with a completely automated system, as well as an automated system with user inputs is analysed. The level of customisation of the conditions consists of setting the minimum WPI threshold provided by the combination of daylight, ceiling light and task light and partially controlling the CCT.

1.2. Hypotheses

Supported by the above discussion on related work, the paper sets out to explore the interplay between DL/EL automatic lighting and its usage by potential end-users. The corresponding hypotheses that will be tested are the following:

1. Automatic daylight strategy allows to save energy without compromising occupant comfort and performance (H1)
2. Allowing users to set their preferred illuminance level increases acceptance and is more energy-efficient (H2)

Overall the aim is to assess the energy savings potential of DL/EL user-centric intelligent control, together with defining the appropriate degree of automation vs user-level control with respect to DL/EL and impact on energy-saving potential.

2. Methods

2.1. Case study building

Room description. The case study was carried-out in the CELLS experimental building located in the city of Fribourg, Switzerland. It consists of two experimental modules of identical characteristics (R1 and R2). The detailed description of the modules, as well as of the monitoring sessions and the virtual model calibration can be found in [26]. In the present study we focused on the module-R1 where the user experiment was conducted. This module has two windows on North and South orientations equipped with curved white venetian blinds (S-80) (see Fig. 1 (a)). The occupant desk was positioned at the center of the room at about 3.0 m distance from South and North walls, and 1.60 m from East and West walls.

On-site monitoring and virtual model calibration. Similarly to the room description, the on-site monitoring and the virtual model calibration process were already described in a previous publication (see Section 2.2 of [26]).

2.2. Daylight and electric light modelling

The adequate daylighting and electric lighting performance prediction is a fundamental step in the process to achieve an integrated control scheme; a further goal is to achieve a timely response in accordance with outdoor conditions. With those aims, the performance of daylight and electric lighting indoors was first estimated with the use of computer simulations as well as based on measured illuminance. Statistical predictions are then employed as alternative methods, for achieving accurate and fast KPIs estimations and for a prompt implementation of the control strategy.

2.2.1. Physical modelling

Daylight performance prediction. An ML surrogate model was created for the daylight performance prediction, which was trained using year-round simulation-derived data. To establish the relation between the input and the target data represented by the KPIs (WPI and DGP), an extensive database was produced with the use of the RADIANCE matrix multiplication methods [64].

For exhaustive description of the simulation process for the acquisition of the data employed to train the ML model, we refer the reader to a previous publication that employed same process within the same building (see Section 2.3 of [26]).

2.2.2. Statistical modelling

The datasets generated for the R1-modules using physical simulations, consisted in more than a million samples that were used to train two machine learning models, one per KPI. As a result of its performance in a previous study [26], the Gradient Boosting Decision Tree algorithm [65] was chosen as a surrogate statistical model for WPI and DGP predictions. This algorithm works very well in practice and reaches state-of-the-art capabilities on various tasks [66,67]. To keep resources as low as possible, we opted for the LighGBM implementation of the algorithm [68].

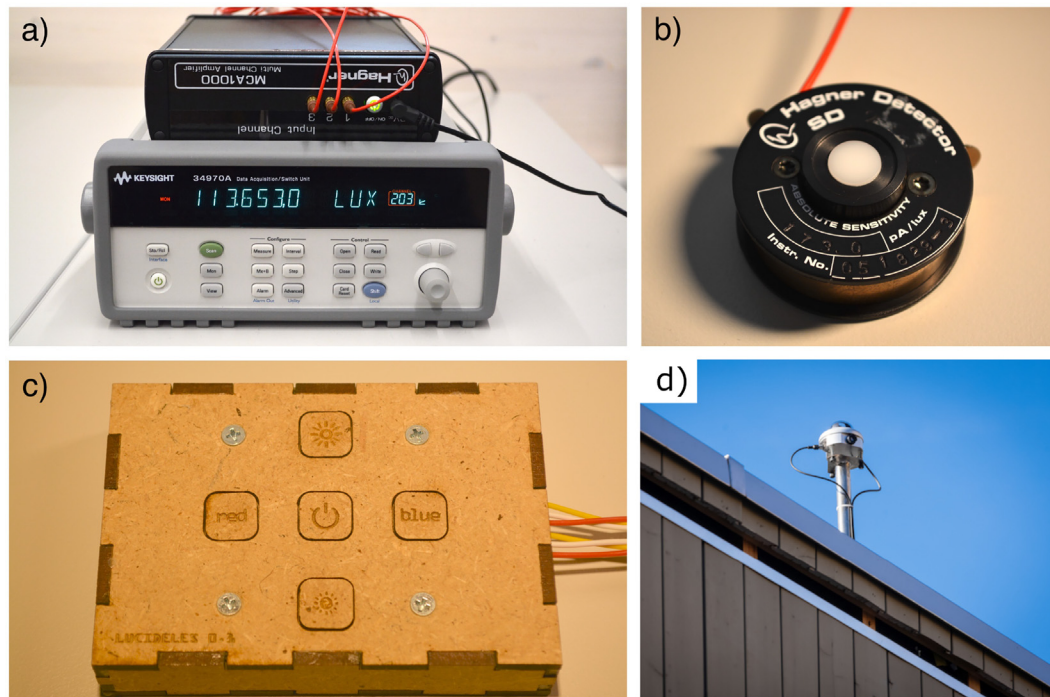


Fig. 1. (a) Interior views of the CELLS module-R1, from the back of the room towards the north-facing window (left) and south-facing window (right). (b) The controlled study setup with (left to right) the control panel, the Joker luminaire, the Hagner lux meters, the webcam for eye-tracking and the computer screen/keyboard/mouse for questionnaire and task completion. (Picture credits: Guillaume Perret, Lundi 13).

The two models were trained using the same methodology, following a standard workflow in machine learning applications. As a first step, the raw data was pre-processed to include the information on the status of the blinds and to encode the solar azimuth. A description of the resulting datasets is given in [Table 1](#).

To evaluate models' accuracy, datasets were split randomly in training (95%) and test (5%) sets. The rationale behind a choice of only 5% for the test samples lies in the large number of datapoint (resulting in a more than 50000 datapoints test set). The training set was further divided into 5 folds for validation. The validation strategy used a modified version of the stratified k-fold cross-validation [69], where the continuous target variable was divided into bins (20 in our case) according to Sturge's rule [70]. This validation strategy was then used to find an optimal set of hyperparameters for each model within a predefined search space. In order to reduce the time needed for this tuning process, the search was done for each hyperparameter separately, or in pairs, in a sequential manner by evaluating a number of evenly spaced values over a specified range. The selected hyperparameters are listed in their tuning order, and their considered search ranges in [Table 2](#).

Finally, a model for each KPI was trained on the training data using the chosen hyperparameters.

Electric Lighting performance prediction. The electric lighting requirements were determined as a compensation of the daylight provision, as output issued from the daylight predictor model. Those were established using a WPI minimum threshold of 100 lx for general lighting and 500 lx for task lighting. In a process similar to the one described in [26], a polynomial regression based on measured illuminance was employed, to establish the relationship between a particular dimming position and the electric power.

A verification process was performed in order to establish the accuracy of the ML model in regards to the RADIANCE simulations (Section 3.1). However, in order to perform an appropriate verification of the KPI for glare (DGP), specialized equipment would have been required, which was unavailable in this study. Therefore, the verification performed here, focuses on the comparison of ML predictions vs. on-site measurements for WPI, while the DGP verification is considered as future work.

Table 1
Description of the data sets used to train the statistical models.

	Unit	Type	Min	Max
Sun altitude	°	Float	−65.91	66.04
Solar azimuth sine	–	Float	−1.00	1.00
Solar azimuth cosine	–	Float	−1.00	1.00
Direct normal irradiance	W/m ²	Float	0.00	1058.13
Diffuse horizontal irradiance	W/m ²	Float	0.00	616.00
Fully open North	–	Boolean	0.00	1.00
Fully open South	–	Boolean	0.00	1.00
Blind angle North	°	Integer	0.00	65.00
Blind angle South	°	Integer	0.00	65.00
WPI	lx	Float	0.00	19709.68
DGP	–	Float	0.01	0.87

Table 2

List of hyperparameters tuned, their ranges, tuning order and chosen values for the models

	Min	Max	Steps	Order	WPI	DGP
max_depth*	6	15	10	1	10	12
num_leaves	20	150	14	1	60	90
min_data_in_leaf	20	100	9	2	20	20
bagging_fraction	0.8	1	3	3	1	1
feature_fraction	0.8	1	3	3	1	1
eta	0.01	0.5	20	4	0.09	0.06

*a value of -1 (IE: no depth limit) was also considered.

2.3. Control system description

With the aim of constantly providing comfortable lighting conditions with minimal energy consumption, an intelligent automated lighting control strategy was implemented for the analysed office setting. The fundamental components of this system are the hardware setup to interface the physical room (including its sensors and actuators) with the control system; the software setup to handle different tasks related to the hardware interface; and the central part of the software solution, the algorithm for automatic lighting control.

2.3.1. Hardware setup

The hardware setup for the automatic lighting system consists of several components to retrieve data useful for the estimation of the best lighting conditions, processing this data, physically changing the room's conditions, and sensing different parameters to analyse the quality of the automation system. Some components of the hardware setup can be found in Fig. 2.

The outdoor daylight conditions are obtained with a Delta-T SPN-1 pyranometer located on the roof of the building, which returns every 3 s the direct and diffuse radiation and the presence or absence of bright sunshine on the office premises. The data from this sensor is collected by a Raspberry Pi 3B via RS232 serial interface and published to an MQTT broker.

The MQTT broker serves the pyranometer data to the central actor (master) of the optimisation process, a low-energy Raspberry Pi 3B, where it is used to find the room settings that provide the

optimal lighting conditions (Section 2.3.2). Once the optimal conditions are found, these values can be applied to the physical room. This is done for the blinds height, position and general lighting through a KNX architecture installed in the office. The intensity and CCT of the used lamp for the task lighting (Regent Lighting Joker) are controlled through a USB-C breakout board connected to the master Raspberry Pi 3B using the Modbus protocol.

To allow manual control of some parameters of the system (e.g., task lighting's CCT and minimum WPI threshold in the user input automation, Section 2.3.3), a control panel with 5 buttons (intensity up/down, CCT up/down and ON/OFF) was implemented and connected via GPIO to the master Raspberry Pi 3B. This control panel was added on the basis of a previous study showing the difficulty of rapid user appropriation of the single-button interface available on the task luminaire [71].

To check the quality of the proposed automation system, several sensors are used to collect information about illuminance and energy consumption. High-quality illuminance sensors (Hagner SD2 with Hagner MCA1000 amplifier) are placed on the experiment's desk to analyse WPI, in the positions mp-n and mp-s (see Fig. 3). This data is processed by the Agilent 34970A data acquisition unit, from where the master Raspberry Pi 3B regularly collects the data via an RS232 serial interface and stores them locally for future analysis.

Energy consumption of the automation system includes the energy used by the general lighting, the blinds, the task lighting, and the optimisation system. Energy used by general lighting and blinds is available through the KNX interface, whereas to retrieve that of the task lighting and the optimisation system, two smart WiFi power sockets NETIO PowerCable REST 101 J are used. A WiFi access point has to be set up on the master Raspberry Pi 3B to exchange data between these two devices with REST APIs using the JSON protocol.

2.3.2. Software setup

The software allowing to interface the physical world with the automatic lighting control is structured in modules with different purposes. The overall software architecture is depicted in Fig. 4. In practice, each of these independent modules is a separate Docker container for consistency, mobility, scalability, and modularity reasons. Information is exchanged within different modules with REST API interfaces.

The central module that is handling all the others is the CORE. Here, the control algorithm, which is described more in detail in Section 2.3.3 is defined. The optimisation system consists in finding the optimal values for blinds, general and task lighting, such that while preserving the comfort of the occupants, the least possible energy is used.

In the CORE, the results from the models presented in Section 2.2 are used. These are handled in the software by the MODELS module. This component retrieves from the external MQTT broker the values of the pyranometer on the roof of the office and then uses this in combination with the blinds and lighting conditions given by the CORE to provide an estimation of the WPI and DGP.

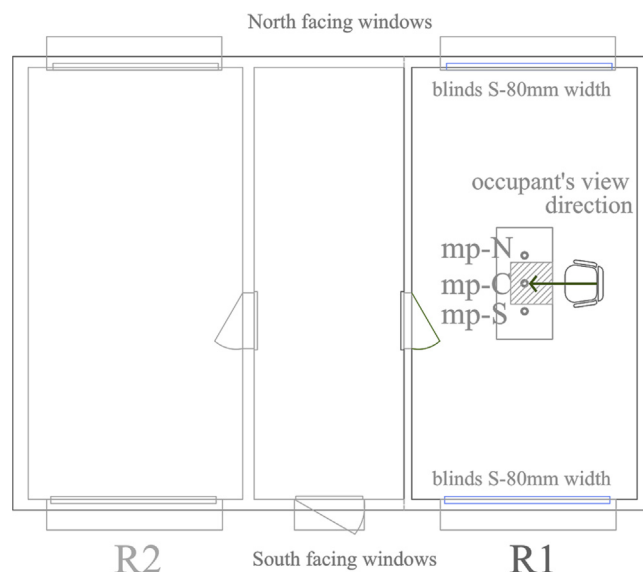


Fig. 2. Some components of the system. a) Agilent 34970A data acquisition unit with Hagner MCA1000 signal amplifier; b) Hagner SD2 illuminance detector; c) Control panel for the system, connected via GPIO to the master Raspberry Pi 3B; d) Delta-T SPN-1 sunshine pyranometer on the roof of the building.

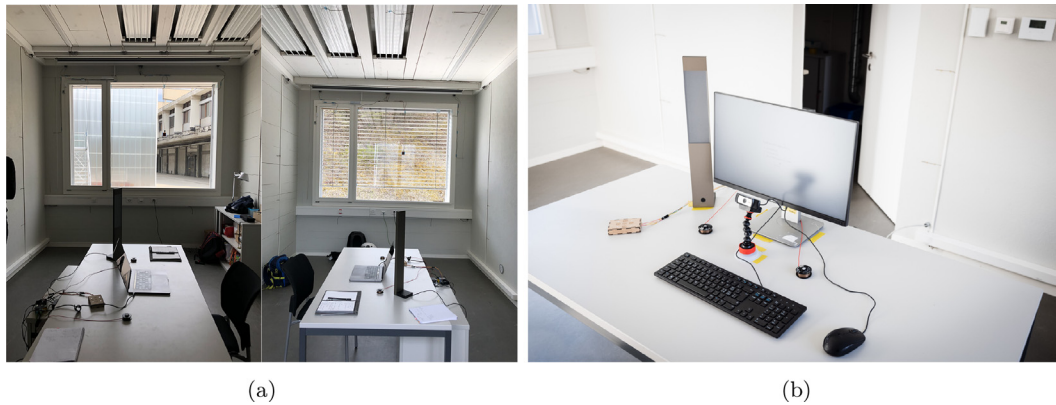


Fig. 3. View of the CELLS floor plan, portraying relevant interior features for this study in module-R1.

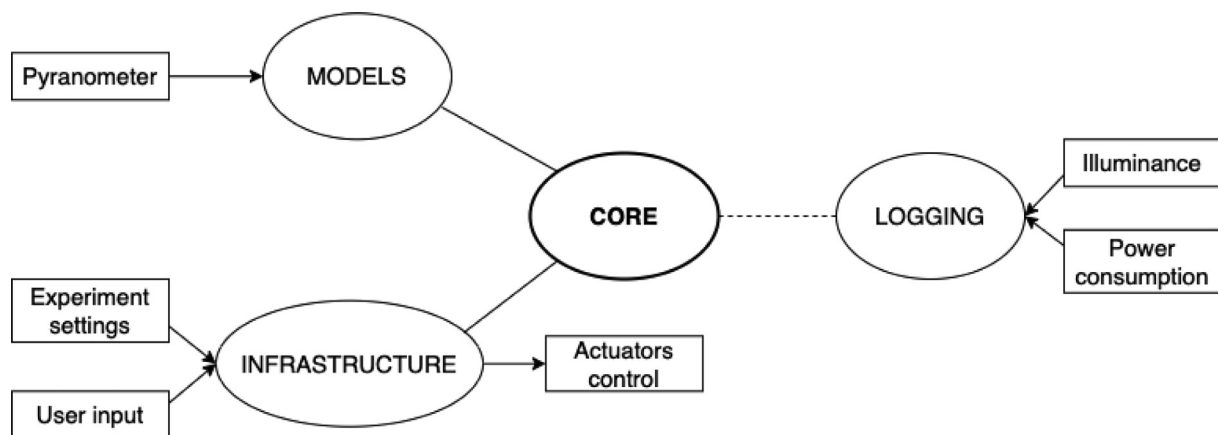


Fig. 4. Software architecture of the overall automatic lighting control system.

When the optimisation process is completed by the CORE, the INFRASTRUCTURE module takes care of updating the physical room by sending out KNX telegrams and Modbus messages. In this component, the input from the control panel and the experiment parameters are also handled.

In the LOGGING module, all data and events to be logged are collected and stored locally.

2.3.3. Automatic lighting control strategy

In this system, the daylight and electric light models from Section 2.2 are used to optimise the room settings (blinds positions, general lighting intensity and task lighting intensity) by continuously running estimations of WPI and DGP on a low energy 32-bit computer (Raspberry Pi 3B), based on measures of direct and diffuse horizontal irradiance from the Delta-T SPN-1 located on the roof of the premises. Once an optimal solution to the problem is found, the physical system is updated using the infrastructure from Section 2.3.2.

The overall strategy for reducing energy consumption consists of providing the highest possible levels of daylight that still are in a comfortable range for the occupants (i.e., 'imperceptible' glare, $DGP \leq 0.35$ [16]). In case that the illuminance provided by daylight alone is not sufficient to reach the minimum WPI threshold, electric lighting is used for compensation (Fig. 5). To further lower energy consumption, a reduced amount of lighting is provided for the background and walking area by the ceiling lights (100 lx threshold), while a more focused but higher intensity task lighting is supplied by a desk lamp (500 lx threshold), in compliance with

the ISO 8995-1:2002 [72] and EN12464-1:2011 [73] workplace lighting standards.

The proposed lighting optimisation process is an extension of [26] and consists in repeating the following procedure every 3 s:

1. Estimating DGP with the current north and south blinds (BN and BS) and sky conditions using m_dgp , the DGP prediction model;
2. Using m_dgp and increments in steps of 5% in the blinds angles, select the blinds position that provides the highest illuminance in combination with adequate lighting comfort ($DGP \leq 0.35$), as in [26];
3. With the found optimal blinds positions, estimate the WPI from daylight alone using m_ill , the WPI prediction model;
4. Using the electric general lighting model, find the minimum intensity which provides at least 100 lx when summed to the estimated daylight WPI (the general light is off if the daylight WPI is higher than $global_ill_threshold = 100$ lx);
5. Using the electric task lighting model, find the minimum intensity which provides at least 500 lx when summed to the estimated global light WPI (the task light is off if the daylight and general light WPI is higher than $task_ill_threshold$, which is 500 lx in automatic mode, and variable starting at 500 lx in the user input automation).

As a further measure to improve user comfort, the blind positions are instantly adapted only in case $DGP > 0.35$ with the current conditions; otherwise, a time interval of at least five minutes is considered between each blind movement. This way

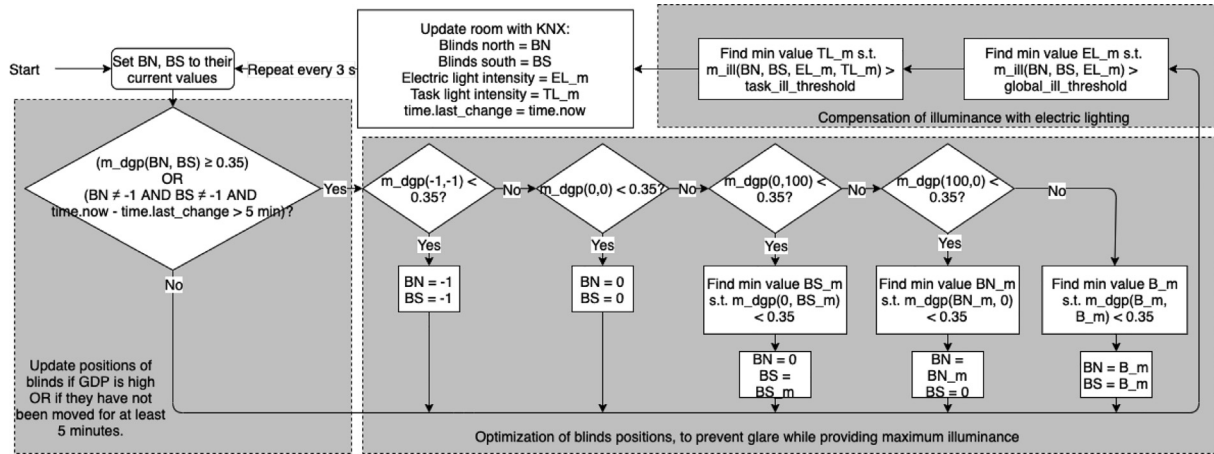


Fig. 5. Automatic lighting control strategy. EL_m and TL_m represent the intensity of general and task lighting.

of operating the system represents a good tradeoff to avoid discomfort glare between comfort (both acoustic and visual) and the frequency of disturbances due to blind motions.

In the experiment, an automatic and a user input control strategy are being investigated. The difference between these two modes consists in the fact that in the automatic mode, the threshold of the illuminance provided by the combination of daylight, general lighting and task lighting is fixed at 500 lx, according to the minimum suggested by the ISO 8995-1 standard [72], whereas in the user input automation this starts at 500 lx but can be increased or decreased manually by the user, using the controls in Fig. 2c).

In the user input automation, the maximum value for the WPI threshold is set to the indicative value of 4000 lx. However, for any WPI threshold higher than the maximum illuminance provided by the task light (~ 640 lx) and ceiling lights (100 lx) combination, one cannot ensure that the WPI will always be higher than the threshold, as this depends on the amount of available daylight. The only difference in setting a threshold higher than 740 lx, is the amount of daylight necessary to reduce the electric lighting intensity.

In both control modes, the threshold of the minimum total illuminance of daylight and general lighting is fixed at 100 lx.

Moreover, in both control modes, the CCT of the task luminaire was controlled to follow a circadian curve to accommodate user preferences, adapting the colour temperature based on the sun's altitude in the sky relative to the minimum and maximum altitude during the day. In the automatic mode, this curve is fixed, with values spacing between 3100 K during the night and 5250 K at solar noon (central curve in Fig. 6), in the user input automation, the whole curve can be moved up or down of a certain amount of Kelvin, with the minimum values ranging between 2700 K and 3500 K at night, and 4000 K and 6500 K at solar noon (Fig. 6). These values were defined based on the color temperature produced by the sun at sunrise and sunset (2500 K–3500 K) and at solar noon (4000 K–7000 K) [74], adapted to the temperatures that the used task lamp could achieve.

2.4. Controlled user experiment

In order to test the automated lighting system described above, a controlled experiment was set up aiming at testing the performance both in terms of comfort and energy saving for lighting with different control strategies: (1) operated entirely manually by the user (*manual*), (2) automated setup (*automated*), and (3) automated with the user being able to operate changes in CCT curve

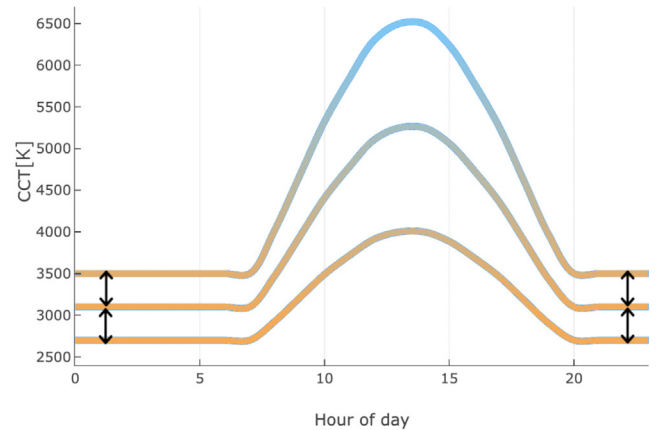


Fig. 6. Circadian CCT curve. For automatic control, the curve in the middle is used. For the user input automation, the user can move the curve up or down of a certain percentage between the minimum and maximum CCT.

(*user input*). In the manual control, the blinds were operated with electronic controls placed below the windows, the general lighting with a switch next to the door of the office, and the intensity and CCT of the task light by means of the control panel of Fig. 2c). Additionally, the case study building presented spaces having large windows on both the north and south sides. This specificity was compensated by testing with blinds fully open or closed on one side or the other. Fig. 1 (b) depicts the controlled study setup.

2.4.1. Participants

60 participants – 53 females; 54 right-handed (aged from 18 to 51 years old; $M = 22.57$, $SD = 5.80$) – took part in this study. All participants were used to office work. Before the experiment, most participants were in a good mood, calm, and comfortable. They all gave informed consent and were informed that they could withdraw their data by the end of the study.

2.4.2. Materials

The Levenson locus of control scale [75] was used to evaluate the locus of control through Powerful others, chance and internal construct. This scale was favoured over classical scales reporting internal and external locus as those two constructs seem to tap different beliefs [75,76]. We adapted the scale according to [77] by removing items that performed poorly.

After each trial, we used the Office Lighting Survey (OLS, [78]) with a likert scale from strongly disagree to strongly agree to evaluate light quality and the Karolinska Sleepiness Scale to evaluate the sleepiness [79]. To analyse participant sentiment toward their emotion and the light after each trial and the object perception at the end of the experiment, we asked participants to tick adjectives within a list following the circumplex method of affects [80]. We inferred those three circumplexes from a previous crowd-sourced online questionnaire with more than 100 participants, using the method described in [81], which will be described in a subsequent publication.

Regarding the assessment of automation acceptance, we selected several models in the literature and extracted meaningful constructs for our goal. More specifically, we combined models of [82,83,60]. We ended with eight constructs, *i.e.*, perceived control (3 items), perceived system reliability (3 items), compatibility (3 items), perceived ease of use (3 items), perceived usefulness (4 items), attitude (3 items), intention to use (3 items) and trust (3 items, see the appendix in Section A for more information about the items used for each construct). All the items were assessed on a Likert scale from strongly agree to strongly disagree.

The task selected was a typing task of texts containing errors. This task appeared to have the right balance between ecology and control. Six texts of 796.17 words on average ($SD = 20.53$) were extracted from the well-known book *Harry Potter and The Philosopher's Stone*. Typing errors — letter replaced by a letter in the surround according to a QWERTZ keyboard layout, letter inversion, or phoneme errors — letters replaced by other letters reading the same sound, *e.g.*, “é” and “et” in french — were randomly inserted every 20 words following a Poisson distribution with $\lambda = 20$.

2.4.3. Procedure

Participants were randomly assigned to an automation condition (either automated, user input or manual) and went through all modalities of the blind condition (both opened, north closed and south closed). Before the experiment started, participants fulfilled a consent form, the questionnaire to assess the locus of control and provided socio-demographical data. Each block started with the setup of the blind condition as well as the possibility for the participants to adjust visual conditions using the blinds (in manual setup only), the general light (in manual setup only), and the task light (intensity: in manual setup and CCT: in both manual and user input setup). Then, during the first trial, participants had to copy and correct a text populated with typing errors for about 3 min. Before a short break during which participants were able to change the visual conditions as stated above, they fulfilled the OLS and KSS scales and select adjectives of the circumplexes for emotion and light. Then a second trial took place and ended with the questionnaires fulfilment mentioned above. Three blocks were repeated with breaks in between to evaluate the three blind conditions. At the end of the experiment, participants fulfilled a questionnaire to assess their acceptance of the automation (see 2.4.2, for more information on specific experimental materials). Overall the experiment lasted between 1 h and 1 h and 30 min depending on the time participants took to answer the questionnaire. Participants were balanced across three different times of the day (Morning (8:00–11:00), Midday (11:00–14:00) and Evening (14:00–17:00)) and were 20 per automation condition (Manual: 6, 11 and 3; User Input: 6, 10 and 4; Automated: 7, 9 and 4, respectively).

2.4.4. Data analysis

Data was analysed using R, and charts were plotted using Python. All data collected was averaged across trials, while questionnaires data was averaged across constructs. The locus of control was investigated using the 3 constructs described in

Levenson [75] and were computed according to the methodology described in this study.

To evaluate the impact of the automation and blind condition, we set up (generalised) linear mixed models (with appropriate distribution, when both conditions were present) and (generalised) linear models (with appropriate distribution, when only the automation condition was considered), with participants as a random factor. We used the Anova function in the car packages in R to generate p-values using Wald Chi-square test. The Bayes factor was computed using the Bayesian information criterion (BIC) of the null model as compared to the model including a factor, both factors or the full model with an interaction effect. This computation allowed us to ensure that the automation condition did not impact on certain variables.

Regarding the circumplexes analysis, Rayleigh tests assessed whether the selected adjectives indicated a direction around the circumplex space. When at least two groups exhibited a direction, a CM test assessed the significance of the difference in directions.

3. Results and analysis

3.1. Physical modelling

Virtual model calibration: on-site monitoring vs RADIANCE simulations. On-site monitored and simulated WPI were first compared to assess the representability of the existing situation by the virtual model. A resulting R^2 of 0.96 was observed, while a MAE of 19 lx and MAPE of 24% were obtained for module in which the experiment was conducted.

3.1.1. Statistical modeling

ML model verification: ML predictions vs RADIANCE simulations. In order to evaluate the performance of the two statistical models on approximating the RADIANCE simulations on the specific case study, a set of unseen samples has to be used. For this reason, 5% of the data was set aside before training the models.

The WPI model achieved a MAE of 2.28 lx and a R^2 of 0.99, while the DGP model achieved a MAE of 0.00058 and a R^2 of 0.99. Furthermore, while situations of high DGP were not common in the considered setting, the DGP model achieved a MAE of 0.0021 and a R^2 of 0.96 on the subset of test samples with a ground truth value higher than 0.20. These results can be observed in Fig. 7, where the distances between the models' predictions and the actual test values are presented. In general, the models' predictions are very close to the target values as simulated with RADIANCE. Few outliers can be seen in the plots, mainly in the WPI predictions for true values above 400 lx. Only in two cases, the predicted WPI is well below the actual values, which would lead the system to provide more light than needed. Despite causing an unnecessary increase in energy use, this behaviour is acceptable as it still guarantees the minimum required illuminance on the workplane. Out of the test samples where the target illuminance was between 200 and 400 lx, in 1.23% of the cases the model predicted a WPI of more than 300 lx when the ground truth was below this threshold. This subset of test samples is particularly relevant as 300 lx is the minimum value that needs to be guaranteed according to the current laws. In such cases, the mean absolute prediction error was 11 lx, with a peak of 111 lx. Concerning the DGP, an important threshold is at 0.35, which is the limit to guarantee visual comfort. While only few test cases were available with a target DGP around this value (43 samples where the simulated DGP was between 0.25 and 0.45), none of them was estimated by the model to be below the threshold when it was not.

ML model verification: on-site monitoring vs ML prediction. In order to assess the performance of the predictor model, the WPI

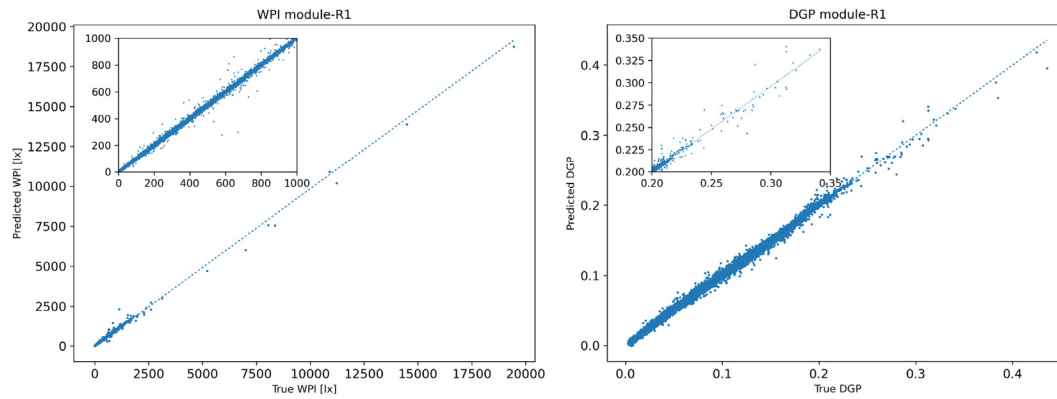


Fig. 7. Scatterplots comparing the statistical models' predictions with the actual values on the test sets for module-R1: WPI (left, with a zoom in the range 0–1000 lx) and DGP (right, with a zoom in the range 0.20–0.35).

results produced by the LightGBM model estimations were compared to on-site monitored data obtained during Spring 2021. As a result, a MAE of 36 lx and a MAPE of 19.28% were reported for module-R1.

3.2. Controlled user experiment

3.2.1. Fatigue and visual comfort

The automation condition had no impact on the rating of the light. This was confirmed by Bayesian analysis showing decisive evidence for no effect ($BF_{10} < 1/100$). This suggests that the automation condition did not have an impact on light ratings. The blind condition reveals a significant impact on the rating of light, $\chi^2(2) = 19.79, p < .001, BF_{10} = 2.52$. Specifically, both blind opened elicited a better rating of lighting conditions ($M = 1.08, SD = 1.00$) than when north blind was closed ($M = 0.61, SD = 0.98, p < .001$) or when south blind was closed ($M = 0.87, SD = 1.14, p < .05$, see Fig. 8). No interaction effect was found. In short, the condition with both opened blinds positively impacts light ratings, whereas the automation condition did not have any impact on ratings.

The automation did not have an impact on the reported fatigue with decisive evidence ($BF_{10} < 1/100$). Regarding the blind condition, it had no impact on the fatigue reported with decisive evidence ($BF_{10} < 1/100$). (see Fig. 8). On overall, neither the automation nor the blind condition impact on the fatigue, preserving participants' arousal.

3.2.2. Performance

The blind conditions had a significant impact on the number of errors, $\chi^2(2) = 8.56, p < .05$. When the south blind was closed, participants made about 1 mistake less ($M = 10.58, SD = 6.64$) than when both blinds were closed ($M = 11.78, SD = 7.62, p < .05$). On the contrary, Bayes Factor indicated no effect with moderate evidence ($BF_{10} = 1/4$). The automation condition did not impact the performance in terms of number of errors with extreme evidence ($BF_{10} = 1/260$). Both conditions did not impact on the typing speed with substantial and decisive evidence ($BF_{10} = 1/4$ and $BF_{10} < 1/100$, respectively). In other words, the automated system or the blind configuration preserve overall the performance of participants, suggesting that participants managed to work efficiently with the proposed automation system.

3.2.3. Light

The automation had no impact on the amount of light. However, the Bayes factor revealed an effect of automation on the amount of light with decisive evidence ($BF_{10} > 100$). Suggesting, that the automated setup provided more light (1427.11 lux on average, $SD = 1639.06$) than the manual setup ($M = 823.79, SD = 1197.44$). Regarding the blind condition, it had a significant impact on the amount of light in the room ($\chi^2(2) = 8.77, p < .05$) with decisive evidence ($BF_{10} > 100$). More specifically, both blind closed eliciting a higher amount of light in the room ($M = 1328.98, SD = 1531.32$) than when the north blind was closed ($M = 952.91, SD = 1215.15, p < .05$) or when

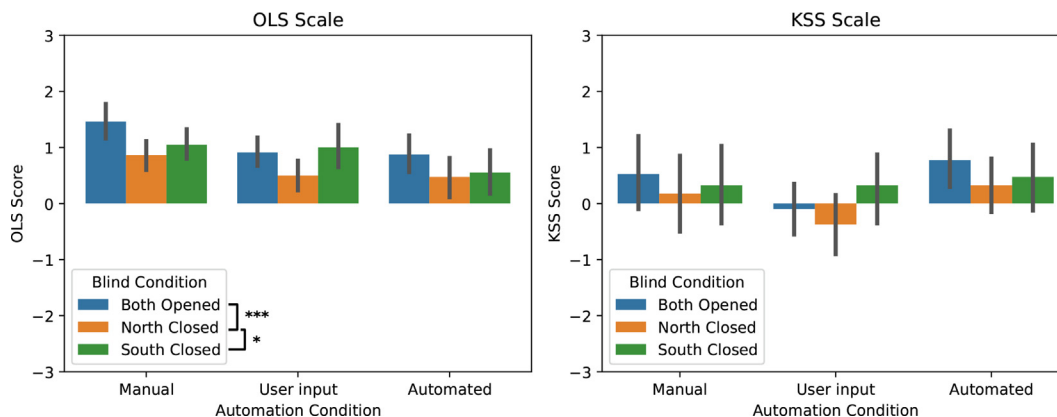


Fig. 8. Violin plots depicting the impact of the automation condition and the blind condition on both OLS and KSS scales. On the left: the OLS averaged score evaluating comfortable lighting conditions, ranging from -3 (Strongly disagree) to 3 (Strongly agree). On the right, the KSS averaged score ranging from -4 (Extremely sleepy) to 4 (Extremely alert). The y axis was truncated to -3 and 3 for readability. Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.

the south blind was closed ($M = 984.44, SD = 1308.75, p < .05$, see Fig. 9). In summary, the blind condition allow more light to enter the room when both blinds were open. However, this possibility is a particularity of our test space that had two windows on each side of the working space. Importantly, while the automation did not impact on the amount of light, the automated setup provided with twice as much light than the manual setup.

3.2.4. Energy consumption

The automated and the user input setup consume more energy for task light ($\chi^2(2) = 6.24, p < .01$), and less energy for the general lighting ($\chi^2(2) = 8.13, p < .001$) than the manual setup. More particularly, the manual conditions consumed less task light energy (about 2.00 Wh on average, $SD = 2.08$) than user input setup ($M = 5.07, SD = 3.81, p < .01$); but consumed more energy from the general lighting ($M = 48.21, SD = 61.95$) than automated ($M = 6.14, SD = 11.87, p < .01$) and than user input setup ($M = 7.79, SD = 14.57, p < .01$). An example of the general lighting intensity control with automated and manual modes is depicted in Fig. 10, where a higher general lighting energy consumption for the manual control, due to the fact that the high majority of users set the desired intensity at the beginning of the experiment and did not change it, despite the changes in external lighting conditions. The automation condition did not reveal any significant impact on the energy consumption of the raspberry pi with strong evidence ($BF_{10} = 1/20$). Altogether, the automation significantly decreased the total energy demand ($\chi^2(2) = 6.67, p < .01$) with substantial evidence ($BF_{10} = 9$). More specifically, the manual setup had a higher energy demand ($M = 53.72, SD = 63.50$) than both the user input automation ($M = 16.37, SD = 17.27, p < .01$) and the automated setup ($M = 13.61, SD = 13.57, p < .01$), with this last condition saving the most energy for lighting. Overall, the automated setup saved on average about 40.11 Wh and the user input saved 37.35 Wh (see Fig. 11). Following the Swiss SIA 2024:2015 Norm, an open space office in an energy efficient design should target 1290 h of lighting on. For a 60 min-long experiment and a 20.12 m² room area, 40 Wh extrapolates to an annual reduction of 51.6 kWh or 2.56 kWh/m². This reduction is valid for a single workplace (in the experiment) in a room where at least 4 workplaces can take place, adding up the savings through the possibility of sharing general lighting.

3.2.5. Circumplexes for emotion, light and object

The circumplex for emotion did not reveal any direction from the automation condition, indicating that the emotion was too uni-

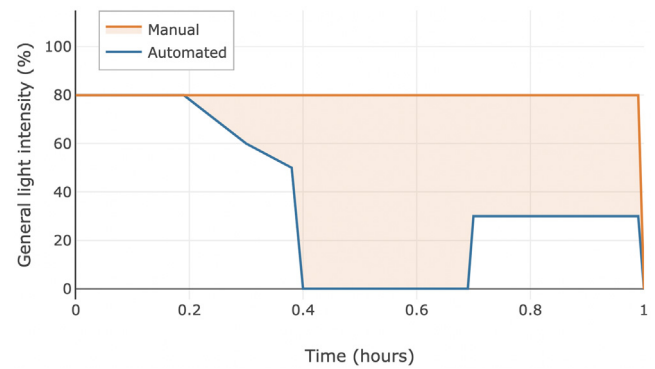


Fig. 10. Example of general lighting intensity with different controls during the experiment. In this example, the experiment started with no daylight. Any change in the daylight availability was compensated by the automated control. In the manual control, participants were observed to set the general lighting at the beginning of the experiment and not modify it until the end. This caused an energy consumption overhead in the automatic mode, shown by the difference between the two curves. User input automation corresponds to the automated curve, as the general lighting threshold is fixed.

formly distributed around the circumplex for each automation setup. Regarding the circumplex for emotion, the blind condition did not reveal any direction. Regarding the circumplex for light, the automation revealed a direction for all setup: automated and manual setups indicated a direction between relaxing and indirect ($S = 15.21, p < .001$ and $S = 4.99, p < .01$, respectively), whereas the user setup indicated a direction close to indirect ($S = 3.18, p < .05$). For the blind condition, the circumplex for light revealed that both opened blinds and north closed indicated the same direction between relaxing and indirect ($S = 13.22, p < .001$ and $S = 4.88, p < .01$, respectively), whereas when the south blind was closed the light was felt as more indirect ($S = 3.06, p < .05$). Fig. 12.

3.2.6. Automation acceptance

For clarity, Table 3 reports all the significant results from the acceptance questionnaire. In short, the manual setup was evaluated as letting participants have more control, was perceived as more reliable and compatible with persons' life as compared to both user input and automated setup. There was no difference across automation conditions regarding, the usefulness, the attitude, the intention to use and the trust toward the systems.

As Fig. 13 shows, overall, acceptance constructs were mainly related to powerful others construct. This was the case for control, system reliability, compatibility, usefulness, attitude and trust that had a significant negative correlation with the powerful others' score. On the opposite, the ease to use construct increases with the internal attribution ($r = .23, p < .05$). The intention to use the system was not related to the locus of control.

Interestingly, separating automation conditions revealed that compatibility had a strong negative and significant correlation with the powerful others construct. In contrast, other acceptance construct did not have any link with the locus of control. The user input setup revealed that the powerful others construct correlated negatively and significantly with the perceived control, system reliability, ease to use and attitude towards the user input system. Finally, the manual setup did not reveal any link with the locus of control.

4. Discussion

This study aimed to set up a state of the art daylight and electrical lighting automatic control system and evaluate this system

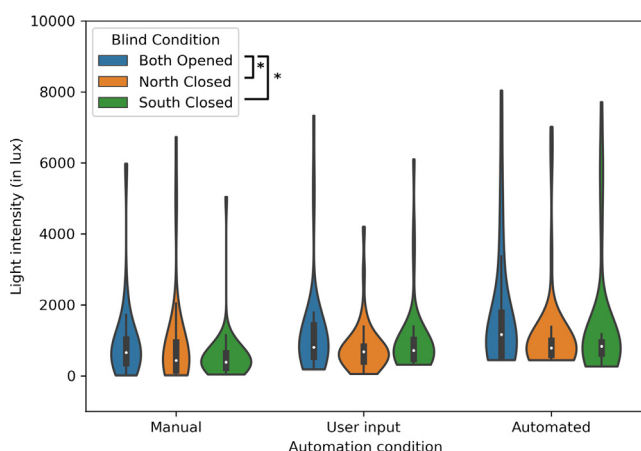


Fig. 9. Violin plots depicting the impact of the automation condition and the blind condition on the quantity of light. Note: *: $p < .05$.

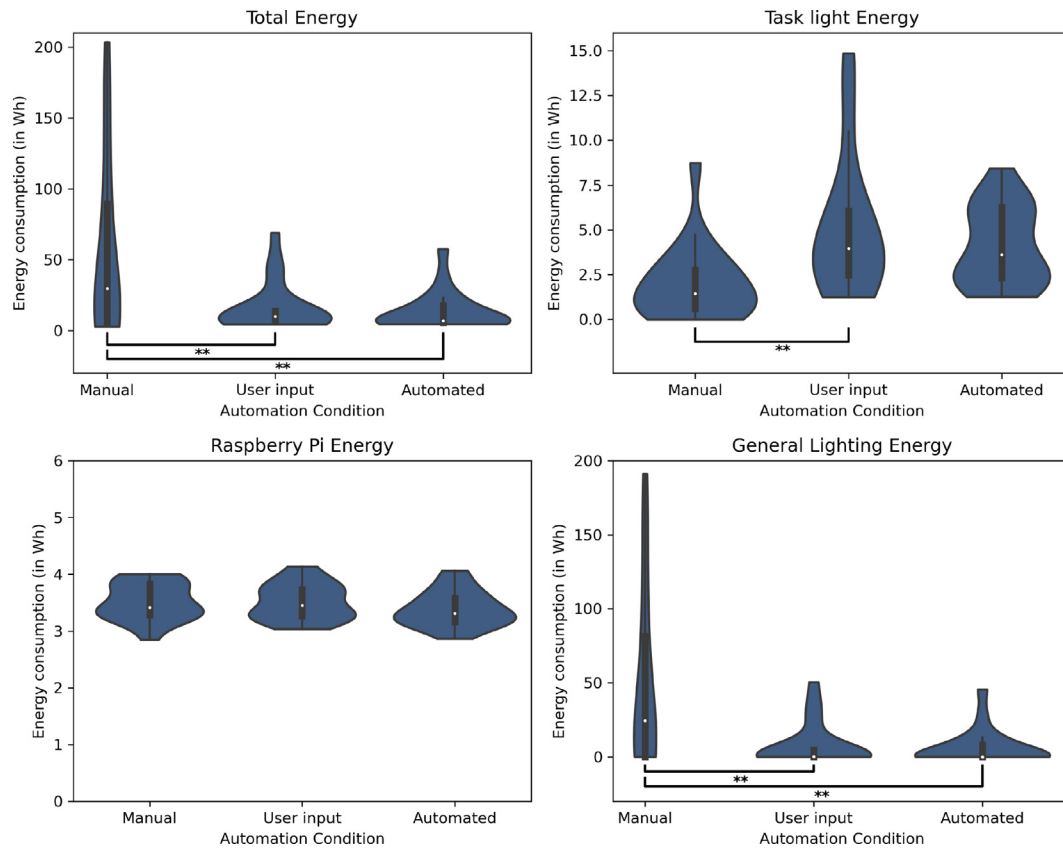


Fig. 11. Violin plots depicting the impact of the automation condition and the blind condition on energy consumption. The total energy consumption, the energy used for the task light, the general lighting and the raspberry pi used for the automation are depicted. Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.

in a controlled user experiment. The system leveraged a lightweight machine learning approach and aimed at maximising daylight supply while minimising the use of global lighting by using a task light. Additionally, discomfort glare was controlled through the use of an automated blind strategy. With such an approach, this system could save energy by distributing light where and when it is the most needed, *i.e.*, on the work-plane.

The achievement of accurate daylight performance estimations as a key purpose in this study was first addressed by the generation of a comprehensive, high-quality simulation dataset comprising two KPIs: the DGP and the WPI. An improved response time of the KPIs estimation was then addressed by integrating DL and EL surrogate models in the control scheme in the pursuit of a prompt and accurate prediction alternative. The accurate ML predictions of the KPIs, along with timely feed measured weather data, lead to a quasi-real-time adjustment of blinds and electric lighting dimming positions. As a performance-based approach, conceived in accordance with energy and comfort guidelines, the proposed process works towards a high-performance regulation of the interior environment. This optimisation consisted as first step in reducing the risk of glare for the occupants by an estimation of the DGP in the analysed space. Regarding DGP evaluation, it is worth mentioning that only a straight view of the occupant towards the wall was considered in this study. While this viewing position and having the desk positioned in the middle of the room decreased the probability of discomfort glare to occur, it allowed us to both comply with the ergonomics norms (*e.g.*, [84]) and have an equal distance between each window and the desk. However, it is important to note that this choice represents a limitation of the prediction capabilities of our method. Secondly, in providing sufficient daylight, to be compensated with the minimum amount of global electric and

task lighting necessary to ensure the minimum requirements. The response time of the system to changes in daylighting conditions potentially causing user discomfort is maximum 3.5 s, varying based on the exact moment when the event occurs between the pyranometer measurements (collected every 3 s) and on the number of computations required to find the optimal interior conditions. The reaction time could be improved by increasing the sampling rate of the pyranometer and the frequency of conditions checking, but one can argue that a 3 s delay provides a good compromise between the number of energy-hungry computations and user comfort. Regarding computing time, the ML approach outperforms the use of computer simulations, as the latter would take at least 8 s to complete each process for an specific time step, this considers simulations as well as the iterations to select the most adequate position.

The design of the controlled experiment aimed first at evaluating several automation approaches (automated and user input) as compared to a typical office operated manually. We additionally took advantage of the specific design of CELLS modules, glazed on both South and North sides (described in Section 2), to test multiple blind closing conditions. The controlled experiment leveraged upon an ecologically valid task consisting in correcting and copying a text. The task was performed while the automation operated the room or, in the manual condition, participants set the lighting conditions to maximise its comfort before completing the task.

While the automation setup did not impact the evaluation of lighting quality and fatigue, the blind closing condition had an impact: when both or the north blind were open, participants judged the quality of light more satisfying. This result can be probably explained by the greater amount of daylight passing through when both blinds were open compared to when a single blind was

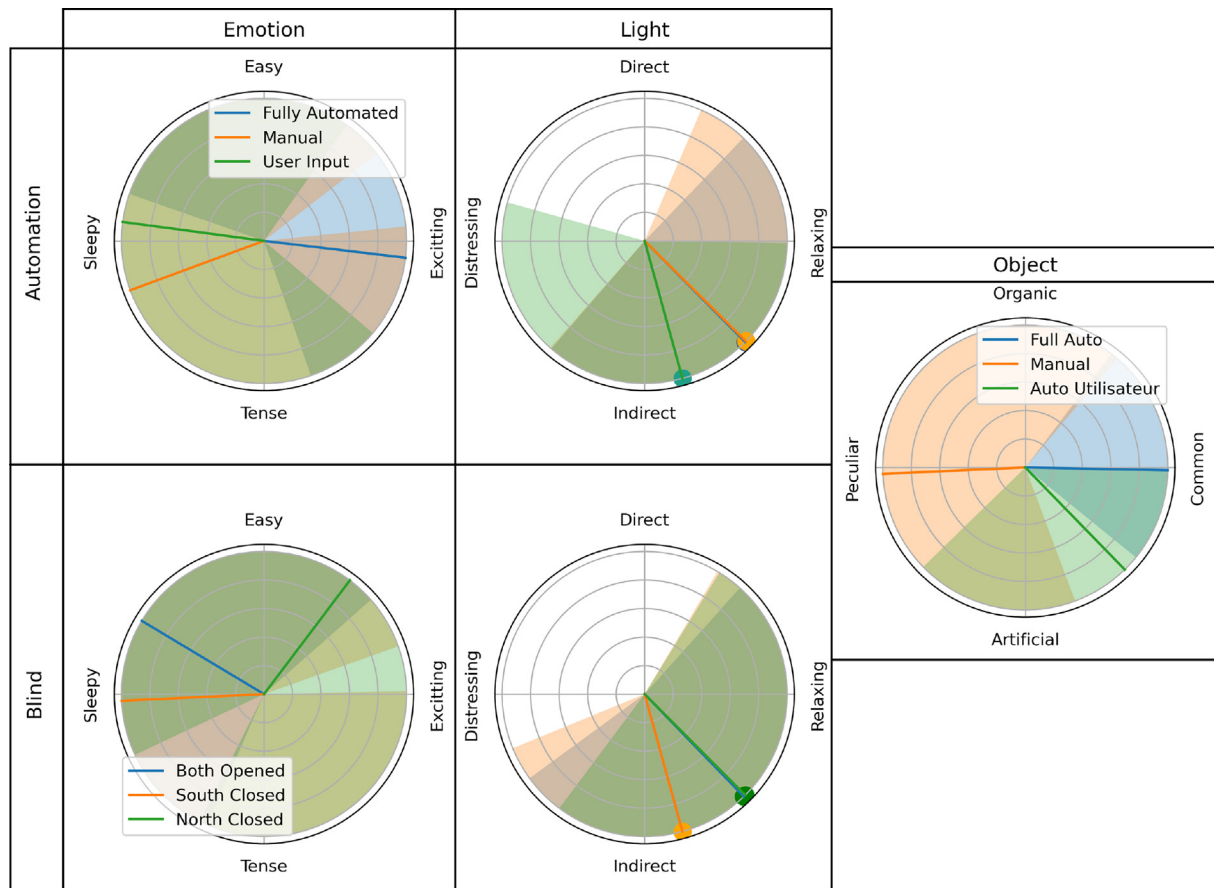


Fig. 12. Circumplexes for emotion light and object. Columns represent the type of circumplex and row the condition (either automation or blind). The rightmost circumplex is the circumplex for objects and was evaluated for the automation condition only. A filled circle represents a significant direction spotted by the Rayleigh test. When there is nothing at the end of the line, the distribution was found to be uniform around the circumplex. The shaded areas represent the 95% confidence interval of the identified direction.

Table 3
Results from the acceptance questionnaire.

		Mean (SD)	F value (df=(2,57))	p-value	BF ₁₀	Post Hoc tests (Tukey's correction)
Control	Manual:	1.62 (0.85)	1.62 (0.85)	<.01	12	Manual-Automated <.01
	User input:	0.72 (1.11)				
	Automated:	0.10 (1.75)				
System Reliability	Manual:	1.53 (1.06)	5.72	<.01	4	Manual-User input: <.01 Manual-Automated: <.05
	User input:	0.43 (1.08)				
	Automated:	0.68 (1.10)				
Compatibility	Manual:	1.70 (0.92)	9.26	<.001	77	Manual-User input: <.01 Manual-Automated: <.01
	User input:	0.33 (1.19)				
	Automated:	0.36 (1.29)				
Ease to Use	Manual:	2.12 (0.50)	3.63	<.05	1/2	Manual-Automated: <.05
	User input:	1.57 (0.88)				
	Automated:	1.42 (1.11)				

open, and by the highest clearance when the north blind was open. However, as stated in the introduction, increasing the proportion of glazed-building facades is part of the solution to lighting energy consumption but raises thermal comfort issues. Importantly, the automation system did not impact either the feelings about the current emotion, the light or toward the task light as an object or on the performance. Those results suggest that the system was well-calibrated to avoid any disturbance of the occupants' work and emotions.

The amount of light was maximised in the automated setup with a greater amount of light than the manual setup. The user input system did not differ from the two others. It is important

to note that about 20% of the participants tested in manual setup completely closed the blinds, whereas the fully automated setup the system completely closed the blinds in 5% of the cases. Altogether, those observations reveal different behaviours between occupants and our automated system. However and crucially, this did not impact on occupants' satisfaction towards visual comfort. Interestingly, this suggests that our automated approach provided a greater light supply, whereas occupants operated the room in a less optimal fashion with less willingness to change the light conditions or to anticipate on potential glary provision of daylight.

Crucially, the goals of the system were successfully completed, as the system, while requiring a greater amount of task light, sig-

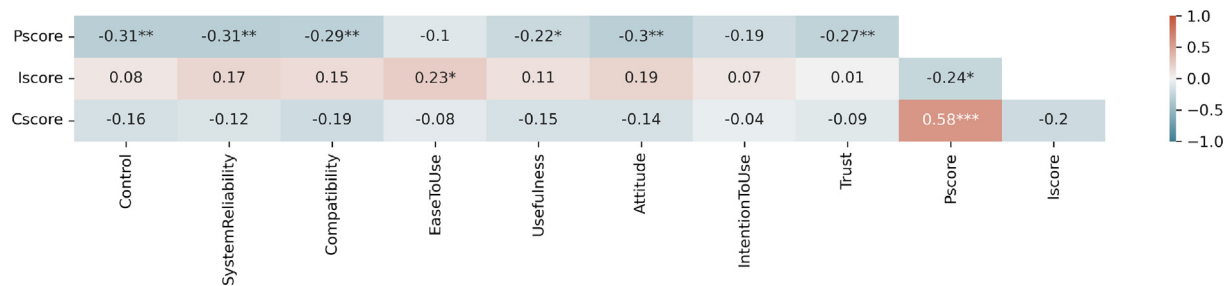


Fig. 13. Heatmap exhibiting the correlation between the locus of control constructs and acceptance constructs (see the appendix in Section A for more information about the items used for each construct). Note: *: $p < .05$; **: $p < .01$; ***: $p < .001$.

nificantly reduced general lighting energy; confirming our first hypothesis (see H1 in Section 1.2). Overall, the total energy demand was greater in the manual setup as compared to when the system was operating the blinds, the general lighting and the task light. Overall, the automated setup allowed to save about 40 Wh and the user input setup about 37 Wh. Taking into account that in a real-world scenario a Raspberry Pi would not be required in an office operated manually, it decreases the energy savings for lighting to about 37 Wh for the automated setup and 34 Wh for the user input setup. In other words, this represents a saving of 68% and 63%, respectively. It is important to note that those results were obtained in our particular setting with a desk at 3 meters from the window. Further studies might want to confirm those results in office space with the desk near the window and an environment more likely to produce glare situations.

Despite that the system allowed to save energy for lighting while providing a greater amount of light as compared to when occupants were operating the room, and this without impacting occupants' comfort and performance, a greater challenge remains to be solved before achieving an ideal system. Indeed, the evaluation of acceptance by occupants revealed weaknesses within compatibility with occupants life, system reliability and perceived control over the system. Interestingly, the automated setup shows only the compatibility with occupants life as being linked to the powerful others locus of control. In contrast, the user input setup allowing occupants to modify the CCT curve revealed a strong link between most acceptance constructs and a locus of control directed towards powerful others, indicating that our second hypothesis is rejected (see H2 in Section 1.2). This indicates that even when the user is in part in the control of an automated system, users think that the system operates under the control of other persons. Consequently, to achieve an automated system that would be accepted and used by occupants, the key is likely to lie in inducing a more user-centered perceived locus of control toward the system. We identified that the problematic characteristics of our automated system might be mainly due to the attribution of the control to the powerful others. Regarding this issue, the authors proposed to make the occupants understand how the system works to the best of their ability and leave the possibility to operate the system manually conjointly to the automation.

4.1. Industrial relevance

The automation of providing sufficient light intensity on the work-plane without causing glare resulted in a reduction of energy usage. This is realised by balancing the operation of daylight, general light and task light through the automated system in an optimal way. In terms of operational relevance, this reduction of energy usage supports the building operator in saving money and fulfilling his environmental goals. Further on, the automation system provides a greater amount of daylight without glare as if

the user is operating the blinds manually. This gives the building occupants the comfort of better lighting conditions.

The strategies for potentially reaching those values were two-fold. On the one hand to use a machine learning system which is controlling the window shades considering the local sun and weather situation on each specific site. On the other hand, to incorporate a specific new task luminaire. The first strategy involves limited manual investment in the commissioning phase, provided the machine learning step can be to a certain extent automated and the preparation of the virtual model of the space simplified. This would be the subject of further research both on the simplification of the commissioning phase using simplified virtual models of the space and generalisable machine learning models.

The second strategy, the use of a specific task luminaire provides added degrees of freedom, enabling occupants to personalise their environment by controlling locally the horizontal illuminance level both in light intensity and light spectra with variable colour temperatures between 2700 and 6500 K. The task luminaire is mobile on the table and can be adapted to personal preferences regarding its position and light direction, and thanks to its visible but glare-free light-emitting surface, the user may potentially experience the colour of light in an even more emotional way. These attributes bear the potential to address the identified problem of lower user acceptance caused by a lower feeling of control, allowing the building operator to partially compensate for the disadvantage in occupants satisfaction caused by the automated system.

Through further validation of these strategies, resulting in highly tailored but lighting situations during the user input automation, a higher value for the market could be created, leading to higher visual comfort, better mood, and higher acceptance of automated light situations. Thus ensuring lower operational energy consumption and at the same time providing a highly personal light quality for the users. Creating a better-balanced solution with higher overall value, fulfilling the needs of the user and the building operator in a holistic way.

With regards to the feasibility of transferring the present method to different building situations, some considerations have to be made. The use of ML models as alternative for daylight prediction in buildings, implies the creation of an extensive database for the training of the surrogate model, representing an important investment in terms of time and computing resources. The method presented here to create such database involves a lengthy preliminary work in order to characterize the building's features in a virtual model, making the application of the present method, impractical for the prediction of daylight in highly complex and large environments. Furthermore, a considerable number of simulations need to be carried out in order to take into account the evolution of daylight conditions over the entire year. This number can significantly grow if the considered room has multiple windows that can be controlled separately, as the contribution of each win-

dow has to be modeled separately. However, certain steps of the method presented here can be simplified or automatized, reducing the manual workload needed to generate the necessary data. For instance, the simulation process can be automatized by means of scripting, for which only few initial steps for the creation of the scene descriptive files would be required. In addition, certain building features can be standardized in the virtual model, such as geometric shapes and dimensions, as well as including a selection of typical windows and interior materials. This would greatly reduce the time needed to prepare the virtual model, which is the step that requires most manual work. Such approach has been previously implemented for the development of software for building performance assessment [85,86].

Finally, it is also worth mentioning that the energy savings for lighting can be extended to the energy savings for heating and cooling. In another case-study [87], we have used EnergyPlus to compute the heating and cooling loads' offset by taking into account the heat gains provided by the daylight penetration in the building, the presence and activity of the occupants, and the electricity consumed by the electric lighting and appliances. The combination of Radiance and EnergyPlus simulations allowed us to broaden the spectrum of our conclusions in the mentioned paper to the heating and cooling loads, with the expense of an additional virtual model for the thermal behaviour of the space under study.

5. Conclusion

An automatic control system arbitrating daylight with general and task electric lighting that leveraged the prediction of two key performance indicators, namely work plane illuminance and daylight glare probability was proposed. To evaluate the performance of this system, a user experiment evaluating 60 participants was set up assessing energy consumption, comfort, locus of control and acceptance of the system. Overall, the system was found to successfully save energy in our setting—cutting the energy demand of an office operated manually by more than the half—by maximising daylight and the use of a task light over general lighting. Importantly, the system did not impact either performance or comfort and led to a decrease of energy usage. However, the crucial point that remains to be addressed is the acceptance of such a system which appears to be linked to the perception by users of powerful others being in control.

Declaration of Competing 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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Appendix A

See Table 4.

Table 4

List of automation acceptance constructs their associated items

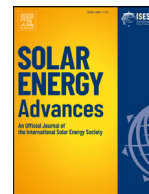
Constructs and items
Perceived control
Using this system is entirely in my control
I have enough knowledge and ability to use this system
I can skilfully use this system
Perceived system reliability
This system performs their functions rapidly
This system is reliable without errors
This system is being immediately responsive to my request
Compatibility
Using this system is compatible with my life
Using this system fits well with the way I like to manage my house
Using this system fits well with the way I want to interact with the components in my house
Perceived ease of use
Using this system is not difficult for me
My interaction with this system is understandable and clear
Interacting with this system does not require my mental effort
Perceived usefulness
Using this system improves my job effectiveness
Using this system makes me accomplish my tasks more rapidly
I think that this system is beneficial in my job
This system is a useful service for houses
Attitude
Using this system in a good idea
I have positive feelings toward this system in general
It is a wise idea to use this system
Intention to use
I recommend others to use this system for their houses
I am likely to continually use this system in my life
I intend to use this system as much as possible
Trust
I believe this system is verified professionally
I believe this system is reliable
I believe this system will be working regarding my expectation

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Integrating daylight with general and task lighting: A longitudinal in-the-wild study in individual and open space working areas

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ABSTRACT

A control strategy targeting energy and comfort goals, is implemented in an individual and an open-space office, to control blinds and dimming lighting as part of an MPC intelligent control system. The study aims to achieve occupant's comfort and an improved energy use in a quasi-real time optimization of the interior environment, using discomfort glare and work plane illuminance as KPIs. By the inclusion of task lighting, the user's preferences in regards to the interior lighting environment (CCT and lighting intensity), are considered. Those are assessed by a longitudinal user experiment, along with its benefits for the electric lighting energy reduction. Aiming to more responsive predictions, daylight and electric lighting surrogate models (LightGBM) were developed for each room based on year-round RADIANCE simulations. Implemented on a 32-bit computer (Raspberry-Pi 3B), the intelligent control system would promptly adjust blinds and dimming lighting through a KNX system, based on the model's prediction of the KPIs. The results showed that the system manages to provide a comfortable interior environment for the occupants, while energy reductions of at least 49% could be achieved compared with a conventional building operation. While a rather uncommitted acceptance of the system was reported by the occupants, improvements can be achieved by allowing a higher level of control that could be customized according to personality traits.

1. Introduction

The use of blinds and lighting controls is a common strategy employed in energy efficient buildings. Their use aims to address intrinsically linked energy reduction and occupant's comfort goals. A performance-based shading operation would lead to improved results in terms of daylight provision and visual comfort [1–3], as well as to energy reduction for lighting, heating and cooling [4]. Several studies indicate that the occupant's perception of the indoor environment improves when they are provided with a certain control of the interior conditions. Favorable effects were found on aspects such as, occupants' satisfaction, performance and productivity [5–7], which are also presumably linked to the positive sensation that occupants experience when they are allowed to create their own environment. However, there are also studies that indicate that the occupant's operation of individual controls not always signify an adequate energy efficient performance [8]. Occupants might adjust the blinds for reasons different than comfort, such as, privacy, maintaining a nice view outside or, contrarily, they

would prevent the adjustment to avoid an irritating noise of the blind's motors [9]. It has also been pointed out, that short term decisions are less frequent when it comes to blinds adjustment, since, when they are made, occupant's fail to perform a correction adjustment once the comfort risk has elapsed [6]. For instance, deploy the blinds to prevent an excessive solar admission, but once the risk is perceived as reduced, the blinds remain deployed; provoking daylight occlusion, with due effects on energy performance and comfort.

Automatic control systems represent an efficient way of regulating the interior environment, by performing an in-sync adjustment of blinds and electric lighting in response to the exterior weather conditions. It has been established, that their use signifies sufficient energy savings for lighting, heating and cooling, while an adequate interior environment is preserved [10–12]. While achieving a sufficient reduction of the energy consumption is a persuasive argument to rely on fully automatic systems, the occupant's individual satisfaction deserves ample consideration. As it has been demonstrated, the occupants would intervene and override the automatic controls to perform adjustments that suit their needs, having an impact on the system's performance [13]. The use of

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control models that replicate the occupants' behavior, or learning algorithms, is a sound strategy that addresses the occupant's individual preferences [9]. However, their use entails further challenges, such as, their applicability to generic users, as well as to solve the conflicting interplay of distinctive performance criteria (thermal, electric lighting, energy savings) [14,15].

Nevertheless, in order to achieve an adequate performance of the combined use of blinds and electric lighting controls, their operation as a unified system needs to be optimized. As a fundamental step, the conflicting interplay between energy and comfort aspects (daylight provision, visual and thermal comfort, and energy savings), needs to be addressed in the control strategy. A prompt response of the blinds and lighting adjustments, in accordance with the exterior conditions, as well as with those occurring indoors (occupancy transitions), is also key to a proper systems integration. Recent research on the domain, led to promising solutions, such as, the implementation of a Model Predictive Control (MPC), based on ML techniques for a quasi-real time adjustment of the building parameters [15,16]. Additionally, an embedded photometric device to control blinds using HDR image sensors, also represents an innovative solution, although in such case, the system's integration is not completely met, as lighting controls are not part of the system [17].

A further step on achieving an integrated system involves the inclusion of personalized solutions on the shape of task lighting, aiming to reach the central figure when it comes to indoor environments: 'an individualized occupant'.

The integration of task lighting In this study, the use of task lighting represents a step forward on the integration of blinds and electric lighting control systems. The latter, due to the task lighting tunable features for light intensity as well as correlated color temperature (CCT), which enable the use of personalized adjustments, hence, a user centric approach is incorporated within the system. It has been demonstrated, that the use of task lighting would signify additional energy reductions, as a result of certain influencing factors, such as presence detection, individual occupancy patterns, as well as users' preferences in relation to light intensity [18,19]. In addition, the effects of lighting color (CCT), on the occupant's comfort and satisfaction have been largely investigated. It has been established that the dynamic feature of daylight is highly appreciated [7,20], hence the replication of its features on interior environments seems to have positive effects on the occupants. As shown in [21], a combination of cooler general lighting and warm direct lighting in clear sky conditions was found preferable by the study subjects, while neutral light for general, and warmer for direct lighting was preferred on overcast conditions. Providing an adjustable CCT feature on task lighting is favored by the users [22], signifying positive effects on alertness, visual comfort, performance [23], as well as on the circadian stimulus [24].

The challenge in open-space working areas The visual comfort of the occupants, as well as their satisfaction with the lighting environment is an important issue concerning the use of automatic controls in open-space offices. Especially in the case of shared working areas without desk partitions, as the lighting environment would be impartially experienced by all the users, causing potential conflict derived from individual preferences. In the case of an automatic presence activation setting, some work-spaces would be lit while others remain in the dark, creating contrast across the room, having implications on visual comfort due to the spatial uniformity, which is a quality parameter to describe the illuminance distribution across the space [25]. In addition, the contrast created by direct sun transmitted through deployed blinds, could also be a hinder for visual comfort, which could be softened with the use of electric lighting. While this is an un-frequently investigated topic, strategies applied in previous studies consisted on implementing methods such as dimming scale approach, to gradually illuminate the room according to areas [26,27]. While few conclusions can be drawn regarding the adequate way to achieve uniformity in an open-space, its evaluation remain relevant as a design and performance indicator of the system's performance.

Aim of the study in an individual and a shared office An integrated control scheme, developed beforehand in a controlled environment [28], is implemented in two real office rooms: an individual and a shared one. The control scheme features fast daylight and glare predictions based on surrogate models, within an embedded device to control blinds, general and task lighting. The interest focusses of this investigation is to objectively assess visual comfort (discomfort glare), thermal comfort as well as the energy savings as a result of the interactions set by the automatic system, and from the user's interventions. The performance is also assessed in a subjective way by means of user's questionnaires, to evaluate their perception of the lighting environment, as well as of the automatic system acceptance.

As previously explained, in office spaces as the ones studied here (e.g. large individual offices as well as multi-occupant ones), the contrast created by highly illuminated task areas and the shaded surrounding of unoccupied desks, would impact the uniformity of the lighting distribution. The latter, is addressed in this study by the test of two configurations for general lighting (1a, 1b), in addition, the effects of CCT change for the task light would be assessed with respect to the occupant's mood (2). As compensation of the daylight provision, the general lighting would be set to a certain dimming position, in order to achieve a maximum contribution of: 1a) 150 lx Work plane illuminance (WPI), 1b) 300 lx WPI. While, the contribution of the task lighting aims to achieve by default a minimum threshold of 500 lx WPI to satisfy the norms, as well as to account for the occupant's preferences in color and intensity. The aim is to assess to what extent the occupants feel comfortable with their lighting interior environment considering such configurations, as well as to contrast the results with the corresponding energy savings.

Regarding the relevance of this study, few issues were addressed aiming to optimize the system's performance as well as the occupants experience indoors. First, it's a performance-based control strategy that focuses on addressing the complex interplay between distinct aspects related to comfort and energy savings goals. A promptly adjustment of blinds and dimming lighting in accordance with exterior conditions signifies an improvement of the system's performance to save energy, as well as to reduce the risk of thermal and visual discomfort. The latter is achieved by replacing the use of simulations with surrogate models for a faster estimation the KPIs at every time-step, an advantage compared to other systems based on simulation or the use of measurement devices [29]. An important feature of the control system refers to its implementation in real settings, as well as on its integration approach. The latter, refers first to a dual blinds and lighting control, a more inclusive approach compared to studies with one building parameter in control [30,31]. An integrated performance also refers to the application of a control strategy that considers relevant aspects related to energy efficient buildings. Those refer to the inclusion of occupants' comfort and energy aspects within the control criteria, an advantage over studies that partially address such issues [32,33]. In the case of this study, the user individual preferences are also integrated within the control criteria. By considering the occupants' preferences with the use of task lighting, the user satisfaction with their environment would improve, representing a further benefit of this study in comparison with other similar that are only based in automatic control [34,35]. An additional advantage, is its implementation in a living-working environment, hence, the longitudinal study was applied to occupants as real users of the office areas.

2. Methodology

The case-study analyzed here consists of two office rooms, one individual and one shared space. Both offices are located on the first floor of the Idiap Research Institute building, in the city of Martigny, Switzerland (Lat. 46.10 N, Long. 7.08 E, 471 m above sea level). The detailed description of the rooms can be found in Section 2.5, while in the sections below, are described the steps that were taken in order to achieve the objectives of this study. First, the actions taken to perform the physical modeling of the two office rooms are shown in

Section 2.1. Then the process for the creation of the statistical modeling (Section 2.2), the process for the implementation of the intelligent control system (Section 2.3) and finally, the description of the controlled user experiment (Section 2.4).

2.1. Physical modeling: simulation methods and Key Performance Indicators (KPIs)

Initially, a virtual model for RADIANCE was created based on the features of the two evaluated rooms, for which, a monitoring process was implemented as first step. The visual reflectance of walls, ceiling, floor and exterior blinds was measured using a Chromameter (Minolta CR-220), while for specularity, a gloss-meter (Minolta GM-060, characterized at 60° incident angle) was employed. The glazing transmittance of the window units (Figs. 3 and 4), was measured using a hand-held digital lux-meter (Minolta CF-70F). Then, the geometrical and photometric features of the two office rooms were reproduced in a virtual model aiming to match as close as possible the existing situations. A calibration process was then performed to verify the representativeness of the existing situations by the virtual model. In order to do that, the WPI was measured on-site in both rooms (at desk height level, 0.80 m), at one-hour intervals (from 7:00 am to 19:00 pm) on specific dates (Summer 2022). Then, simulations were carried-out using solar irradiance data (W/m^2), as measured by a local weather station (Section 2.3). The aim was to assess the correspondence of the simulations with the existing situation by comparing the WPI results of the same monitoring dates. In the case of this study, seven testing scenarios were created for each room, one to represent the reference case (RC, blinds retracted), and six representing the blinds in a deployed position from 0° tilt (open, horizontal position) to 50° (closed, in vertical position), see Figs. 3 and 4. Unlike the study previously performed in the individual room [12,36], in this study the blinds positions were determined from preliminary tests to assess the most frequent position set by the KNX system, corresponding to six positions in both rooms. Several parameters were modified during the calibration process until an agreeable match between the measured and simulated WPI was achieved. Those are: building geometry and orientation, material properties (surface reflectance and glazing transmittance), interior furniture arrangement and features, external and internal obstructions. The results of the calibration of the daylight physical model are presented in Section 3.1. The following step was to produce a database for the training of the surrogate models, for which, year-round simulations were generated using the RADIANCE matrix multiplication methods [37]. Two KPIs were derived, the WPI to assess sufficiency of the daylight provision and the daylight glare probability (DGP) [38] to assess the risk of glare.

The latter was performed for each of the seven blinds positions, producing as a result a large amount of data representing a year-round daylight situation for the two rooms. As explained in [16,28], statistical techniques have been successfully employed as alternative method for the daylight performance prediction. The particularities of such method in the case of this study are explained in the following section. Thanks to the light superposition principle, the electric lighting simulation is done separately from the daylight one and only with a simple statistical predictor model introduced in the next section as well.

2.2. Statistical modeling: daylight and electric lighting predictions

As previously mentioned, carrying out physical simulations for the daylight-related KPIs estimation represents a time-consuming process that is incompatible with the need for achieving nearly real-time decision making by the control system. If several testing-case scenarios are considered, as in the case of this study (seven blind positions are evaluated in two different rooms), the process could be markedly extended.

A different alternative is employed in this study, which consists in replacing the use of simulations with simplified surrogate models. A common and powerful approach to create surrogate models is to use

Machine Learning (ML) algorithms, which build an approximated model based on sample data, monitored or simulated. In this work, two different ML algorithms are employed for the prediction of, first, the two KPIs as issued from daylighting, then, the WPI provided by electrical lighting.

2.2.1. Daylight predictor model

The aim of the daylight surrogate model is to estimate the daylight-related KPIs on each occupant's position based on the outdoor conditions and the position of the blinds. As described in [36], a daylight predictor model was previously developed for the individual office #103. From that work, it was concluded that the Gradient Boosting Decision Tree (GBDT) algorithm [39] (XGboost implementation [40]), showed better accuracy on such task than other tested approaches. As described in [16], the implementation of the control system on a real setting required a predictor model of reduced RAM usage to be successfully deployed on a Raspberry Pi. For which, the LightGBM implementation [41] represented an 'affordable' solution in terms of memory use. In continuity with those studies, LightGBM was used to build a total of 12 models - 8 for WPI and 4 for DGP, from which four desks were excluded (desks d2, d4, d5 and d6) in office #107 as they are facing away from the window (Figs. 3 and 4). The seven inputs of the models are the same used in [36], with the only difference that due to the limitations described in Section 2.1 the maximum blind angle is 50° instead of 65°, while the training procedures are the same as described in [28].

The models were trained on year-round simulation data generated using the physical model (explained in Section 2.1). As different blinds scenarios were simulated, the dataset available for each desk contained 61.320 samples. Of these, 5% were randomly selected and held out as a test set, while the remaining data was employed to find suitable sets of hyperparameters using an adaptation of the stratified k-fold cross-validation algorithm to regression problems, with 5 folds, as well as to train the final models. The choice of a test set size of 5% was made in order to include a comprehensive variety of month, hour and blind angle combinations while reducing the risk of removing important information from the training data. In order to reduce the complexity of the tuning phase, the considered hyperparameters were tuned separately in a sequential way. The list of hyperparameters found for all models is given in Table 1.

The capability of the predictor models to approximate the physical simulations was assessed by comparing their outputs with the test data that was held out from the full data sets. Those results of this verification are presented in the first part of Section 3.2. In a subsequent step, the capabilities of the surrogate model to predict WPI was evaluated by comparing the model predictions with daylight monitored data obtained in two different days in Summer 2022.

The latter was performed in a similar way as the one described in Section 2.1, where monitored WPI was obtained in hourly basis from 7:00am to 19:00 pm for each of the seven blind situations in each room. In the case of the office room #103, on-site measurements were obtained on the 20th of July, while for the office #107, measurements were taken on the 24th of July at identical times. The measured WPI was then compared with predicted values generated by the daylight surrogate model for the same date/time as the monitored ones. The correspondence results are also presented in Section 3.2, and shown in Fig. 5.

2.2.2. Electric lighting predictor model

Based on the output issued from the daylight predictor model, the electric lighting requirements were determined as compensation of the daylight provision using as threshold two testing scenarios, where general lighting would provide: 1a) 150 lx, 1b) 300 lx, in both cases a 500-lux threshold is aimed to be reached by the contribution of task lighting. Simple models for WPI and electric power consumption estimation were created using a similar process as that previously described in [16].

Table 1
Hyperparameters used to train the surrogate models.

	WPI								DGP			
	103				107				103		107	
	1	1	2	3	4	5	6	7	1	1	3	7
Max_depth	11	-1	-1	12	14	14	-1	-1	10	11	11	9
num_leaves	150	90	90	60	70	120	120	130	70	20	20	20
min_data_in_leaf	20	20	20	20	20	20	20	20	20	20	20	20
bagging_fraction	1	1	1	1	0.8	0.8	0.8	0.8	1	0.8	0.8	0.8
feature_fraction	1	1	1	1	0.8	0.8	0.8	0.8	1	1	1	1
eta	0.09	0.01	0.01	0.09	0.01	0.01	0.01	0.04	0.04	0.19	0.06	0.06

2.3. Implementation of an intelligent control system

An integrated control system based on the daylight and electric lighting predictor models (Section 2.2), is implemented in both office rooms. The predictor models allow for the simulation of the best room parameters to obtain the desired lighting, without impacting on the comfort of the user by adapting the conditions by trial and error. Characterized by a quasi-real time optimization of the interior environment, the system performs constant targeted adjustments of blinds and dimming of electric lighting according to exterior weather conditions to provide a balance between the room occupants' visual comfort and energy efficiency.

2.3.1. Technical infrastructure

The infrastructure employed for the control of the interior lighting conditions is composed, first, by a set of sensors to retrieve the sky conditions on-site, as well as to measure the lighting conditions on each desk for model validation purposes. Then, actuators enable the activation of the different types of blinds and lights in both rooms. Centralized control management is provided by a control hub, together with a web and button-based user interface which allows the setting of personal lighting preferences. The software infrastructure implements the control strategy as well as communication between the different hardware modules. The infrastructure employed in this study corresponds to the one implemented in [28], with the exception that several task lights and personal controls (i.e., one per each desk) are used in the open-space office.

A Delta-T BF5 solar radiation sensor located on the roof of the premises, provides sky conditions information by measuring the direct and diffuse solar radiation (W/m^2) at 5 s intervals, as well as presence or absence of bright sunshine, according to the WMO standard [42]. This data is published on a MQTT broker to be accessible to the control hub, implemented in a Raspberry Pi 3B. The data is then employed to determine the blinds and electric lighting positions, aiming to achieve optimal room conditions in terms of energy and occupant's comfort by means of the control strategy presented as follows in this Section. The found conditions are then set via KNX and DALI interfaces.

To control the illuminance and CCT at a personal level, each workstation is provided with a Regent Lighting Joker task light. Each fixture is controlled by a Raspberry Pi Zero W to compensate the general lighting and reach the illuminance threshold desired by the desk occupant. Connected to the same device, an Adafruit VEML 7700 Ambient Light Sensor logs the illuminance at a single location on each desk. This device is also employed as presence detector, to activate or deactivate the task lighting and general lighting fixtures when hand-covered for 3 s to communicate the occupant's arrival or departure at the desk. A web interface is also provided as an alternative method to communicate user's presence. The users' personal preferences concerning the illuminance and CCT control, are controlled by a single button on the task light fixture, according to the commands defined by the manufacturer.

On a software level, the infrastructure is composed by various modules implemented as Docker containers, communicating through MQTT,

which handle the necessary operations for the control of the rooms' conditions. Those are: communication with sensors, logging, optimization of the room parameters, control of the general room's physical settings, and control of the lighting on a personal level, including the interaction of users with the system.

The energy consumption of the general lighting is measured via a KNX interface. The one corresponding to the task lighting is estimated by a model based on the energy consumption as a function of the lighting intensity, which was measured using a NETIO PowerCable REST 101 J WiFi power socket. For the main control hub, a constant power of 3 W is considered, in line with what was observed from measurements during a system's testing period of approximately three months. The same approach is taken for the Raspberry Pi Zero W, which controls the personal lighting, for which a constant power of 1 W is considered.

2.3.2. Control strategy: the decision-making process

As in the study presented in [28], the implemented lighting control strategy focuses on providing an adequate interior environment with a reduced energy consumption. In the present study, the challenge is to deploy the strategy also in an open space office, in which the presence of multiple occupants has an impact on the optimization of the lighting conditions. The adopted control strategy is summarized in Fig. 1.

First, the daylight provision is controlled in order to provide visual and thermal comfort to the occupants. The daylight predictor models (Section 2.2) are employed to find the blinds positions that maximize the daylight provision with a reduced risk of glare for all the occupants currently registered as present in the room. This is done by adjusting the blinds position (B in Fig. 1) to provide the highest possible illuminance, while achieving an "imperceptible level" of the glare risk ($dgp(B) \leq 0.35$ in Fig. 1). Additionally, to prevent overheating, the blinds positions are adjusted to keep the incident solar radiation on the rooms' facade ($rad(B)$ in Fig. 1) below the threshold of 150 W/m^2 . For the latter, we can reference to a previous study where a multi-objective control strategy was implemented in the office room #103 [12]. In which, different criteria were employed to achieve visual and thermal comfort as well as energy reduction (lighting, cooling and heating). While in this study, the thermal comfort assessment was performed in a subjective way via questionnaires, in the previously mentioned one, a more comprehensive evaluation was performed which includes thermal comfort as an objective evaluation.

Next, aiming to compensate for an insufficient daylight provision, the LED general lighting (EL in Fig. 1), is dimmed to the minimum intensity necessary to reach the general illuminance threshold for all occupied desks. In order to investigate the effects of two different general lighting strategies, the 150 lx and 300 lx general thresholds ($general_thresh$ in Fig. 1) are alternated during the experiment as specified in Section 2.4.

Finally, the occupant's preferences of the lighting conditions are considered, by providing a preference-matching operation of the task lighting. The task lighting fixture on every desk i (TL_i in Fig. 1) is set to compensate the illuminance from natural and general lighting until the desired WPI is matched. This value can be individually selected by the occupant by adjusting the task lighting intensity. Once selected, the sys-

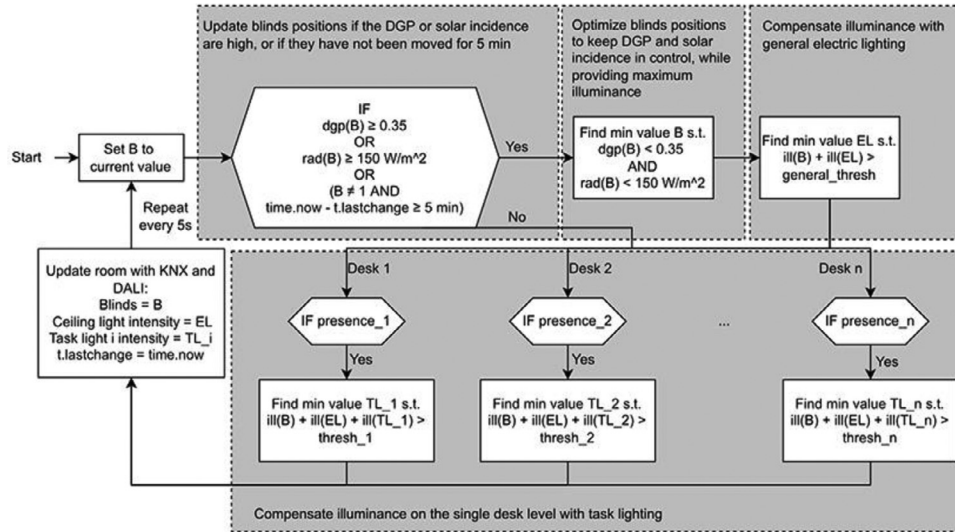


Fig. 1. Flow control scheme diagram of the automatic lighting control strategy.

tem tries to keep this WPI constant, independently of the changes of the general illuminance in the room.

Thus, the total WPI on each desk is estimated as the sum of the ones obtained from the daylight and electric lighting predictor models, also considering the task lighting predictor model ($ill(TL_i)$ in Fig. 1). The latter, is obtained by applying a polynomial regression based on measured WPI as function of the task lighting dimming position (Section 2.2), and [16,28].

To adapt the lighting based on the varying occupation of the several desks in the rooms, the functions $dgp(B)$, $ill(B)$, $ill(EL)$ in Fig. 1 indicate an aggregation of the daylight and electric light predictor models computed on each desk where an occupant is present. For $dgp(B)$, the maximum value of $dgp_i(B)$ computed on the desks with an occupant is considered, for $ill(B)$ and $ill(EL)$, the minimum value is taken.

Regarding task light CCT control, users can choose using the web interface between two strategies. The first strategy consists in allowing them to set a fixed CCT between 2700 K and 6500 K, which remains the same every time that the lamp is employed (unless it is explicitly changed). The second strategy, is set to replicate, to a certain extent, the CCT provided by sunlight, by performing an adjustment in function of the sun's elevation through the day. For the latter, the minimum value in the range between 2700 K and 3500 K is considered (when sun elevation ≤ 0), and the maximum value (at solar noon, when the sun elevation is maximum) ranges between 4000 K and 6500 K, according to the user's preferences, as in [28]. In this case, the user can select their preference between a warmer or colder light, and set their CCT curve during the day to a range that, for instance, would correspond to warm light (between 2700 K and 4000 K).

2.4. Controlled user experiment

2.4.1. Participants

From eight occupants, five were kept in the data analyses —1 woman, 4 men— aged from 25 to 44 years old ($M = 33.80$, $SD = 7.66$). The older male participant used exclusively the individual room, while one male participant used the two rooms at different times during the experiment (spent 16.67% of the time in the individual room). The latter was organized in order to replace sporadic absences occurring in the individual office room. The open space was exclusively used by 3 participants ($M = 31.25$, $SD = 5.91$).

2.4.2. Procedure

The experiment performed in this study, was foreseen on a period of 6 weeks: from Monday 7th of March to Friday 15th of April 2022.

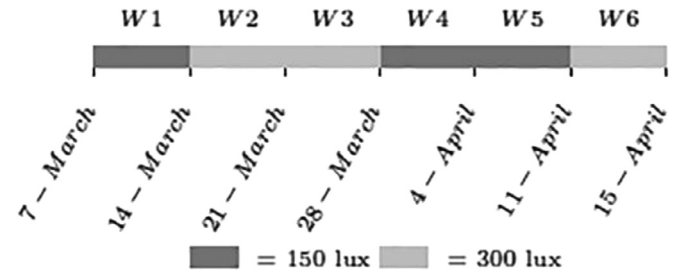


Fig. 2. Course of the experiment alternating between amount of light in space (W stands for Week).

During this period, the general lighting provision levels were alternated between 150 lux and 300 lux. The first week was set at 150 lux, the 2 following weeks were set at 300 lux followed by the reversed pattern: two weeks at 150 lux and 1 week at 300 lux (for a depiction see Fig. 2). This experimental design aimed at minimizing the seasonal difference in daylight across conditions, while maintaining a low number of switches between assessed lighting conditions, and scheduling the switches over the weekend to make the changes less noticeable.

The participants were instructed to work as usual at their respective working place. They were not made aware that a change in the general lighting setting was occurring in order to avoid any anticipations or reactions. They were asked to fulfill a personality questionnaire at the beginning of the longitudinal experiment, as well as a daily questionnaire about their feelings and visual comfort. A final questionnaire was administrated at the end of the experiment, to gather information about occupants' acceptance of the automated system and whether or not they noticed the switch between the two conditions of general lighting.

A normal day unfolds as follows: at their arrival, occupants notify their presence by using the light sensor or the web interface; the automatic control continuously adjust blinds and electric lighting (general and task lighting) according to the exterior conditions (Section 2.3). A questionnaire is sent by email every evening (4pm); at their departure, occupants notify again the system before leaving.

2.4.3. Materials

The satisfaction towards the comfort provided by the system was assessed through several questionnaires, as well as personality traits of occupants, which are described more in depth below.

2.4.3.1. Entry questionnaire. The entry questionnaire aimed at evaluating psychological traits of the occupants, in specific, the locus of control was evaluated using the Levenson locus of control scale [43] (see [28]). Personality traits were evaluated using the Big-Five personality test [44,45] allowing to quantify personality over 5 traits: Extroversion, Openness, Conscientiousness, Neuroticism and Agreeableness. Additionally, we also evaluate the morningness-eveningness using the Chronotype questionnaire from Oginska [46,47].

2.4.3.2. Daily questionnaire. The daily questionnaire aimed at assessing the occupants preferences, in regards to the visual and thermal comfort, their emotion toward lighting, and their preference for a specific light source (e.g. daylight, or either the general or task lighting). The participants sentiment toward the light after each day, as well as their emotions, were analyzed using several questions related to feelings. As for instance, using a scale from -3 to 3 (the bigger the digit the better the match with light), the occupants were asked whether the light matched the following pairs of antonym adjectives: Distressing-Relaxing, Focused-Open, Cold-cosy, Gloomy- Exciting, Private-Public and Unhappy-Happy. Additionally, on a Likert scale from strongly agree to strongly disagree, the occupants were also asked to rate whether the light could be associated with the adjectives: Candlelight, Sunset, Window and Fireplace. As for CCT, questions were asked in regards to general and task light as well as for general light coupled with daylight. In addition, to collect occupants' feelings, they were asked to tick adjectives within a list, according to the circumplex method of affects [48], as used in a previous study [28].

2.4.3.3. Exit questionnaire. The exit questionnaire aimed at evaluating the occupants acceptance of the automation system, including if the automatic switch between the two general lighting conditions was noticeable or not. The perception of the occupants in regards to the uniformity of the interior lighting environment was also assessed, aiming to account for an irregular lighting distribution, characteristic of open space areas (as explained in Section 1). To be more familiar to the general public, the questionnaire used the terms "homogeneous-heterogenous" to avoid using uniformity, perhaps too technical, as employed in the field of lighting. For more details regarding the selection of the models to assess the automation acceptance, please refer to [28].

2.4.4. Data analysis

First, the data was filtered according to the occupants' presence at their desks, as well as according to users' response rate in the entry, daily (regularly), and the exit questionnaires. Questionnaire data was averaged across constructs in cases of standardized questionnaires.

The impact of the lighting condition and the room were analyzed through (generalized) linear mixed models (with appropriate distribution, when both conditions were included in the model) with participants as a random factor. The Anova function was used from the car package in R to generate p-values using the Wald Chi-square test. To ensure the lack of impact of conditions, the Bayes factor was computed using the Bayesian Information Criterion (BIC). To do this, the null model was compared to models including the factors. This computation allowed us to ensure that the automation condition did not impact on certain variables, such as visual comfort. T-test were performed to compare two modalities of a condition or to compare ratings against one value using the python package pingouin providing Bayes factor as well as frequentist statistics.

Regarding the circumplexes analysis, Rayleigh tests were used to assess whether the selected adjectives, indicated a direction within the circumplex space. When at least two groups exhibited a direction, a CM test assessed the significance of the difference in directions.

2.5. Description of the case-study

The building where the two rooms are located, it has a rectangular shape of approximate 60 m length by 50 m width. As mentioned pre-

viously, two rooms were analyzed, one individual and one open space with seven occupants, both located on the same floor, at the middle and extreme east wing side respectively. The properties of interior materials were measured using special equipment; as common to both rooms, an 8% reflectance was measured for the floor, 24% for the ceiling concrete material, 34% for concrete wall, and 70% for the white wall, which procedure is described in detail in [12,36]. The window (also identical in both rooms), is divided in four sections, one of which is a casement bound for natural ventilation, the upper and lower sections have translucent glazing of 31% T_{vis} , while the central section with transparent glazing is 73% T_{vis} . The electric lighting was retrofitted in both rooms for energy savings purposes, where fluorescent tubes T8 of 58 W were replaced by LED linear lamps with dimmable features. Additional distinctive features about each room are described below.

2.5.1. Individual office #103

The first evaluated room is an individual office of approximately 23 m², of rectangular shape and dimensions of 7.05 m depth by 3.05 m width and 3.06 m height. The room is side lit with a Window to Wall Ratio (WWR) proportion of 66%, and oriented 56° due to the South West (See Fig. 3). As individual office, it has a regular occupancy pattern from 9:00 am to 6:00 pm Monday to Friday. More details about the room description can be found in the above-mentioned study.

2.5.2. Open space office #107

The second room, is an open space office of 33 m² of irregular trapezoidal shape and approximate dimensions of 4.35 m front and 5.6 m on its parallel longer side, 6.7 m depth and 3.06 m height (See Fig. 4), its orientation is 34° due to the South East. The material properties of the interior space correspond with those of the first room, except for the north west wall of beige color and 64% reflectance. The office is naturally illuminated by only one window of identical characteristics as in the first room and 53% WWR, only three of seven occupants face the window, while the others face the unique access door. The windows are equipped with metal exterior horizontal blinds of halved rounded hexagonal shape, 96 mm width and 25% reflectance. The room is lit by four LED linear lamps of 41 W lit the room, which are linearly arranged in two rows suspended from the ceiling, to correspond with the desk's arrangement, while not aligned atop. Utilized by interns, PhD students and post-docs, the occupancy schedule shows an irregular pattern, still formally set from 9:00 am to 6:00 pm Monday to Friday

3. Results and analysis

3.1. Physical modeling: virtual model calibration

As described in Section 2.1, in order to establish correspondence between the existing situation and the virtual model, WPI measured on-site was compared to RADIANCE simulated results obtained for the same date-time as the monitored ones. A resulting R^2 of 0.92 was observed for the individual office #103 and a MAE (mean absolute error) of 93 lx. In the case of the shared space #107, R^2 of 0.82 and MAE of 12 lx was obtained as average of the four desks for which the WPI was evaluated.

3.2. Statistical modeling verification

The performance assessment of the surrogate models was performed according to the methods described in Section 2.2. The verification of the surrogate models against the 5% test set held out from the simulated data is presented first. Then, the verification of the model predictions against on-site measurements, with an alongside comparison with RADIANCE simulations is presented as following in this section.

3.2.1. Verification on the 5% test set

The verification of the statistical model was achieved on 5% of the total physically-based RADIANCE simulations. The comparison between

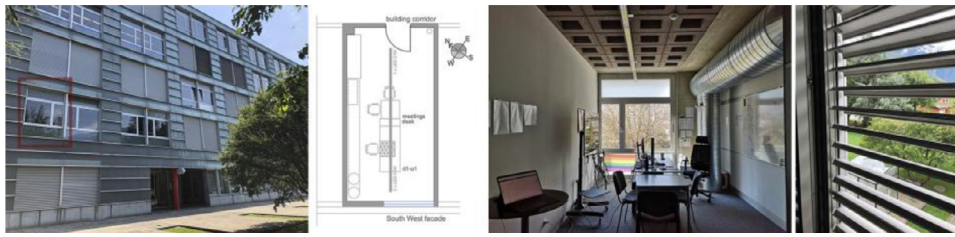


Fig. 3. Office room 103, from left to right: exterior view of the building, high-lighted in red the room's window; floor plan view; interior view of the individual office in spring equinox at 12:00 pm; close view of exterior blinds.

the results of RADIANCE and the ones of the statistical model are presented in what follows for the individual and the open-space offices.

3.2.1.1. The individual office #103. The WPI model for the individual office achieved an accuracy of 0.97, a MAE of 5.95 lx and a R^2 of 0.99 on the test data. The lowest accuracy (0.74) was found to be at 4pm with the blinds tilted at 0° . The DGP model on the other hand showed a nearly perfect accuracy, with only two wrong predictions in correspondence of the boundaries identified for the different DGP classes: in one case the model predicted a DGP of 0.349 where the target value was 0.355, while in the second case the output was 0.466 instead of 0.407. The MAE between the predictions and the simulated values was 0.003, while the R^2 was 0.98.

3.2.1.2. The open space office #107. Different behaviors were shown by the WPI models for the seven desks in the open space office. All models except those for desks d4 and d5 (located near the window), achieved an accuracy of 0.99 and a MAE below 1 lx. The R^2 values for these desks were between 0.97 and 0.99, with the exception of desk d2 for which the R^2 was 0.93. Concerning desk d4, the accuracy was slightly lower at 0.97, with a MAE of 2.72 lx and a R^2 of 0.96.

Grouping the results by hour of the day and position of the blinds, the worst performances for desk d4 were found at 1pm, where the accuracy was 0.95 or lower, with the lowest value of 0.5 at a blind angle of 0° (horizontal position).

With respect to the position of the blinds, most errors were identified in the reference case (blinds fully open): in this situation, the accuracy of the model decreases towards midday, with the worst accuracy of 0.42 at 2pm. Finally, the WPI model for desk d5 had the worst accuracy, 0.91, with a MAE of 15.32 lx and R^2 of 0.98. In this case, the worst results are found at 11am, where the model showed a very low accuracy at all blinds position, with the lowest accuracy being 0.37 at a blind angle of 0° . All three DGP models achieved a MAE of 0.001 and a R^2 of 0.98 or more, with only one wrong prediction made by the model for desk d3, which estimated a DGP of 0.337 (imperceptible glare) in a case where the target value was 0.353 (perceptible glare).

3.2.1.3. Overall analysis. The WPI estimations given by the proposed surrogate models had a very good agreement with the test data, with notable exceptions occurring in desks d4 and d5 of the shared office #107. For these desks, the accuracy of the predictions dropped significantly at 11am and 2pm respectively, a range of time when the sun hits the area near the window where they are located. In situations when direct sunlight impinges on the facade, a high illuminance variation could be created in such area owed to particular features of the #107 office.

Those refer to orientation, irregular shape of the room, as well as intricate sun/shadow patterns created by deployed blinds at low tilting angles (0° to 30°). The training process of the model could be affected in presence of such variations, hence its accuracy, due to a reduced ability to approximate predictions to the simulated KPIs. However, less accurate predictions would be acceptable at low blind angles in cases like this study, due to the control criteria and the automatic implementation. Since, in situations of direct sun incidence, the blinds would be adjusted to protecting higher tilting positions (40° – 50°), transitioning to a more diffuse luminous environment when the predictions would be more accurate. Potential ways to improve the performance of ML in these situations could be to a) generate more training data within relevant input ranges (i.e. during office hours) with special regard for situations where complex phenomena need to be learned; b) give more weight during training to samples where the sun reaches the desks. Concerning the DGP estimation, we can conclude that for our case studies and needs the proposed surrogate models can replace RADIANCE simulations without any significant loss in accuracy. It should be noted, however, that in the considered setup glare occurs rarely, and DGP is most of the time below 0.35, falling within the first class of imperceptible glare.

3.2.2. Verification on-site monitoring vs ML predictions, alongside comparison with radiance simulations

As explained in Section 2.2, the WPI surrogate model's prediction were compared back to daylight monitored data to establish the correspondence of the surrogate model relative to the real situation. As illustration, original RADIANCE simulations that correspond to the same measured data obtained in July 2022 are plotted alongside in Fig. 5.

For the ML results in room #103, an R^2 of 0.92 was obtained and MAE of 80 lx, in the case of room #107, an R^2 of 0.81 and MAE of 9 lx. The comparison with RADIANCE simulations shows a similar performance by achieving an R^2 of 0.93 and MAE of 83 lx for room #103, while for room #107, the R^2 of 0.84 and MAE of 9 lx. In #103 RADIANCE simulations tend to globally underestimate the illuminance, while the ML predictions tend to be closer to the $y = x$ line but still underestimating. This behavior may lead to overestimate the need of electric lighting, thus limiting the potential electricity savings. On the contrary, in #107 the RADIANCE predictions are close to the $y = x$ line, but overestimating the daylight provision.

The situation is worse for the ML model in #107, as it may lead to a slight underestimation of the general electric lighting needs, which in any case can be overcome by the use of the task light. Concerning the relevant range of 300 lx, an overestimation of the model predictions is



Fig. 4. Office room #107, from left to right: exterior view of the building; floor plan view; interior view of the open-space office in spring equinox at 15:00 pm; close view of the exterior blinds.

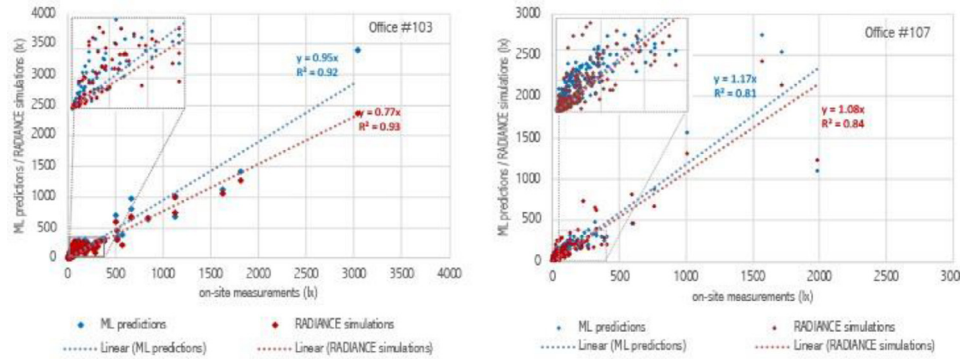


Fig. 5. Correspondence of measured WPI vs. ML model predictions, alongside a comparison with RADIANCE simulations, for room #103 (left) and room #107 (right). A zoom display indicating the 300-lx range is shown in the upper-left side.

observed 62% of the time in room #103 and 80% in #107, corresponding to an average of 60 lx and 40 lx respectively. A ‘shortfall’ general light provision might signify an increased use of task lighting, however the contribution of such illuminance range to the electric lighting is still considered low, while the energy savings potential would be conditioned by the users’ preferences.

3.3. Longitudinal user experiment

3.3.1. Work plane illuminance

3.3.1.1. System’s predictions. The WPI predicted by the system differed between the two rooms (as expected due to the different orientations), and the two assessed lighting conditions (defined in Section 2.3). First, significantly more general light was delivered in the open space (Room #107, $M = 130.96$, $SD = 146.53$) than in the individual room (Room #103, $M = 29.37$, $SD = 74.93$; $\chi^2(1) = 150.12$, $p < .001$). In regards to the two lighting conditions, as expected, a higher WPI was observed in the 300-lx setting ($M = 178.62$, $SD = 178.68$) than in the 150 lx one ($M = 60.56$, $SD = 79.63$; $\chi^2(1) = 1041.07$, $p < .001$). Additionally, the interaction effect between the room and the light condition (i.e., the fact that the effect of the room condition depends on the light condition and reversely) was significant, $\chi^2(1) = 64.45$, $p < .001$. In regards to daylighting, a higher WPI was predicted in the individual room (Room #103, $M = 558.48$, $SD = 468.92$) than in the open space (Room #107, $M = 152.11$, $SD = 603.70$; $\chi^2(1) = 53.51$, $p < .001$). In regards to the two lighting conditions assessed in this study, no difference was observed in daylight between 150 lx and 300 lx conditions, while decisive evidence for this lack of effect was observed ($BF_{10} \frac{1}{164}$). On the opposite, the inter-

action effect between the room and the light condition was significant, $\chi^2(1) = 11.61$, $p < .001$.

3.3.1.2. Task light. The WPI from the task light differed across the analyzed rooms as well as lighting conditions. First, the task light WPI significantly increased in the individual room (Room #103, $M = 241.55$, $SD = 256.15$) than in the open space (Room #107, $M = 153.61$, $SD = 203.45$; $\chi^2(1) = 176.31$, $p < .001$). Regarding the lighting conditions, an increased use of task lighting was observed when the general light was set at 150 lx ($M = 221.69$, $SD = 236.67$), compared to the 300-lx setting ($M = 115.32$, $SD = 177.11$; $\chi^2(1) = 394.99$, $p < .001$). Additionally, the interaction effect between the room and the light condition was significant, $\chi^2(1) = 263.06$, $p < .001$. In regards to the CCT, it differed between the two rooms and according to the lighting conditions, in specific, the CCT was set significantly whiter/colder in the individual room (Room #103, $M = 5072.61$, $SD = 864.03$) than in the open space (Room #107, $M = 4811.88$, $SD = 831.24$; $\chi^2(1) = 12.96$, $p < .001$). Regarding the two lighting conditions, the CCT was set more whiter/colder when the general light was at 300 lx ($M = 5182.84$, $SD = 731.35$) than when it was at 150 lx ($M = 4683.80$, $SD = 857.55$; $\chi^2(1) = 111.13$, $p < .001$). There was no significant interaction effect.

3.3.1.3. Overall analysis. These results suggest that the reduction in general light illuminance (150 lx vs 300 lx) was compensated by the task light. Moreover, a larger provision of daylight signified a diminished use of the general light, which was compensated with task lighting. Those insights were confirmed by a descriptive analysis of the aggregation of all sources of light in Fig. 6. In general, we observed a compensation of the reduction of general light by task light. Moreover, the different pro-

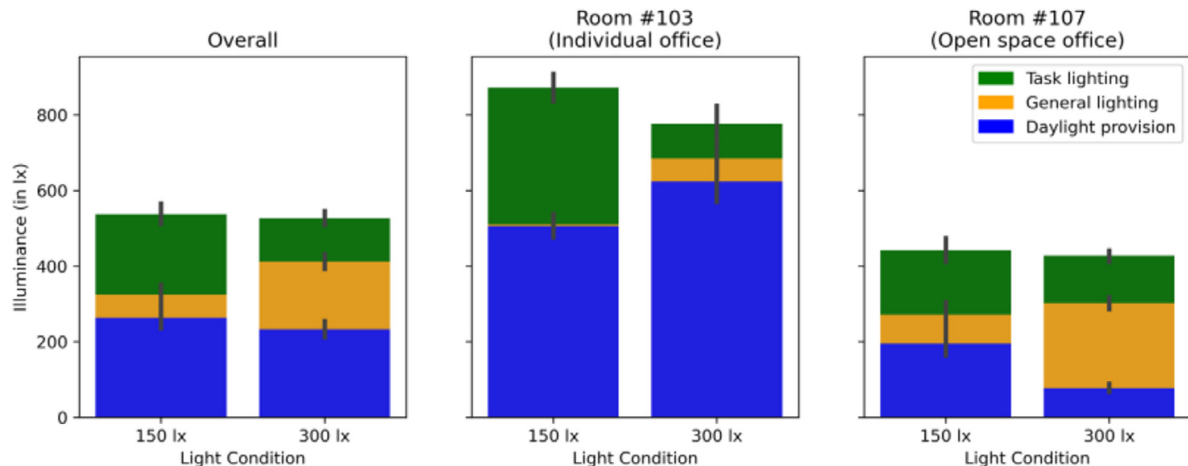


Fig. 6. Stacked bar plot representing the light compensation from daylight and electrical lighting changing according to light condition. From left to right: overall, office #103, office #107. Black lines represent the 95% confidence intervals.

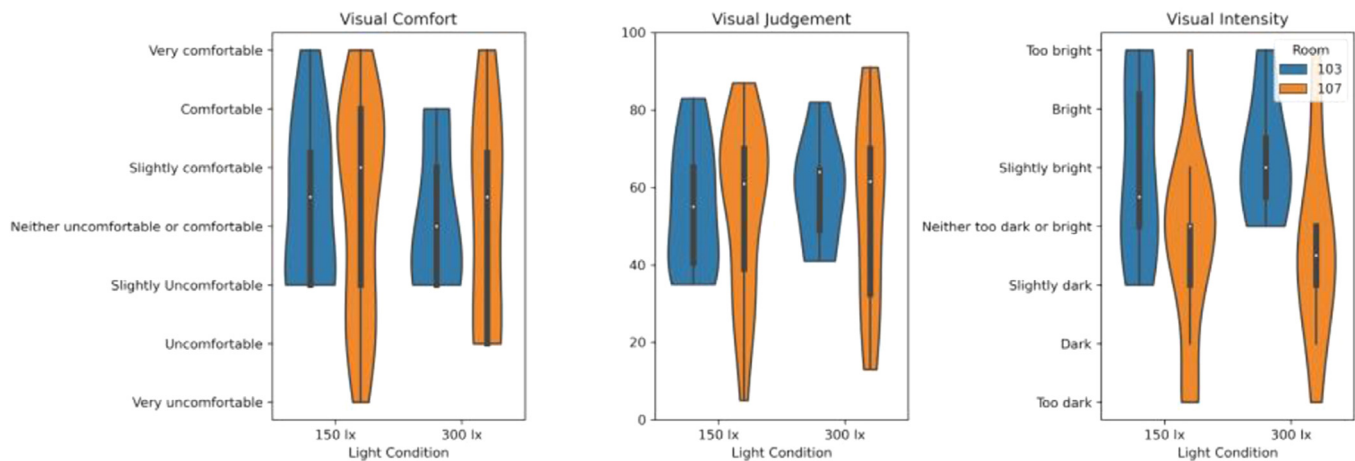


Fig. 7. Violin plot displaying overall visual comfort for perceived comfort, judgement and intensity according to the light and room conditions.

vision of daylight between the weeks at 150 lx and the weeks at 300 lx were compensated by task lighting as particularly exhibited in the room #103 at 150 lx with almost no general light (see Fig. 6 middle graph).

3.3.2. Visual comfort

The visual comfort was judged on average as between “neither uncomfortable nor comfortable” and “slightly comfortable” ($M = 0.26$, $SD = 1.63$) with strong evidence for no impact of the room ($BF_{10} = \frac{1}{25}$) and decisive evidence for no impact of the light condition ($BF_{10} = \frac{1}{840}$). Assessed on average on a scale from 0 to 100 it was found slightly above 50 ($M = 55.46$, $SD = 20.27$) with weak evidence for no impact of the room ($BF_{10} = \frac{1}{2}$) and strong evidence for a lack of effect from the lighting conditions ($BF_{10} = \frac{1}{76}$). Regarding the impact of the light intensity of the occupant’s visual perception of the environment, the individual office was judged as “slightly bright” #103 ($M = 1.05$, $SD = 1.35$) while in the open space #107 was described as “neither too bright not to dark” and “slightly dark” ($M = -0.38$, $SD = 1.52$, $X^2(1) = 9.91$, $p < 0.01$). In regards to the two lighting conditions assessed, no decisive evidence ($BF_{10} = \frac{1}{960}$), see Fig. 7) was found of such impact on the occupant’s visual perception of the interior environment.

Regarding the perception of the CCT, there was no difference except that the CCT of the overall light was perceived as colder in the individual room than in the open space (see Table 2). The exit questionnaire reflects the occupant’s overall impression of the lighting conditions over the course of the experiment, in which no differences were found regarding the comfort provided by the system during sunny and cloudy/rainy days.

According to the occupants, the system manages to provide sufficient comfort, judged as “comfortable” and “very comfortable” ($M = 2.60$, $SD = 3.58$). During the experiment, the lighting was perceived between “neither heterogeneous nor homogeneous” and “slightly heterogeneous” ($M = -0.20$, $SD = 2.28$). While the Bayes factor shows anecdotal evidence for a difference between the two rooms ($B_{10} = 1.39$), the latter is considered as ‘no significant’.

3.3.2.1. Overall analysis. Results revealed little significant difference between the two rooms, in regards to satisfaction and perception of light, while no impact was observed in regards to the two lighting conditions 1a) and 1b).

3.3.3. Thermal comfort

In regards to thermal comfort, no difference was found between the two lighting conditions assessed (Comfort: $BF_{10} = \frac{1}{187}$), Intensity $BF_{10} = \frac{1}{703}$, and Judgement: $BF_{10} = \frac{1}{25}$), nor for the two rooms (Comfort: $BF_{10} = \frac{1}{13}$), Intensity: $BF_{10} = \frac{1}{29}$ and Judgement: $BF_{10} = \frac{2}{3}$).

The exit questionnaire reveals the overall impression of the thermal comfort over the course of the experiment, showing that occupants perceived the environment between “slightly homogeneous” and “homogeneous” ($M = 1.20$, $SD = 1.30$). No significant difference was found between rooms, since the Bayes Factor shows only anecdotal evidence for no difference $B_{10} = \frac{2}{5}$).

Table 2

Statistical results regarding the perception of CCT for each source of light and according to the room and light conditions.

	Room condition				Statistics		Light condition				Statistics	
	103		107				150		300			
	M	SD	M	SD	χ^2	BF_{10}	M	SD	M	SD	χ^2	BF_{10}
CCT (Color)												
Overall lighting	0.53	1.22	−0.22	1.13	1.06	$\frac{1}{17}$	−0.08	1.12	0.26	1.37	0.65	$\frac{1}{1038}$
Task Light	−0.58	0.77	−0.41	0.60	0.36	$\frac{1}{33}$	−0.46	0.65	−0.47	0.70	0.40	$\frac{1}{1722}$
General Lighting & Daylight	0.74	1.28	−0.05	1.20	0.52	$\frac{1}{22}$	0.16	1.26	0.32	1.34	0.64	$\frac{1}{1295}$
CCT (Heat)												
Overall lighting	−0.58	1.17	0.43	0.96	4.10*	$\frac{1}{11}$	0.08	0.92	0.11	1.49	0.13	$\frac{1}{1298}$
Task Light	0.53	0.77	0.16	0.73	0.12	$\frac{1}{13}$	0.38	0.72	0.11	0.81	0.12	$\frac{1}{630}$
General Lighting & Daylight	−0.68	1.25	0.00	1.11	0.75	$\frac{1}{27}$	−0.14	1.13	−0.42	1.31	0.40	$\frac{1}{1027}$

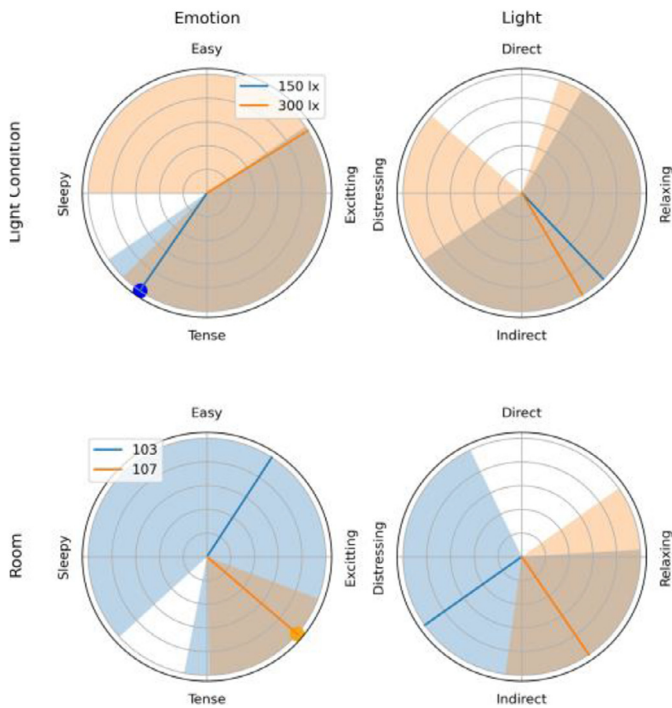


Fig. 8. Plot of emotions computed from the ticking of adjectives by occupants. The emotion is plot within the circumplex space. When a direction is not uniform a dot at the end of the line indicate a significant direction identified by the Rayleigh test. Shaded areas represent the 95% confidence intervals.

Altogether, these results suggest that there was no difference in ratings between rooms and time as the lighting condition did not reflect any differences.

3.3.4. Emotions and feelings about light

3.3.4.1. Feelings and associations. In regards to “feelings”, the pairs of adjectives (Section 2.4, Materials), were not able to discriminate between feelings, as all scores around a neutral value showed no significant difference between rooms and lighting conditions. While, “decisive evidence” was obtained most of the time, “very strong evidence”, with less frequency, and rarely “strong evidence” for the lack of effect of the conditions. Regarding “associations”, the same pattern was found, except that ‘General light and daylight’ were found to be associated differently between rooms. In the individual room (#103) the general light and daylight were found more associated (between slightly agree and agree; $M = 1.42$, $SD = 1.43$) than the open space (#107; $M = 0.00$, $SD = 1.55$), $\chi^2(1) = 14.47$, $p < .001$. Then, the Task lighting was less associated to sunrise in 150 lx lighting condition (between neutral and slightly disagree; $M = -0.51$, $SD = 0.90$) than in the 300 lx one (neutral; $M = 0.00$, $SD = 0.67$).

3.3.4.2. Circumplexes. Regarding the circumplexes, precise directions were identified in the circumplexes for emotion, since the condition with 150 lx raised an emotion between sleepy and tense ($R = 3.07$, $p < .05$) while an emotion between tense and exciting ($R = 8.04$, $p < .001$) was observed in the open space (Room #107). Due to the lack of direction for the two rooms and for the two light conditions in each circumplex, we were not able to compute any statistical test to compare directions between conditions (see Fig. 8).

3.3.4.3. Most impactful source of light. The occupants were asked to indicate which source of light had the most impact on their emotions in regards to CCT. Most of the occupants mentioned general light and daylight as having the most impact over their emotion about CCT (84%), some mentioned the task light (11%) and others replied that neither of

the source as they had the same impact on their emotions (5%). While the results differed between the rooms and lighting conditions, it was deduced, that reducing the light intensity did not have a significant impact over the occupant’s feelings and emotions towards light.

3.3.5. General lighting. Illuminance transitions between conditions

3.3.5.1. Number of notices. In the individual office, the transitions of the general light were detected by the main user but not by the user who was using the office partially (Section 2.4, Participants). In the open space the light transitions were noticed by half of the participants ($N = 2$) and remained unnoticed by the other half ($N = 2$). The only characteristic allowing to discriminate between occupants who noticed the change is age (noticed: $M = 27.00$, $SD = 2.83$ and unnoticed: $M = 35.50$, $SD = 4.95$). This might indicate that operating the transition in regards to quantity of light during the week-end allows participants to adapt directly on the next Monday.

3.3.5.2. Adequacy of general lighting illuminance. For the people who noticed the transition, they judged the light more appropriate in the 300 lx light condition ($M = 2.00$, $SD = 0.00$) than in the 150 lx light condition ($M = -2.00$, $SD = 1.00$), $t(2) = 6.92$, $p < .05$.

3.3.5.3. Satisfaction switch between lighting conditions. A more in-depth analysis of visual comfort of both light conditions revealed that only one participant expressed a different visual comfort. This male participant did notice the changed, scored high on the openness scale as well as on the scale for “safeguarding against positive self-representation” and was 29 years old. The different visual comfort expressed between visual conditions manifests with a higher comfort with the general light in the 300 lx condition (Comfort: $M = 1.33$, $SD = 0.56$, Judgement: $M = -77.00$, $SD = 12.12$) than in the 150 lx light condition (Comfort: $M = -0.75$, $SD = 1.26$, Judgement: $M = 43.50$, $SD = 16.05$; $t(6) = -2.62$, $p < .05$ and $t(6) = -3.00$, $p < .05$ respectively). The latter, seems to confirm the weak impact of the change in general light on the occupant’s level of comfort as illustrated in Fig. 9.

The occupants found the 300-lx setting more appropriate, however, in overall, half of them did not noticed the switch in general light, which suggest that the 150 lx had no conscious impact on the occupant’s feelings and comfort.

3.3.6. Energy

Over the course of the experiment, the two offices consumed together 59.90 Wh in the 150-lx light condition and 92.86 Wh in the 300-lx light condition. The reduction of the intensity of the general lighting, signified energy savings of 32.96 Wh over the experiment’s period, hence 35.45%. When considering the usual operation of the building before the implementation of the control system (general light at 100%, during occupied hours), the consumption would have averaged to 182.24 Wh, which represents energy savings of:

- 122.34 Wh or 67.13% at 150 lx.
- 89.38 Wh or 49.05% at 300 lx.

The latter, represent a double achievement, by the reduction of the energy consumption without disrupting the occupant’s comfort.

3.3.7. System comfort, disturbance and acceptance

3.3.7.1. System comfort and disturbance. According to the occupants, a comfortable interior environment was achieved by the automatic operation of the control system, within a frequency judged as ‘sometimes’ and ‘often’ ($M = 0.61$, $SD = 0.91$). Such impression did not change in regards to the lighting conditions (with decisive evidence $BF_{10} = \frac{1}{1694}$) nor due to the room (with strong evidence $BF_{10} = \frac{1}{19}$). Moreover, the occupants declared to be rarely disturbed by the system ($M = -1.02$, $SD = 1.12$), judgement that did not differed between the two conditions (with decisive evidence: $BF_{10} = \frac{1}{225}$), and rooms (with strong evidence:

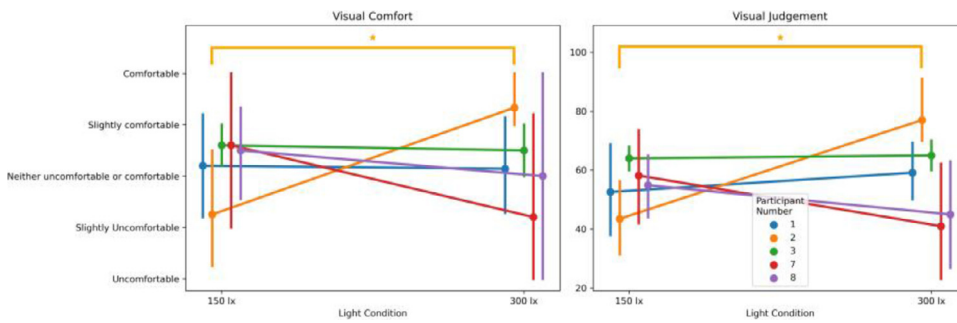


Fig. 9. Point plot depicting visual comfort of each participants within light conditions. On the left: visual comfort and on the right: visual judgement. The vertical line starting from the dot indicate the 95% confidence intervals and the colored line at the top with the asterisk indicates significance at $p < .05$ for the occupants depicted in the same color.

$BF_{10} = \frac{1}{21}$). Those results suggest that the system managed to maintain a comfortable environment while not disturbing occupants during its operations.

3.3.7.2. Acceptance of the system. The acceptance of the system did not reveal any decisive tendency, according to the occupants assessment, while all constructs did not differ significantly from a neutral perspective without any evidence towards H0 nor H1 (BF revealed only anecdotal evidence). However, the descriptive statistics revealed some constructs that seem to stand out. In regards to the system's perceived control, the occupant's opinion was found between "slightly disagree" and "neutral" ($M = -0.60$, $SD = 2.13$); system reliability ($M = -0.47$, $SD = 1.30$); compatibility ($M = -0.67$, $SD = 1.29$), usefulness ($M = -0.65$, $SD = 1.04$) and trust ($M = -0.60$, $SD = 1.28$). In regards to the ease of the system's operation, the occupants "slightly disagree" or "disagree" with such statement ($M = -1.80$, $SD = 1.10$), while showing a positive attitude towards the system ($M = -2.00$, $SD = 1.16$), and their intention to use ($M = -1.33$, $SD = 1.63$).

Due to the lack of evidence towards a marked acceptance of the system, the results seem to suggest a high variability in the responses, with some user accepting the system and some other not accepting the system. In order to deeper investigate such tendency, a personality correlation was performed, as well as the chronotype scales, and locus of control. The locus of control scale revealed that, the more the occupants had an internal locus of control, the more negative their attitude would be versus the system (the reverse is equally true due to correlation nature; $r = -0.92$, $p < .01$). The chronotype scale showed that, the more the "eveningness" the higher the ease of use is perceived (the reverse is equally true due to correlation nature; $r = 0.89$, $p < .01$). Regarding personality, no trait except "agreeableness" revealed significant correlation with acceptance (see Fig. 10). More specifically, the lower the "agreeableness" the higher the perceived usefulness ($r = -.95$, $p < .01$), the better the attitude ($r = -.82$, $p < .05$), the higher the intention to use ($r = -.95$, $p < .01$), and the higher the trust in the system ($r = -.89$, $p < .01$, see Fig. 10). Altogether, the results seem to indicate that acceptance could be increased by an adapted explanation about the system to the occupants, or, by allowing an interaction with the system in accordance with personality and user wishes.

3.3.8. Discussion: on the limitations of the longitudinal study

The main limitation of this study is related to the low number of participants, as the data of five users was considered as relevant (Section 2.4, Participants). Therefore, results obtained here should be taken with caution, considering the applicability to a larger population. A related limitation, refers to the participation of a partial user in room #103, to compensate occasional absences of the exclusive user. While his presence was restricted to 16% of the time, the relocation between rooms could have influenced his perception of the lighting conditions, inducing a loss of commitment to adapt the light to the specificity of the room. The brief duration of the user's experiment represents an additional limitation, as the occupant's impressions were assessed during

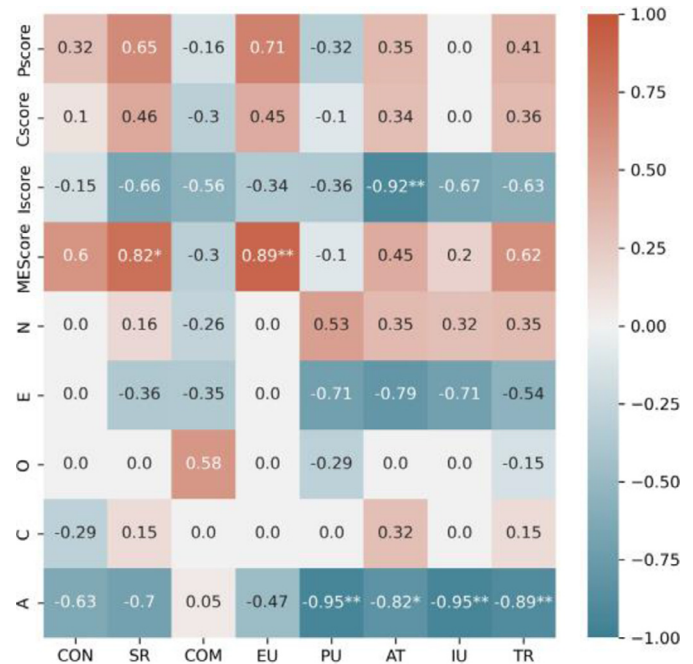


Fig. 10. Grid of correlations between personality, locus of control as well as chronotype and acceptance. Note: * = $p < .05$, ** = $p < .01$ and *** = $p < .001$.

only six weeks in spring time. The latter, represents a further disadvantage, since a long-lasting assessment of the impact of lighting conditions on occupants, covering the dynamicity of daylight according to seasonal changes would have been valuable for this study. However, a spring evaluation represents an advantage itself, as the occupants were exposed to a balanced day/night transitional period, beneficial for the study to assess both daylight and electric lighting conditions in a similar proportion.

4. Conclusions

With the aim to achieve satisfactory occupant's visual and thermal comfort with reduced use of energy, an intelligent lighting control strategy was implemented in an individual and a shared office space. Subject to surrogate model's predictions of two KPIs as initial step, exterior blinds and electric lighting are promptly adjusted in accordance to a performance-based control strategy. An optimized interior environment is created by new blinds and lighting settings, to maximize the daylight provision while maintaining a reduced risk of glare. The daylight contribution is then compensated with the combined use of general and task lighting, targeting a minimum illuminance to satisfy the norms, then to allow the occupants to create a lighting environment according to their preferences. In room situations as the ones analyzed in this study, the use of task lighting might alter the interior light distribution.

The latter, due to the contrast created by localized lighting fields of the occupied desks and a darkened background created by the unoccupied ones. Two conditions for general lighting are tested in this study to evaluate the occupant's perception in regards to light uniformity, while their impact on the energy consumption is also assessed. The general lighting is set to provide a maximum of: 1a) 150 lx WPI and 1b) 300 lx WPI, while the task lighting is set in both conditions, to a value that can be customized by the user starting at a minimum of 500 lx WPI.

The evaluation was performed during six weeks, where comfort and energy use were assessed, as well as the perception of five occupant's through a longitudinal study. When compared to the baseline (before the control system implementation), a firm reduction of the lighting energy consumption was demonstrated in the two conditions assessed. According to the occupants, the visual and thermal environment was maintained within a comfortable range, while the uniformity of the interior lighting distribution was given a rather positive impression, regardless of the condition assessed. In addition, the occupant's perception of the system indicates a rather 'narrow' positive perception. The previous allegations confirm that the control strategy implemented in this study allows a reduced energy use for lighting, while creating an interior environment that does not represent discomfort for the occupants. Additional results indicate that occupants seem to relate a higher illuminance with a whiter/colder CCT, as the user's preferences show in two indicative situations (room #103, and general lighting condition '1b'). In addition, it was found that overall, neither the room nor the lighting conditions impacted over the occupant's emotions and feelings about light and visual comfort. It is worth mentioning that an increased energy use could be unnecessarily estimated as a result of inaccuracies caused by the model predictions for WPI, especially in the case of the desks near the window. When considering the relevant range (300 lx), the task lighting could be employed as an alternative to compensate for illuminance shortfalls (result of wrong estimations), yet it remains reliant on user preferences.

When referring to the uniformity of the light distribution, for the two lighting conditions. A rather "neutral" perception was reported by occupants to the reciprocal noun used in the questionnaire (homogeneous, heterogeneous). In addition, increased energy savings were observed with the lighting condition '1a' (150 lx) than with the '1b' condition (300 lx), corresponding to 67% and 49% respectively. The latter might suggest a certain advantage of the condition '1a' over the condition '1b', however, a decisive conclusion cannot be established due to the limitations of the longitudinal study (Section 3.3, Discussion).

Certain actions should be taken in future studies in order to overcome such limitations, few mentioned as following. With respect to the user experiment, performing a larger scale study over a longer period of time, potentially covering an entire year to consider all possible variations in daylighting conditions. The latter would be favorable for the study to evaluate energy savings and user preferences in accordance to prevalent situations, either leaning to an increased use of electricity (winter time), or of the natural source (summer). In addition, a larger number of participants would allow gaining more precise insights over the details of these observations. Potentially including the perception of people with more varied sensitivity to light, lighting preferences and requirements. Additional lighting conditions could be assessed once the limitations are addressed, where lower general lighting thresholds could be tested for energy savings as well as to occupant's perception.

Additional opportunities for the improvement of this study were shown by the results. To achieve more accurate WPI model predictions, an increased proportion of training data within a relevant time range (working hours), could be generated as first step. Then the efficiency of the training data for specific room areas of demonstrated challenging performance could be further enhanced. In addition, the control strategy could be adjusted to allow the occupants with further dominance of the control settings, according to distinct levels of desired control as well as to personality traits.

Declaration of Competing 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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An exploratory interplay between daylight, general and task lighting for visual comfort and electricity savings in a personal office space

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Abstract

In working environments, an adequate lighting planning is set-on-sight by addressing a sufficiency in daylight provision for an efficient use of electricity for lighting, as well as a reduced risk of glare. Blinds and electric lighting are commonly employed to regulate the thermal and visual environment indoors, by controlling the daylight admission and preventing its unfavorable effects on comfort and the energy balance. The regulation by an automatic control system based on machine learning models is implemented in an individual office, to adjust blinds and electric lighting for an improved performance. The individual preferences of the occupants are addressed by including a task light as an additional fixture, to allow them to set their most satisfying lighting conditions. To assess the occupant's lighting preferences, as well as the acceptance of the automatic control, a longitudinal user experiment was conducted. The preliminary results for two weeks showed a smooth operation of the automatic control, well tolerated by the occupants, leading both to a satisfaction of the users' visual comfort and energy savings.

Keywords: daylight and electric lighting, visual comfort, blinds and lights controls, energy efficiency

1. Introduction

Due to its characteristics, the use of daylight in buildings would impact several aspects related to human activity indoors. As a freely distributed natural source, its use would contribute to a compensation of the electric lighting, resulting in a reduced energy demand. Its high intensity would allow a better visual performance by favoring a better discernment of details in the view scene, as well as color discrimination due to its high color rendering (Knoop et al., 2020). In addition, its full continuous spectrum would have an impact on human health-related aspects such as the circadian system and sleep-wake cycles, which is particularly sensitive to light wavelengths within the blue spectrum (Beute, 2014). The view-out would have psychological effects on performance and well-being sensation, due to its dynamic directionality and temporal variations (Aries et al., 2013). However, an unplanned use of daylight in buildings might signify unfavorable effects for the occupant's comfort as well as for an efficient use of the energy. Its use also signifies the admission of solar heat gains, which especially in summer time, would impact the occupant's thermal comfort and result in additional energy use for cooling where available. Similarly, poor daylight planning might result in adverse effects for the occupant's visual comfort, such as, allowing the sunlight peaks to directly strike their visual field, causing discomfort glare (Altomonte, 2008) (Ingabo and Chaiwiwatworakul, 2021). While the daylight admission indoors should be maximized in order to take advantage of its benefits, potential risk situations must be promptly identified in order to ensure the occupant's comfort. Shading devices are a common and efficient strategy employed for the regulation of the visual and thermal interior environment. However, it has been observed that people barely perform blind adjustments, while long-term events dominate their decisions rather than prompt reactions to efficiently correct potential comfort risk

situations (O'Brien et al., 2010). An inappropriate user's manipulation that could result in unfavorable effects on energy use and comfort could be prevented by the use of fully automated blinds and electric lighting. However, it has also been established that a connection exists between higher control and occupant's satisfaction, which also represents a greater motivation for occupants to achieve their own preferred conditions (O'Brien, 2013). Hence, concerning an optimal blinds and electric lighting operation, a known tight-spot is newly addressed: while an adequate control can be constrained by the occupants' actions, yet it should be driven by their preferences.

This research evokes a previous study (Basurto Davila and Kaempf, 2020) where, an intelligent control strategy is applied on the aforesaid individual office, aiming to achieve comfort and energy goals. An evolution to that research consisted on investigating the use of surrogate models for the KPIs predictions as a faster, yet accurate alternative method to the use of RADIANCE simulations (Basurto Davila et al., 2021b). The implementation of the intelligent control system in real settings constituted the following step on the achievement of a unified approach, by the integration of the predictor models and the intelligent control scheme (Basurto Davila et al., 2021a; Papinutto et al., 2022). The incorporation of a desk lamp within the system was also part of such development, to account for the occupant's individual lighting preferences as well as a strategy for energy reduction. The latter approach is based on discoveries performed by previous studies, where the use of task lighting is associated to the reduction of electric lighting use (Ingabo and Chaiwiwatworakul, 2021), as well as the improved performance on certain tasks (Newsham et al., 2005). In the present research, a further step is taken by performing the control system evaluation in a real-life office environment.

An exploratory interplay between daylight, general and task lighting is investigated here by the implementation of a control strategy that could emulate a background-foreground approach. The daylight and general lighting are automatically controlled in the 'background' by a performance-based-control-criteria ruled according to two KPIs: work-plane illuminance (WPI) and the risk of glare (DGP). As strategy employed for energy reduction, the task lighting intends to complement the general lighting, therefore, it is operated as a part of the automatic system. However, the light intensity and CCT can alternatively be controlled individually, creating a 'foreground' approach where the occupant's commands lead. In order to evaluate the impact of the control system on occupants, a longitudinal study is conducted where the user's response to the system's performance is taken into account. In the latter, the occupant's level of satisfaction in regards to the self-regulated interior environment, as well as their acceptance of the automatic system is analyzed. The associated effects of the interconnected system on thermal comfort is also considered.

2. Methodology

2.1 The individual office: from simulations to model predictions

The case-study is located in the city of Martigny, Switzerland, consisting of an individual office of rectangular shape and 23m², with approximate dimensions of 7.05 m deep by 3.05 m width and 3.06 m height. Important room features, comprise the metal exterior blinds of a halved hexagonal shape and clear grey matte color of 30% reflectance and dimensions of approximately 9.0 by 3.0 cm. The electric lighting was refurbished by replacing three fluorescent tubes of 58 W, by three suspended LED dimmable T8 tubes of 41W and 21 W placed at the central axis along the room. The research work that precedes this study is described with more detail in (Basurto Davila et al., 2021b; Basurto Davila and Kaempf, 2020). It consists of the on-site monitoring of the office room for the creation of a virtual model, the generation of year-round RADIANCE simulations to estimate two KPIs - WPI and the DGP - and the use of the resulting database for the training of daylight surrogate models, with the goal to get faster yet accurate estimations of the two KPIs. As described in the above-mentioned study, a gradient boosting machine (GBM) model (Friedman, 2001) achieved the highest prediction accuracy for the same case-study evaluated here. However, for the present research, a lighter version of the GBM model was required in order to implement the control system on a 32-bit computer (Raspberry Pi 3B).

In order to do that, a new model based on the LightGBM framework (Ke et al., 2017) was trained instead, achieving a better performance on the Raspberry Pi 3B and similar accuracy on the test data, with a reduced use of memory. The workflow employed to find the best hyperparameters and train the model was not changed, however, differently from the previous work, only blind angles between 0° and 50° were considered. The procedure is similar to the one described in (Basurto Davila et al., 2021b, 2021a), while the process to obtain the electric lighting prediction model is also described in the above-mentioned studies. In order to verify the

performance of the surrogate model in regards to the real situation, the WPI daylight predictions were compared to real measurements obtained on spring 2022, considering all blind positions. The results are shown in Figure 4.

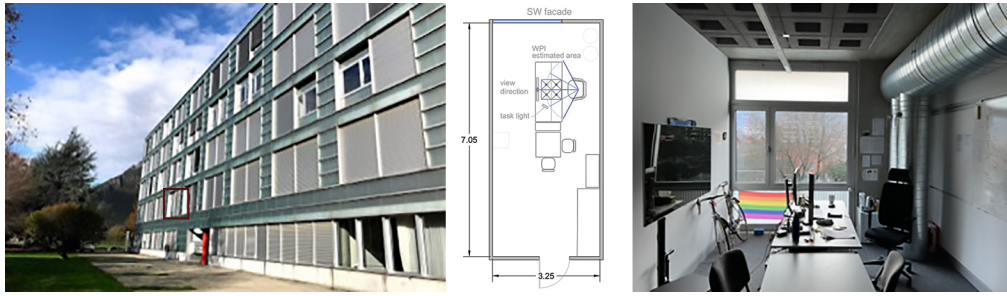


Figure 1. Office #103, from left to right: exterior view of the case-study building, floor plan view and interior view of the room.

2.2 Control system implementation

The aim of the integrated control scheme is to provide an adequate visual and thermal environment with a reduced use of energy, while allowing the occupants to have an individual control of the lighting conditions. The daylight and electric lighting predictor models first perform the predictions of the two KPIs based on measured sky conditions obtained by a Delta-T BF5 solar radiation sensor. Then, blinds and electric lighting adjustments are performed via KNX and DALI interfaces, according to settings established by a performance-based control strategy (Papinutto et al., 2022). The control criteria target glare protection and daylight provision as primary interest, where blinds are forthwith deployed if a DGP above 0.35 is predicted by the daylight model from the occupant's position (See Figure 1). The blinds would be adjusted to maximize daylight provision, set to achieve a threshold of 150 lx WPI, obtained by the combined use of daylight and a dimmed LED general lighting. The use of task lighting is explored in this study, to further engage the present research on the user lighting preferences, and its related benefits for performance and energy savings. While the task lighting fixture is integrated within the automatic system, the users are able to adjust the intensity as well as the color (CCT curve) to a setting that makes them feel more comfortable. Occupants can benefit from the use of the desk lamp, first, by setting their individually preferred WPI, as a compensation of that provided by daylight and general lighting. Then, by performing CCT adaptation according to preferences to be set to certain Kelvin range, between 2700 and 3500 K for a warmer color, and 4500 and 6500 K for a cooler CCT (Papinutto et al., 2022). The use of the task lighting fixture as employed in this study is portrayed in Figure 3. Then, an adequate thermal environment is ensured by activating the blinds deployment when the solar incidence on the façade surpasses 150 W/m². As an additional solar protection action, the blinds would be tilted to a cut-off angle position according to the sun elevation.

Table 1. The control strategy implemented in office #103

Control Criteria		Action	Control Mode
Glare DGP	$DGP > 0.35$	Blinds deployment	A
WPI Daylight + GL	150 lx threshold	Blinds and dimming lighting adjustment	A
WPI Task Light	≥ 500 lx, adjustable	Dimming lighting	A and M
Thermal comfort	< 150 W/m ²	Blinds deployment	A
In – Out office	Presence detector	System activation / deactivation	M
Unoccupied winter	Day time Night time	Blinds retracted Blinds deployed	A
Unoccupied summer	Day time Night time	Blinds retracted Blinds deployed	A

Additional actions are set to protect the interior environment during non-occupied hours, in winter time, during the day the blinds are retracted to allow sun penetration to warm up the interior environment, while during the night they are deployed to avoid air leakages. The opposite actions are taken during summer time, the blinds are deployed during the day for solar protection, while retracted during the night to allow possible natural ventilation. A presence activation system is also set, to ensure the use of electric lighting only when is needed. At arrival, the occupants activate the system by placing their palm-hand on a lighting sensor placed on the desk, and perform the same action upon their departure. Alternatively, users can also set their presence using an optional web interface. A description of the control strategy is shown in Table 1 where a manual or automatic control mode is specified by the designation ‘M’ and ‘A’. In addition, a detailed depiction of the control scheme can be found in Figure 2.

2.3 Monitored performance

In order to monitor the performance of the control strategy, some features related to energy consumption and visual comfort are constantly measured in order to compare these with baseline measures. This allows to verify that the proposed solution effectively reduces the lighting-related energy consumption and that the use of the lighting models correctly estimate the target WPI. Energy consumption of the general lighting is measured via a KNX interface, while the one of the task lighting is estimated by a model expressing the energy consumption as function of the lighting intensity. The latter, is built by manually varying the intensity while measuring the energy via a NETIO PowerCable REST 101 J WiFi power socket, a similar approach is also described in (Papinutto et al., 2022). For the main control hub and the desk control hub (raspberry Pis 3B), a constant power of 3 W and 1 W respectively is considered, in line with what was observed during a testing period of approximately three months. The approximate estimation of the performance of the WPI prediction models, was achieved through an illuminance sensor placed on top of the desk control hub, which takes care of the task lighting control, situated on the desk in a position chosen by the user (Figure 3).

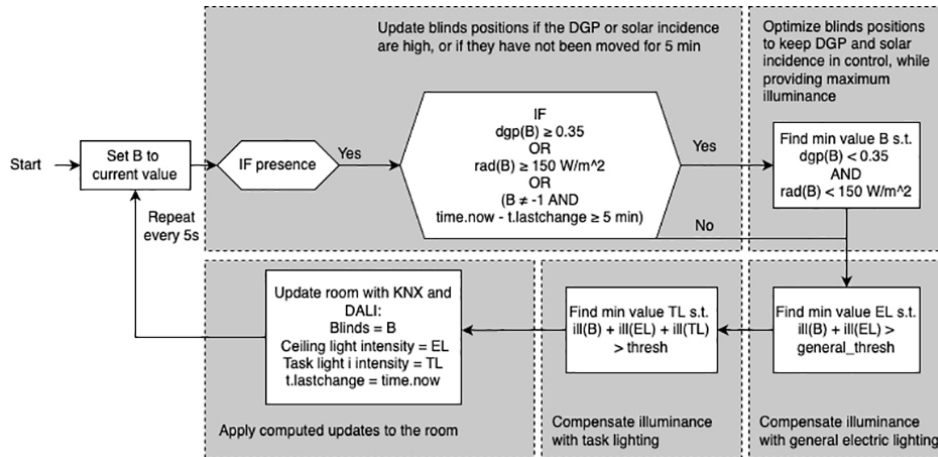


Figure 2: Control strategy to reduce energy consumption while providing visual and thermal comfort

2.4 The longitudinal user experiment

A longitudinal study was implemented to investigate the occupant’s perception of the lighting situation and of the acceptance of the automatic control system during their usual work activities. Two participants (named p-A and p-B) took part in this study, for whom, similar psychological traits were identified in terms of locus of control (Levenson locus of control scale (Levenson, 1974)), morningness /eveningness (Chronotype questionnaire from Oginska (Oginska, 2011; Oginska and Mojsa-Kaja, 2017), and personality. For the latter, they were mostly at the same level in most traits on scales with five levels, but differed from two steps in some traits (Satow, 2021, 2012). The office was used independently by both participants during two weeks, they were instructed to perform their usual activities and requested to complete three questionnaires.



Figure 3. Task lighting fixture and operation. From left to right: the presence activation procedure, the task lighting setting on the occupant's desk, and a view of its use on evenfall exterior lighting conditions.

An entry questionnaire was first given to the users in order to evaluate their personality traits. A daily questionnaire would evaluate their perception of interior environment in relation to visual and thermal comfort as well as their emotions towards the lighting conditions. Finally, an exit questionnaire was applied at the end of the evaluation period, intended to evaluate the occupant's acceptance of the automatic system. Further information relative to the questionnaires can be found online: <https://www.idiap.ch/~jkaempf/AllQuestionnaires.pdf>.

3. Results and analysis

3.1 Verification on-site monitoring vs ML predictions, alongside comparison with RADIANCE simulations

A comparison of the WPI surrogate model predictions vs on-site monitored data obtained on the 21st March 2022 is shown in Figure 4. The RADIANCE simulations corresponding to the same measured data are plotted alongside to illustrate its performance. For the correspondence between the WPI measured data and the daylight predictions, an R^2 of 0.77 and MAE (mean absolute error) of 570 lx was obtained. In the case of the comparison between the measured data and the RADIANCE simulations an R^2 of 0.95 and MAE of 254 lx was observed, highlighting an adequate representation of the real situation by virtual model. Regarding the discrepancies observed for the predicted values, a balanced proportion of under and over estimations can be observed in overall. However, there is a slight tendency to a higher proportion of overestimations (57%), which might signify a slim possibility of underestimate the general lighting requirements. In such situations the use of task lighting would signify an advantage to compensate for the occupants preferred lighting conditions.

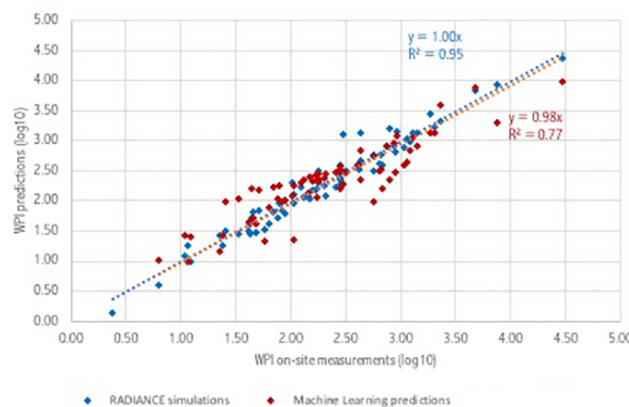


Figure 4. Correspondence of measured WPI vs. ML predictions, alongside a comparison with RADIANCE simulations. The illuminance values are expressed as logarithmic scale 10.

3.2 Longitudinal user experiment

As shown by the results, no significant differences were found in terms of predictions for general lighting (with substantial evidence $BF_{10}=\frac{1}{5}$). However, during the study, p-A experienced a significantly higher amount of daylight, with an average of 617.77 lx (SD=347.03), while p-B had an average of 529.53 lx (SD=336.59, $t(290.75) = 2.60$, $p < .01$, $BF_{10}=2.81$). Interestingly, the duration of the exposure was not significantly different between both users (with weak evidence $BF_{10}=\frac{1}{2}$), as p-B experimented 205 mins of sunshine per day (SD=209.93) while p-A 120 mins (SD=180.75).

In addition, the usage of task light differed significantly between the occupants. It was observed that p-A selected a brighter CCT (CCT of 5060.27 K on average, SD=866.39), as well as an increased amount of light (on average 442.59 lx, SD=216.37). While p-B had a CCT of 4425.27 K (SD=718.24, $t(254.59) = 7.83$, $p < .001$, $BF_{10}=2.81$ (anecdotal evidence)) and a WPI of 304.38 lx (SD=263.01, $t(356.31) = 6.01$, $p < .001$, $BF_{10} > 100$ (extreme evidence)). This expresses potential participant's idiosyncrasies in lighting condition preferences.

Altogether, the participants mostly employed task lighting to compensate an insufficient daylight provision, thus reach their desired level of illuminance (around 1062.04 lx on average for p-A, SD = 402.05 and 836.94 lx on average for p-B, SD=469.17). Those levels differed significantly from each other, $t(343.65) = 5.36$, $p < .01$, $BF_{10} > 100$ (extreme evidence) as illustrated in Figure 5.

The energy used for task lighting (to compensate an insufficient daylight provision) did not differ between the users (p-A used on average 11.47 Wh, SD=28.10 and p-B 18.55 Wh, SD=20.76, $BF_{10}=\frac{1}{2}$). Moreover, in a comparison of the system performance versus the use of a permanently switched-on general light, the system allowed to save 746 Wh over the two weeks, corresponding to 93.09 Wh per day on average, or about 86.38% reduction. Considering an efficient building, according to Swiss norms lighted 1290 hours per year, the total energy saved by the system evaluated here, amounts to 120 kWh per individual office space, corresponding to a specific value of 5.2 kWh/m² per year.

Regarding visual comfort, the perception of the lighting environment did not differ significantly between the occupants, despite the previously mentioned differences in lighting conditions. Both, p-A and p-B, described the lighting conditions as 'slightly comfortable', being 'neither too dark nor too bright' (with anecdotal evidence $BF_{10}=\frac{1}{2}$ for both measurements). In overall, both users found that the system provided a comfortable visual environment that was judged as 'satisfying', in a frequency from 'often' to 'always' (with anecdotal evidence $BF_{10}=\frac{3}{4}$).

Regarding thermal comfort, p-A reported a sensation from 'slightly cold' to 'neither too cold or warm' considered as between 'neither uncomfortable or comfortable' and 'slightly comfortable', whereas p-B reported 'neither too cold or warm' only as being between 'comfortable' and 'very comfortable'. Those reports do not differ significantly from each other (with anecdotal evidence for both the temperature sensation: $BF_{10}=\frac{2}{3}$ and felt comfort: $BF_{10}=\frac{4}{5}$).

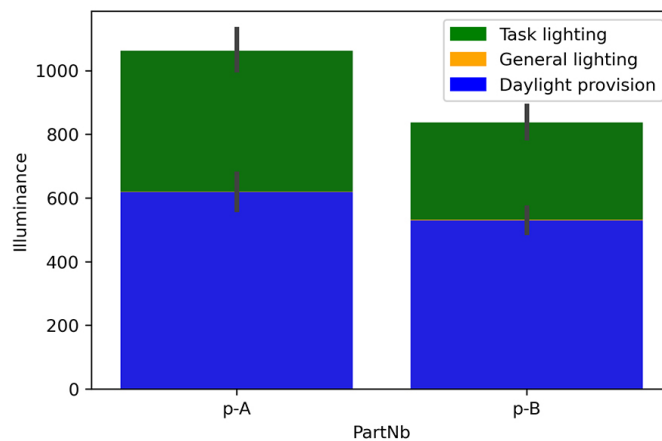


Figure 5. Stack plots representing the amount of light in lx used by the occupants and coming from different sources. The black lines represent the 95% confidence intervals.

In terms of system disturbance, p-B reported to feel more often disturbed by the system actions than p-A. Indeed, p-B reported to be disturbed ‘rarely’ whereas p-A was ‘never’ disturbed by the system’s operation ($t(5) = 3.16$, $p < .05$, $BF_{10}=4$). Altogether, the results suggest that the automatic system managed to perform a smooth operation that was tolerated by the occupants, while creating a comfortable interior environment that satisfies the occupants and achieves a significant reduction in electricity consumption.

4. Conclusions

The paper presents the results of a longitudinal study in which an automatic system controlling blinds, general lighting, as well as a task lighting fixture was implemented. The objective was to reduce the risk of glare (DGP), as well as to provide a sufficient daylight on the work plane (WPI), which in return would reduce the energy consumption for electric lighting. The set-up was conducted in an individual office that, due to its orientation (South-West), is prompt to a higher glare sensation for the occupants in the afternoon hours, leading to a more frequent use of the blinds. The designed automated system performed by maximizing the daylight provision while avoiding glare, consequently, minimizing the need of electric lighting. The results of the longitudinal study, showed that occupants reported that comfort was met most of the time without disturbances and with electricity savings of the order of 90 Wh over the testing period, compared to an always-lit office. Projected to an annual use, the savings would be in the order of 5.2 kWh/m² per year, while the comfort would be maintained to an adequate level. Thus, the occupants would benefit from an adequate interior environment, which would be reflected in their productivity-and-well-being.

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