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Energy saving first or productivity first? — Maximize the economic benefits of urban office buildings

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ABSTRACT

The enhancement of the indoor environment could typically enhance user productivity; however, it may also result in additional energy consumption. In order to address the trade-off between employee productivity and energy consumption in office buildings for maximizing economic benefits, this study conducted an investigation on the optimal indoor environmental parameters including temperature, humidity, and ventilation rate. The relation between cognitive performance and the environment was established at the laboratory experiment, while the relation between energy consumption and the environment was determined through energy consumption simulation. By linking productivity to energy consumption using economic indicators, the optimal environmental parameters for maximizing economic benefits are calculated. The results indicate that the optimal indoor environment settings for maximum economic benefits are very similar to those for achieving maximum productivity. Prioritizing office workers' productivity assurance is crucial when designing air conditioning parameters for office buildings to enhance overall economic gains. However, as the ratio of economic-output-to-electricity-price decreases, there is a gradual increase in differences between these two sets of parameters. Therefore, it is more meaningful for economically underdeveloped regions to establish optimal office building parameters by considering energy saving factors more comprehensively. It is also suggested that the validity of the economic optimization results can be further enhanced by developing productivity evaluating methods for real-life office settings and employing more accurate fitting models.

1. Introduction

The rapid growth of energy consumption and carbon emissions in the construction industry has garnered increasing global attention, owing to the development of cities and rapid economic growth worldwide [1]. According to reports [2], urban built environment are responsible for approximately one-third of global primary energy consumption and contribute to one-third of total direct and indirect energy-related greenhouse gas emissions. Office buildings are among the top five most energy-consuming buildings [3]. The energy consumption of office buildings is not only closely associated with environmental conservation, but also incurs significant energy expenses. Taking China as an example, recent surveys indicate that the energy consumption of office buildings typically exceeds 100kWh/(m^2·year) [4,5], which means that the annual energy expenditure for an office building can amount to hundreds of thousands of dollars.

The energy consumption of a building can be attributed to Heating, Ventilation and Air Conditioning (HVAC) systems, accounting for nearly 50 % [6]. The implementation of more energy efficient parameters for the HVAC systems can lead to significant savings in energy costs. However, it is important to acknowledge that altering indoor environmental parameters may also impact the productivity of office users. Temperature and relative humidity exert their influence on cognitive performance through the modulation of thermal sensation experienced by individuals. Most of the relevant studies focused on the single factor, temperature. The study conducted by Seppanen et al. demonstrates that cognitive performance is modeled as a cubic function in relation to changes in temperature [7]. The study conducted by Kim and Hong revealed a distinct inverted U-shaped relation between temperature and cognitive performance, wherein the optimal cognitive performance was observed at 25.15 °C. Deviating from this temperature range either above or below resulted in a decline in cognitive performance [8]. Few studies purely worked on relative humidity. Reducing humidity can

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Nomenclature

A	Accuracy
A_x	Accuracy in a given environment x
A_0	Accuracy with RP_{max}
a, b, c, α, β and γ	Coefficient
d and δ	Constant
EE	Electricity expenses
EP	Electricity price
$Output$	Economic output of stuff
$Output_{max}$	Output with RP_{max}
$Productivity$	Productivity of stuff
Q	Ventilation rate
RP	Relative productivity
RP_{max}	Maximum relative productivity
RP_x	Relative productivity in a given environment x
RT	Response time
RT_x	Response time in a given environment x
RT_0	Response time with RP_{max}
t	Temperature
W	Electrical energy consumption
$Work$	The amount of total work
φ	Relative humidity

alleviate cognitive performance loss caused by high temperatures [9]. But a too low humidity may cause eye discomfort, and a relative humidity of 40 %-60 % is recommended for workers [10]. The influence on cognitive performance has been measured in some studies by integrating parameters such as temperature, air velocity, clothing, and others into the Predicted Mean Vote (PMV). These studies have expressed relative cognitive performance or cognitive performance loss as a function of PMV [11–13]. The cognitive performance may also be influenced by ventilation rate. Seppanen et al. contend that there is a positive correlation between increased ventilation rates and enhanced cognitive performance. Furthermore, they assert that this beneficial impact of heightened ventilation is more pronounced for lower ventilation rates but diminishes at higher ventilation tares [14]. Ben-David et al. posited that enhancing ventilation rates could yield dual benefits of improving productivity and reducing absenteeism rates (thus increasing work time), and they established a correlation between productivity and absenteeism rates in relation to ventilation rates [15]. The aforementioned studies collectively demonstrate that enhancing indoor air quality has a positive impact on individuals' productivity. However, it is worth noting that the improvement of indoor air quality also results in an augmented energy consumption, thereby establishing a seemingly contradictory relation between energy conservation and productivity.

If a suitable mediating factor cannot be identified, balancing the dual concerns of energy conservation and productivity enhancement becomes challenging [16]. Economic benefits are a crucial incentive driving changes in energy policies [17]. The relation between energy consumption and productivity has been extensively examined from an economic perspective in several studies. Fisk et al. demonstrated that increasing ventilation rates resulted in a productivity improvement benefit that exceeded the associated increase in energy costs by over 200 times, using office buildings in the United States as an example [18]. The temperature and ventilation rate for maximizing economic benefits were determined by Dai et al. based on a hypothetical coupling relation using previous data [19]. The variation of optimal temperature and ventilation rate at different productivity levels was investigated by Mofidi and Akbari [20]. Using an office building in Seoul as a case study, Kim and Hong conducted experiments and energy consumption simulations to explore the optimal environmental parameters [8]. Khovalyg et al. taken Swiss open-space offices as examples to calculate the optimum temperature considering energy, healthy symptoms, and productivity [21]. However, previous studies only focused on one to two environmental parameters, and the sample size of some studies applied in the cognitive performance tended to be small. There is also a lack of investigation into the relation between energy consumption and productivity, considering the comprehensive influence of various environmental parameters. Additionally, extant research fails to consider different types of work and varying levels of economic development.

The objectives of this study are to find the indoor environmental settings of office buildings that effectively balance productivity and energy-saving in order to achieve maximum economic benefits, and to explore how local economic status affects the optimal settings. To achieve the objectives, this study utilized the weighted sum method of multi-objective optimization (MOOP) to achieve the Pareto optimal solutions. As for the objective of productivity, previous studies obtained the comprehensive effect of three environmental parameters, namely temperature, relative humidity and ventilation rate, on the cognitive performance of perception, expression and number calculation tasks, through the central composite design [22,23]. Based on the experimental data, this study raised a new approach which is more suitable for office scenarios to evaluate productivity and establishes a fitting relation between productivity and environmental parameters. As for the objective of energy consumption, this study took an office building in Shanghai as a case study. energy consumption simulation is conducted using DeST software, followed by nonlinear regression analysis to determine the relation between simulated energy consumption results and environmental settings. Compared to the existing literature on optimizing indoor environmental parameters in office buildings, this study improves upon the traditional cognitive index integration method and derives a productivity calculation method from an economic benefit perspective. Additionally, three significant environmental factors that affect building energy consumption are included in the analysis to avoid biased estimates caused by interaction effects between these factors, which were not considered in previous single-factor studies. The impact of economic status on calculation results is also explored. Furthermore, through an extensive review of previous literature on productivity assessment, we discuss how even minor improvements in the accuracy of the productivity model can significantly influence calculations related to economy.

2. Method

The enhancement of the indoor environment typically enhances people's productivity; however, it may also result in additional energy cost. The conventional approach in previous studies was using multi-objective optimization (MOOP) methods [20,24,25]. Researchers could identify the optimal indoor environmental settings by proposing Pareto optimal solutions. Most of studies applied weighted sum method [19,26,27], which could transform the multi-objective into a single objective problem. Kim and Hong [8] used the particle swarm algorithm to solve the economic optimum problem. As both objects optimized in this study can be represented through function fitting, the weighted sum method can be utilized to obtain a more precise solution.

If we consider the economic output of personnel as a function of relevant environmental parameters, then when the disparity between the economic output and air conditioning cost (Equation (1)) reaches its maximum value, t, φ, and Q represent the optimal indoor environment levels for achieving maximum economic benefits.

$$Output(t, \varphi, Q) - EE(t, \varphi, Q) \quad (1)$$

where, *Output* represents the total economic output value of all staff during the cooling season; *EE* represents the electricity expenses incurred during the cooling season. The formulas for *Output* and *EE* related to the indoor environment settings can be derived through cognitive performance experiments and energy consumption simulations, respectively.

2.1. Productivity of office workers

The productivity is commonly evaluated by assessing the cognitive performance in previous studies [8,13,22,23]. In the field of ergonomics, cognitive performance is typically described using accuracy (*A*) and response time (*RT*) as separate dimensions that should be observed and discussed independently [28,29]. The importance of accuracy and response time is often considered equally [30], thus they are assigned equal weightage of 0.5 in the calculation of productivity (as shown in Equation (2)).

$$Productivity = (A^{0.5} \times \frac{1}{RT^{0.5}})^2 \tag{2}$$

In fact, Equation (2) can be simplified to show that *Productivity* is the ratio of *A* to *RT*. This indicator is consistent with the widely used Performance Index (PI, computed by dividing *RT* by *A*) proposed by Lan [13]. But the matter is that although nearly all relevant studies have used this method to integrate *A* and *RT* indicators, we have not found any study that clearly explains the rationale behind this integration method by tracing the citation chain of literature.

In real office scenarios, personnel often need to allocate additional time and effort towards correcting or reprocessing incorrectly completed work, resulting in extra time costs. $\frac{A}{RT}$, however, refers to the rate of accurately completed tasks per unit time, excluding any negative consequences resulting from incorrect tasks in the equation. Therefore, this paper proposes a productivity calculation method based on actual office scenarios.

We used the data of Wu et al. [22,23] to investigate the impact of temperature, humidity, and ventilation rate on office performance. They conducted an experimental study in a controlled environment chamber, and collected and data from the neurobehavioral ability test under various conditions of temperature, humidity, and ventilation rate. In their experiments, participants were required to complete a set of cognitive tasks and the computer recorded their accuracy and response time without requesting them to rectify any incorrect answers. However, in actual office scenarios, it is necessary for office workers to rectify or redo such erroneous work. It is assumed that the total time required for checking, correcting, or redoing is equivalent to the time needed for initially completing this portion of work. As illustrated in Fig. 1, given the same workload, if the completion time achieved in laboratory settings is denoted as RT_x, then the actual completion time in an office environment should be $(2\text{-}A_x)\cdot RT_x$.

The maximum relative productivity (*RP*) of office workers is assumed to be 100:

$$RP_{max} = \frac{Work}{(2 - A_0) \times RT_0} = 100 \tag{3}$$

where, *Work* represents the amount of total work, and is not a quantified value; A_0 and RT_0 respectively represents the accuracy and response time when *RP* is maximum. The relative productivity RP_x in any given environment can thus be expressed as:

$$RP_x = \frac{Work}{(2 - A_x) \times RT_x} = \frac{Work \times 100}{(2 - A_x) \times RT_x \times 100} = \frac{Work \times 100}{(2 - A_x) \times RT_x \times RP_{max}} = \frac{(2 - A_0) \times RT_0}{(2 - A_x) \times RT_x} \times 100 \tag{4}$$

The previous experimental data are analyzed and fitted using this method, resulting in the fitting outcomes of the three cognitive tasks: perception, expression, and number calculation with respect to the environmental parameters as demonstrated in Equation (5):

$$RP_x = a_1 \bullet t^2 + a_2 \bullet \varphi^2 + a_3 \bullet Q^2 + b_1 \bullet t \bullet \varphi + b_2 \bullet t \bullet Q + b_3 \bullet \varphi \bullet Q + c_1 \bullet t + c_2 \bullet \varphi + c_3 \bullet Q + d \tag{5}$$

where, *t* represents temperature, $t \in (20^{\circ}\text{C}, 30^{\circ}\text{C})$; φ represents relative humility, $\varphi \in (40\%, 90\%)$; *Q* represents ventilation rate, $Q \in$ (6l/(perÂ·s), 25l/(perÂ·s)); *a*, *b*, *c* represents coefficient, *d* represents constant. Previous studies have demonstrated an inverted U-shaped relationship between temperature and cognitive performance [8]. Relative humidity, as a factor influencing thermal sensation, exhibits a similar impact on cognitive performance as temperature does. While enhancing ventilation rate can enhance cognitive performance, it is important to note that there is no infinite improvement in cognitive performance with continuous enhancements in ventilation rate. Research suggests that the enhancement of cognitive performance resulting from increased ventilation rate gradually diminishes as the ventilation rate increases further [14]. The quadratic function adequately captures the relationship between these environmental factors and cognitive performance. Additionally, considering potential interactive effects among these factors [31], the fitting function also incorporates interaction terms.

2.2. Energy consumption of HVAC system: A case study

In order to establish the correlation between air conditioning energy consumption and indoor environmental parameters in office buildings, a case study of an office building is conducted. The case building serves as a research center for an enterprise, situated in the Pudong New District of Shanghai. The building structure and the working schedule of the staff and the equipment that could cause heat dissipation were acquired through on-site investigation.

DeST is an integrated building simulation software, developed by

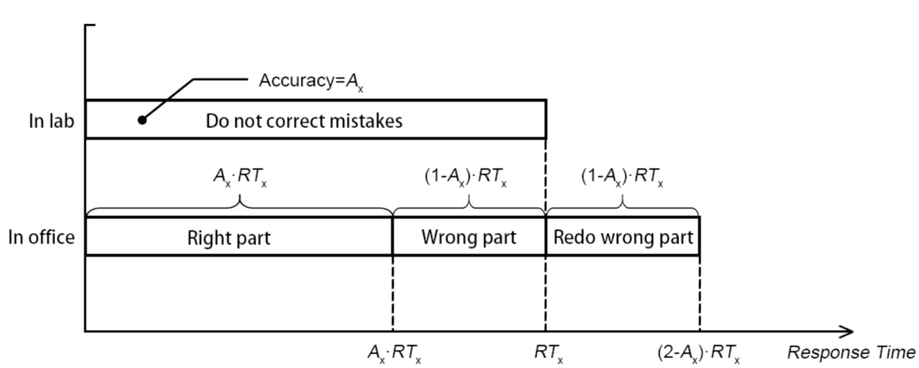


Fig. 1. The comparison of response times between laboratory and office.

Tsinghua University. DeST can be used to simulate and analyze both building energy consumption and HVAC (heating, ventilation and air-conditioning) system, which can then help to improve the reliability of system design, to ensure the quality of the system performance, and to reduce energy consumption of buildings [32]. DeST was widely used in studies relevant to energy consumption simulation and has been proven to be highly accurate [33].

The typical models for building energy consumption include feature analysis, clustering, regression, classification, and probability distribution fitting [34]. Since the energy consumption data for this study was obtained through energy simulation rather than actual measurement, and only three environmental factors were used as independent variables, regression methods are more commonly employed in similar studies [19,35]. Nonlinear fitting with quadratic terms and interaction terms has been demonstrated to yield high accuracy for such problems [36]. Therefore, The DeST software is utilized to simulate its energy consumption, followed by nonlinear fitting analysis of the simulation results to establish the relationship between energy consumption and environmental parameters. This section provides a comprehensive introduction to one layer of the case building, as illustrated in Fig. 2.

The case building is a five-story structure, and for this study, one floor was selected for energy consumption simulation, specifically the office floor located on the third level of the building. This floor encompasses a total area of 887.52 m^2, with a cooling area of 601.42 m^2, constituting 67.8 % of the total floor space. It accommodates up to 40 individuals and includes 2 open offices, 6 private offices, and 1 conference room. Within the open offices, multiple employees share relatively private individual work units.

The energy consumption simulation for the building's HVAC system is conducted during the cooling season. Table 1 presents the input parameters for the energy consumption simulation.

All input parameters are determined for simulation except indoor environmental settings, as shown in Table 1 (e). $t \in (20^{\circ}\mathrm{C},\ 30^{\circ}\mathrm{C})$, $\varphi \in (40\%,\ 90\%)$ and $Q \in (6(\mathrm{l}/(\mathrm{per}\hat{\mathrm{A}}\cdot\mathrm{s}),\ 25(\mathrm{l}/\mathrm{per}\hat{\mathrm{A}}\cdot\mathrm{s}))$ are the ranges for the cognitive performance experiment. To enhance the accuracy of fitting, it is imperative to narrow down the ranges and gradients for input environmental parameters. The ranges for energy consumption simulation should be further narrowed on this basis. The previous experiment revealed a quadratic (inverted U-shaped) relation between temperature and humidity and their impact on cognitive performance [23]. When the performance reaches the maximum value, there is a continued decrease in temperature and humidity, resulting in a decrease in performance and an increase in energy consumption. Therefore, attempting to simulate the energy consumption within this interval becomes meaningless. The assumption is made that the temperature and humidity at which the maximum benefits are achieved will not significantly exceed the temperature and humidity at which the maximum performance is attained, considering that enhancing performance yields greater advantages compared to cost savings from energy reduction[18]. The upper limits of temperature and humidity were increased by 2 °C and 10 %, respectively, based on the optimal conditions obtained from the cognitive experiment. The gradient of 0.5 °C and 2 % was set for temperature and humidity, respectively. Similarly, the lower limit of ventilation rate was reduced by 10 l/(per·s) based on experimental results, with a gradient of 2 l/(per·s).

The simulation results were subsequently fitted, revealing that the multivariate quadratic function in the form of Equation (6) exhibited the highest level of fitting accuracy:

$$W = \alpha_1 \bullet t^2 + \alpha_2 \bullet \varphi^2 + \alpha_3 \bullet Q^2 + \beta_1 \bullet t \bullet \varphi + \beta_2 \bullet t \bullet Q + \beta_3 \bullet \varphi \bullet Q + \gamma_1 \bullet t + \gamma_2 \bullet \varphi + \gamma_3 \bullet Q + \delta \tag{6}$$

where, W represents electrical energy consumption, kW·h; α, β, γ represents coefficient, δ represents constant.

2.3. Economic analysis

2.3.1. Pareto optimal solutions

Assuming a proportional relation between the output value and the productivity, the output value in any given environment $Output(t,\ \varphi,\ Q)$ can be expressed as:

$$Output(t,\ \varphi,\ Q) = Output_{\max} \bullet \frac{RP(t,\ \varphi,\ Q)}{100} \tag{7}$$

where, $Output_{\max}$ represents the output value with the maximum relative productivity; $RP(t,\ \varphi,\ Q)$ represents the relative productivity in any given environment. The determination of $Output_{\max}$, however, poses a significant challenge. The output value in the study conducted by Dai et al. is considered to be analogous to employees' salaries [19], however, this perspective is evidently inappropriate. The salary paid to employees is considered as an operational expense for enterprises, rather than a part of the enterprise's profit. Mofidi and Akbari established a continuous range for the output value, ranging from $4/hour to $16/hour [20], thereby avoiding the need to define a specific value for it. The utilization of Gross Value Added as a metric for measuring output value, as demonstrated by Kim and Hong [8], presents a more rational approach in contrast to other methods. Therefore, this study employs Gross Domestic Product as a proxy for Gross Value Added due to its accessibility in public databases and utilizes it to estimate the output value of office workers.

The average RP of the three types of tasks is determined to be 90.8–91.7 by evaluating the definite integral of the productivity fitting function derived from Equation (4) and Table 1. Therefore, $Output_{\max}$ can be estimated to be approximately $\frac{1}{0.9}$ times Gross Domestic Product per capita:

$$Output_{\max} = \frac{GrossDomesticProductpercapita}{0.9} \tag{8}$$

The Gross Domestic Product per capita of Shanghai in 2021 amounts to $26,900. It can be inferred that the total economic output of the office per floor (consisting of 40 individuals) during the cooling season

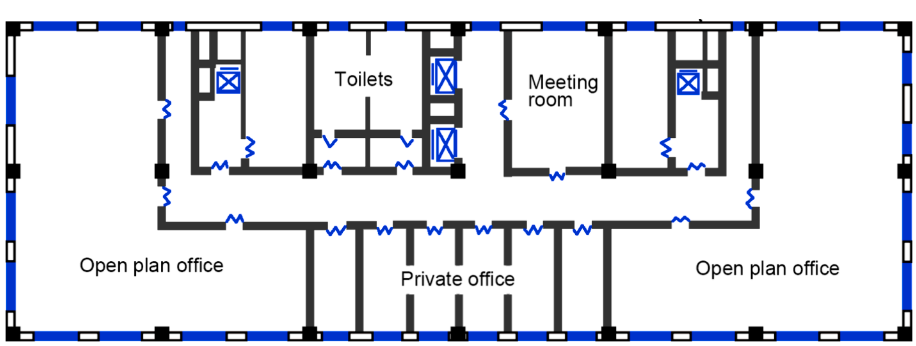


Fig. 2. The architectural layout of the office building.

Table 1
The input parameters for energy consumption simulation.

(a)Date and climate

Date	Climate
May 22nd to September 21st	Climate data of Shanghai, China

(b)Building envelope

Building envelope	Materials	Heat transfer coefficient (W/(m^2·K))	Thermal inertia index	Solar heat gain coefficient (SHGC)
Exterior wall	240 mm concrete porous brick, 20mm cement mortar layer, 30mm polystyrene particle insulation paste layer and 20mm cement mortar layer.	1.042	3.346	N/A
Interior wall	20mm cement mortar layer, 180mm ceramsite concrete layers and 20mm cement mortar layer.	1.515	2.690	N/A
Floor	20mm cement mortar layer, 10mm expanded vermiculite layer, 100mm reinforced concrete layer and 20mm lime mortar layer.	0.566	2.424	N/A
Window	N/A	2.200	N/A	0.261

(c) Heat sources and staff/facility schedules

Room	Heat dissipation (W/per)	Moisture generation (kg/(h·per))	Light power density (W/m^2)	Equipment power density (W/m^2)	Schedule		
					Percentage of occupancy	Date	Time
Open plan office	70	0.109	22	13	100%	Weekdays	09:00–13:00 14:00–18:00
					50%	Weekdays	13:00–14:00 18:00–19:00
					20%	Weekdays	19:00–21:00
Private office	70	0.109	30	13	100%	Weekdays	09:00–13:00 14:00–18:00
Meeting room	70	0.109	30	13	100%	Weekdays	14:00–16:00

(d) HVAC system

Room	HVAC system	Air change rate due to building envelope leakage (h^{-1})
Open plan office	Variable Air Volume System	0.4
Private office and meeting room	Fan-coils and fresh air system	0.4

(e) Indoor environmental settings

Room	Temperature (°C)	Relative humility (%)	Ventilation rate (l/(per·s))
Open plan office	Undetermined	Undetermined	Undetermined, 17 persons per room
Private office	Undetermined	Undetermined	Undetermined, 1 person per room
Meeting room	Undetermined	Undetermined	Undetermined, 8 persons

(spanning 4 months) reaches $398,519.

$EE(t, \varphi, Q)$ can be determined using Equation (9):

$$EE(t, \varphi, Q) = EP \bullet W(t, \varphi, Q) \quad (9)$$

where, EP represents the electricity price for commercial use at the office building's location, $/kW·h. The commercial electricity price in Shanghai is $0.111/kWh. The values of t, φ, and Q for maximizing economic benefits can be obtained by substituting Equations (7) to (9) into Equation (1) using MATLAB.

2.3.2. Variation of optimal settings in relation to economic status

The aforementioned results were predicated on the economic conditions of Shanghai. In the event of any changes in these economic conditions, the optimal environmental parameters will change accordingly. Hence, this study also compares countries/cities across different economic levels worldwide. Given that the energy consumption data in this paper are simulated based on Shanghai's climate, it is crucial to select countries/cities with climatic conditions as similar to Shanghai as possible for comparison purposes. Azerbaijan, Miami, Osaka, Paraguay, and Sydney – five countries/cities with highly comparable climatic conditions to Shanghai [37] – have been chosen for comparison (Fig. 3 (a)). The Gross Domestic Product and commercial electricity price data were sourced from the government websites, International Monetary Fund and GlobalPetrolPrice.com. With the exception of Osaka (2019), all other data are from 2021. Substituting each region's Gross Domestic Product and electricity price into Equation (8) and Equation (9) respectively yields the optimal set value of office environment parameters when maximizing economic benefits using Equation (6). The ratio of Gross Domestic Product per capita to electricity price serves as an indicator quantifying the economic level, with Shanghai being used as a benchmark at 1.0.

3. Results

According to Equation (5), the relationship between productivity and environmental factors was fitted, and the results for different tasks are presented in Table 2.

The quadratic function shows very good fitting accuracy (R^2 = 0.89–0.93). The main effect is complicated by the interactions. There are maximum extremes of productivity within the given temperature and humidity range, and both too high and too low temperature and humidity have negative effects on productivity. Productivity of perception and expression tasks increases monotonically within a given ventilation rate range. Productivity of number calculation tasks reaches its maximum within the range of 15.3–22.3 l/(per·s) (the specific value is affected by the interaction of the other two factors), which may be due to the fact that ventilation rate does not improve the productivity of number calculation tasks significantly, and the quadratic function is over-fitted to this task.

According to the productivity equation and coefficients in Table 2, the environmental settings with maximum productivity could be calculated. Based on the principles of input environmental parameters for energy consumption simulation as shown in Section 2.2, the ranges of input parameters could be determined, and are shown in Table 3.

The environmental input parameters in Table 3 were entered into DeST energy consumption software in order to generate a series of

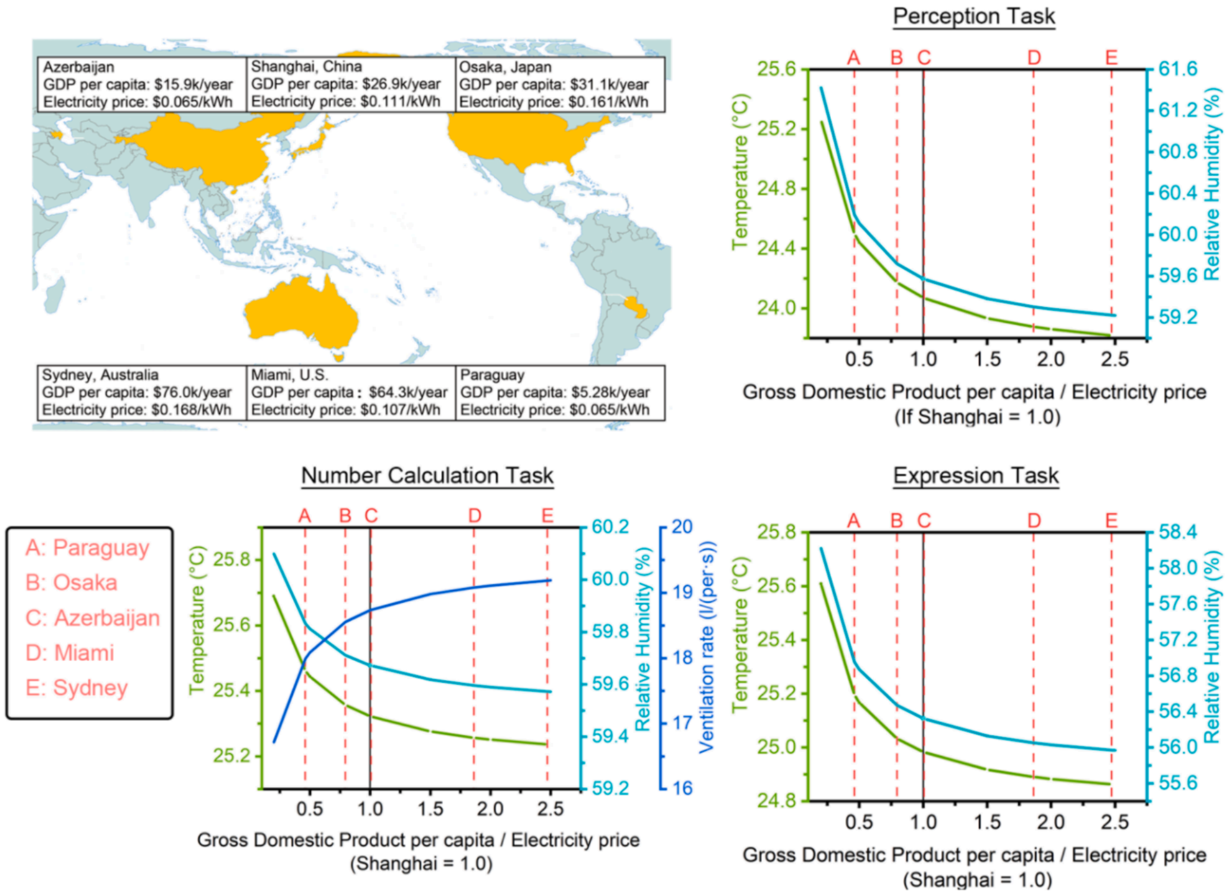


Fig. 3. The variation of the optimal parameter points set for indoor environments in office buildings across different cities/countries, considering the economic levels.

Table 2
The coefficients a_1-d and the R^2 of the fitting function for relative productivity.

Type	a_1	a_2	a_3	b_1	b_2	b_3	c_1	c_2	c_3	d	R^2	p-value
Perception	−0.317	−0.009	0.016	−0.036	0.050	−0.005	15.891	2.069	−1.236	−137.589	0.89	0.005
Expression	−0.627	−0.018	−0.004	−0.020	0.055	−0.013	30.786	2.724	−0.199	−357.432	0.93	0.002
Number calculation	−0.407	−0.013	−0.015	−0.026	0.006	0.003	21.901	2.116	0.220	−241.544	0.90	0.011

Table 3
Input environmental parameters for energy consumption simulation.

Type	Environmental parameters at maximum productivity			Input environmental parameters for simulation		
	Temperature (°C)	RH(%)	Ventilation rate (l/(per·s))	Temperature (°C)	RH (%)	Ventilation rate (l/(per·s))
Perception	23.63	58.97	25.00	23.5–25.5	59–69	15–25
Expression	24.78	55.72	25.00	24.5–26.5	55–65	15–25
Number calculation	25.17	59.50	19.53	25.0–27.0	59–69	11–21

energy consumption values. According to Equation (5), the relationship between energy consumption and environmental factors was fitted, and the results for different tasks are presented in Table 4.

The quadratic function shows very good fitting accuracy (R^2 = 0.97–1.00). The fitting results show that the more dry and cold the thermal environment is, and the higher the ventilation rate is, the higher the unit cost of improving the environment is. At the same time, the increase in energy consumption caused by the simultaneous

Table 4
The coefficients a_1-d and the R^2 of the fitting function for energy consumption.

Type	α_1	α_2	α_3	β_1	β_2	β_3	γ_1	γ_2	γ_3	δ	R^2	p-value
Perception	922.2	7.1	19.7	157.0	−431.2	−46.8	−52727.3	−4377.9	13928.0	738157.9	>0.99	<0.001
Expression	1097.0	12.2	30.0	187.0	−432.9	−51.9	−63323.0	−5660.9	13883.4	910929.1	>0.99	<0.001
Number calculation	945.8	6.4	27.5	153.6	−312.4	−28.8	−55543.9	−4496.6	9400.5	814200.5	0.97	<0.001

improvement of multiple environmental factors is higher than the simple addition of the increase in energy consumption caused by the single factor improvement. The fitting results are consistent with the common sense of energy use.

Then the Pareto optimal values were solved using the method outlined in section 2.3.1 and the fitting functions above. The results are presented in Table 5.

Fig. 3 shows the change curve depicting how optimal office building temperature, relative humidity, and ventilation rate vary with respect to different economic levels while maximizing economic benefits.

4. Discussion

4.1. The Pareto optimal solutions for maximizing economic benefits

According to the economic analysis results, there are slight disparities between the environmental parameters with maximum economic benefits and those with maximum productivity. However, these differences are not substantial. For the perception task, the temperature and humidity with maximum economic benefits are 0.44 °C and 0.61 % higher compared to those with maximum productivity; for the expression task, they are 0.20 °C and 0.61 % higher; while for the number calculation task, they are 0.15 °C and 0.17 % higher respectively. Nevertheless, the difference is smaller than the minimum adjustable range of most air conditioning equipment, making it challenging to distinguish between two parameter setting schemes.

The upper limit of ventilation rate, as determined by the results of previous experiment, is 25 l/(per·s). Within this range, there is an increase in economic benefits with higher ventilation rates. Seppanen et al. proposed a logarithmic relation between ventilation rate and cognitive performance [14], indicating that as the ventilation rate increases, the improvement in cognitive performance gradually diminishes. Therefore, the maximum economic benefits are achieved when the ventilation rate reaches a certain value; any further increase beyond this point would result in higher energy costs outweighing the benefit of improved productivity. For perception and expression tasks, the optimal ventilation rate for maximum economic benefit exceeds 25 l/(per·s), while number computation task achieves the highest benefits at 18.73 l/(per·s), which is only 0.80 l/(per·s) lower than the ventilation rate with maximum productivity.

In general, there is minimal disparity between the temperature, relative humidity and ventilation rate settings that yield maximum economic benefits and those that result in optimal productivity. This output can be attributed to the fact that the energy consumption cost of office buildings is significantly lower than the economic output generated by office workers. Fisk et al. discovered that increasing the ventilation rate per capita from below 10 l/s to 10 l/s and 15 l/s would enhance annual economic benefits for U.S. offices by $5.6 billion and $13.5 billion respectively (primarily through improved productivity), and the rise in energy costs would not exceed $0.04 billion [18]. According to our simulation results on energy consumption, even at its highest level (t = 23.5 °C, φ = 59 %, Q=25 l/(per·s)), the air conditioning electricity expense for per floor's cooling season amounts to only $3,230, which accounts for approximately 1 % of the total economic output of the office during this period. This indicates that the advantages gained from enhancing indoor environmental quality (IEQ) in the office building far outweighs any associated energy consumption costs.

The impact of economic status on optimal indoor environmental parameters has long been a topic of interest. Mofidi and Akbari [38] examined the influence of various economic outputs on the Pareto optimal solution. However, focusing solely on economic output is limited as it overlooks the important factor of electricity price. Conclusions drawn under the assumption of constant electricity price are only applicable to specific study locations. Therefore, Dai et al. [19] utilized the salary electricity price ratio indicator in their study, and our research further enhances this by substituting salary with Gross Domestic Product per capita, which better reflects employee economic output. It should also be noted that the economic output electricity price ratio may not necessarily be low in economically underdeveloped regions due to potentially lower electricity prices; similarly, economically developed areas may have a lower ratio due to higher electricity prices. In comparison to Shanghai and Azerbaijan, Osaka has a higher Gross Domestic Product per capita but a lower ratio due to high energy prices. Similarly, Sydney has a higher Gross Domestic Product per capita than Miami but a lower ratio. Furthermore, with Shanghai as a benchmark, the ratio varies between −50 % and 250 % from less developed to more developed regions (Fig. 3), which aligns closely with Dai et al.'s estimation, indicating that the economic status analysis is reasonable within this range.

A higher ratio of economic output to electricity price indicates a greater emphasis on improving productivity for economic benefits. Fig. 3 shows that as the ratio of economic output to electricity price gradually increases, the optimal parameter point becomes closer to the point with the optimal productivity, which aligns with the findings of Dai et al. [19] and Mofidi and Akbari [38]. If the ratio in an area is very low, then there will be significant differences between the optimal parameter points with maximum economic benefits and maximum productivity. Taking Paraguay as an example, temperature and humidity differences range from 0.29-0.87 °C and 0.33–1.23 % respectively, while ventilation rate difference for number calculation task is 1.54 l/(per·s). Therefore, for economically underdeveloped areas where these differences may exceed minimum adjustable range of HVAC systems, it is more meaningful to determine setting parameters through economic optimization calculations for office buildings in such regions. However, for economically developed areas, setting parameters can be directly determined based on maximizing productivity.

Table 5
Comparison of optimal environmental setting levels for different purposes.

Type	Factor	Set-point		
		Productive [a]	Energy-saving	**Profitable** [b]
Perception	Temperature	23.63 °C	No A/C	**24.07 °C**
	RH [c]	58.97 %	No A/C	**59.58 %**
	VR [d]	25.00 l/(per·s)	0 l/(per·s)	**25.00 l/(per·s)**
Expression	Temperature	24.78 °C	No A/C	**24.98 °C**
	RH	55.72 %	No A/C	**56.33 %**
	VR	25.00 l/(per·s)	0 l/(per·s)	**25.00 l/(per·s)**
Number calculation	Temperature	25.17 °C	No A/C	**25.32 °C**
	RH	59.50 %	No A/C	**59.67 %**
	VR	19.53 l/(per·s)	0 l/(per·s)	**18.73 l/(per·s)**

[a] Productive = optimal productivity.
[b] Profitable = maximize economic benefits considering both productivity and energy saving.
[c] RH=relative humidity.
[d] VR=ventilation rate.

4.2. The precision of productivity model significantly influences the optimization solutions

From the above discussion, we contend that in order to achieve greater economic benefits, office buildings should prioritize productivity when setting air conditioning parameters. However, previous studies have tended to strike a compromise between productivity and energy conservation. Dai et al. established the temperature and ventilation rate parameters at maximum productivity as 24 °C and 30 l/(per·s), resulting in profitable parameters of 25.1 °C and 17.9 l/(per·s) [19]. Mofidi and Akbari discovered that during the cooling season, the economical temperature parameter deviated from the comfort temperature by approximately 1 °C when assuming the economic output of $4 per hour for office workers [20]. Kim and Hong set the temperature at 25.15 °C for achieving maximum productivity and found that on average, the optimal temperature was about 1.54 °C higher than that in June, around 0.93 °C higher in July, and roughly 0.55 °C higher in August [8]. In fact, these studies collectively demonstrate that the economic output of office workers outweighs energy costs significantly; however, discrepancies arise due to differing opinions on how environmental changes impact office workers' productivity. The comparison of results from various ergonomic studies is presented in Table 6. Taking the most extensively researched temperature as an example, this table illustrates the percentage of productivity decline when the temperature increases by a consistent unit relative to the temperature with optimum productivity. Most studies encompassed a broad range of temperatures spanning from cold discomfort to warm discomfort when examining productivity; economic-focused studies concentrated within a narrower range instead. Many researchers came out that the economic-optimal temperature should be approximately 1 °C higher than what productivity-optimal temperature; hence Table 6 compares how a 1 °C increase impacts productivity.

In the study conducted by Dai et al., a 1 °C increase from the productivity optimal point resulted in only a 0.04 % decrease in productivity. The possible cause for this could be their incorrect conversion of the TSV and productivity equation into the temperature and productivity equation. Furthermore, other studies have reported productivity decline ratios ranging from 0.11 % to 0.27 %. However, this study found a higher decline ratio of 0.32 %-0.63 %, possibly due to the quadratic nature of the fitted function used in this study. The dependent variable of the quadratic function exhibits a greater rate of change around the extreme point compared to higher-order functions. Additionally, this study integrates three environmental factors into its fitting relation, whereas previous studies often consider single factors and maintain control factors at comfortable or moderate levels without considering the interactions with control factors. Consequently, when these factors deviate from neutral levels, their influence is amplified and leads to larger changes in productivity near the optimal point as observed in the productivity model [31]. As a result, the economic optimal points calculated by this study align closely with the productivity optimal state points.

The slight variations in productivity near the productivity-optimal point raise a new question: Is the environmental level at which productivity is maximized a point or can it be considered as a range? This aligns with two commonly employed models to describe cognitive performance: the inverted U-shaped model (Fig. 4(a)) and the maximal adaptability model (Fig. 4(b)). While Zhang et al. noted that the inverted U-shaped model enjoys greater acceptance in indoor environmental research [42], Porras-Salazar et al., after conducting a *meta*-analysis of 35 studies, found that both models exhibit nearly identical fitting accuracy for cognitive performance [43]. However, Porras-Salazar et al.'s analysis was conducted at a broader level and does not address the specific question raised in this paper, necessitating further comprehensive research and analysis. If the maximal adaptability model proves more applicable, then substituting it into economic optimization calculations holds greater potential for energy conservation.

Table 6
The comparison of the impact on productivity based on the temperature with maximum productivity, resulting from a 1 °C increase in temperature.

Reference	Task type	*RP*(*T*)	T_{maxRP}	*RP* loss [a]
The data [22,23] used in this paper	Perception Expression Number calculation	Please find in formula (4) and Table 1	23.6 °C 24.8 °C 25.2 °C	0.32 % 0.63 % 0.41 %
Seppanen et al. [7]	Meta-analysis of 26 studies before 2006	$6.23\times10^{-5}T^3-5.83\times10^{-3}T^2+0.165T-0.469$	21.7 °C	0.16 %
Cui et al. [39]	Memory typing	$-5.913T^2+268.03T$	22.7 °C	0.21 %
Dai et al. [19]	Multi-tasks	$-1.151\times10^{-5}T^3+4.045\times10^{-4}T^2+5.053\times10^{-4}T+0.921$	24.0 °C	0.04 %
Geng et al. [40]	Multi-tasks	$-0.0027T^2+0.1262T-0.4134$	23.4 °C	0.27 %
Yeganeh et al. [41]	Meta-analysis of 28 studies before 2018	N/A	N/A	≈0.11 %
Kim and Hong [8]	Multi-tasks	$-0.0357^3+0.184T^2-2.6171T+56.264$	25.2 °C	0.16 %

[a] *RP* loss from T_{maxRP} to (T_{maxRP}+1°C).

5. Limitation

Section 2 proposes a novel approach to measure productivity that is more applicable to real office settings. However, it remains uncertain whether cognitive performance can serve as a substitute for actual office productivity given the complexity of daily work tasks performed by office workers. While subjective self-rated productivity is commonly used in research, Glenn et al. have shown that it cannot fully replace objective measures due to significant discrepancies between the two [44]. Nevertheless, objectively evaluating productivity in an actual office environment poses considerable challenges. Lamb and Kwok attempted to assess objective productivity by sending regular emails containing Stroop tests on weekdays to office workers [45]. Despite their efforts to survey both actual workers and scenarios, they were still unable to accurately gauge the true performance of office tasks. Multi-dimensional Correlation Model demonstrates the intricate nature of the interaction between the environment and humans [46]. Evaluating the productivity of real-life office scenarios solely based on cognitive ability may be oversimplified. Exploring how other interaction factors contribute to productivity is also a crucial area of investigation.

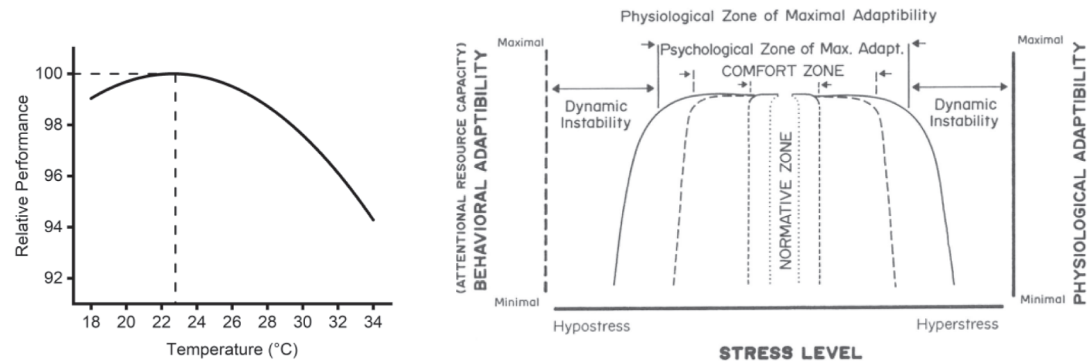
The two MOOP objectives of this study are the economic output and HVAC system energy consumption. However, there is a lack of consideration for many crucial factors such as comfort, health, and well-being [47]. These factors are challenging to evaluate using economic indicators. Fisk et al. [18] have estimated the economic impact of absenteeism resulting from poor IEQ, but this rough estimate does not offer assistance for the MOOP problem.

The extension of the MOOP model to other countries or regions is predicated on the assumption of identical climate conditions. Despite selecting regions with similar climate conditions to Shanghai for comparison, there will always be subtle differences in climate between these regions and Shanghai, which may introduce error into the results. Additionally, there is a lack of discussion about the regions with significant different climate conditions from Shanghai. In regions characterized by hot and humid summers, there will likely be greater benefits in terms of energy savings, whereas in dry and cold regions, improving productivity may yield higher benefits.

The results can also be influenced by absenteeism. The COVID-19 pandemic has brought about significant shifts in the approach of work [48]. Even though COVID-19 may no longer be as prevalent, its lasting impact has fundamentally altered work behaviors. Many employees have embraced remote work as a viable and legitimate option, reshaping perceptions about where work can effectively take place. This shift may potentially contribute to increased absenteeism of offices, which could diminish the economic benefits associated with improving the office environment. The balance between energy consumption and productivity benefit in hybrid work scenarios is a worthwhile issue to explore in the context of following the COVID-19 pandemic.

6. Conclusion

The study utilized an office building in Shanghai as a case study and reveals that the optimal indoor environment settings for maximizing economic benefits are the same with those for achieving optimum



(a) Inverted U-shaped model[43] (b) Maximal adaptability model[42]

Fig. 4. Two models commonly used to describe changes in cognitive tasks.

productivity. Consequently, prioritizing office workers' productivity is crucial when designing air conditioning parameters for office buildings to enhance overall economic gains.

The disparity between indoor environmental parameters that yield maximum economic benefits and those at optimum productivity will progressively widen as the economic-output-to-electricity-price ratio decreases. For economically underdeveloped regions, attaining optimal air conditioning parameters for office buildings by striking a balance between productivity and energy conservation will result in greater advantages.

The economic output of office workers significantly outweighs the energy consumption cost of air conditioning. Even minor adjustments to the productivity model can have a substantial impact on the economic calculation results. Therefore, higher requirements are imposed for enhancing evaluation accuracy in terms of productivity, including improving the productivity evaluation method and optimizing the fitting model.

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CRediT authorship contribution statement

Yongxiang Shi: Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Junmeng Lyu:** Software, Formal analysis, Data curation. **Julie T. Miao:** Writing – review & editing. **Zhiwei Lian:** Conceptualization, Writing – review & editing, Methodology. **Li Lan:** Writing – review & editing.

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.

Data availability

No data was used for the research described in the article.

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