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WorkLife +: A Conceptual Design of an AI-Driven Adaptive Office Environment Regulation System

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Abstract

Focusing on the high energy consumption and discomfort issues of office environments, this research conducted a preliminary survey of 115 office workers to identify major pain points of traditional office environment. Taking IoT and AI as the core, the research integrates multi-modal data and proposes a conceptual design of an intelligent environmental perception system. It aims to establish an adaptive environmental regulation system through standardized sensors and intelligent control models, balancing energy conservation and health. The research is expected to form reusable solutions and prototype systems.

Keywords

Intelligent office environment; IoT; Artificial Intelligence; Adaptive Regulation; Healthy office

1. Introduction

1.1. Research Background

Against the backdrop of global climate change and the strategic pursuit of "Dual Carbon" goals (carbon peak and neutrality), energy conservation in the building sector has become a critical issue (Jiang et al.,2021). Commercial buildings account for over 40% of global energy consumption, with environmental control systems such as heating, air conditioning, and lighting being major sources of energy waste due to inefficient operational models (Pérez-Lombard et al.,2008).

Concurrently, modern workplace employees commonly face health and efficiency issues stemming from poor environmental conditions. Research indicates that suboptimal physical environments can lead to a 15-20% decline in employee productivity, resulting in significant economic losses for businesses (Lan et al.,2019).

Traditional office environmental control systems, which predominantly rely on fixed thresholds for uniform regulation, suffer from two primary deficiencies: First, they cannot perceive dynamic environmental changes (e.g., localized temperature increases or CO_2 accumulation due to occupant gatherings). Second, they fail to respond to individual differences, leading to the classic "one-size-fits-none" dilemma. The rise of hybrid work models in the post-pandemic era has further heightened the demand for precise and flexible environmental adjustment.

Motivated by these challenges, this conceptual study proposes a core concept: to explore the facilitating of constructing an intelligent system capable of simultaneously "sensing environmental data" and "inferring human states ," thereby facilitating a potential transition from "passive control" to "active optimization." This directly addresses the following key research problems.

1.2. Research Problems

This research aims to systematically identify and explore key problems at three levels within the context of a conceptual design:

1.2.1. The Data Fragmentation

Existing system designs often lack a coherent framework for synchronized, coordinated perception of multi-modal environmental parameters (e.g., temperature, humidity, lighting, noise, air quality) and occupant states (e.g., desk occupancy, inferred comfort levels). This results in conceptual data silos within system architecture,which would prevent comprehensive and consistent input for any intelligent decision-making module (Zhao et al.,2019).

1.2.2. The Lack of Intelligence

Traditional rule-based control strategies are inherently rigid. This study examines the challenge of developing algorithmic models and frameworks that could, in principle, enable autonomous learning and optimization of control strategies, representing the core conceptual hurdle in achieving environmental intelligence for dynamic spaces.

1.2.3. The Weak Value Proposition

Many existing system concepts offer only basic data visualization and fail to propose clear methodologies for deeply correlating environmental data with core business concerns—employee productivity and operational energy costs. This lack of a quantitative analytical framework in design proposals leaves the value proposition for management decision-makers unclear and obscures the potential return on investment.

1.3. Research Significance

The significance of this conceptual research is twofold, encompassing both theoretical and practical dimensions:

Theoretical Significance: By proposing an integrative framework that combines IoT sensing paradigms, deep reinforcement learning algorithms, and human factors engineering principles, this study explores the theoretical relationship between "people, environment, and efficiency." It aims to contribute to the application discourse of AIoT in the smart building sector by providing a novel methodological framework and research paradigm for conceptualizing human-centric, adaptive environmental systems.

Practical Significance(Conceptual Implications):

Social Impact Potential: The proposed concept, if realized, could enhance the energy efficiency of buildings, thereby contributing to carbon emission reduction goals. Furthermore, its human-centric design philosophy highlights the importance of fostering healthier office environments for employee well-being.

Economic Impact Potential: The conceptual system outlines a pathway for potential economic benefits. It suggests a mechanism for lowering operational costs through optimized control (with cited energy saving potentials from literature). Indirectly, it frames a value proposition linking environmental improvements to potential gains in employee productivity.

Technical Impact Potential: The "WorkLife+" system concept and architectural prototype presented in this study proposes a design for a cost-effective, lightweight intelligent office solution. It addresses, at a conceptual level, the application barriers of cost and complexity that currently limit the adoption of advanced building management systems, particularly for small and medium-size enterprise(SMEs).

2. Literature Review

With the rapid development of IoT, big data, and artificial intelligence technologies, the intelligent office environment, as a crucial component of smart buildings, has become a focal point for both academia and industry. This project aims to conceptualize an intelligent workplace environment regulation system. Reviewing the current research status in this field is essential for clarifying the project's research starting point and research direction.

2.1. Domestic Research

2.1.1. Research Overview

Although research on intelligent office environments in China started relatively late, it has shown vigorous development in recent years. Domestic research in this field has formed a multi-level framework, ranging from theoretical exploration to technological application, laying a solid foundation for this project.

2.1.2. Main Research Directions

Theoretical Research: Scholars have deeply explored the impact of intelligent regulation technologies on specific environmental factors. In response to the limitations of traditional centralized cloud computing, the edge computing paradigm has been introduced, confirming that localized data processing can reduce transmission delays, lower energy consumption, and enhance privacy security, providing theoretical support for intelligent offices (Shi et al., 2016). Additionally, it has been demonstrated that noise is a key factor affecting employee satisfaction and work efficiency, highlighting the significant role of an appropriate acoustic environment in improving workplace comfort (Zhou et al., 2023). For HVAC systems, the shortcomings of traditional model predictive control in accurately modeling thermodynamics have been analyzed, and a data-driven approach to intelligent regulation has been proposed (Wei et al., 2017).

Applied Research: Domestic scholars have extensively explored the implementation pathways of IoT technology in office environment monitoring. Early research focused on SCADA-based systems for collecting and locally monitoring parameters such as temperature and humidity (Li et al., 2016). As technology advanced, the research emphasis shifted to the deep integration of cloud platforms and wireless communication, leading to the development of intelligent office management systems that integrate environmental monitoring, device control, and security (Liu et al., 2019). Solutions involving private cloud IoT platforms have been proposed to integrate multiple business systems, including security, energy consumption, and environmental management, reflecting the trend toward integrated and intelligent management (Chen et al., 2018). In terms of core equipment regulation, deep reinforcement learning (DRL) has been applied to HVAC systems, addressing the challenge of action space explosion in multi-zone systems through Markov decision process-based algorithms to balance energy consumption and comfort (Wei et al., 2017). Edge computing has been implemented for local data preprocessing through edge gateway mechanisms (Shi et al., 2016).

2.1.3. Research Conclusions

Domestic research has made significant progress in areas such as the mechanisms of environmental factors, sensor networks, and cloud platform integration. However, existing systems have limitations, with many focusing on single-modal data collection and lacking deep integration of multi-modal data, as well as insufficient personalized adaptation of intelligent algorithms.

2.2. International Research

2.2.1. Research Overview

Current international research focuses on leveraging advanced information, sensing, and decision-making technologies to create intelligent workspaces that balance energy efficiency and well-being. The trend is shifting from macro architectures to scenario-specific applications and from single control to multi-modal sensing, forming a "complete chain" of theoretical modeling, technological implementation, and scenario adaptation. This provides a solid foundation for this project.

2.2.2. Main Research Directions

Theoretical Research: Early studies established a systematic design framework for intelligent office environments. Literature proposed an integrated architecture for environmental control, device management, and user interaction, establishing the core paradigm of "perception-decision-execution" and laying the theoretical foundation for subsequent research (Gal et al., 2001). Subsequent research expanded on models such as the PMV model, introducing the PPV personalized thermal comfort model for precise prediction of individual comfort states (Gao et al., 2013). Reinforcement learning was integrated into HVAC control, constructing a data-driven Markov decision process framework (Wei et al., 2017). A multi-agent decision-making model integrating rationality and emotion was also proposed (Ramos et al., 2010), enriching the theoretical landscape and providing a theoretical basis.

Applied Research: The literature demonstrates a trend from macro system construction to specific problem-solving. The "Monica SmartOffice" integrated multiple sensors and interaction modules, validating the feasibility of intelligent offices (Ramos et al., 2010). The "SPOT" system achieved personalized thermal comfort control through multiple devices and the PPV model (Gao et al., 2013). DRL algorithms were developed to address the challenges of multi-zone office regulation (Wei et al., 2017). Six core scenario technology pathways were outlined to enhance office environments (Papagiannidis et al., 2019), and the LAID laboratory supported distributed asynchronous decision-making. Additionally, more advanced multi-modal deep learning methods were introduced to recognize group activities in office environments by fusing visual and sensor data (Florea et al., 2020).

2.2.3. Research Conclusions

Internationally, a comprehensive theoretical framework and application pathways have been established, with notable achievements in personalization and energy efficiency optimization. Studies have demonstrated that intelligent office environments can effectively enhance comfort and energy utilization efficiency, maintain individual comfort precisely, and that DRL algorithms can significantly improve office efficiency through intelligent decision-making systems.

3. User Needs and Design Requirements: An Empirical Analysis

To ground the theoretical framework of “Worklife+” system in empirical data and validate the market needs identified in the project plan, a structured questionnaire was designed and administered. The survey aimed to transition from theoretical assumptions to data-driven insights, with the objectives of :

a. quantifying the prevalence and severity of environmental deficiencies in contemporary offices;
b. assessing user receptiveness and concerns regarding an AI-IoT based personalized regulation system;
c. systematically deriving prioritized functional and non-functional design requirements. This section details the methodology, analyzes key findings, and

synthesizes them into concrete specifications for system development.

3.1. Methodology of the Preliminary User Survey

The survey employed a structured online questionnaire disseminated across professional and academic networks to capture a diverse range of office workers. A total of 115 valid responses were collected. The demographic profile of respondents is summarized in Table 1. The sample encompasses a broad spectrum of occupations, industries, and work modes, with a predominant representation of full-time, on-site employees (77.39%). This diversity enhances the generalizability of the findings and ensures that the derived requirements are relevant to the core target market outlined in the project plan.

Table 1. Demographic Profile of Survey Respondents (N=115)

Category	Subcategory	Count	Percentage
Occupation	Enterprise Employee (Staff)	43	37.39%
	Management	16	13.91%
	Government/Public Institution	20	17.39%
	Education/Research	17	14.78%
	Freelancer/Remote Worker	11	9.57%
	Other	8	6.96%
Industry	Education/Training	24	20.87%
	Administration/Public Service	22	19.13%
	Manufacturing/Engineering	19	16.52%
	IT/Internet	12	10.43%
	Education/Training	27	23.48%
Work Mode	Administration/Public Service	89	77.39%
	Manufacturing/Engineering	23	20.00%
	IT/Internet	3	2.61%
Occupation	Other	43	37.39%
	Full-time On-site	16	13.91%
	Hybrid	20	17.39%
	Fully Remote	17	14.78%

3.2. Key Findings: Top Environmental Pain Points

Table 2 presents the distribution of overall satisfaction with the current office environment based on responses from 115 participants. Satisfaction scores ranged from 1 (Very dissatisfied) to 5 (Very satisfied), with a mean score of approximately 3.57. While a notable segment of respondents reported high satisfaction (Score 5: 29.57%), a notable minority expressed clear discontent (Scores 1 and 2 combined: 16.53%). This disparity underscores the failure of uniform environmental control systems to meet the diverse comfort needs of all occupants.

Table 2. Distribution of Overall Satisfaction with Current Office Environment

Satisfaction score	Description	Count	Percentage
1	Very dissatisfied	9	7.83%
2	Somewhat dissatisfied	10	8.7%
3	Neutral/Moderate	34	29.57%
4	Somewhat satisfied	28	24.35%
5	Very satisfied	34	29.57%
Total		115	100%

As detailed in Table 3, the most critical stressors were air quality (46.09%) and noise (46.09%), closely followed by temperature discomfort (33.04%). These findings align with and quantify the project plan's initial observations. Crucially, these factors are frequently interlinked (e.g., poor ventilation raising CO_2 levels and causing stuffiness), necessitating the integrated, multi-modal sensing approach central to “Worklife+” system's design.

Table 3. Prevalence of Office Environmental Stressors (Multiple Responses Allowed)

Environmental Stressor	Count	Percentage
Air Quality	53	46.09%
Noise	53	46.09%
Temperature	38	33.04%
Spatial Privacy	38	33.04%
Lighting	23	20.00%
Other	16	13.91%
Humidity	14	12.17%

Furthermore, these environmental deficiencies correlate strongly with self-reported physiological impacts (Table 4). Headaches or eye strain (40.00%) and drowsiness/lack of motivation (36.52%) were most prevalent, providing empirical support for the project's hypothesis that suboptimal environments directly impair employee well-being and, by extension, organizational productivity.

Table 4. Self-Reported Work-Related Discomfort (Multiple Responses Allowed)

Reported Discomfort	Count	Percentage
Headaches or Eye Strain	46	40.00%
Drowsiness/Lack of Motivation	42	36.52%
No Significant Discomfort	44	38.26%
Difficulty Concentrating	30	26.09%
Anxiety or Irritability	36	31.30%

3.3. User Expectations and Concerns for Intelligent Systems

A survey was conducted to explore the market's readiness for an intelligent solution. Results in Table 5 shows that awareness of such systems was moderate (56.52% heard of but not used), latent demand was high as 51.30% of respondents were "very interested" in a state-adaptive system. However, user expectations are nuanced. Regarding monitoring methods reflected in Table 7, environmental sensors (73.91% acceptance) were strongly preferred over more invasive options like cameras (12.17%) or wearables (23.48%). This underscores a critical user requirement for non-intrusive monitoring. Privacy in Table 6 emerged as a paramount concern, cited by 49.57% of respondents as a key factor, necessitating transparent data governance.

Table 5. Market Awareness and Initial Interest in Intelligent Office Systems

Question / Metric	Response Category	Count	Percentage
Awareness (Q11)	Have used	19	16.52%
	Have heard but not used	65	56.52%
	Never heard	31	26.96%
Initial Interest (Q12)	Very interested, willing to try	59	51.30%
	Interested but concerned about privacy	18	15.65%
	Neutral, need more information	33	28.70%
	Not interested	5	4.35%

Table 6. User Priorities and Concerns Regarding System Implementation

Key Concern	Count	Percentage
Real improvement in comfort	72	62.61%
System accuracy & stability	58	50.43%
Privacy & data security	57	49.57%
Cost & maintenance	52	45.22%
Potential work interference	42	36.52%

Table 7. Acceptable Methods for Environmental & User State Monitoring

Monitoring Method	Count	Percentage
Environmental sensors (temp, CO_2, etc.)	85	73.91%
Occupancy sensors (IR/pressure)	28	24.35%
Wearable devices (smart bands)	27	23.48%
Cameras (facial/pose recognition)	14	12.17%
Unwilling to accept monitoring	21	18.26%

3.4. Derived Functional and Non-Functional Requirements

Synthesizing the empirical findings with the technical objectives from the project plan yields the following prioritized requirements for "Worklife+" system:

(1). Functional Requirements (FR):

a. FR1 (Air Quality Management): The system must continuously monitor CO_2 and PM2.5 levels, triggering alerts or activating ventilation when exceeding thresholds (e.g., CO_2 > 1000ppm as per GB/T 18883-2022). *(Source: Top pain point - Air Quality, 46.09%)*

b. FR2 (Zoned Thermal Comfort): Implement dynamic, per-workstation or zone-based temperature regulation within the 21-26°C range to address individual preferences. *(Source: Pain point - Temperature, 33.04%; Project plan's reference range)*

c. FR3 (Noise Monitoring & Alerting): Detect ambient noise levels and provide real-time visual alerts or suggestions when exceeding a set threshold (e.g., 45 dB(A)). *(Source: Top pain point - Noise, 46.09%)*

d. FR4 (User-Interpretable Feedback): Provide a real-time "Comfort Score" or similar intuitive metric, as 62.61% of users believed this would aid self-awareness. (Source: User feedback on comfort score)

(2). Non-Functional Requirements (NFR):

a. NFR1 (Privacy-by-Design): The system architecture must prioritize data privacy, employing ambient sensors over personal biometric trackers and ensuring clear data usage policies. *(Source: Low acceptance of cameras/wearables; High concern for privacy, 49.57%)*

b. NFR2 (System Responsiveness): Environmental adjustments must occur with low latency to be perceived as effective and not disruptive, aligning with the goal of "real-time" response in the project plan.

c. NFR3 (User-Centric Value Proposition): The system's primary interface and messaging should emphasize personal comfort and health benefits, reflecting the preference of 57.39% of users, while energy savings are presented as a synergistic outcome.

In conclusion, the questionnaire analysis provides robust empirical validation for "Worklife+" project's direction. It transforms abstract user pain points into a structured set of verifiable functional and non-functional requirements. These requirements directly bridge the gap between identified market needs and the subsequent technical design and development phases, ensuring the system is both technically feasible and user-acceptable.

4. System Architecture: The "WorkLife+" Framework

4.1. Design Philosophy

The system is built upon three core principles: human-centric design that prioritizes personalized comfort reported by 62.61% of surveyed users; adaptive capabilities that eliminate the need for manual intervention indicated by 50.43% of surveyed users; and privacy preservation through anonymized data aggregation reflected by 73.91% of surveyed users, achieving a high user acceptance rate essential for successful deployment.

4.2. Holistic "Cloud-Edge-Device-User interaction " Architecture

The framework employs a four-tier architecture that balances local real-time response with global intelligent optimization. The Device Layer serves as the sensory periphery, deploying standardized sensor kits to monitor environmental parameters and control endpoint equipment. The Edge Layer functions as the local autonomic nervous system, making millisecond-level decisions for critical events like CO_2 exceedance without cloud dependency. The Cloud Layer acts as the centralized intelligent brain, running deep learning algorithms for global optimization, training policy models, and generating strategic analytics reports for management. The User Interaction Layer (via mobile app) acts as the user-system bridge, which displays real-time environmental/comfort data, collects user comfort feedback (e.g., sliders), and provides reward signals for the DRL model's optimization.

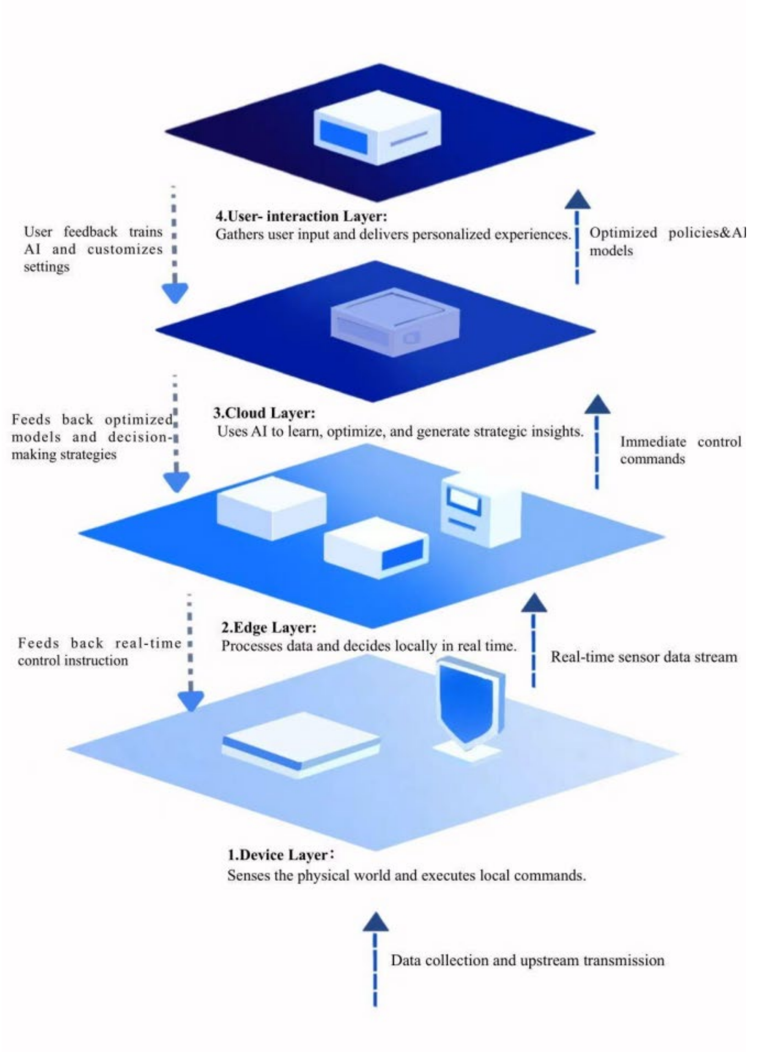

Figure 1. A Conceptual Framework of “Worklife+” System Architecture

4.2.1. Device Layer: Standardized Multi-Modal Sensor Kit

This layer implements an integrated sensor suite for comprehensive environmental monitoring and control. Each sensor serves a specific function in ensuring occupant comfort, health, and energy efficiency, with selection criteria based on standards, user needs, and technical requirements.

Table 8. Function and Selection Criteria of Sensors in the Device Layer for Intelligent Office Environments

Sensor Type	Core Function	Key Selection Basis
Temperature&Humidity	Maintain thermal comfort (20-26°C); Optimize HVAC.	National standards; 85.22% user preference (21-26°C).
CO_2	Ensure air quality (≤1000ppm); Trigger ventilation.	Mandatory health standard; Cognitive function impact.
PM2.5	Monitor air cleanliness; Activate purification.	Respiratory health risk; System linkage need.
Noise	Quantify & mitigate steady-state noise issues.	Direct response to 46.09% user-reported problem.

Light / Illuminance	Enable daylight harvesting; Ensure visual comfort.	47.83% user preference; Significant energy-saving potential.
Presence / Occupancy	Enable on-demand service; Trigger personalization.	Core for energy savings (30-60% lighting); 73.91% user acceptance.

4.2.2. Device Layer: Real-Time Local Decision Engine

Deployed locally in office zones, the edge gateway enables autonomous operation through its lightweight rule engine and pre-trained models from the cloud. It achieves sub-second response times for critical environmental adjustments while performing essential functions including protocol conversion for diverse equipment, data pre-processing before cloud upload, and maintaining basic operations during network interruptions.

4.2.3. Cloud Layer: AI-Driven Optimization and Analytics Platform

As the system's cognitive center, the cloud platform hosts Deep Reinforcement Learning models that process aggregated edge data and user feedback to generate optimized control strategies. The reward function R = w1*Comfort + w2*Energy Saving + w3*Air Quality allows adjustable weighting based on organizational priorities. The platform also provides comprehensive analytics dashboards that transform operational data into strategic insights through multi-dimensional reports on energy efficiency, comfort trends, and productivity correlations.

4.2.4. User Interaction Layer: Mobile App with Integrated Comfort Feedback

The mobile application completes the system's feedback loop by displaying real-time environmental data and comfort scores to users. Its intuitive feedback interface allows direct comfort voting through sliders for parameters like temperature and noise levels. These explicit user inputs serve as critical reward signals for the DRL model's continuous optimization, directly addressing the needs of 57.39% of users seeking improved personal work experience through data-driven environmental adjustments.

5. Technical Feasibility and Implementation Roadmap

This section delineates the technical backbone of the proposed “WorkLife+” system, assessing the viability of its core components and charting a pragmatic implementation path. The design prioritizes leveraging mature technologies and adopting a modular, phased deployment strategy to ensure feasibility within the constraints of a conceptual research project.

5.1. Hardware Feasibility: Off-the-Shelf Sensors and Gateways

The proposed hardware layer is intentionally designed to be non-invasive and cost-effective, utilizing widely available commercial components. Environmental perception will be achieved through a suite of off-the-shelf sensors capable of monitoring parameters such as temperature, humidity, CO_2, PM2.5, ambient noise (dB), and illuminance. This choice is directly validated by the user survey, which showed a 73.91% acceptance rate for environmental sensors. At the “edge” layer, the system envisions employing industrial-grade microcomputers (e.g., Raspberry Pi or similar single-board computers) as gateways. These devices possess sufficient computational power to run lightweight inference models and execute real-time control logic, enabling millisecond-level local responses to dynamic changes (e.g., activating a local air purifier upon detecting a CO_2 spike). This “Smart Edge” architecture is both technically mature and scalable.

5.2. Algorithmic Feasibility: DRL Model Structure

The core intelligence of the system is envisioned to be driven by a Deep Reinforcement Learning (DRL) model. DRL is well-suited for sequential decision-making problems in complex environments, such as building control, where the goal is to learn an optimal policy that balances competing objectives (comfort vs. energy savings). While the full training and deployment of a bespoke DRL agent is beyond the scope of this conceptual study, we propose a viable model structure informed by prior research.

Proposed Framework: The system can be modeled as a Partially Observable Markov Decision Process (POMDP), where the agent (controller) takes actions (adjusting HVAC setpoints, lighting levels) based on partial observations (sensor data, occupancy) to maximize a cumulative reward signal.

Reference Algorithm: Algorithms such as Proximal Policy Optimization (PPO) or Deep Deterministic Policy Gradient (DDPG) are promising candidates (Gao et al., 2013). Deep reinforcement learning can be used for building HVAC control (Wei et al., 2017). Our proposed model would incorporate multi-modal inputs (environmental + occupancy data) and a composite reward function reflecting both comfort metrics (derived from inferred states or user feedback) and energy penalties.

5.3. Data Flow and Communication Protocols

A reliable and efficient data pipeline is critical. The proposed system adopts a hybrid communication strategy:

Sensor-to-Edge: Sensors within a localized zone (e.g., an open-plan area) communicate with the edge gateway via low-power protocols like Bluetooth Low Energy (BLE) or Zigbee, forming a Wireless Sensor Network (WSN).

Edge Gateway Processing and Aggregation: The edge gateway performs real-time data aggregation, filtering, and lightweight pre-processing. It enables millisecond-level local decision-making and device control based on embedded rules or models, ensuring rapid response without relying on cloud feedback.

Edge-to-Cloud: The edge gateway aggregates and pre-processes data, then transmits it to the cloud platform for long-term storage and advanced analytics using lightweight protocols such as MQTT (Message Queuing Telemetry Transport) over Wi-Fi or Ethernet. MQTT’s publish-subscribe model is ideal for IoT applications, ensuring efficient and reliable data transmission.

Cloud Platform and Applications: The cloud is responsible for long-term data storage, advanced analytics, and DRL model execution. It provides users with system status dashboards, historical reports, and personalized recommendations via web consoles or mobile applications, completing the closed-loop data workflow.

5.4. Phased Deployment Strategy

To manage complexity, ensure early success, and gather iterative feedback, the implementation is proposed to proceed in distinct phases:

Phase 1 (Minimum Viable Product - MVP): Focus on core environmental assurance. Deploy sensors and gateways to achieve automated control of air quality (CO_2, PM2.5) and temperature/humidity within healthy, standards-compliant ranges. This directly addresses the top two user pain points (air quality and thermal comfort) and establishes the basic data collection and control loop.

Phase 2 (Feature Expansion): Introduce noise monitoring and alerting (addressing the third major pain point) and develop the initial personalized recommendation engine. This phase would begin incorporating user feedback (e.g., a comfort voting mechanism via a mobile App) to refine the DRL model's reward function towards personalization.

Phase 3 (System Maturity & Analytics): Fully integrate the trained DRL agent for autonomous optimization and activate the advanced data analysis layer. This phase would generate the comprehensive value reports correlating environmental data with productivity proxies, delivering the full value proposition to management.

6. Expected Contributions and Theoretical Implications

6.1. Theoretical Contribution

This study proposes a human-centric intelligent environment model with a "Perception-Decision-Interaction-Optimization" closed loop, which integrates Internet of Things (IoT), edge computing, and Deep Reinforcement Learning (DRL). The model addresses the core pain points of office environments (poor air quality, noise interference, etc.) identified in the survey by constructing a dynamic adaptive framework: IoT sensors realize real-time perception of environmental parameters and physiological feedback; edge computing ensures low-latency processing of personalized demand data; DRL algorithms optimize adjustment strategies based on user preferences and environmental changes. This theoretical framework enriches the research on intelligent office systems by emphasizing human-machine interaction and dynamic optimization, breaking through the limitations of traditional static environmental regulation models.

6.2. Practical Value Proposition

Aimed at small and medium-sized enterprises (SMEs) with limited budget and technical resources, this study provides a lightweight, low-cost, and high-acceptance intelligent office solution. Based on survey results (e.g., 73.91% acceptance of environmental sensors, low acceptance of intrusive monitoring), the solution prioritizes non-intrusive hardware (environmental sensors, smart bracelets) and modular functions. It avoids high-cost and high-intrusive equipment such as cameras, balances personalized needs and energy conservation, and provides dual output of "comfort score + energy consumption report" to meet both employee experience and enterprise cost control demands. This solution lowers the threshold for SMEs to adopt intelligent office systems, promoting the popularization of practical environmental optimization technologies.

6.3. Policy Relevance

This research supports the construction of energy-saving paths for buildings under the "dual carbon" (carbon peaking and carbon neutrality) goal. The survey shows that 32.17% of respondents support balancing personal experience with enterprise energy conservation, and the proposed intelligent system achieves energy saving through precise regulation (e.g., avoiding unnecessary equipment operation based on dynamic office scenarios such as hybrid work). By integrating energy-saving indicators into the system's core evaluation, the research provides empirical support for the formulation of green office policies, aligns with national strategies for building energy efficiency improvement, and offers a feasible technical path for reducing carbon emissions in commercial office spaces.

7. Conclusion

Based on 115 valid questionnaires covering multi-occupation and multi-industry office workers, this study identifies the pain points of office environments, user acceptance of intelligent systems, and core demand orientations, and proposes a conceptual framework of “Worklife+” system architecture to address the inefficiencies, high energy consumption, and poor personalization of traditional office environments. Centered on IoT and AI technologies, its framework design adopts a four-layer architecture to achieve a closed loop of "data-driven intelligent regulation-personalized service." The research has clear technical routes, reasonable progress arrangements, and sufficient preliminary research foundations. Its expected outcomes, including operational prototypes and academic achievements, not only break through the limitations of single-discipline research and shallow data application in existing studies but also provide a low-cost, easy-to-deploy systematic solution for office environment optimization. With significant social, economic, and technical value, it holds broad prospects for promotion and application in small and medium-sized enterprises and shared office spaces.

7.1. Current Limitations

Despite the valuable insights, this study has several limitations: First, the research is based on questionnaire data and has not been actually deployed in real office scenarios, so the practical effectiveness of the proposed system remains to be verified; second, the training of the DRL algorithm in the theoretical model relies on simulation environments or historical data, and the adaptability to real-time dynamic changes in actual office environments (e.g., sudden increases in personnel density) needs to be improved; third, the survey does not consider extreme working conditions such as special ventilation requirements during public health events (e.g., pandemics), which may affect the system's applicability in complex scenarios.

7.2. Future Validation Plan

To address the above limitations, future research can be focused on practical validation and optimization: First, to build a small-scale office scenario in the laboratory for A/B testing, comparing the comfort experience, work efficiency, and energy consumption data between the intelligent system and traditional environmental regulation models to verify the system's effectiveness; second, to cooperate with enterprises for pilot deployment, and select 50-100 workstations in enterprises that value employee welfare for 3-6 months of trial operation, collect real-world data on user adaptation, system stability, and energy saving effects; third, to optimize the algorithm based on pilot results, incorporate extreme working condition parameters into the model training, and improve the system's scenario adaptability and robustness. Through these steps, the research will form a closed-loop of "theoretical proposal - practical validation - model optimization" to promote the mature application of intelligent office environmental systems.

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