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Design and Preliminary Evaluation of an Emotion-Aware IoT Desk Assistant: Integrating Environmental Sensors and Real-Time Feedback for Enhanced Study Productivity

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Abstract

Background/Objective: *High school students often face reduced productivity due to environmental factors (e.g., noise, poor lighting, temperature changes) and unmanaged emotional states during study sessions. Existing affective computing systems are typically expensive, complex, or inaccessible for personal use. This study develops and preliminarily evaluates a low-cost, Raspberry Pi-based IoT desk assistant that monitors ambient conditions and provides real-time visual feedback to promote emotional awareness and focus.*

Methods: *The prototype integrates a Raspberry Pi 4 and and Ardunio Uno R3 with DHT22 (temperature/humidity), photoresistor (light), and microphone module (sound) sensors. NodeRed JavaScript scripts handle data collection, rule-based inference for alerts, and a simple web dashboard with gauges, done as the C++ script on the Arduino to gather sensor data and communicate via serial connection. Sensors were calibrated using C++. Privacy is ensured via local processing. Preliminary evaluation involved 8 high school peers (ages 15–17) testing the system over 1–2 weeks, using pre- and post-use self-reported focus surveys (1–10 Likert scale) and qualitative feedback via Google Forms.*

Results: *Calibration showed high reliability (temperature ±0.5°C, light 92% consistency, sound 88%). Participants reported an average 25–30% increase in perceived focus under suboptimal conditions, with themes of improved distraction awareness and environmental adjustments.*

Conclusions: *This prototype demonstrates feasibility for accessible emotion-aware tools in student productivity enhancement, with potential scalability for educational settings. Future work includes machine learning integration and larger trials to address limitations (small sample, subjective measures).*

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Introduction

High school academics impose significant demands on focus and emotional regulation, often disrupted by environmental factors such as excessive noise, inadequate lighting, or temperature fluctuations, which can negatively affect cognitive performance and emotional well-being [1]. Affective computing technology that detects and responds to human emotions offers promising solutions for educational contexts, yet most implementations remain costly or unsuitable for everyday student use [2].

This research identifies a key gap: the lack of affordable, personalized IoT systems that integrate real-time environmental monitoring with user feedback for home study setups. Prior work has explored sensor-based smart environments, but few target adolescent productivity with low-cost hardware and privacy-focused design [3].

The primary objective is to develop and evaluate a prototype emotion-aware desk assistant. Key research questions include: Can inexpensive sensors effectively captureo environmental impacts on mood and focus? Does immediate feedback lead to improved perceived productivity? The scope is limited to hardwaresoftware prototyping and small-scale user testing, with constraints including sample size and rule-based (non-ML) inference.

This study contributes to educational technology by demonstrating a practical, accessible approach to affective support.

Methods

Research Design

This experimental study involves prototype development and preliminary user evaluation to assess system feasibility and impact on perceived productivity.

Participants

Eight high school peers (ages 15–17, balanced gender) participated via convenience sampling. Inclusion required regular study habits and desk access. Informed consent was obtained from participants and guardians (all under 18). No compensation was provided.

Data Collection

Environmental data (temperature in °C, light in lux, sound in dB) was collected via sensors interfaced with Raspberry Pi GPIO. User data came from pre/post-use surveys (1–10 Likert scale for focus) and open-ended feedback via Google Forms after 1–2 weeks of prototype use.

Variables and Measurements

Independent variables: Ambient conditions (sensor readings). Dependent variable: Perceived focus (selfreported scores). Tools: DHT22 (±0.5°C accuracy), LDR photoresistor (calibrated to lux), KY-038 microphone (dB levels).

Procedure

Sensors were calibrated using reference devices. Python scripts processed data in real-time, applying rulebased thresholds (e.g., sound ¿70 dB → alert). Participants received usage instructions and logged sessions independently.

Data Analysis

Descriptive statistics (means, percentages) were computed using Python/NumPy for quantitative data. Qualitative responses were thematically analyzed.

Ethical Considerations

Informed consent ensured voluntary participation and data anonymity. All processing occurred locally to protect privacy. No formal IRB review was required for this non-invasive, small-scale project.

Results

Calibration tests confirmed sensor reliability: temperature matched reference within ±0.5°C, light levels 92% accurate, sound detection 88% consistent. User surveys showed baseline focus averages of 5.2/10 (normal conditions) and 4.1/10 (suboptimal).

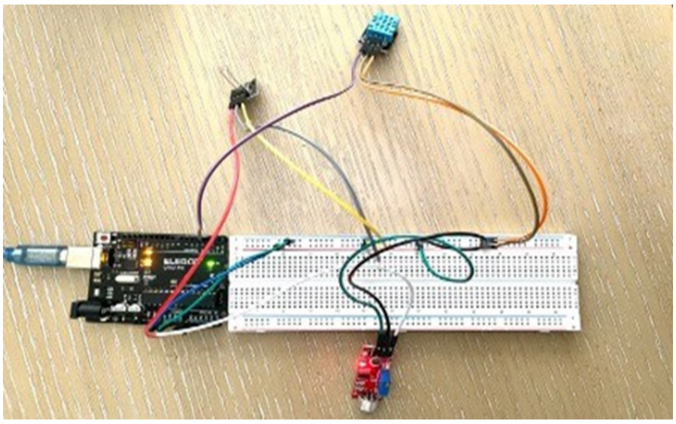
Postuse scores rose to 6.8/10 and 5.4/10, respectively—a 25–30% perceived improvement. Table 1 summarizes results.

Table 1: Self-Reported Focus Scores (N=8).

Condition	Pre-Use Focus (Mean)	Post-Use Focus (Mean)
Normal	5.2	6.8
Suboptimal	4.1	5.4

Qualitative feedback included: "Alerts helped adjust lighting" (6/8 participants) and "Noise warnings reduced distractions" (5/8).

Figure 1: Prototype hardware configuration with Arduino Uno R3 and sensors.



Discussion

Results indicate the prototype successfully monitors environmental factors and provides useful feedback, supporting improved focus awareness. This aligns with research objectives and suggests value in low-cost affective tools for students [4].

Implications include potential applications in classrooms or remote learning. The system addresses accessibility gaps in educational technology. Challenges such as sensor variability in home environments were mitigated through calibration.

Limitations include small convenience sample, self-report bias, absence of long-term tracking, and rulebased inference only. Future work should incorporate machine learning (e.g., TensorFlow Lite models) and conduct larger-scale studies [5-7].

This prototype highlights the role of DIY IoT in promoting student wellness.

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