Al for Health Equity Through STEM Education: Introducing HealthBot, an Innovative Student-Developed Kiosk

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Abstract

Health disparities severely limit access to preventative care in underserved regions, such as remote Greek island communities. Addressing this critical gap, "HealthBot" was conceived - an innovative, AI-powered health kiosk developed by motivated high school students to provide immediate, accessible initial health insights and enhance health equity. This paper details HealthBot's design, which uniquely integrates diverse sensors (weight, height, custom MAX86150 biometrics) with AI for non-invasive preliminary assessments, including cloud-based ML-driven skin lesion analysis and demographic estimation, leveraging a Large Language Model (GPT-4 mini) to interpret data and offer personalized, non-diagnostic wellness advice. Initial usability feedback gathered from 24 participants indicated manageable workload, although perceived system performance was rated lower due to sensor calibration issues during the prototype testing phase. In conclusion, while further validation is required, the HealthBot project demonstrates a feasible model for enhancing health equity through readily available, technologically advanced community health tools, serving as a compelling case study for project-based STEM education where student innovators address real-world problems.

Keywords: Artificial Intelligence, health equity, project-based learning, STEM education

Introduction

Health disparities limit preventative care access in remote Greek island communities like Kos, due to geographical distance and resource strain. This challenge necessitates innovative technological solutions to promote health equity. While smart healthcare and IoMT offer potential, challenges in cost, security, and ethics persist. (Millet News, 2025; Healthwatch.gr, 2024).

Inspired by a student competition, this project addresses these challenges through "HealthBot"—an AI-powered health kiosk. This initiative serves a dual purpose: it is both a technological tool designed to improve healthcare access and a powerful exercise in Project-Based Learning (PBL) for STEM education (University of Iowa, 2024).

This paper details HealthBot's design, implementation, and preliminary evaluation. The kiosk integrates diverse sensors (weight, height, MAX86150 biometrics) and AI (OpenCV/DeepFace for demographics, ML for skin lesion analysis, GPT-4 mini via API) to interpret data with user context (e.g., emailed medical notes) and provide personalized, non-diagnostic wellness advice. HealthBot aims to enhance community health and equity through accessible preliminary screening, while simultaneously showcasing the educational impact of student-led innovation in STEM. The paper then discusses background, system design, the educational journey, functionality, observations, and concludes with a discussion of significance and future directions.

Background and context

Traditional healthcare faces global pressures, especially in underserved regions. Smart healthcare, leveraging the Internet of Medical Things (IoMT) [Figure 1], aims for intelligent, efficient systems by interconnecting medical devices and sensors for real-time data analysis, promising benefits like improved monitoring, diagnostics, and patient empowerment. This "Healthcare 4.0/5.0" evolution emphasizes digitalization, AI, and preventative care, though IoMT deployment faces challenges in security, interoperability, cost, and ethics.

AI, including ML and LLMs, significantly enhances health kiosks. AI analyzes sensor data for risk patterns and sophisticated feedback (Mishra & Singh, 2023; Pournik et al., 2023). ML aids in preliminary image analysis like skin lesion classification (Adebiyi et al., 2024; Debelee, 2023), while computer vision automates demographic data. LLMs enable natural language processing and personalized, context-aware wellness advice. However, AI use, particularly LLMs, requires caution regarding accuracy, reliability, bias, and maintaining the non-diagnostic boundary (Kim & Vajravelu, 2025; Panch et al., 2019; Pournik et al., 2023).

HealthBot [Figure 2] originated as a student-led STEM competition project. Project-Based Learning (PBL) in STEM fosters critical thinking and problem-solving (University of Iowa, 2024). Addressing real-world community needs with technology enhances motivation and applies STEM concepts (National Math and Science Initiative, 2024), allowing students to develop 21st-century skills with tools like AI and IoT (CSIRO, 2024a; CSIRO, 2024b), thus showcasing student innovation.

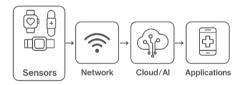


Figure 1. The IoMT infrastructure

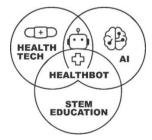


Figure 2. Health, AI & STEM education combined

The HealthBot kiosk: Design and implementation

HealthBot, an autonomous health kiosk, was developed to facilitate regular health assessments and preventative service access in community settings, balancing functionality, cost, portability, and ease of use. Its architecture integrates hardware for sensing/interaction with software for control, data processing, and AI-driven analysis.

System architecture and hardware components

The modular kiosk (2.0m x 0.6m x 0.5m) [Figure 3] features a 3-part metal frame and 3D-printed enclosures. A Raspberry Pi 4 (8GB RAM) serves as the core processing unit, managing AI tasks and sensor interfacing via a Grove Base Hat. User interaction occurs through a 7-inch touchscreen. Key components are detailed in Table 1.

Sensing modalities and implementation details

See the Appendix.

AI integration and user interaction workflow

Beyond specific ML models, HealthBot uses a Large Language Model (GPT-4 mini via OpenAI API) to synthesize sensor data and user-provided context (e.g., emailed medical notes) into user-friendly feedback. Structured prompts were developed for various scenarios. Critically, the LLM is prompted not to provide medical diagnoses but general wellness information, interpret results, suggest lifestyle considerations, and recommend professional consultation. The system attempts to handle sensor inaccuracies by focusing prompts on trends. Output is displayed and optionally emailed, with data privacy protocols planned (Ayers et al., 2023; Dave et al., 2023; Pournik et al., 2023).

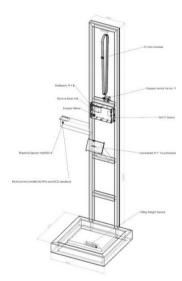


Figure 3. The initial 3D design of HealthBot

The educational journey: A high school project case

The development of HealthBot was not only a technological endeavor but also a significant educational experience undertaken by a team of motivated high school students from the Greek Island, Kos, under the mentorship of their coach at the robotics center. The project spanned approximately six months, from July to December. The team's workflow was structured around weekly meetings of about two consecutive hours, which were supplemented by independent work. To ensure these collaborative sessions were productive,

team members completed preparatory assignments and various asynchronous tasks, such as 3D printing, between meetings. This consistent effort culminated in an intensive final week dedicated to daily, rigorous testing and system refinement. The project originated as an entry for a national competition, providing an authentic context for applying STEM principles to address a pertinent local issue - limited healthcare access. This aligns with established benefits of Project-Based Learning (PBL) in STEM, which fosters deeper engagement and the application of theoretical knowledge to solve real-world problems. (University of Iowa, 2024; National Math and Science Initiative, 2024).

The student team, consisting of three members in the 3rd grade of Gymnasium and 1st and 3rd Grade of Lyceum (Filippos Papanikolaou, Tasos Syris, and Yiota Nikoloudaki, respectively) drove the project from conception to implementation. Based on collaborative brainstorming and iterative design discussions, team members took on distinct roles while maintaining close cooperation. Two members focused primarily on the mechanical construction, hardware integration, and physical testing of components. The other member, collaborating remotely, concentrated on software development, including sensor interfacing, UI logic, and AI integration. The coach (Alex Kaiserlis) provided guidance and support throughout the process, facilitating learning and problem-solving.

The project presented numerous authentic challenges that required the students to develop new skills and resilience. On the technical side, difficulties included ensuring the mechanical stability and accuracy of the weight sensor base, selecting a Raspberry Pi model with sufficient processing power for the AI tasks, and overcoming the lack of existing libraries for the MAX86150 biosensor by developing custom code. These hurdles provided valuable hands-on experience in debugging, iterative design, and adapting solutions based on experimentation. Furthermore, the process implicitly fostered crucial 21st-century skills such as teamwork (including remote collaboration), communication, project management, and critical thinking, mirroring the benefits highlighted in STEM PBL literature (National Math and Science Initiative, 2024). The team also gained experience in utilizing advanced AI tools, such as creating a custom GPT model through structured prompts to aid in software development and system logic, demonstrating an ability to leverage cutting-edge technology within their project constraints.

Presenting this project, therefore, not only showcases the technological innovation of HealthBot but also serves as a case study illustrating the potential of guided, project-based STEM initiatives at the high school level to empower students to tackle complex problems, develop advanced technical and collaborative skills, and create meaningful solutions with potential community impact (e.g., Roy Chowdhury, 2023.; FIRST Robotics, 2019).

Functionality and preliminary observations

This section details HealthBot's user workflow and preliminary usability feedback.

User workflow

The touchscreen-guided interaction is straightforward. A typical session involves:

- Activation & initial measurements: User steps on the scale; if weight >40kg, system
 activates, measures weight (median algorithm), height (camera/stepper motor with
 face detection; Bradski, 2000), and estimates age/gender (approx. 30s)
- Main menu & measurements: User selects options:
 - ° Submit Doctor's Notes via Email: For LLM processing.
 - ° Acquire Biometric Data: MAX86150 sensor for HR, SpO2, RR, PTT (approx. 60s).

 Skin Lesion Analysis: Detachable camera for image capture, cloud analysis via ModelDerm.

- ° Proceed to Results. On-screen prompts guide actions.
- Results & options: LLM-synthesized wellness advice is displayed (non-diagnostic, user-friendly). Options include emailing results or exiting.
- System reset & info: System resets after user departure. Hygiene/FAQ info is accessible.



Figure 4. The camera assembly & the LCD touchscreen interface

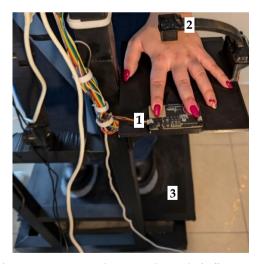
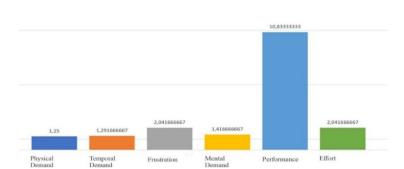


Figure 5. For biometric measurements, the user places their fingers on the sensor [1]. An infrared thermal sensor is positioned above the hand [2]. The weight scale base, where the user places their feet [3]

Preliminary usability observations

Initial feedback from 24 community volunteers in Kos (with informed consent) involved using the kiosk and completing the NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988) [Figure 6]. NASA-TLX data [Figure 6] indicated manageable mental, physical, and temporal demands, effort, and low frustration. However, perceived 'Performance' was rated relatively poorly. This observation is directly attributed to the prototype's development stage; the sensors (particularly weight and height) were undergoing calibration during the testing phase. This led to occasional technical issues and measurement inconsistencies, which understandably impacted the users' perception of the system's effectiveness and the reliability of its results. This feedback, while critical, proved invaluable. It highlighted the absolute necessity of rigorous sensor calibration, complete system validation, and refining the way results are presented to manage user expectations about accuracy before any wider deployment.



Nasa TLI / 24 total responces

Figure 6. The results of the NASA-TLX evaluation are presented, displaying the median value for each workload category

Discussion

This paper presented HealthBot, an AI-powered health kiosk developed as a high school STEM project to improve health equity in underserved Greek communities. We detailed its design, integrating multiple sensors and AI (ML for analysis, LLM for feedback), and reported preliminary NASA-TLX usability observations from 24 users. This discussion interprets these aspects, highlighting significance, limitations and future directions.

Significance, contributions, and observations

HealthBot's significance spans technology, community health, and education. Technologically, it demonstrates feasible integration of low-cost sensors and advanced AI on a Raspberry Pi platform, with custom MAX86150 code being a notable student achievement. From a community health perspective, it offers a tangible approach to addressing healthcare access disparities through accessible, non-diagnostic screening and wellness guidance, with potential for public health insights from aggregated data. Educationally, it is a compelling STEM PBL case study, showcasing students engaging with cutting-edge technologies to solve real-world problems and fostering technical and soft skills.

The preliminary NASA-TLX evaluation indicated manageable user workload (mental, physical, temporal demands, effort, frustration). However, lower 'Performance' ratings were attributed to the prototype's uncalibrated sensors during testing, impacting measurement reliability and user perception of effectiveness. This underscores the critical need for rigorous technical validation (sensor calibration) and refining results presentation for clarity and managing user expectations.

Limitations, challenges, and future directions

HealthBot, a prototype, has limitations. Technical limitations include the need for further accuracy validation of measurements (custom HX711/MAX86150 algorithms, DeepFace, ModelDerm (AI Competence, 2024; Han et al., 2022)) against clinical standards, reliance on cloud services, and untested long-term hardware robustness. Evaluation limitations include the preliminary 24-participant usability study, with no clinical validation or assessment of its impact on health behaviors yet performed.

Ethical considerations are paramount: A crucial principle of HealthBot is that it is an informational tool, not a diagnostic one, a distinction that must be communicated unequivocally to all users. Data privacy and security require a robust framework, particularly for compliance with regulations like GDPR. This includes obtaining informed consent, ensuring secure data transmission (e.g., for the cloud-based skin lesion analysis), and implementing strict data anonymization and deletion protocols. Furthermore, potential AI biases, whether in the demographic estimation models or the skin lesion classifier, must be actively monitored and mitigated to ensure the tool is equitable for all users. These challenges are central not only to HealthBot but to the broader field of IoMT.

Compared to commercial kiosks, HealthBot's uniqueness is its student-led, community-focused, and resource-constrained development integrating accessible hardware with ML and LLM for holistic assessment under resource constraints (Eichenberger et al., 2025; Roy Chowdhury, 2023).

Future work must prioritize sensor accuracy, clinical validation, physical frame and UI refinement based on TLX feedback. Exploring advanced AI (sophisticated LLM interactions, edge AI) and sustainable deployment models with local healthcare stakeholders is key to realizing HealthBot's health equity goals, while addressing broader IoMT challenges like interoperability and security.

Conclusion

This paper presented "HealthBot," an innovative, AI-powered health kiosk conceived and developed by a team of high school students to address healthcare access disparities in underserved Greek communities. We detailed the kiosk's design, which integrates multiple sensors (weight, height, PPG/ECG, camera) with machine learning algorithms (for demographic estimation and preliminary skin lesion analysis via the cloud-based ModelDerm service) and a large language model (GPT-4 mini for personalized, non-diagnostic feedback). The project successfully demonstrates the technical feasibility of creating a low-cost, multimodal health screening tool using accessible hardware like the Raspberry Pi and advanced AI services.

Furthermore, this work serves as a compelling case study in project-based STEM education, illustrating how guided student initiatives can foster technical skills, problem-solving abilities, and engagement with real-world challenges related to community well-being and health equity. The preliminary usability evaluation, while highlighting areas for

improvement in communicating results, indicated that the kiosk interaction itself imposes a manageable workload on users.

Despite the promising potential, HealthBot remains a proof-of-concept prototype. Key limitations include the need for rigorous validation of sensor accuracy, clinical assessment of the screening outputs, and further development considering ethical guidelines and data privacy regulations inherent to IoMT applications. Future work should prioritize these validation steps, refine the user interface based on feedback, and explore sustainable deployment models in collaboration with local healthcare stakeholders.

In conclusion, HealthBot represents a significant step towards leveraging accessible technology and student innovation to promote health equity. It highlights the potential of integrated AI and IoMT solutions, developed through practical STEM education, to contribute meaningfully to preventative healthcare and community well-being in resource-constrained environments.

Acknowledgements

The development of the HealthBot project was a collaborative effort, and we wish to extend our sincere gratitude to those who supported this initiative. Firstly, we deeply appreciate the dedication, enthusiasm, and hard work of the student team from the Instudies center - Filippos Papanikolaou, Tasos Syris, and Yiota Nikoloudaki - who brought the HealthBot concept to life through their commitment during the national competition. Their efforts in design, construction, programming, and presentation along with their critical thinking and problem-solving skills were fundamental to the project's success.

We are also particularly grateful to Manos Nikolaos, researcher at the University of the Aegean, for his invaluable advice and generous willingness to assist the team throughout the project's development. Furthermore, we extend our gratitude to Segraidos Domiki for their essential contribution in fabricating the kiosk's structural frame.

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Appendix

HealthBot incorporates distinct sensing subsystems:

Table 1. Key hardware components of the HealthBot kiosk

Component	Specification/Model	Primary Function in
		HealthBot

Central Processing Unit	Raspberry Pi 4 Model B (8GB RAM)	Main controller, runs software, AI processing, sensor interface
Sensor Interface	Grove Base Hat for Raspberry	Easy connection interface for
Hat	Pi	multiple sensors via Grove ports
Display & Input	7" Capacitive Touchscreen	User interface display and touch input
Weight Sensing	HX711 Amplifier + 150kg Load Cell(s)	Measures user's weight
Camera & Height	Pi Camera Module 3	Captures images (face, skin),
Measurement	(Autofocus)	used with stepper for height
Height Adjustment	Nema 17 Stepper Motor	Moves camera vertically for
Motor	11	height measurement
Motor Driver	Stepper Driver	Controls the Nema 17
	**	stepper motor
Biometric Sensor	Protocentral MAX86150	Acquires heart rate, SpO2,
(PPG/ECG)	Breakout	ECG signals
Thermal Sensor	MLX90614	Measures non-contact
		infrared temperature
Structural Frame	Custom Metal Frame (3 parts)	Provides main structure and
		support for components
Additional	3D Printed Components	Custom housings,
Enclosures/Parts		mounting brackets,
		aesthetic parts

- Weight measurement: An HX711-amplified load cell system in the base [Figure 5] measures weight, using a median value from an 8-second reading period to ensure stability. Custom calibration corrected for non-linear sensor behavior.
- Height measurement: A Pi Camera Module 3 on a stepper motor-driven mechanism determines height by detecting the user's face (OpenCV Haar Cascade Classifier; Bradski, 2000) and calculating vertical travel.
- Age/gender estimation: Facial detection data feeds into DeepFace models for indicative demographic estimates (Serengil & Ozpinar, 2021).
- Biometric sensing (PPG/ECG): A Protocentral MAX86150 module [Figure 5] non-invasively collects HR, SpO2, RR, and potentially PTT via custom-developed Raspberry Pi code, as existing libraries were lacking. Basic signal processing filters noise (Analog Devices, n.d.; Goda et al., 2024).
- Non-contact temperature: An MLX90614 infrared sensor [Figure 5] measures hand skin temperature, with an algorithm estimating core body temperature considering ambient temperature.
- Skin lesion analysis (cloud AI): A detachable Pi Camera [Figure 4] captures skin lesion
 images, uploaded securely for analysis by the ModelDerm algorithm (Han et al., 2022),
 a deep learning network for skin condition recognition. Results (classification and
 confidence) are returned to the kiosk, with users advised this is a preliminary, nondiagnostic screening.