

Original Article

Experimental Analysis of Thermal Behavior and Computational Workload in AI-Enabled Wearable Devices

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ABSTRACT

AI-powered wearables are increasingly performing increasingly complex functions such as physiological signal classification, activity recognition, anomaly detection and personalised health monitoring. But high workloads of inferences may also raise the temperature, energy consumption, and time for processors to complete their tasks, which can impact user comfort, battery life, and system reliability. The authors introduce a framework for experimental analysis of the correlation between the computational load and thermal performance of a wearable device powered by AI. The proposed methodology combines the workload characterization, temperature monitoring, utilization measurement of processors, estimation of power consumption, and inference performance evaluation under various operating conditions. Representative AI workloads are classified based on their computational complexity, model execution frequency and memory requirements. The performance measurement of thermal response includes temperature rise, heating rate, steady state temperature, and thermal recovery time; computational performance includes inference latency, throughput and energy efficiency. A controlled experimental protocol and a well-documented analytical framework are created to evaluate lightweight and intensive models. No physical measurement data are provided, so the results obtained are not reported as experimental findings. Rather, the article provides a strict foundation for future validation of hardware and thermal-aware AI workload management within wearable computing systems.

KEYWORDS

Artificial Intelligence, Wearable Devices, Thermal Behavior, Computational Workload, Edge Computing, Energy Efficiency, Inference Latency, Embedded Machine Learning, Temperature Monitoring, Thermal-Aware Scheduling.

1. INTRODUCTION

1.1. Background and Motivation

The wearable computer has grown from an activity tracker to a smart sensor system that can continuously monitor the human body, identify human motions, analyze human behaviors, and make decisions based on the context. Today's smart wearables combine a number of sensors, a microcontroller, wireless communication hardware, and machine-learning models to process data from electrocardiography, photoplethysmography, as well as accelerometers, gyroscopes and skin-temperature sensors. Local inference means that they can respond to this in real time, are less reliant on the cloud and have better data privacy. These computational abilities, however, lead to higher power consumption, higher memory access and higher utilization of the processor, which poses further thermal challenges. The electricity that is used for calculation is mostly converted to heat, then stored depending on the load, frequency, processor architecture, enclosure materials, and environmental factors. The wearable devices are located near human skin, and their limited space for heat dissipation may lead to high temperature, which may reduce the user's comfort, the reliability of components, the efficiency of batteries, and continuous inference performance. Hence, experimental investigation of thermal behavior in conjunction with computational load is crucial to design energy efficient, thermally reliable and comfortable smart wearable devices for continuous intelligent monitoring applications powered by AI.

1.2. Problem Statement

The connection between AI computational load and temperature in wearable devices is a complicated one, as the thermal responses differ for each machine learning model based on the ratio of processing workload, memory access, operating frequency and hardware acceleration. Different models with the same inference latency can produce differing levels of heat when operating under the same conditions.

A simple measurement of processor utilization/execution time is not a reliable method for assessing thermal stress. To be able to comprehend the thermal impact of continuous AI processing, a holistic analysis of the complexity of the models, the frequency of inference, the usage of power, the variation in temperature, and the performance of the computation is required.

Moreover, the thermal performance of wearable devices is different due to the various design of enclosures, location of sensors, battery structure, and mechanisms for heat dissipation. Therefore, an experimental environment with controlled and reproducible workloads is necessary to assess workload-related changes in temperatures, as well as to reduce the impact of environmental and hardware-specific factors.

1.3. Research Objectives



Fig 1 - Research Objectives

1.3.1. Establishing a Controlled Experimental Methodology

This study intends to propose an experimental methodology that is systematic and controlled to measure the thermal response of AI-based wearable devices under various computational conditions. The methodology takes into account the ambient temperature, the device configuration, the sensor placement, and the workload settings of the system, achieving reliable, repeatable and comparable observations during the experiment.

1.3.2. Characterizing the Influence of Computational Workload

This study aims to explore the effects of inferences frequency, complexity of machine learning models, and workload duration on temperature rise and heating rate of wearable devices. The study aims to examine various workload scenarios and pinpoint computational patterns associated with thermal accumulation when processing AI workloads continuously and intermittently.

1.3.3. Investigating Relationships among Performance, Energy, and Temperature

This goal is to look at how processor utilization, energy usage, inference latency and device temperature are related. The analysis will focus on understanding the contribution of computational demand and energy consumption to thermal differences, as well as the possible trade-offs between energy and processing efficiency, and between energy and thermal performance.

1.3.4. Developing Mathematical Models for Thermal Behavior

The goal of the study is to create mathematical models to describe the transient heating and cooling phenomena under typical computational workloads. These models take into account power dissipation, thermal resistance, thermal capacitance and workload duration, and can be used to predict the evolution of temperature to assist in predicting thermal behavior under different operating conditions.

1.3.5. Identifying Thermal-Aware Workload-Management Strategies

The ultimate goal is to come up with strategies for workload management which are thermal aware and have a good balance between predictive accuracy, computational efficiency, energy consumption, and user comfort. Possible solutions could be adaptive inference scheduling, model selection, dynamic workload adjustment and even reducing the intensity of the processing in order to avoid unnecessary temperature increase when the wearable device runs for a long time.

2. LITERATURE SURVEY

2.1. Learning Support Technologies for the Rehabilitation of Vision Impairment

The goal of AI-driven wearable computing architectures is to equip a wearable device with sensing units, signal preprocessing modules, embedded processors, and wireless communication interfaces that are built into compact structures and are used for real-time intelligent applications. They can be as simple as a microcontroller running lightweight machine learning models or as sophisticated as a processor featuring digital signal processors (DSPs) and neural processing units (NPU). While edge-based inference can lower the communication burden, the ability to choose appropriate hardware not only necessitates considering computational power, memory usage and energy consumption but also thermal management to ensure continuous operation with reliable performance.

2.2. Thermal Characteristics of Wearable Electronic Devices

Thermal performance of wearable electronic products is affected by the power dissipation of the product, thermal resistance, thermal capacitance, ambient temperature, enclosure material, and skin contact. Prolonged high temperatures can impact user comfort, battery efficiency, component reliability, and continued computational performance. A previous study on wearable thermal systems has also shown that the temperature and data-driven modelling are key to understanding complex thermal behaviour and that the temperature of the processor, the temperature of the surface of the enclosure and the temperature of the skin (which is at the interface of the enclosure and the skin) should be distinguished when evaluating a system in the field.

2.3. Computational Workload, Energy Consumption, and Thermal Management

Thermal behavior of wearables is directly affected by computational load, which includes processor usage, frequency, memory transactions, peripherals, etc. AI inference can also consume a significant amount of power and cause the hardware to heat up, leading to dynamic voltage and frequency scaling (DVFS) or thermal throttling to prevent hardware damage. AI inference can also consume a lot of power and cause the hardware to heat up, which can trigger dynamic voltage and frequency scaling (DVFS) or thermal throttling that protects the hardware. Previous work has shown that computational efficiency and thermal regulation can be enhanced through using machine learning for thermal prediction, adaptive inference scheduling, model compression, and processor-frequency control. These methods, however, have to be balanced with inference latency, energy usage, predictive accuracy and temperature change to see how well they perform on the constrained wearable platform.

2.4. Research Gap and Study Positioning

Studies have already been conducted on the efficiency of embedded AI, thermal prediction of processors, thermal sensing via wearables, and human thermal comfort, but these research areas do not necessarily offer a consistent methodology to calculate computational workload and thermal behavior at the same time. There are significant gaps in the measurement intervals used, the representation of compact wearable enclosures, and the lack of analysis of the heating rate, cooling characteristics, and performance changes with time. Thus, the study suggests a repeatable experimental setup for the correlation of the characteristics of the AI workload with the temperature, energy, and latency of the inference processes with the trade-offs of the predictive accuracy and thermal efficiency in various operating conditions.

3. METHODOLOGY

3.1. Experimental Design and System Architecture

The proposed approach is a repeated measures controlled experimental design to study the thermal response of smart wearables with AI-driven capabilities under varying computational loads. Different sets of workloads are applied to the same hardware platform, with the same ambient temperature, software configuration, sampling intervals and initial thermal state. The five key experimental architecture modules are: wearable computing platform, AI inference engine, thermal instrumentation, power and performance monitoring unit, and synchronized data acquisition and analysis. Machine learning models run on the computing platform and internal temperature telemetry and external sensors capture temperatures of the processor and enclosure. The relationships between computational demand and thermal response are established by logging electrical power, processor usage, memory usage, inference latency and throughput. Final validation should be done with a real wearable device as the thermal properties on the development board will not necessarily reflect those of a finished enclosure.

There are three workload classes, each representing a different level of computational needs. The low-complexity workloads are logistic regression, decision trees, small convolutional neural networks (CNNs) and recurrent models; medium-complexity workloads are small CNNs and temporal neural architectures; and high-complexity workloads are larger CNNs and temporal neural architectures. Each application scenario contains models that process identical or equivalent input samples, with input dimension, quantization precision, runtime implementation and accelerator configuration provided to ensure the model can be reproduced. Independent variables are model complexity, inference frequency, workload duration, and operating mode, while dependent variables are temperature, electrical power, energy per inference, latency, throughput, and predictive accuracy. The factors that affect the control variables are ambient temperature, initial device temperature, sampling rate, enclosure configuration, power-supply conditions, and the firmware version.

Standard measurement units are used to record the experimental parameters. Ambient temperature ((T_a)), processor temperature ((T_c)), and surface temperature ((T_s)) are measured in °C units. The utilization of the processor ((U)) is a percentage, electrical power of the

processor (P) in watts, and the usage of the processor in inferences per second (f_i) in milliseconds. The energy per inference (E_i) is measured in millijoules per inference; the maximum temperature rise ($\Delta T_{\max}$) measures thermal response and the model accuracy measure (A) measures the predictive performance. Multiple trials and synchronous measurement facilitates statistical comparison, uncertainty calculation and repeatable evaluation of the thermal response under workload.

3.2. Thermal and Computational Measurement Procedure

The experimental procedure starts with the initialisation of the device, as well as the calibration and verification of the thermal and computing acquisition systems, to assure reliable thermal and computational measurements. The wearable device is given to a certain thermal condition before every trial, and the initial temperature of the processor of the wearable device, the initial temperature of the surface of the enclosure of the wearable device, and the initial temperature of the ambient temperature are measured. Then each chosen AI model is tested with continuous and intermittent inference to explore continuous heat buildup and temperature drop during idle periods. During each experiment, the temperature, voltage, current, processor utilization, memory utilization and inference timestamps are collected with synchronized clocks. Internal processor temperature telemetry is taken wherever available and external temperature sensors are used to measure the temperature of the surface of the enclosure without altering significantly heat transfer or device operation. The experimental sequence involves recording of environmental conditions, running the known workload, continuous measurement of thermal and performance data, conclusion of the observation time, end of the computation and monitoring of the following cooling.

If safety limits are pre-defined, then measurements are stopped, and all interruptions are recorded. Five separate repetitions of workload conditions are suggested for preliminary characterization although no final sample size was defined but should be based on assessment of variability and statistical power analysis. Where practicable, the order of the trials is randomized so that there is as little systematic ordering effect and environmental influence as possible. One possible initial protocol is to keep the ambient temperature as close as possible to $(23 \pm 1)^\circ\text{C}$, allow the system to stabilize for 10 minutes, run the computation for 20 minutes and observe cooling for another 10 minutes. These times are suggested experimental lengths and are not necessarily standards; adjust as needed for preliminary tests. In analysis, all measurements are synchronized and average and peak temperatures, temperature rises, heating and cooling rates, average power, cumulative energy consumption and inference latency are calculated. The energy per inference is estimated by dividing the energy used by the workload plus the energy used while idle and baseline (where applicable) by the number of workload inferences completed. Finally, descriptive statistics, confidence intervals and appropriate significance tests are used to summarise repeated-trial measurements. This systematic approach allows to make reproducible comparisons between the thermal behavior, computational efficiency and sustained performance of inferences of different workload configurations and operating modes.

3.3. Mathematical Formulation of Thermal and Computational Behavior

Mathematical models are developed that quantify the transient heating, energy consumption, and inference performance of the thermal and computational behavior of AI-enabled wearable devices. The temperature rise is given by $\Delta T(t) = T_c(t) - T_a(t)$, which is the temperature of the processor at time t minus the ambient temperature at time t . The maximum temperature rise in an observation time is given by $\Delta T_{\max} = \max_{0 \leq t \leq t_f} \Delta T(t)$ where t_f is the final observation time. The instantaneous heating rate is estimated from a series of temperature readings as, $r_T(t) = (T_c(t + \Delta t) - T_c(t)) / \Delta t$ in degree Celsius/second or minute. A lumped thermal model is also used to describe the transient thermal behavior, $C_{th} dT_c/dt = P_{heat}(t) - [T_c(t) - T_a(t)]/R_{th}$, where C_{th} is the effective thermal capacitance, R_{th} is the effective thermal resistance, and P_{heat} is the dissipated power that contributes to the modeled thermal node. The temperature of the processor under an approximately constant ambient temperature and heating power is $T_c(t) = T_a + P_{heat} R_{th} (1 - e^{-t/\tau})$, where the thermal time constant is $\tau = R_{th} C_{th}$. This first order approximation may need to be expanded if there are several components with different thermal responses. The total energy consumed by the computation is computed as $E_{total} = \int_0^{t_f} V(t)I(t) dt$, where $V(t)$ and $I(t)$ are measured voltage and current. When used, the energy per inference is calculated as $E_i = E_{total}/N_i$ where N_i is the number of inferences completed in the time interval of the measurement. The average of the inference latencies is given by $\bar{L} = (1/N_i) \sum_{j=1}^{N_i} L_j$ and the throughput is $Q = N_i/t_f$. These metrics can be used to systematically compare thermal accumulation, energy efficiency, and computational performance for various types of AI workloads and operating conditions.

3.4. Data Processing, Statistical Analysis, and Reproducibility

The gathered experimental telemetry is systematically processed to guarantee data quality, statistical reliability and repeatability when assessing the thermal and computational performance of wearable devices powered by AI. First, temperature, voltage, current, processor use and inference records are synchronized by time stamping and checked for missing data points, sensor issues, clock drift, and missing data. Data exclusions are clearly documented with rationale prior to making statistical comparisons. Descriptive statistics such as the mean, standard deviation, median, 95th percentile inference latency, peak temperature and temperature rise rate are computed for each workload condition to capture the performance variability and thermal response characteristics. Where applicable, the extent of uncertainty in estimation is reported as a confidence interval. To assess the effect of workload class, inference frequency, and execution mode on the measured temperature, repeated-measures analysis or mixed-effects statistical modeling is used. The model used for a representative device is given as:

$$T_{ijk} = \beta_0 + \beta_1 W_i + \beta_2 F_j + \beta_3 M_k + u_{\text{device}} + \epsilon_{ijk},$$

where (W_i) represents workload class, (F_j) represents inference frequency, (M_k) represents execution mode, (u_{device}) represents device-level variability, and (ϵ_{ijk}) represents residual error. As appropriate for the experimental design, interaction terms are added to the model and tested for significance along with effect sizes and confidence intervals. Reproducibility is facilitated by recording the device model, firmware version, machine learning architecture, inference runtime, sensor accuracy, sampling interval, ambient conditions, power-measurement technique, and trial duration. Raw measurements, processing procedures and analysis scripts are maintained when privacy and data sharing requirements allow. In addition, the analysis clearly separates measured quantities from those derived from a model or simulated. Parameters are estimated from documented assumptions and suitable model fitting procedures, and uncertainty is reported whenever possible, for example, effective thermal resistance, thermal capacitance and time constants. Further enhancing reliability are sensor calibration and repeated trials and consistent experimental protocols. This integrated approach can be used to make meaningful comparisons of computational workloads, can help identify statistically significant trends in temperature, can provide a clear foundation for validating thermal-aware workload-management strategies on various wearable platforms.

4. RESULT AND DISCUSSION

4.1. Thermal Response and Workload-Dependent Behavior

The proposed experimental setup allows for the systematic assessment of the thermal response of an AI-equipped wearable device with low, medium and high complexity computational load. Because there are no measured data or observations of a physical device, the description of thermal behavior is not included here; instead, the discussion is based on engineering interpretation of thermal behavior. In continuous inference, the temperature of the processor will rise if the amount of heat generated is greater than the amount of heat dissipated; the magnitude of increase in temperature will be determined by the level of load, effective thermal resistance, thermal capacitance, ambient temperature and initial temperature of the device. In general, this rate of temperature increase will decrease as the device approaches thermal equilibrium since the larger temperature difference between the device and its environment will lead to higher heat transfer. The concept of intermittent inference is useful to compare since the cooling periods between inferences allow for the excess heat to dissipate, lowering the peak temperature and the average thermal stress.

However, the cooling response will vary based on the duration of idle time, enclosure characteristics and thermal time constant, so workloads that have the same number of inferences can have different cooling profiles for different execution schedules. The relationship between the thermal load and the complexity of the model can be positive, as high-complexity models can cause a higher thermal load, due to more processor activity, more memory transactions, and more computational demand; or it can be negative, as hardware acceleration and power-management mechanisms may change the relationship, but only measurement can confirm actual temperature difference. These internal processor temperatures and external enclosure surface temperatures, therefore, need to be recorded and analyzed separately to locate the differences between the temporal

responses. If these locations show a persistent temperature difference, it could be a temperature difference within the instrument, but only when the instrument is calibrated properly, the position of the inserted sensors is known and measurement uncertainty is taken into account. In addition, the temperature profile should be analyzed with the inference latency, processor usage and electrical power to look for any correlations between the thermal accumulation and computational performance. When thermal throttling is observed, a rise in temperature can result in a longer inference latency and/or lower throughput, depending on the load and temperature; this needs to be confirmed with synchronized telemetry. Overall, the proposed analysis enables a structured comparison of sustained and intermittent workloads, characterize thermal accumulation patterns, and set experimentally proven guidelines for energy-efficient and thermally reliable AI inference in wearable computing systems.

4.2. Percentage-Based Comparative Evaluation

Thermal behavior, energy use, and computational performance improvements are measured in percentages and compared under various AI workload conditions. A clear baseline, such as continuous inference from a reference model with default processing settings, helps to create a consistent reference.

Table 1: Percentage-Based Comparative Evaluation

Evaluation metric	Baseline	Test condition	Percentage change
Peak temperature rise	Measured value	Measured value	$\frac{\Delta T_{\max}}{T_{\max}} (\%)$
Average power consumption	Measured value	Measured value	$\frac{\Delta P}{P} (\%)$
Energy per inference	Measured value	Measured value	$\frac{\Delta E_i}{E_i} (\%)$
Mean inference latency	Measured value	Measured value	$\frac{\Delta \bar{L}}{\bar{L}} (\%)$
Throughput	Measured value	Measured value	$\frac{\Delta Q}{Q} (\%)$
Model accuracy	Measured value	Measured value	$\frac{\Delta A}{A} (\%)$

4.2.1. Peak Temperature Rise

The difference in peak temperature rise between the baseline and test cases is used to assess the effect of workload scheduling or model complexity on thermal accumulation. A negative percentage change means that the peak temperature rise is lessened, which could be a positive sign of better thermal performance as long as predictive accuracy and computational load are satisfactory.

4.2.2. Average Power Consumption

Average power consumption is calculated to study the electrical power consumption during AI inferences under various operating conditions. Any reduction over and above the baseline is a positive sign of better power efficiency, but should be interpreted in the light of the other outcomes listed below: Inference frequency, Workload completion, and Processing performance.

4.2.3. Energy per Inference

Energy per inference is the amount of electrical energy it takes to make a single predication by an AI. This metric can be used for comparisons to understand if model optimization or adaptive

inference scheduling achieves improvements in computational energy consumption while preserving prediction performance.

4.2.4. Mean Inference Latency

Mean inference latency is the average time it takes the AI model to process an input and output a prediction. The percentage change shown is the change in latency for the model, with a negative change reflecting greater performance in terms of latency and inference speed, and a positive change possibly reflecting extra computational loading or the model being thermally throttled during prolonged inference loads.

4.2.5. Throughput

The throughput is the number of completed inferences per unit time, which represents the processing capability of the wearable device. Positive percentage change indicates improvement in the throughput of the inferences, provided the system has appropriate thermal, energy efficiency and prediction performance.

4.2.6. Model Accuracy

Model accuracy calculates the percentage of the samples that are correctly classified and indicates predictive performance for each test condition. When interpreting percentage change, it is important to remember that percentage points and percentage change should not be interpreted separately; if the absolute percentage change is small, it may be a magnification of the small differences between the baselines in the case where the accuracy is high.

4.2.7. Comparative Analysis and Interpretation

The change in each metric is expressed as a percentage change, $\Delta X(\%) = [(X_{\text{test}} - X_{\text{base}}) / X_{\text{base}}] \times 100$. Negative values represent decreases and positive values increases from the baseline. Reporting of actual measured values, with repeated trial variation and confidence intervals, should be reported to allow reliable comparisons; the results table should provide a template for reporting until experimental measurements are obtained.

4.3. Interpretation, Design Implications, and Limitations

Both thermal and computational metrics are used in the combined evaluation to give a thorough evaluation of the operational characteristics of AI-powered wearables. Evaluation of temperature, processor use, inference latency, power usage, and energy per inference allows for a well-rounded comparison of the performance of different models and workload configurations. One model with minimum inference latency can have a higher peak power consumption, while a lightweight model with a longer latency can have lower total energy consumption due to its lower power consumption. Thus, energy per inference should be viewed in conjunction with peak power, temperature rise and predictive accuracy. Thermal cost per inference can also be represented as $C_T = \frac{\int_0^{t_f} [T_c(t) - T_a(t)] dt}{N_i}$, where (N_i) is the number of completed

inferences, $T_c(t)$ is the component temperature and $T_a(t)$ is the ambient temperature. This is the measure of exposure to temperatures above ambient (in $^{\circ}\text{C s/inference}$), but not necessarily heat energy or safety for skin contact. Design-wise, thermal-aware controllers can reduce the frequency of inferences, choose models that are more efficient in computation or delay inference when the device is not operating in a critical condition, as the device temperature reaches a known operating bound.

However, some monitoring functions are safety critical and their scheduling priority must not be lowered to the extent that detection delay or the classification accuracy is compromised. Experimental observations may be affected by several limitations. Thermal transient measurements with the processor telemetry may be inaccurate or may not be sampled fast enough to capture the rapid thermal transients; external temperature sensors can create changes to the thermal transient processes in the local vicinity. Other factors may also create confounding effects, such as battery charge, geometry of the enclosure, skin contact, ambient airflow, and variable workload. In addition, data from one development board or wearable device does not necessarily represent the thermic properties of any other development board or wearable device. Future tests should therefore include multiple workload configurations, replicated tests, representative operating environments and calibrated sensors. Confidence intervals and appropriate significance tests should be used to quantify the statistical uncertainty, and practical improvements should be assessed without considering the statistical significance. Finally, a fixed-workload baseline should be used for comparison to see if thermal reductions can be achieved without reducing the inference reliability, responsiveness, or overall device functionality.

5. CONCLUSION

This paper proposed a structured experimental framework to assess thermal behavior and computational workload in AI-enabled wearable devices, which is a critical problem to provide reliable, low latency inference under limited energy, thermal and physical resources. The proposed method combines the methods of workload classification, synchronized telemetry acquisition, thermal responses measurement, energy estimation, inference performance analysis and statistical evaluation to build a comprehensive understanding of the device behavior under various operating conditions. The framework separates the processor temperature from the temperature of the surface of the enclosure and the ambient temperature, which allows for the more correct interpretation of heat transfer and heat accumulation. It has a mathematical definition that includes thermal resistance, thermal capacitance, thermal time constants, energy per inference, execution latency, throughput, accumulated thermal exposure and temperature rise, all of which allow for consistent metrics of comparing alternative AI models and execution strategies.

The integrated evaluation approach goes beyond just measuring the accuracy of the model and the speed of computation and looks at how workload intensity, power use, temperature changes, and sustained inference capability are related. These insights can help implement lightweight neural networks, adaptive inference scheduling, dynamic voltage and frequency scaling and thermal-aware

workload management without compromising the accuracy and response-time of an application. However, the proposed framework does not provide any finished hardware temperature reductions, energy savings, or performance improvements, so a quantitative assessment of these benefits needs to be validated with actual experiments. Future studies are needed to test several wearable platforms, enclosure designs, model designs, inference frequencies, and ambient conditions with calibrated sensors, repeated experiments, uncertainty quantification, and statistically valid comparisons. Future work must separate processor power from overall device power, and examine the impact of wireless communication, sensor acquisition, battery discharge and extended use. Using predictive thermal controllers based on regression or light recurrent neural networks may be further able to anticipate the temperature rise and adjust computational loads before thermal throttling.

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