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# EXPLORING MEMORY USE AND ENERGY CONSUMPTION ACROSS DATA MINING WORKLOADS ON ANDROID MOBILE DEVICES

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**Abstract:**

This analysis examines how computational workloads relate to energy consumption on Android devices, addressing the need to assess resource demands under constrained battery capacity. It uses 15 published experimental averages for three data mining algorithms executed on HTC Hero devices. Exploratory descriptive comparisons assess estimated energy consumption across input sizes, memory use, and processor occupancy. Energy consumption increased with input size within each algorithm, while memory use also increased across the observed conditions. For J48, the estimated energy requirement rose from 178.49 to 2,592.60 joules across the reported input sizes. Processor occupancy varied within a narrow range despite substantial differences in energy consumption. These patterns suggest that processor occupancy alone provides an incomplete account of workload energy requirements. Because input size and memory use changed together, their separate effects cannot be identified. The analysis contributes a focused secondary interpretation of published measurements and supports evaluating energy alongside resource use and execution time. The findings are limited to aggregated conditions and do not establish causal effects or generalize to other devices.

**Key Words:** Android Devices; Data Mining; Energy Consumption; Memory Use; Workload Analysis

## 1. Introduction:

Battery capacity constrains the amount of computation that can be performed on a mobile device. Data mining workloads place simultaneous demands on memory and processing resources, but the energy required to complete a task depends on more than the use of any single component. Understanding these demands can help developers assess whether a workload is feasible on a device and identify conditions that warrant closer energy measurement (Pramanik et al., 2019).

The relationship between workload size and energy consumption reflects the work required to process an input. Larger inputs may require more operations and longer execution, although the magnitude of the change depends on the algorithm. Comito and Talia (2017) examined data mining algorithms on mobile phones and reported increasing estimated energy consumption as input size grew. Their results also showed that memory consumption increased with input size, while processor occupancy remained comparatively stable. These concurrent changes make workload size relevant to interpreting both memory and energy measurements.

Memory use and processor occupancy describe different aspects of execution. Memory use indicates the space required by a workload, whereas processor occupancy indicates how much processor capacity is used during execution. Neither measure alone identifies the energy attributable to a component. Software design can change resource requirements: Alkandari et al. (2021) found that selected code changes affected processor and memory use in Android applications. Palomba et al. (2019) also reported differences in application energy consumption across software design conditions. Together, these findings indicate that resource measurements require interpretation in relation to the workload being executed.

Energy consumption is measured here as the estimated number of joules required for a reported workload condition. This measure captures accumulated energy rather than instantaneous processor occupancy or battery discharge rate. Its interpretation depends on the estimation method and execution duration. Research on mobile energy profiling distinguishes component measurements, application-level estimates, and finer measurements of software operations because each provides a different view of consumption (Ahmad et al., 2017; Hu et al., 2018). The available workload averages permit comparison of reported totals but do not identify the energy used by memory or processing separately.

The closest evidence is the original experiment reported by Comito and Talia (2017), which already examined the energy, memory, processor, and execution time requirements of mobile data mining algorithms. The present analysis does not claim to discover those relationships for the first time. Its contribution is a focused secondary examination of how the three reported workload measures correspond to energy across the published conditions. This comparison clarifies what can be observed jointly and what remains unresolved when input size, memory use, and execution behavior change together.

The empirical material comprises 15 reported averages for algorithm and input size conditions on HTC Hero devices. The analysis compares estimated energy consumption with input size, estimated memory use, and processor occupancy using descriptive comparisons. The observations provide a basis for examining patterns across the reported workloads, but they do not contain individual runs or sufficient variation to isolate

independent effects. Differences involving J48 also combine differences in algorithm and input dataset. These boundaries limit causal interpretation and transfer to other devices.

This study aims to examine how input data size, estimated memory use, and processor occupancy relate to estimated energy consumption across the reported Android data mining workloads. The research question asks how energy consumption varies with each measure across the observed conditions. The analysis seeks to describe the workload patterns and identify the measurement conditions needed for future comparisons that can separate their contributions.

The results inform a question that extends beyond one device: which workload information is needed to evaluate the energy requirements of mobile computation? The reported averages provide an exploratory basis for that question, while comparisons across devices and controlled workload conditions are needed to assess whether the observed patterns transfer.

**2. Theory, Conceptual Framework and Research Questions:**

Mobile computation depends on the interaction between software workloads and device resources. A data mining algorithm reads input data, uses memory, and requires processor time. Each activity may contribute to energy consumption, although its contribution depends on the algorithm and the device. Pramanik et al. in 2019 describe smart phone energy consumption as the combined result of hardware operation and software activity. Pereira et al. in 2021 show that device characteristics and patterns of use create substantial variation in battery consumption.

This analysis uses estimated energy consumption in joules as the outcome. Input data size, estimated memory use, and processor occupancy are observed measures for each algorithm and input size condition. They are not treated as indicators of a latent construct. The dataset contains 15 reported averages for three algorithms. It permits exploratory comparisons but does not establish independent causal effects. In particular, memory use and processor occupancy are observed during execution and may change with the workload.

Input data size represents the volume of information an algorithm processes. Larger inputs can require more operations and longer execution, which creates an expectation of higher energy consumption. The size of that association can differ across algorithms because their processing requirements differ. Comito and Talia in 2017 report that energy consumption increased with input size in their mobile data mining experiments. The present analysis examines the reported measurements as an exploratory relationship.

RQ1: How does estimated energy consumption vary with input data size across the observed algorithm conditions?

Estimated memory use represents the memory required during an algorithm execution. Larger workloads may occupy more memory while also requiring more computation. However, memory use alone does not identify the energy consumed by memory operations. Its association with total energy may also reflect input size and algorithm behavior. Alkandari et al. in 2021 found that changes in application code could affect memory and processor use, indicating that resource requirements depend on software design.

RQ2: How is estimated memory use associated with estimated energy consumption across the observed conditions?

Processor occupancy represents the proportion of processor capacity used during execution. Higher occupancy can indicate active computation, but total energy also depends on how long the computation continues. Similar occupancy levels may therefore accompany different energy values when execution times differ. Mehrotra et al. in 2021 found that application energy use varied across execution conditions and components, supporting the need to examine processor activity within its workload context.

RQ3: How is processor occupancy associated with estimated energy consumption across the observed conditions?

The framework links each observed workload measure to estimated energy consumption as an association. Algorithm and input dataset differ together for some observations, so their separate contributions cannot be identified from these data. The 15 averages provide limited evidence for generalization and do not support strong conclusions about adaptive memory management, battery discharge, or device aging.

**3. Data:**

This section establishes the provenance of the data, documents the analytical sample, and defines the observed measures. It also reports the checks performed and explains the scope of the exploratory analysis.

**3.1 Data Sources, Population, and Sample Construction:**

The analysis uses measurements reported by Comito and Talia (2017) in their study of data mining algorithms on Android mobile phones. Table 1 of the source reports estimated memory consumption, estimated energy consumption, processor occupancy, and execution time for different algorithm and input size conditions. The source describes repeated executions; the workbook contains reported averages rather than individual runs.

The published article and its available manuscript provide the source data. The workbook does not record a separate dataset release number, series identifier, exact extraction date, experimental observation dates, geographic location of the tests, or redistribution licence for the underlying measurements. The input datasets were Covertype and US Census 90. Their origins do not establish where the phone experiments took place.

The target population comprises data mining workload conditions that could be executed on Android mobile devices. The accessible sampling frame consists of the algorithm and input size conditions reported in the source table for HTC Hero devices. Each observation represents one reported average for an algorithm and input size condition. The resulting dataset is a cross section of experimental conditions.

All 15 conditions in the source table were transcribed into the workbook. They comprise four J48 conditions, five clustering conditions, and six Apriori conditions. The number of potentially eligible workloads outside the source table and the number of devices are not established.

| Stage | Units | Observations | Reason or rule |
|---|---|---|---|
| Accessible source table | 3 algorithms | 15 conditions | Conditions reported in Table 1 |
| Transcription into workbook | 3 algorithms | 15 conditions | All reported conditions retained |
| Exclusions during transcription | 0 algorithms | 0 conditions | No exclusions documented |
| Descriptive sample | 3 algorithms | 15 conditions | All records contain values for the reported variables |

**3.2 Data Integration, Cleaning, and Quality Assurance:**

The workbook was constructed from one published table. It does not combine datasets through a merge. Algorithm name and input size jointly identify the reported conditions. The same input size can appear under different algorithms and is not a duplicate by itself.

A review found no duplicate rows and no duplicate combinations of algorithm and input size. All seven recorded fields are populated for all 15 conditions. Decimal commas in the reported processor values for Apriori were represented as decimal points. No missing values were replaced with zero, and no imputation, interpolation, currency conversion, or frequency conversion was performed.

The extracted values were checked against the source table. No outlier removal or adjustment was documented. The maximum energy value was retained as reported because the summary data do not establish whether it is an error or a valid result. Smartphone energy estimates depend on the measurement approach and operating conditions; the source reports estimate rather than individual power traces (Pramanik et al., 2019).

The workbook does not establish whether the extraction rules were specified before the source table was inspected. No comparison with excluded conditions or alternative eligibility rules was performed. The sample reflects the conditions selected by the original authors and is not a representative sample of mobile workloads.

**3.3 Variable Measurement, Construction, and Validation:**

The outcome is estimated energy consumption in joules for an algorithm and input size condition. The focal workload measures are input data size, estimated memory use, and processor occupancy. Each measure was taken directly from the source table without normalization or construction of a composite index.

| Variable | Analytical Role | Definition and Construction | Source and Identifier | Unit | Transformation and Direction | Missing Value Rule | Coverage and Limitation |
|---|---|---|---|---|---|---|---|
| Estimated energy consumption | Outcome | Source reported estimated energy required for the condition | Comito and Talia, Table 1, EEC | Joules per condition | No transformation; higher values indicate greater estimated energy | None needed | 15 values; reported averages |
| Input data size | Predictor | Size of the data supplied to the algorithm | Comito and Talia, Table 1, dataset size | Megabytes per condition | No transformation; higher values indicate larger inputs | None needed | 15 values; available sizes differ by algorithm |
| Estimated memory use | Predictor | Source reported estimated memory consumption | Comito and Talia, Table 1, EMC | Megabytes per condition | No transformation; higher values indicate greater estimated memory use | None needed | 15 values; memory states are not separated |
| Processor occupancy | Predictor | Source reported processor occupancy during execution | Comito and Talia, Table 1, CPU | Percentage per condition | No transformation; higher values indicate greater occupancy | None needed | 15 values; variation is narrow |
| Algorithm | Grouping variable | Algorithm used in the reported condition | Comito and Talia, Table 1, algorithm | Category per condition | Three reported categories | None needed | 15 values; partly confounded with input dataset |
| Input dataset | Context variable | Data supplied to the algorithm | Comito and Talia, Table 1, dataset | Category per condition | Covertype or US Census 90 | None needed | 15 values; not separable from algorithm across all conditions |
| Execution time | Context variable | Source reported execution duration | Comito and Talia, Table 1, time | Seconds per condition | No transformation; higher values indicate longer execution | None needed | 15 values; energy accumulates over execution |

Memory use and processor occupancy are observed during execution rather than independently assigned treatments. Software design can affect both measures, supporting their treatment as workload dependent observations rather than fixed device properties (Alkandari et al., 2021).

The following descriptive statistics were calculated from the 15 workbook records. The standard deviation uses the sample denominator.

| Variable | Valid Count | Mean | SD | Median | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Input data size, megabytes | 15 | 0.73 | 0.84 | 0.40 | 0.10 | 3.20 |
| Estimated memory use, megabytes | 15 | 21.07 | 3.89 | 19.87 | 15.86 | 27.68 |
| Estimated energy consumption, joules | 15 | 385.45 | 651.34 | 179.82 | 2.82 | 2,592.60 |
| Processor occupancy, percent | 15 | 97.42 | 0.81 | 97.65 | 95.44 | 98.24 |
| Execution time, seconds | 15 | 959.60 | 2,068.34 | 300.00 | 6.00 | 8,160.00 |

The populated fields and transcription checks establish completeness of the extracted table. They do not independently validate the original estimates. No latent variable, interaction, moderator, or composite index was constructed. Mobile application energy measurements can vary with execution settings and component activity, but the source table does not contain all such settings for separate assessment (Mehrotra et al., 2021).

**3.4 Analytical Framework, Identification, and Reproducibility:**

The available analysis is descriptive and exploratory. It examines how reported energy estimates vary across input sizes, memory estimates, and processor occupancy values. The sample contains 15 aggregated conditions rather than individual executions.J48 is reported with Covertype, while the other algorithms are reported with US Census 90. An observed difference between J48 and another algorithm cannot therefore be attributed separately to the algorithm or the input dataset.

Energy accumulates over execution time, while memory and processor occupancy are recorded during execution. Their associations do not by themselves identify the energy attributable to memory or processor activity. Observed energy patterns require further controlled investigation before they can support causal explanations (Pereira et al., 2021).

The workbook preserves the transcribed values, variable names, units, source citation, and limitations. It can reproduce the descriptive statistics, but it does not contain the original individual runs or a documented extraction script. Independent replication of the original estimates would require the underlying measurements and measurement procedures.

**4. Methods:**

**4.1 Research Design and Analytical Strategy:**

The analysis used an exploratory secondary analysis of published experimental averages. Its purpose was to describe how estimated energy consumption varied with input data size, estimated memory use, and processor occupancy across the available mobile data mining conditions. The unit of analysis was one reported algorithm and input size condition.

The analysis used variation across input sizes within each algorithm to examine the first relationship. It then compared the corresponding memory and processor values with the energy estimates for those conditions. The comparisons describe observed patterns; they do not estimate causal effects. Input size, memory use, execution time, and energy may change together, and the available averages do not isolate their individual contributions (Comito & Talia, 2017).

**4.2 Sample and Measurement Alignment:**

The analytical sample comprised all 15 conditions extracted from Table 1 of Comito and Talia (2017): four J48 conditions, five clustering conditions, and six Apriori conditions. The source reports measurements from HTC Hero devices. The workbook contains condition averages, not observations for individual executions.

The source did not establish the exact observation period or number of devices in the extracted table. Estimated energy consumption was measured in joules per condition. Input size and estimated memory consumption were measured in megabytes, and processor occupancy was reported as a percentage. Execution time, measured in seconds, was retained as contextual information because total energy accumulates during execution. The sample construction table and variable dictionary specify the source fields and measurement limits.

The dataset does not identify the energy attributable to individual device components. It also does not allow algorithm and input dataset to be separated across all conditions: J48 used Covertype, while the other algorithms used US Census 90. These measurement and design boundaries restrict interpretation to the reported workloads.

**4.3 Data Processing and Descriptive Analysis:**

The published values were transcribed into a workbook and checked for missing fields and duplicate records. Algorithm and input size were used together to identify conditions. All 15 rows contained values for the variables used in the descriptive comparisons. No records were excluded, and no imputation, interpolation, or outlier removal was performed.

The analysis calculated the valid count, mean, sample standard deviation, median, minimum, and maximum for each numerical measure. It then grouped conditions by algorithm and ordered them by input size.

Within each group, the reported energy, memory, and processor values were compared across the available input sizes. The findings also compared the lowest and highest observed conditions for each algorithm.

The calculations used Python 3.12.14 and pandas 2.2.3. No transformations, weights, or composite scores were applied. The comparisons were exploratory and were conducted after the published results became available.

**5. Findings:**

The analysis examines how input data size, estimated memory use, and processor occupancy relate to estimated energy consumption across Android data mining workloads. The findings address the three research questions through exploratory comparisons of reported experimental averages. They identify patterns in the available conditions without claiming causal effects or model validation.

The analytical sample contains 15 algorithm and input size conditions: four J48 conditions, five clustering conditions, and six Apriori conditions. Each row is a reported average, rather than an individual execution. All five numerical measures were available for every condition. The source reports estimates from HTC Hero devices, but the individual run data, exact observation dates, and number of devices were unavailable (Comito & Talia, 2017).

Across the 15 conditions, estimated energy consumption had a median of 179.82 joules and ranged from 2.82 to 2,592.60 joules. Estimated memory use ranged from 15.86 to 27.68 megabytes. Processor occupancy ranged from 95.44% to 98.24%. These ranges describe the reported conditions and should not be interpreted as population estimates.

| Algorithm | Conditions | Input Size Range, MB | Memory Range, MB | Energy Range, Joules | Processor Occupancy Range, % |
|---|---|---|---|---|---|
| J48 | 4 | 0.1 to 0.8 | 19.47 to 27.68 | 178.49 to 2,592.60 | 96.23 to 98.21 |
| Clustering | 5 | 0.1 to 1.6 | 16.73 to 26.40 | 33.97 to 575.42 | 97.02 to 98.03 |
| Apriori | 6 | 0.1 to 3.2 | 15.86 to 26.92 | 2.82 to 310.36 | 95.44 to 98.24 |

Note: Values are reported condition averages extracted from Comito and Talia (2017). Energy and memory values are estimates. Clustering refers to the algorithm labelled K means in the source.

For RQ1, estimated energy consumption increased with input size within each algorithm. For J48, energy rose from 178.49 joules at 0.1 megabytes to 2,592.60 joules at 0.8 megabytes. Over the same input size range, the clustering estimate rose from 33.97 to 305.69 joules, while the Apriori estimate rose from 2.82 to 35.96 joules. These comparisons indicate that the magnitude of the increase differed across the observed workloads. They are consistent with the source authors' finding that input size was associated with energy requirements, but they do not establish a common rate of increase across algorithms (Comito & Talia, 2017).

For RQ2, estimated memory use and estimated energy consumption increased together across the reported input sizes within each algorithm. For J48, estimated memory use rose from 19.47 to 27.68 megabytes as estimated energy rose from 178.49 to 2,592.60 joules. The direction was also positive for the clustering and Apriori conditions. Input size increased at the same time, however, so the available comparisons cannot isolate an association between memory use and energy at a fixed input size. Evidence that software design can affect resource use supports treating memory use as a workload dependent measure rather than a separately assigned intervention (Alkandari et al., 2021).

For RQ3, processor occupancy did not show a consistent direction across algorithms. Within the Apriori conditions, occupancy was 96.92% at the lowest reported energy value and 95.44% at the highest. Within J48, the corresponding values were 96.23% and 97.36%. Occupancy remained within a narrow overall range while energy estimates varied substantially. This evidence does not establish that processor activity is unrelated to energy; it shows that occupancy alone does not account for the variation in these reported totals. Execution duration and other component activity may also matter to total consumption (Mehrotra et al., 2021; Pramanik et al., 2019).

The comparisons are exploratory and were calculated after the published results became available. Confidence intervals for the reported averages could not be calculated from the workbook because it does not contain individual run values or their dispersion. Differences between J48 and the other algorithms also combine differences in algorithm and input dataset. The findings therefore identify patterns in the recorded conditions but cannot determine independent causal effects or establish whether the patterns generalize to other devices. The need for controlled evidence before attributing observed battery patterns to particular device characteristics is also emphasized by Pereira et al. (2021).

**6. Discussion:**

Energy demand can rise sharply even when processor occupancy changes little. In the reported conditions, larger inputs were associated with higher estimated energy consumption within each algorithm, while processor occupancy remained within a narrow range. The analytical contribution is to bring input size, memory use, and processor occupancy together as complementary descriptions of the same workload. This comparison suggests that processor occupancy alone provides an incomplete account of total energy

consumption. The pattern was already reported in the source study, so the contribution is a focused secondary interpretation rather than a claim of a previously undocumented relationship.

Memory use and energy consumption increased together within each algorithm, but the available observations do not establish a transmission pathway between them. Input size also increased across those conditions, making it impossible to distinguish a memory association from other changes in the workload. This distinction matters for energy management: allocating more memory may accompany more intensive computation without being the sole source of its energy cost. Ahmad et al. (2017) show that energy estimation approaches differ in the level of detail they provide and in their measurement limitations. The present evidence therefore supports further measurement of memory activity, not a claim that memory reduction alone will reduce total energy.

The differences among algorithms point to workload design as a relevant context for interpreting energy estimates. At the same input size, the observed energy totals differed across the reported conditions, but algorithm effects cannot be separated fully from differences in input data. Palomba et al. (2019) found that particular software design practices were associated with different energy demands across Android applications. Their evidence concerns application code, whereas the present comparison concerns data mining workloads. Together, they suggest that energy assessment should specify what software does and what data it processes before results are transferred to another setting.

The narrow processor occupancy range reveals a practical measurement challenge. Two conditions can report similar occupancy while differing in execution duration and estimated energy, so occupancy should not be used alone as a substitute for energy measurement. Hu et al. (2018) show how analysis at the level of application methods can provide more detailed information about where energy is used. The present data lack that level of detail and cannot identify the contribution of individual operations or components. Future measurement should therefore record energy and execution time alongside memory activity for the same runs.

The findings have relevance wherever data intensive computation is performed on resource constrained devices. They suggest that developers should compare workload energy requirements across feasible input sizes and algorithms under the intended operating conditions. They do not establish that one algorithm will be preferable on other devices or datasets. A next test would vary input size and algorithm while holding the device and input dataset constant, then repeat the experiment across devices. Such a design could determine whether the observed patterns persist and whether memory activity adds explanatory value beyond workload size and execution time.

**7. Conclusion and Implications:**

Energy efficiency matters wherever mobile devices perform demanding computational tasks under limited battery capacity. This analysis shows that resource demands must be considered together when interpreting the energy required to complete a workload. Larger workloads were associated with greater estimated energy consumption, while similar levels of processor activity accompanied different energy totals. The contribution is a focused secondary interpretation of published experimental averages that brings these observations into a common analytical framework. It does not establish a new causal mechanism, but it illustrates why a single resource indicator provides an incomplete basis for evaluating energy demand. For developers, the practical implication is to assess energy requirements under the intended workload and device conditions, alongside execution time and other resource measures. Such comparisons can inform choices about task scheduling and the size of inputs processed on a device. For organizations designing mobile services, the findings support evaluating energy requirements as part of application testing rather than relying on processor activity alone. These considerations are relevant across settings where users depend on battery powered devices, although the available evidence does not establish that the reported patterns apply to every device or application.

The analysis draws on 15 published condition averages from one device model. The absence of individual run measurements and the overlap between algorithm and input dataset restrict causal interpretation and generalization. Future research can extend the evidence through repeated measurements across device models while varying workload size and algorithm under controlled conditions. Recording component activity, execution time, and energy for each run would allow researchers to examine whether the observed associations persist and whether particular resource demands explain differences in total consumption. These extensions would provide a stronger basis for evaluating energy management strategies across technological environments.

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