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Design Project – Consulting Report

PROJECT OVERVIEW AND FINAL RECOMMENDATIONS

IBEHS 4P03 – Health Solutions Design Projects IV

Tutorial T02

Team 10

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Executive Summary

The Rehabilitation Centre for Children (RCC) currently faces substantial inefficiencies in battery testing, documentation, and maintenance due to unstandardized procedures, incomplete data records, and manual record-keeping practices, as noted in an interview with S. Klatt, Oct 28, 2025. These gaps result in redundant battery testing, delayed equipment readiness, and limited visibility into actual battery health.

The primary action plan proposes developing a centralized web-based battery inventory and logging system, along with a battery health modelling AI, to replace the RCC's current inefficient testing practices. The web application would assign unique IDs to all batteries, store standardized testing records, and make these logs accessible to all 250+ RCC staff, improving coordination and reducing repeated testing. The next component adds a machine-learning battery health model using Amazon's *Chronos-2* to forecast battery condition, predict failure dates, and recommend proactive testing at one-third of the estimated lifespan, allowing staff to identify declining batteries before failure. This model would strengthen battery management by providing accurate, data-driven assessments based on both historical and public data. The final component introduces a standardized battery testing procedure that collects a comprehensive health assessment, including temperature, charge/discharge cycles, and partial/full charges, and stores these protocols within the web application to ensure consistent testing practices. Labour requirements for this plan are minimal: development, testing, and deployment can be completed by existing RCC staff without hiring external developers. The pre-trained Chronos-2 model reduces labour and technical burden by requiring only standardized input data from staff. By relying entirely on internal staff, the primary action plan remains economically viable, with a net present value of $27,153.50.

However, a broader feasibility assessment reveals that this plan relies on several critical assumptions, including sufficient internal expertise, staff capacity, and the availability of reliable historical battery data, that may not hold in practice. These dependencies introduce risks that outweigh the potential benefits in terms of feasibility. Alternatively, utilizing a custom in-house model and hiring an external team of professionals could alleviate these feasibility concerns; however, this approach would be economically impractical, significantly increasing development

costs, training requirements, and long-term maintenance expenses. Consequently, our final recommendation is to maintain the current system rather than proceed with implementation. A "do nothing" strategy avoids the financial, workflow, and training risks associated with adopting a complex technological solution without the necessary foundational resources.

Background

The purpose of this consulting project was to analyze and propose the best plan of action for the RCC to address the problem of uncoordinated and unstandardized battery testing leading to poor management and assessment of batteries.

The Rehabilitation Centre for Children, based in Manitoba, Canada, is a clinic that specializes in providing clinical services, assistive technologies, education, and research to disabled children and their families in order to support them in daily life and help them grow and thrive [1]. The RCC is a large organization, with $19,000,000 in revenue and $18,300,000 in expenses as of 2021, and with operations spanning across or even beyond the province of Manitoba [2]. The RCC also works in collaboration with other organizations such as the Winnipeg Regional Health Authority, Manitoba Health, and the Canadian National Institute for the Blind [1].

Our consulting work focused on the electronics department of the RCC. The electronics department contributes to the assistive technology area of the RCC, producing a variety of electronic devices for children by fitting clinical products, modifying consumer products, or even custom designing and fabricating solutions in-house using tools like 3D printers or CNC plasma cutters. The types of devices produced include wheelchairs, accessible input devices, and eye-gaze communication systems [3].

The team's contact in the electronics department of the RCC is Stephen Klatt. Stephen Klatt has been with the RCC for about 5 months as a Clinical Technologist, specializing in electronics engineering. He has a Master's of Physical Therapy and a diploma in electrical engineering technology, and has worked in the past in a technologist capacity on hydro, aerospace, and radiology technology [4]. Clinical technologists are responsible for maintaining and operating healthcare equipment, while electrical engineers design, develop, and test electronic systems [5], [6]. An example of Stephen's work with the RCC at the intersection of these two fields is switch modification, where buttons on toys are wired up to larger external interfaces so that children with motor or sensory disabilities can play with them [3].

One of Stephen's responsibilities, and a responsibility of the electronics department as a whole, is the management of the RCC's stock of batteries. Many of the assistive devices require batteries to operate, the most important of which are proprietary rechargeable lead-acid batteries for the largest devices, such as wheelchairs, scooters, ride-on cars, and other child-sized vehicles, per an email from S. Klatt, Oct 2, 2025. The reliability of these devices is crucial, as any device failures can impair the everyday lives of children who depend on them for their mobility. In turn, battery reliability is also crucial, because failed proprietary lead-acid batteries cannot be easily replaced by families at home and will thus cause a major device failure. As devices are sent out for families to use in an outpatient setting for periods of months, it must be ensured that batteries are functional not just in the present, but also that they will remain functional well into the future [3].

To do this, tests must be done to check each battery's health. However, there is currently no standard of battery testing for Stephen and his coworkers to follow at the RCC. Battery testing is done by volunteers on an irregular schedule. They do not follow standardized testing procedures and only take measurements of battery voltage under load, which is insufficient data to model battery health. They record the data on paper, which can only be accessed locally, and do not record when the data was taken or how it was taken. As such, electronics department staff struggle to assess battery health and often conduct additional battery testing when a battery is requisitioned to double-check each battery's voltage under load, per an interview with S. Klatt, Oct 28, 2025.

This disorganization is what results in battery health being poorly tracked and predicted, necessitates redundant testing leading to time loss, and risks battery failure during device operation, creating inefficiencies and losses at the RCC. The plan of action proposed by this consulting project is intended to address these issues, improving results for both the RCC's staff and patients.

Objectives

Table I: List of design inputs with their corresponding problem requirements.

Problem Requirements	Design Inputs
Should be able to receive relevant battery data inputs for decision-making	Should be able to receive battery data inputs, including **battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age data** [7], [8].
Should provide accurate battery health information	Should be able to estimate battery health information **within ±10% accuracy of reality** [8].
Should provide comprehensive battery health information	Should provide information on **remaining battery lifetime and expected battery reserve time** [8].
Should provide an accurate battery testing schedule	Should recommend additional battery testing **at a date that is 1/3 of the way to the estimated failure date** [8].
Testing procedures should gather relevant battery data	Testing procedures should gather **battery voltage under load, environmental temperature, and number of charge and discharge cycles, number of times partially charged, and number of times fully discharged** [7], [8].
Should keep comprehensive historical logs of battery data	Should keep comprehensive historical logs of **past battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age** [7], [8].
Should be able to separately manage logs of multiple batteries	Should be able to separately manage logs of **at the minimum 30 batteries or more,** per email (S. Klatt, personal communication, Oct 2, 2025)
Should be able to be operated and take inputs	Should be able to take inputs from **at the**

from multiple RCC staff	**minimum 300 RCC staff or more** [9].
Should provide data that is accessible and readable by multiple RCC staff	Should provide data that is accessible and readable by **at the minimum 300 RCC staff or more** [9].

Aim Statements

Aim Statement 1: The battery health modelling AI should accept as inputs battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age data and be able to use them to calculate estimates for battery health data [7], [8].

Baseline: Currently, the battery data gathered and used by the RCC for battery health analysis only consists of voltage under load, per an interview with S. Klatt, Oct 28, 2025. This results in an incomplete assessment of battery health.
Target: The creation of a battery health modelling AI that could incorporate and utilize all the above listed data to assess battery health would result in more scoping and accurate assessments of battery health [7], [8].
Timeline: This capability should be **immediately** part of the battery health modelling AI's functionality on launch.

Aim Statement 2: The estimates of battery health made by the battery health modelling AI should be accurate to within ±10% of reality, assuming accurate battery data inputs.

Baseline: Currently, estimates of certain key metrics of battery health are completely absent at the RCC, per an interview with S. Klatt, Oct 28, 2025.
Target: A target accuracy range of +/- 10% would align with established standards set by existing battery health modelling softwares [8].

Timeline: Even though the battery health modelling AI should be able to give estimations immediately, achieving the accuracy target might be **moderately delayed** as the AI model refines itself and the accuracy of its predictions over time.

Aim Statement 3: The estimates of battery health made by the battery health modelling AI should include estimated metrics on remaining battery lifetime and battery reserve time.

Baseline: Currently, battery health assessment done by the RCC only returns the metric of voltage under load at the immediate moment, per an interview with S. Klatt, Oct 28, 2025. This does not adequately describe battery health.
Target: The creation of a battery health modelling AI, which could return metrics on estimated remaining battery lifetime and battery reserve time would more completely describe battery health for the RCC's purposes [8].
Timeline: This capability should be **immediately** part of the battery health modelling AI's functionality on launch.

Aim Statement 4: The battery health modelling AI should recommend a date 1/3 of the way to a projected battery's failure for additional testing of that battery.

Baseline: Currently, battery testing at the RCC is only done when needed. When a battery is requested for use, batteries will be tested until one with an adequate voltage for use is found. This may uncover several failed batteries, delaying battery acquisition. This was confirmed in an interview with S. Klatt, Oct 28, 2025.
Target: The targeted recommendation of battery testing 1/3 of the way through the battery's projected lifetime is supported by existing data demonstrating exponential decay of a battery's voltage as it ages, and would thus avert delays caused by battery failure when a battery is needed [8].
Timeline: This capability should be immediately part of the battery health modelling AI's functionality on launch, but is **constrained by the moderate delay of Aim Statement 2** with respect to the accuracy of battery lifetime estimates.

Aim Statement 5: The testing procedures used to gather information for the battery health modelling AI should gather relevant data, including battery voltage under load, environmental temperature, and number of charge and discharge cycles, number of times partially charged, and number of times fully discharged [7], [8].

Baseline: Currently, the battery data gathered by the RCC for battery health analysis only consists of voltage under load, per an interview with S. Klatt, Oct 28, 2025. This is insufficient information for the battery health modelling AI to make predictions off of.
Target: The targeted standards for battery testing procedures would provide a more comprehensive suite of battery health data, which would be able to inform the battery health modelling AI's estimations [7], [8].
Timeline: These testing procedures should be instituted **immediately** in order to ensure the battery health modelling AI has the data it needs to function.

Aim Statement 6:There should be digital logs made of battery data that document past battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age [7], [8].

Baseline: Currently, the RCC's logs consist only of physically labelling each battery with its voltage taken at the time of the most recent test, per an interview with S. Klatt, Oct 28, 2025. This is insufficient data to describe battery health and an insufficient timeframe to describe trends in battery health.
Target: The targeted standards for battery data logs would more completely describe battery health trends over time, allowing for analysis and verification of the battery health modelling AI's estimations of battery health [7], [8].
Timeline: Logs of battery data should be created **nearly immediately.** This aim is constrained by Aim 5 because it can only be achieved after the new battery testing procedures are conducted for the first time, which is an immediate aim.

Aim Statement 7: The digital logs of battery data should be able to separately manage the logs of at least 30 batteries sorted by ID, with the ability to add additional batteries in the future.

Baseline: Currently, the RCC is in possession of 29 batteries, and keeps logs of each battery by physically labelling the battery with the most recent test results, which is a disorganized and informal way to keep logs, per an interview with S. Klatt, Oct 28, 2025.
Target: The targeted standards for battery data logs would be able to more effectively sort and store information on each individual battery by ID for RCC use and future-proof the logs to the addition of more batteries.
Timeline: Logs sorted by battery ID should be created **immediately.**

Aim Statement 8: The battery health modelling AI should be able to be operated via the input of battery data by at least 300 RCC staff.

Baseline: Currently, there is no coordinated form of battery testing among RCC staff, which leads to irregular and confusing battery tests, per an interview with S. Klatt, Oct 28, 2025.
Target: The targeted supported user count would allow all 250+ staff of the RCC to be able to operate the battery health modelling AI [9], although only a subset of RCC staff are responsible for battery testing. RCC staff responsible for battery testing would benefit from improved coordination through the use of a shared software.
Timeline: This capability should be **immediately** part of the battery health modelling AI's functionality on launch.

Aim Statement 9: The battery health modelling AI should be able to be accessed and provide battery health data estimates to at least 300 RCC staff.

Baseline: Currently, there is no coordinated form of battery data distribution among RCC staff, which leads to inaccessible and limited battery data, per an interview with S. Klatt, Oct 28, 2025.

Target: The targeted supported user count would allow all 250+ staff of the RCC to be able to access the battery health modelling AI [9]. Many departments of the RCC could benefit from access to health estimates of the batteries used in the RCC's assistive devices.

Timeline: This capability should be **immediately** part of the battery health modelling AI's functionality on launch.

Plans of Action

The current battery management practices at the RCC are characterized by an incomplete assessment of battery health, disorganized physical logs, and a lack of standardized testing, which leads to significant inefficiencies and delays in identifying failed batteries. To resolve these core issues and meet the stated aims, the project proposes the development of a comprehensive web application and battery health modelling system. This integrated software establishes a centralized, digital inventory and record-keeping system, replacing informal physical labels and ensuring the coordination of new, standardized testing procedures. Its central component is a battery health modelling AI, which is designed to accept a comprehensive suite of battery data inputs and generate accurate, proactive health estimates (such as remaining lifetime and recommended future testing dates) that are accessible to all 250+ RCC staff. The two action plans diverge on the strategy for developing this core AI model and managing the necessary labour: the primary plan focuses on integrating a fine-tuned, pre-trained model like Amazon's *Chronos-2*, while the alternative plan proposes developing a custom, in-house solution.

Primary Action Plan

The preliminary action plan aims to improve the RCC's battery testing quality and organization to reduce time lost to battery management. The first component is to create centralized logs and an inventory of the RCC's battery stock. Currently, the RCC's battery inventory is available only locally and contains limited, unstandardized battery information, such as battery capacity and the last full battery charge. The current system involves testing the batteries when needed for a project and tracking battery information by placing sticky notes on the batteries, which can quickly become unorganized and burdensome. This was confirmed in an interview with Stephen Klatt, Oct. 28, 2025. This is an inefficiency leading to time loss for both battery testers and technicians.

This solution would take the form of a web application that manages battery inventory, storing logs and test procedures for the variety of batteries used at the RCC. The web application solution will assign IDs to all batteries entered into the application, requiring that each battery's model, manufacturer, and serial/model number be entered before it can be registered into the database. Once a battery is registered in the system, the web application will allow the user to create new testing records in which the following information can be tracked: the applied load used during the test, the date the test was conducted, the duration of the test, the voltage drop observed over time, and the total battery health/capacity. The application will require all battery testing information to be recorded before submitting a new testing record to the database, ensuring all records are complete. In addition to tracking battery inventory and testing, the web application will store available battery testing instructions/procedures based on the battery type and model. By creating an inventory and logs, they can improve the RCC's ability to manage and coordinate their battery testing to cut down on redundant testing. Instead of technicians having to re-test batteries to verify or clarify the work of battery testers, they can simply refer to the logs and inventory for all the information they need. The web application would be available to access or update online by the RCC's 250+ staff, per Aims 8 and 9. This provides users with a centralized reference point for proper testing and maintenance protocols, ensuring consistency across all procedures and reducing the likelihood of human error. Furthermore, it helps facilitate knowledge transfer among technicians, enhancing efficiency by making documentation readily available to all users. The inventory would need to be able to sort data for and identify the RCC's 29 batteries, with room to account for more batteries in the future, per Aim 7. The logs would need to hold data on past battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age, per Aim 6. Overall, the use of the web application will provide an organized and easily accessible solution to their current lack of maintenance. In creating this inventory, they make the assumption that the RCC can provide the equipment to support, access, and interface with the digital inventory to all of its staff. They are limited by the fact that the logs must be, to a partial degree, usable and readable by the general RCC staff, not all of whom have electronics training. They are constrained by the RCC's incomplete battery data logs until present, such as a lack of past age data or usage data for their batteries, so the logs may not be comprehensive.

The second component is the development of a battery health modelling AI. This model will be central to improving the RCC's battery management by providing accurate and comprehensive health assessments based on historical and future data. Currently, the RCC can only estimate battery health at the current time based on present voltage under load, which does not adequately describe battery health or predict future battery health. For the battery health modelling AI, Amazon's Chronos-2 would be integrated into a web application through an API that connects the app's backend to the model. When new battery test results are entered, the backend can automatically collect recent data from the database, sending it to the model in a structured format. The model then analyzes trends to calculate estimates for battery health metrics, such as remaining battery lifetime and expected battery reserve time, as mentioned in Aim Statement 3. This will improve the RCC's knowledge of their batteries' health. The AI will accept a comprehensive suite of battery data inputs as outlined in Aim Statements 1 and 5, including battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age. AI prediction will target an accuracy of ±10% of reality and will proactively recommend additional battery testing at a date one-third of the way to the estimated failure date, addressing Aim Statements 2 and 4. These insights will be sent back to the application and displayed on a dashboard. Research shows that AI-powered predictive maintenance offers substantial improvements in operational efficiency, maintenance cost reduction, and reliability across various industrial applications [10]. While reusing a pre-trained model offers a cost-effective and efficient alternative to developing a custom one, their use of Chronos-2 within the web application assumes that all battery test data entered is accurate. Additionally, this approach is constrained by the need to protect sensitive data when communicating with the API. They are also constrained by the RCC's incomplete battery data logs until present, such as a lack of past age data or usage data for their batteries, so the AI cannot be given a full selection of data in the early stages of the action plan's implementation, per email communication with S. Klatt, Oct. 2, 2025.

The development of this application requires a secure and scalable hosting environment to support data storage. Amazon Web Services (AWS) will be utilized to host the web application and database, ensuring it is scalable and secure. This approach leverages the existing AWS infrastructure, including services like Sagemaker for fine-tuning the Chronos-2 AI model, which was found on Hugging Face. This integration allows for efficient data management, AI model deployment, and secure access for over 300 RCC staff members.

The labour required to implement this system is more cost-effective than contracting the work out and can be developed and managed by existing staff. Initial setup would involve dedicated work from the current development or IT team to develop a web application with a simple user interface, connecting the web application to the fine-tuned model. Staff would continue routine data collection by entering battery test information that can be used by the model. Additionally, the model will access publicly available data based on the battery models within the database. Ongoing work would mainly involve periodic system monitoring, refinement, and minor updates to improve prediction accuracy. Overall, the project requires a moderate technical effort and regular data entry, making it feasible without additional hiring.

The third and final component is the development and implementation of new battery testing procedures to provide the data needed for the AI model and battery logs. Currently, there is no standardized battery testing procedure, and the only data taken during battery testing is voltage under load, per an interview with S. Klatt, Oct 28, 2025. This leads to incomplete estimates of battery health. Per Aim Statement 5, the new testing procedure should take not only battery voltage under load, but also environmental temperature, number of charge and discharge cycles, number of times partially charged, and number of times fully discharged.

Battery voltage under load is already taken by the RCC, using the BK Precision 8540 150W DC Electronic Load, per email communication with S. Klatt, Oct. 2, 2025. Environmental temperature can be taken in the RCC's dedicated battery charging rooms with a thermometer. The number of charge and discharge cycles, partial charges, and full discharges can be taken and summed after each time a battery is sent out for use. This would be done via a questionnaire given to the RCC patients and their families regarding how many days the device was used, how many times it died, how many hours it was charged each night, and other such behaviours from which relevant data can be inferred. This questionnaire would be written in conjunction with RCC staff to ensure that it suits the RCC's purposes.

In creating these testing procedures, they make the assumption that the RCC's testing instruments are accurate and reliable. They are limited by the RCC patients' inevitably imperfect recall of their device usage, which introduces error into the charge and discharge cycle count, partial charge count, and full discharge count. They are constrained by the available person-hours that the RCC has available to run these expanded testing procedures, which is so far only guaranteed to be one person working several hours per week, per an interview with Stephen Klatt, Oct. 28, 2025.

This overall project is constrained by the RCC's budget limitation of $3000 and their existing workforce, since the RCC cannot afford to hire additional personnel.

Alternative Action Plan

Similar to the primary action plan, the alternative action plan consists of the same core web application solution; however, it differs in the development of the AI model and the labour approach. Rather than using a fine-tuned, pre-trained model like Chronos-2, a custom model would be developed in-house.

Additionally, integrating a custom AI model into the web application can leverage historical test data and publicly available data on in-house batteries to predict the expected deterioration date and recommend future testing schedules. The in-house model would be trained using historical and real-time battery data collected by the RCC, resulting in a more specialized, fine-tuned predictive system tailored to the specific characteristics of the batteries used. However, this approach is limited by the lengthy data collection period, which could delay implementation and limit the model's initial accuracy due to the lack of sufficient training data. In creating this AI model, we make the assumption that the RCC can provide sufficient computational power and storage space to run the AI. Similar to the primary action plan, we are constrained by the RCC's incomplete battery data logs until present, so the AI cannot be given all the necessary information at first, per email communication with S. Klatt, Oct. 2, 2025.

Regarding the labour required, a team of professionals based in Canada is needed to manage and execute the development of the web application. A project manager is required to oversee the entire development process and coordinate between technical specialists to ensure the project's requirements are met. A UX designer is essential for creating an intuitive and user-friendly experience, focusing on user research, wireframing, and prototyping. A full-stack developer is essential for developing both front-end and infrastructure aspects of the web application. This would include designing the user interface, setting up and maintaining backend infrastructure, and configuring the AWS environment required to support the application. Finally, a machine learning engineer will handle all AI-related aspects of the project, including initial data collection, model training, testing, and integration into the web application. This approach assumes sufficient funding for domestic hiring and access to technical expertise within the country. By employing locally, the project benefits from easier coordination between specialists. However, this would introduce higher labour costs, thus increasing the overall project budget. Building a custom AI model can create a system that’s better suited to a specific domain and more precise overall. However, this approach also requires a large amount of data, strong computing power, and a team with the right technical skills to train and maintain it [11].

Do Nothing Scenario

In the do-nothing scenario, no web application would be developed, and the organization would continue relying on existing manual methods for tracking battery maintenance and documentation. This approach assumes that current processes can continue to sustain basic operations; however, it presents limitations in efficiency and consistency. Without a centralized database, battery testing data will remain unorganized, incomplete, or prone to error, leading to missed maintenance schedules and preventable equipment failures. Additionally, this scenario would result in unnecessary delays. Research suggests that manual inventory management can result in excessive inventory errors as there is an increased likelihood of human error [12]. Without the AI-predictive aspects, future testing schedules and early detection of declining battery health will need to be conducted manually, which may increase the likelihood of human error and reduce the efficiency and reliability of maintenance operations.

Economic Analysis of Plans of Action

The primary and alternative action plans present distinct approaches to solving the RCC's battery management challenge, differing primarily in the strategy for the battery health modelling AI development and the associated labour costs. To determine the financially superior option, a rigorous economic analysis is required. This analysis will use Net Present Value (NPV) calculations to evaluate the long-term financial viability of each plan over a projected four-year lifespan, factoring in initial implementation costs, ongoing operational expenses, and quantifiable expected benefits derived from improved efficiency and reduced battery failure. A four-year projection was chosen to ensure the project with the longer development phase achieves a steady state, allowing for a valid comparison of scaling costs across at least two years of deployment.

The NPV is calculated using the formula:

$$\mathrm{NPV} = \sum_{n=1}^{N} \frac{F_n}{(1+i)^n}$$

where:

- F_n is the net future value at a given cash flow period,
- N is the total number of cash flow periods,
- i is the required rate of return per cash flow period.

The projects were evaluated at an 8% MARR, corresponding to a rate of return of 0.67% per cash flow period.

Primary Action Plan

The Net Present Value analysis for the Primary Action Plan was performed using the following set of receipts and disbursements. Key assumptions and sources for these values can be found in Key Assumptions for Economic Analysis.

Table II: List of receipts for the Primary Action Plan.

Cash Flow Description	*Cash Flow Type*	*Period (Single Flows)*	*Interval (Annuities)*	*Amount (CA$)*
(1) Initial RCC Seed Grant	Single Cash Flow	n = 0	N/A	$3,000
(2) Estimated Operational Savings	Annuity	N/A	Monthly (n = 6 onwards)	$832.80

Table III: List of disbursements for the Primary Action Plan with indication of fixed and variable costs.

Cash Flow Description	*Cash Flow Type*	*Variable or Fixed Cost*	*Period (Single Flows)*	*Interval (Annuities)*	*Amount (CA$)*
(3) AWS Development Cost (SageMaker)	Annuity	Variable	N/A	Monthly (n = 1 - 4)	$274.18
(4) AWS Operations Costs (Year 2)	Annuity	Variable	N/A	Monthly (n = 12 - 23)	$2.57
(5) AWS Operations Costs (Year 3)	Annuity	Variable	N/A	Monthly (n = 24 - 35)	$2.96
(6) AWS Operations Costs (Year 4)	Annuity	Variable	N/A	Monthly (n = 36 - 47)	$3.40

(1) This is the initial starting grant amount provided by the RCC for the project.
(2) Productivity gains from digital inventory management were estimated as a monthly annuity. Key assumptions for this annuity are highlighted in Assumptions on Monetization of Saved Time.
(3) SageMaker costs were determined using the 14-week model development phase and AWS costs with assumed usage. Key assumptions are outlined in Assumptions on Application Development.
(4) - (6) Operational costs were based on a conservative 15% growth rate for AWS usage. Key assumptions are outlined in Assumptions on Application Usage and Costs.

The Net Present Value of the Primary Action Plan amounts to **$27,153.50**. Below is the cash flow diagram:

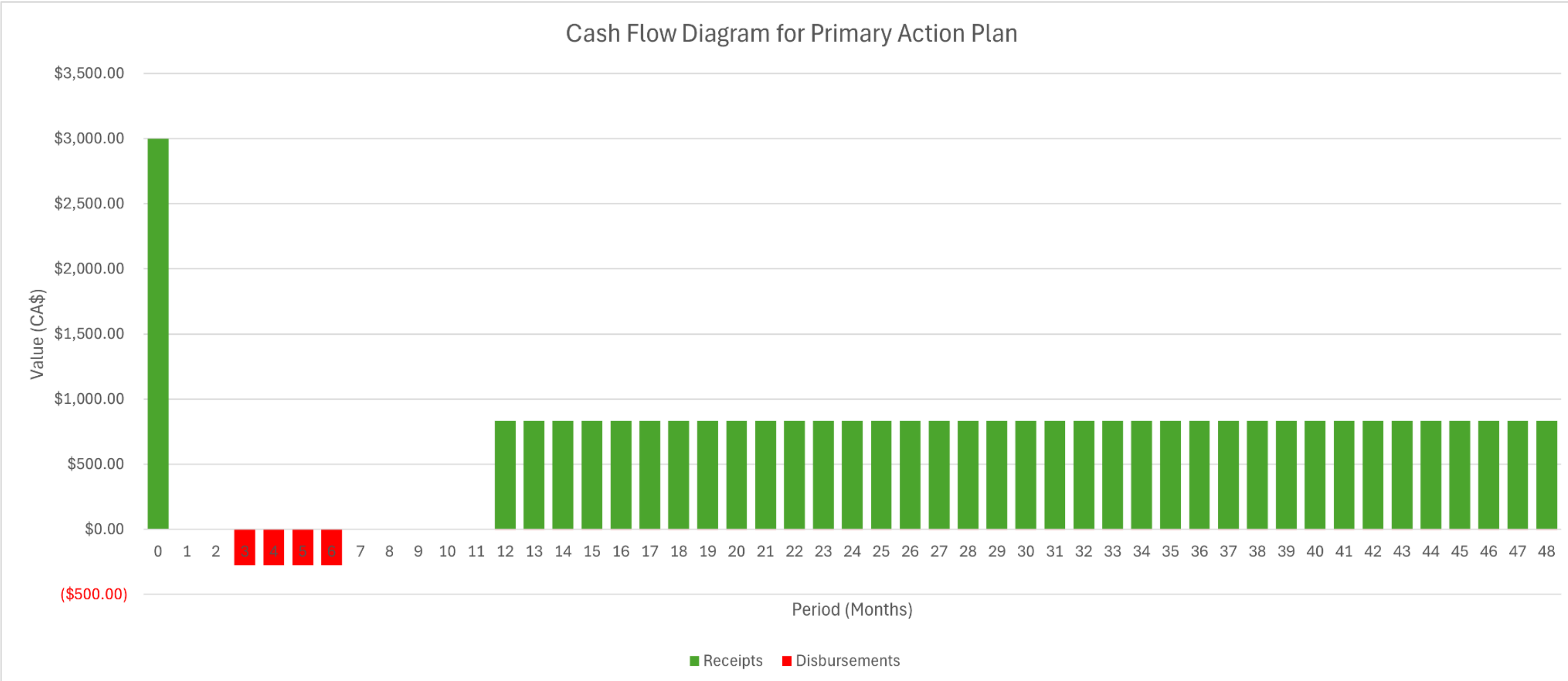

Fig 1. Cash flow diagram for the Primary Action Plan.

Alternative Action Plan

The Net Present Value analysis for the Alternative Action Plan was performed using the following set of receipts and disbursements. Key assumptions and sources for these values can be found in Key Assumptions for Economic Analysis.

Table IV: List of receipts for the Alternative Action Plan.

Receipts				
Cash Flow Description	*Cash Flow Type*	*Period (Single Flows)*	*Interval (Annuities)*	*Amount (CA$)*
(1) Initial RCC Seed Grant	Single Cash Flow	n = 0	N/A	$3,000
(2) Estimated Operational Savings	Annuity	N/A	Monthly (n = 6 onwards)	$832.80
(3) CSBFP Loan	Single Cash Flow	n = 0	N/A	$450,000

Table V: List of disbursements for the Primary Action Plan with indication of fixed and variable costs.

Disbursements					
Cash Flow Description	*Cash Flow Type*	*Variable or Fixed Costs*	*Period (Single Flows)*	*Interval (Annuities)*	*Amount (CA$)*
(4) AWS Operations Costs (Year 3)	Annuity	Variable	N/A	Monthly (n = 25 - 36)	$2.57
(5) AWS	Annuity	Variable	N/A	Monthly (n = 37 -	$2.96

Operations Costs (Year 4)				48)	
(6) CSBFP Registration Fee	Single Cash Flow	Fixed	n = 0	N/A	$9,000
(7) Loan Repayments	Annuity	Fixed	N/A	Monthly (n = 1 onwards)	$5,329.84
(8) Salaries - Technical Project Manager	Annuity	Fixed	N/A	Monthly (n = 1 - 12)	$11,200.00
(9) Salaries - UX Designer	Annuity	Fixed	N/A	Monthly (n = 1 - 12)	$6,560.00
(10) Salaries - Full-Stack Developer	Annuity	Fixed	N/A	Monthly (n = 1 - 12)	$9,600.00
(11) Salaries - Machine Learning Engineer	Annuity	Fixed	N/A	Monthly (n = 13 - 24)	$10,056.00

(1) This is the initial starting grant amount provided by the RCC for the project.
(2) Productivity gains from digital inventory management were estimated as a monthly annuity. Key assumptions for this annuity are highlighted in Assumptions on Monetization of Saved Time.
(3) Canadian Small Business Financing Program loan via the Assiniboine Credit Union over ten years.
(4) - (5) Operational costs were based on a conservative 15% growth rate for AWS usage. Key assumptions are outlined in Assumptions on Application Usage and Costs.
(6) Registration fee for the CSBFP Loan is 2.0% of the loan amount.

(7) Monthly loan repayments. Information is outlined in Information on Loan Financing for Alternative Action Plan.
(8) Average salary for a Technical Project Manager in Canada. See Assumptions on Application Development.
(9) Average salary for a UX Designer in Canada. See Assumptions on Application Development.
(10) Average salary for a Full-Stack Developer in Canada. See Assumptions on Application Development.
(11) Average salary for a Machine Learning Engineer in Canada. See Assumptions on Application Development.

The Net Present Value of the Alternative Action Plan amounts to **-$179,939.59**. Below is the cash flow diagram:

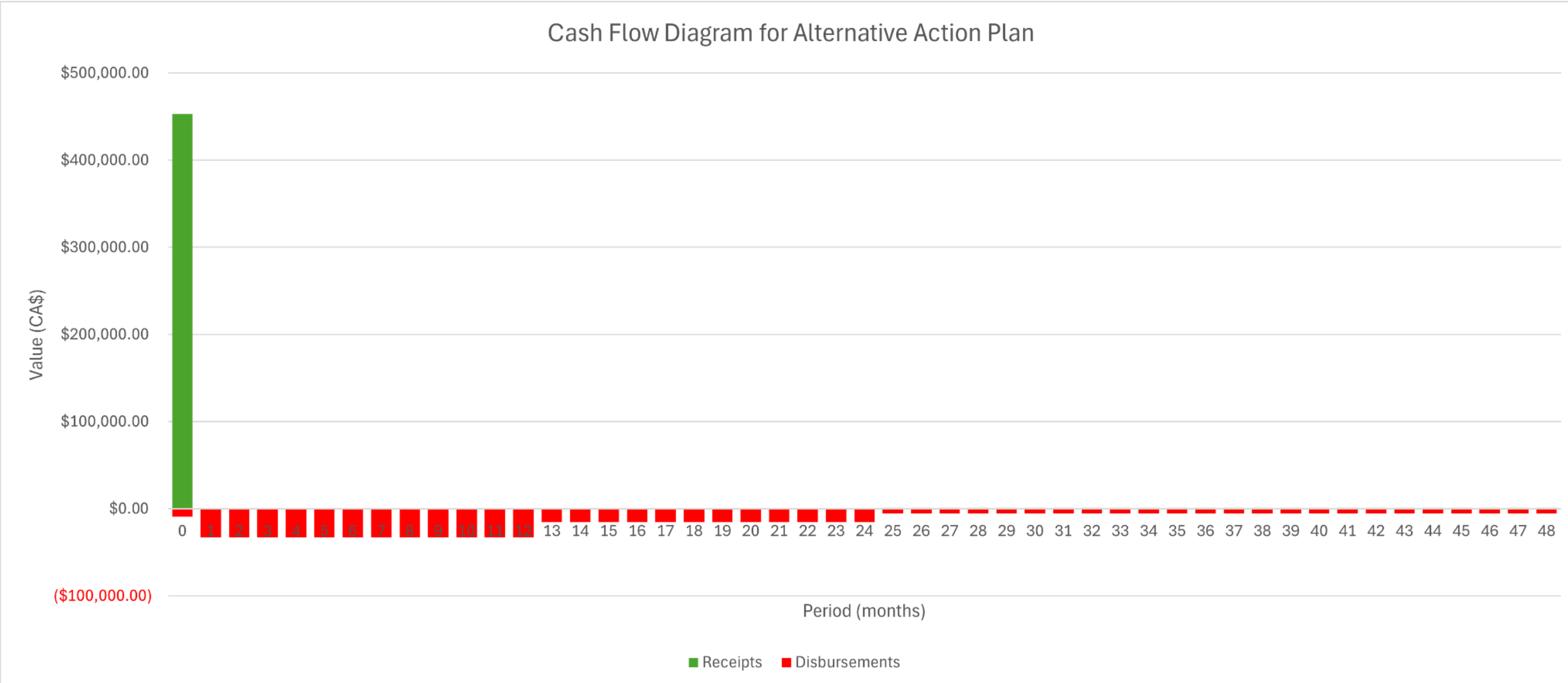

Fig 2. Cash flow diagram for the Alternative Action Plan.

Do Nothing

"Do Nothing" contains no receipts or disbursements as no action is taken (including initial grant funding). As a result, the economic analysis yields a Net Present Value of **$0.00**.

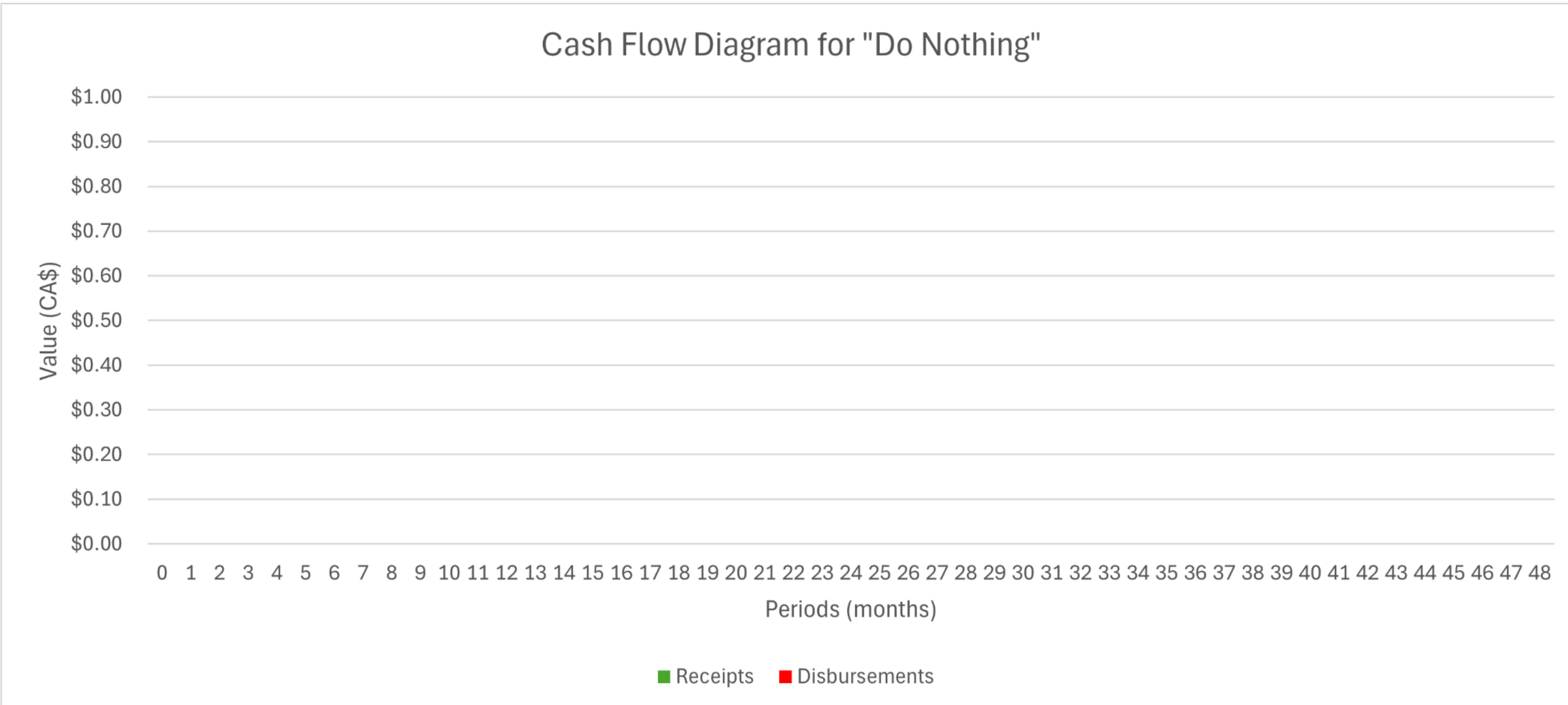

Fig 3. Cash flow diagram for "Do Nothing."

Key Assumptions for Economic Analysis

Assumptions on Application Usage and Costs

To simplify the economic analysis, we will assume the use of a single cloud provider for all website infrastructure; specifically, we will use the pricing from AWS, given its market leadership. All services will be assumed to operate out of the *us-east-1,* which is a standard practice.

For Simple Storage Service (S3), the service which stores the data that will be collected, billing is based on storage volume and activity. The first 50 TB of storage is charged at US$0.023/GB/mo [13]. Operations that write data to the database cost US$0.005 per 1000 actions, while read operations cost US$0.0004 per 1000 actions [13]. **However, the first 5 GB/mo stored is free, along with 2,000,000 read requests/mo and 30,000 write requests/mo** [13]**.**

For the web application itself, AWS Amplify will be used. This service charges US$0.023/GB/mo, which is a recurring charge until the application is deleted [14]. The service also charges US$0.15 per GB served, and US$0.30 per 1 million requests to the web application [14]. **However, the first 5 GB of web application storage is free, along with 2,000,000 requests/mo and 15 GB served/mo** [14].

AWS Lambda will likely be used for the website backend. For a standard deployment with x86 machines, the cost is US$0.0000166667 per GB-second (a computed metric representing a combination of memory and time resources used) for the first 6 billion GB-seconds per month; this roughly equates to US$0.20 per 1 million requests [15]. **However, the first 1,000,000 requests/mo are free, along with 400,000 GB-seconds/mo** [15].

Finally, AWS SageMaker AI will be used for the deployment of the developed AI model. We predict that the trained model will take no more than 2 GB of memory, which sets the price of inference at $0.0000400 per GB-second, with US$0.016 per GB of data transferred in and out [16].

The following list is a set of assumptions for the usage the application can expect to see:

- The number of Active Daily Users (ADU) is expected to be 50, derived from the total staff count in Aim Statement 9 and with the assumption that about 1/6th of the total staff are active daily.
- The total number of managed batteries is 36, derived from Aim Statement 7 and assuming 20% growth as a conservative estimate.
- Each data record is assumed to be about 2 KB in size; a data record houses one test log, including collected data and notes on testing.
- We estimate that the amount of data ingested would be 200 records/mo.
    - 36 batteries with 4 tests and a questionnaire a month puts us at 180 records. An extra 20 records were added to account for testing variability.
    - The frequency of testing was assumed based on the need to collect enough data points for the machine learning algorithm to sufficiently find patterns; 4 tests a month is about a test per week, which is sufficiently granular for most time-series models.
- Assuming five years of historical data as a baseline for storage usage, this puts us at ~24 MB of total storage.
- The total estimated API calls per month to AWS Lambda is estimated at 30,200/mo.
    - The total number of API read calls is assumed at 30,000/mo.
        - 50 ADU with 20 dashboard calls a day as a conservative estimate.
    - The total number of API write calls is the same as the amount of data ingested at 200/mo
- We estimate 15,000 inference calls/mo to AWS SageMaker AI.
    - 50 ADU average 10 “view battery health” actions a day over the course of a month.

- We also estimate that the total amount of data transferred per month for AWS SageMaker AI will not exceed 1 GB, due to all the data being numbers and characters, which results in requests being no larger than a few kilobytes each.

Based on these assumptions:

- The costs incurred by S3, Amplify, and Lambda **are $0.00 combined**, as the usage falls within free tiers.
- For SageMaker AI:
    - We assume a request takes 3 seconds on average to account for cold starts (times where the virtual machine needs to start up before serving the request).
    - $15,000\,requests\ \times\ 3\,s\ \times\ US\$0.0000400\ +\ US\$0.016\ =\ US\$1.816.$
    - After conversion, this yields **CA$2.57/mo in AI inference costs**.
- However, we will also assume a conservative 15% growth factor in usage every 12 months. This is based on estimates for data growth in healthcare (about 36% a year) and general SaaS platforms (about 13% per year) [17], [18].

Assumptions on Application Development

For the primary action plan, the main assumptions were based on the time required to curate a dataset from open-source battery data, as well as fine-tuning of the existing model for the RCC's purpose. The following key assumptions were made for the costs required to develop the model on the AWS SageMaker AI platform:

- Dataset curation would be done on a notebook instance on a *ml.g4dn.xlarge* machine, billed at US$ 0.7364/hr [16].
- Model fine-tuning would be performed on a *ml.p3.2xlarge* machine due to its more powerful specifications, which is charged at US$ 3.825/hr [16].
- We make the following assumptions:
    - For dataset curation, it would take roughly 20 hours a week. This is a professional estimate based on initial inspection of open source battery data and the tentative time-series model that would be used, *Chronos-2* [19] [20].

- A similar professional estimate was made for the fine-tuning of the model which surmises 30 hours a week of worth.

- Given the current weekly estimates of tasks B and L:
    - Curation would cost US$ 88.368 in total.
    - Fine-tuning would cost US$ 688.50 in total.
    - After rounding and division over four months of development (based on current estimates), it **yields approximately CA$ 274.18/mo.**

For the alternative action plan, we assumed the following for the salaries of the roles required for development, not accounting for insurance, income tax, or any other overheads, and assuming an average of 160 working hours a month:

- A Technical Project Manager has a salary of $70/hr [21].
- A mid-level UX Designer (given the scale and complexity of the project) has a salary of $41/hr on average [22].
- The high-end salary of a Full-Stack Developer (given the scale and complexity of the project) is $60/hr [23].
- The salary of a Machine Learning Engineer is $10,056/mo [24].

Assumptions on Monetization of Saved Time

Time saved by this inventory system was estimated based on two independent case studies of inventory management systems, which concluded that they helped store managers save an average of 6 hours a week [25], [26]. These case studies are analogous to Stephen Klatt's role at the RCC, so we can also assume savings of approximately 6 hours.

To monetize the time saved, we used the average base salary of a technologist in Manitoba, which is $34.70/hr [27]. We assume 48 workweeks in a single year, not accounting for vacation or other sources of variability [28]. This yields

$6\,hrs/wk \;\times\; 48\,workweeks/yr \;\times\; \$34.70.hr \;\div\; 12mo/yr \;=\; \$832.80/mo$ in savings.

Information on Loan Financing for Alternative Action Plan

For the Alternative Action Plan, a Canadian Small Business Financing Program (CSBFP) loan worth $450,000 was acquired via the Assiniboine Credit Union in Manitoba. A repayment length of 10 years was assumed at a 7.45% interest rate. This loan covers the salaries and development fees associated with the project. Using their official loan repayment calculator, each monthly payment was calculated to be $5,329.84.

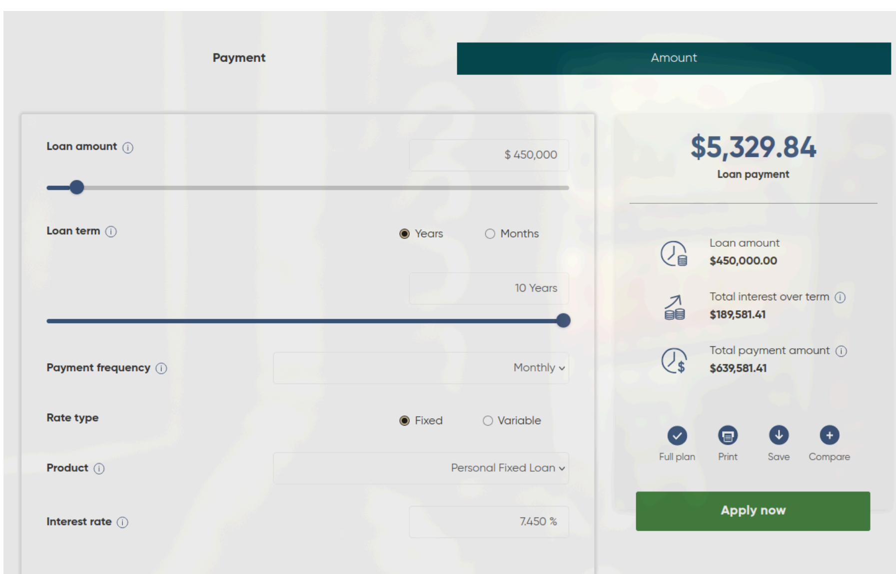

Fig 4. Screenshot of results from Assiniboine Credit Union loan repayment calculator.

Final Recommendation

Based on the comprehensive analysis, the economic evaluation concluded that the Primary Action Plan is financially feasible, with a positive Net Present Value of **$27,153.50** over the projected four-year lifespan. However, this financial viability is outweighed by practical and organizational feasibility concerns related to the RCC.

Considering the background of Stephen Klatt and the RCC, several critical assumptions underpinning the Primary Action Plan are unlikely to hold in practice. Specifically, the RCC is likely to lack the necessary in-house technical expertise and staff capacity required to successfully execute and maintain a project of this complexity, which the task table estimates to take a total of 30 weeks for development and deployment. Furthermore, the scope and complexity of the primary solution, including the integration of a fine-tuned, pre-trained AI model like *Chronos-2* for predictive maintenance, may not justify the effort, as some features are beyond the immediate, core needs of the RCC. Simpler, process-improvement-focused solutions may be sufficient to meet the organization's requirements.

The Alternative Action Plan also cannot be recommended. Economic evaluation concluded that the plan is financially unfeasible, with a negative Net Present Value of **-$179,939.59** over the projected four-year lifespan. Furthermore, the plan as it is does not outline strategies for repayment of the CSBFP loan that would be required to finance the delegation of application development to an external Agile team.

Given these circumstances, a recommendation is made to maintain the current procedures and systems currently in operation at the RCC and to not pursue either the Primary or Alternative Action Plans. The RCC is advised to continue investigating process-focused solutions that may be sufficient to meet the organization’s requirements without the initial capital investment required for the proposed solutions. The following sections outline the secondary factors that influenced the final recommendation:

Quality Improvement

Much of the primary action plan has been designed with existing industry standards or best practices in mind. The data that the primary action plan has proposed for gathering, interpretation, and logging are battery voltage under load, environmental temperature, number of charge and discharge cycles, number of times partially charged, number of times fully discharged, and battery age. This selection of data aligns with existing standards set by other machine learning algorithms used successfully to predict the health of lead-acid batteries [7], [8]. This is relevant because the RCC also uses lead-acid batteries, per email communication with S. Klatt, Oct. 2, 2025.

The estimation accuracy minimum of ±10% also aligns with existing industry standards. It was achieved by traditional electrochemical calculations of battery health, which are said to "may[be] fail to achieve a high accuracy" [8].

Our use of Chronos-2 for the battery health modelling AI also aligns with best practices, as Chronos-2 is a robust AI model specialized in forecasting based on time series data, which suits our purposes for battery health modelling. Chronos-2 has been shown to outperform competitors on numerous empirical metrics [20].

However, we have also identified two key areas of improvement for our primary action plan. The first is the timescale of data. Data from batteries was taken for one year to inform an existing machine learning algorithm [7]. Because much of the data we require for our battery health modelling AI is not currently recorded by the RCC, it will take at least 1 year to catch up to an industry-standard quantity of data. In particular, the time series data (number of charge and discharge cycles, number of times partially charged, number of times fully discharged) will be incomplete. As the action plan is implemented and battery data is taken, the time-series data will fill in and approximate completion. An immediate improvement can be made by using a database of open-source battery data to roughly inform the battery health modelling AI [19], but this approach falls well below industry standards and is strictly temporary.

The second area of improvement for our primary action plan is the questionnaire for patients and their families on their battery usage habits. As the questionnaire is to be written in conjunction with the RCC staff, it is yet to be finalized. It should be written according to established best industry practices on survey writing in order to ensure that it is valid, reliable, clear, succinct, and interesting. This will give the RCC the most accurate data possible on each battery's number of charge and discharge cycles, number of times partially charged, and number of times fully discharged [29], [30].

Furthermore, our plan for sustaining change involves verifying and improving the accuracy of the battery health modelling AI's estimations, verifying and improving the quality of the battery testing schedule, and quantifying the primary action plan's impact on operations at the RCC. The battery health modelling AI can be checked for accuracy by comparing the estimated battery failure dates to the batteries' actual failure dates. The actual battery failure dates can be fed back into the battery health modelling AI to refine its future estimations, ensuring lasting change and improvement.

Second, the battery health modelling AI's recommendation of additional battery testing at a date that is 1/3 of the way to the estimated failure date is intended to catch batteries as they decline but before they fail, based on existing data demonstrating exponential decay of a battery's voltage as it ages [8]. If it is found that batteries have either consistently already failed or consistently not yet meaningfully declined from baseline by this date, the additional battery testing schedule can be adjusted to be closer to or farther from the estimated failure date in order to achieve the original intention.

Lastly, the primary action plan's impact on operations at the RCC can be quantified in two ways. First, battery testing at the RCC was often done multiple times due to a lack of standardization and coordination, per an interview with S. Klatt, Oct 28, 2025, leading to wasted time. The development of standardized battery inventories, battery data logs, and a testing schedule is intended to fix this issue. This effect can be quantified by summing the number of hours per month spent on battery testing before and after the implementation of the primary action plan.

Second, due to the limited and unstandardized battery data available, battery testing was often done on the spot to find a working battery when batteries were requested, delaying the acquisition of batteries, per an interview with S. Klatt, Oct 28, 2025. The development of expanded battery testing procedures, battery data logs, and a battery health modelling AI is intended to fix this issue. This effect can be quantified by recording the average turnaround time from battery requisition to battery acquisition before and after the implementation of the primary action plan, in line with the industry standard of measuring requisition approval time as a key performance indicator [31].

Task Table and Time Estimates

Table VI: Primary Action Plan tasks with estimated durations and slack. Estimates made by IEEE Standards [32]

Task ID	Task Description	Predecessors	Duration (weeks)	Earliest Start (weeks)	Earliest Finish (weeks)	Latest Start (weeks)	Latest Finish (weeks)	Slack (weeks)
A	Finalize system requirements & scope	-	2	0	2	16	18	16
B	Defining new testing procedures and patient questionnaire	A	2	2	4	18	20	16
C	Create external battery care documentation	B	1	4	5	20	21	16
D	Design system & database architecture	A, B	3	4	7	10	13	6
E	Develop backend API	D	6	7	13	13	19	6
F	Develop web app front-end	D, E	6	13	19	13	19	0
G	Create internal	C, F	3	19	22	21	24	2

	system documentation and guidelines							
H	System and user acceptance testing	E,F,G	2	22	24	24	26	2
I	Deploy web app to production	H	1	24	25	26	27	2
J	Conduct staff training on new system and procedures	G, I	1	25	26	27	28	2
K	Curate and normalize open-source battery data and synthesize into dataset for training, and determine data to model pipeline	B	6	4	10	6	10	0
L	Build the data-to-model pipeline.	K	3	10	13	10	13	0
M	Create an initial model using the generalized dataset with	L	6	13	19	13	19	0

	human-in-the-loop.							
N	Integrate and deploy the AI model into the web app	E, F, M	3	19	22	19	22	0
O	Build the continuous pipeline to pull and retrain the model with new data.	N	4	22	26	22	26	0
P	Update internal documentation for AI features	O	2	26	28	26	28	0
Q	Final acceptance testing	J,P	2	28	30	28	30	0

Node Diagram

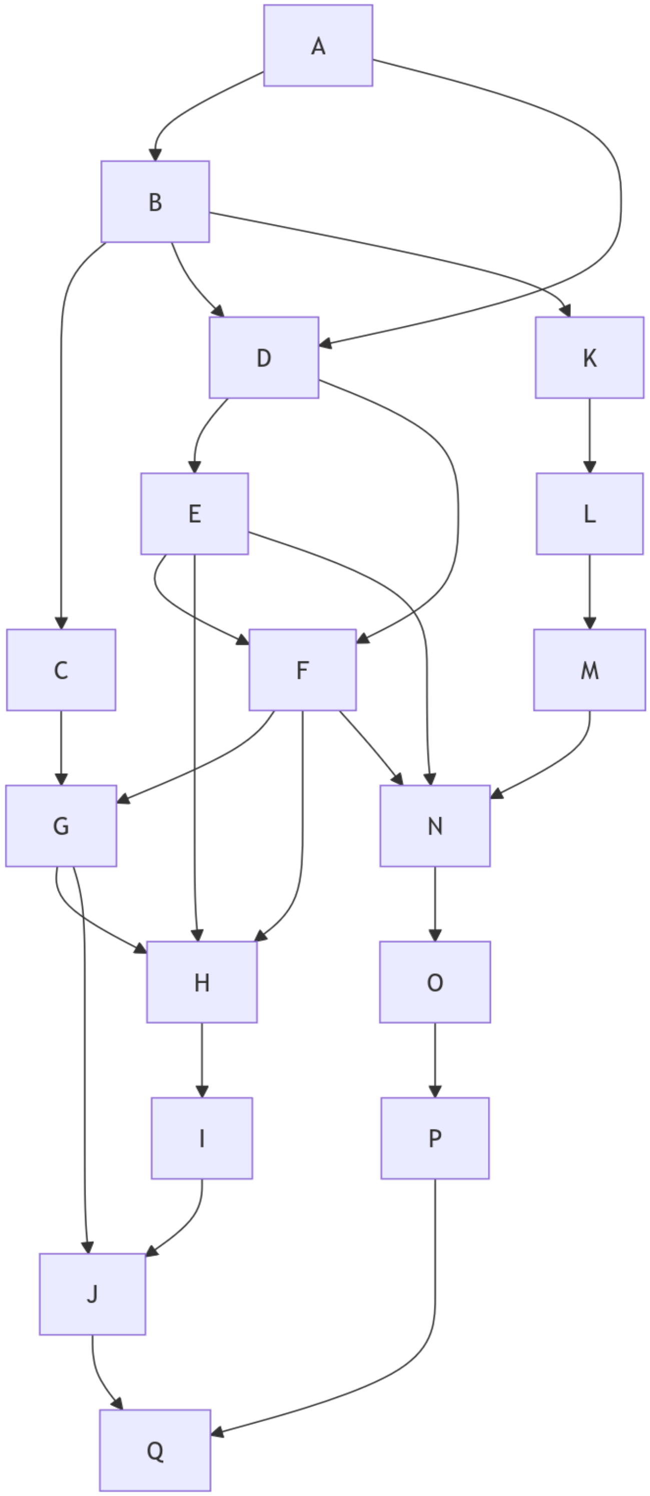

Fig 5. Dependency node diagram of Primary Action Plan tasks.

Sample Calculation: Task C

$EF_C = ES_C + T = 4 + 1 = 5$

$LS_C = LF_C - T = 21 - 1 = 20$

$S_C = LS_C - ES_C = 20 - 4 = 16$

Critical Path

A → B → K → L → M → N → O → P → Q

This is the path that goes from start to finish with the least amount of slack.

Capital vs Labour Trade-off

In both capital and labour-intensive approaches, the primary action plan is to develop and implement a web application that manages battery inventory, testing procedures, and predictive maintenance using a fine-tuned, existing model. However, what differs between the two approaches is the allocation of resources, shifting the balance between technological investments and human labour.

If the preliminary action plan were implemented using a capital-intensive approach, the focus would shift toward greater investment in technology, automation, and infrastructure rather than manual labour. This would include significant upfront fixed costs related to licensing fees for integrating the Chronos-2 model, cloud-based data storage, and backend system maintenance. Additional fixed costs may include software development tools and API expenses to further improve the AI model. Variable costs are comparatively lower and limited to occasional software updates, minimal staff oversight, and increased cloud storage as data volume increases. This approach emphasizes automation, reducing manual tasks like data entry, testing documentation, and report generation, thereby lowering ongoing labour costs. By focusing capital investments on the technology, it would reduce the need for continuous human maintenance by automating procedures such as battery data collection, model training, testing, documentation, and predictive features such as battery deterioration estimation and future testing schedules. As the Chronos-2 model improves with continued data input, its predictions become more accurate, further reducing the need for manual oversight. In the long term, this approach would streamline operations, lower maintenance costs, and minimize the need for additional staff or training [11].

The labour-intensive approach also utilizes the Chronos-2 framework, but instead of relying on a pre-trained version, the model would be custom-trained internally using the RCC's own historical and real-time battery data. This would require hiring or reallocating data scientists and engineers to preprocess data, fine-tune the model, and maintain it over time. In this approach, fixed costs would include salaries for contracted staff, workspace expenses, and essential computing equipment required for development. Variable costs would include the ongoing maintenance and model retraining, potential overtime or hourly wages during testing and data-collection phases, and additional short-term labour required to support technical adjustments or troubleshooting. While this method demands higher labour costs and a longer setup period, it allows for greater customization and adaptability. This means the AI can learn the specific performance patterns and usage data of the RCC's batteries. Over time, this could lead to more accurate and specific predictions, though it would also require ongoing monitoring, retraining, and technical support [33]. However, the initial phase would likely result in delays, limited predictive accuracy, and inconsistency until sufficient data is collected and the model is properly optimized.

Economies of Scale

Scaling this potential battery management system outside of the RCC could help reduce costs in some areas, but could also create new challenges that outweigh the benefits of scaling.

Firstly, scaling this product would reduce the software costs per user. As the RCC grows and more people start using the program, it would cost much less per user, as the fixed costs of development would be spread across more people and data, reducing cost per capita [34]. As well, by scaling the product, more staff at the RCC would become familiar with the system, so it would be more efficient to add battery data into the system, which would improve the AI model and accuracy in the predictions.

However, scaling the battery management system could introduce some diseconomies. Scaling up this product would require much more staff training, which would increase costs and also take up lots of unnecessary time. As well, data quality and consistency could decrease if there are too many people inputting data into the system, which could harm the AI model's accuracy [35]. Furthermore, an increase in users could create extra costs as more data security and monitoring would be required [35].

Based on the economies and diseconomies of scaling, our recommendation is not to scale this project beyond the RCC. The RCC only has around 30 batteries and around 250 staff, so this is not a system that should require so many resources. Adding more efficiency and accuracy to the AI model is a bit overboard for the magnitude of the problem at the RCC [36]. Scaling up this project would add significant costs, and the benefits would not be clear or guaranteed [37]. For all these reasons, we recommend not scaling up this project, but rather keeping it in-house at the RCC.

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