



Universidade de São Paulo



The Volvo HS

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H335 VCE USP & BTH

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Abstract

This report presents the development of a comprehensive Product-Service System (PSS) for Volvo Construction Equipment (Volvo CE), aimed at reducing unplanned downtime in the construction industry. Leveraging advanced technologies such as IoT, AI, and Machine Learning, the project suggest to create a digital twin framework to support the lifecycle management of construction equipment.

The project team conducted extensive need-finding through expert and user interviews, identifying key pain points in sales, procurement, and maintenance processes. Four critical prototypes were developed and tested, including augmented reality interfaces, AI-driven chatbots, and predictive maintenance tools. The findings underscored the importance of real-time data integration and the role of operators as 'human sensors' in providing contextual machine data.

The final solution, Volvo HS, integrates these prototypes into a unified system that enables operators to conduct daily machine check-ups, report anomalies, and access troubleshooting guides. This solution enhances operational efficiency by improving machine uptime and facilitating proactive maintenance.

The proposed business model includes revenue streams from licenses, maintenance services, and e-commerce sales, aligning with industry trends towards servitization. The report concludes with recommendations for further development to refine the user interface and expand predictive capabilities, highlighting the potential for significant impact on the construction industry.

Introduction

Currently there is an emergence of supporting services in society, such services are beginning to emerge within the construction industry. Schimanski et al. (2019) highlight a lack of advanced supporting services in this sector and emphasize the need for their implementation at various stages of construction developments. Baines et al. (2007) argue that the concept of Product-Service Systems (PSS) is a specific aspect of servitization that integrates services with products. Parallel studies by Persson (2024) and Bååth (2024) confirm PSS's relevance in construction, focusing on product customization and digital twins. The solution was developed as a part of a project within the SUGAR Network and was designed based on findings both from the literature and the exploration phase of the project. The aim of the solution is to address the problem of unplanned downtime within the construction industry caused by lacking contextual data and actionable information by utilizing PSS as a framework. The following sections follow the development from the initial prompt given by Volvo CE, to the final solution, the Volvo HS.

The team

The team consisted of seven students from both Blekinge Institute of technology in Sweden, and University of Sao Paulo in Brazil, connected through the SUGAR Network. All students specialized in different areas, making the team diverse and offering knowledge to be used at different parts of the project. The fluent nature of the roles used throughout the project enabled knowledge overlapping to be further utilized and strengthening the team. Contact info can also be found in Appendix A.

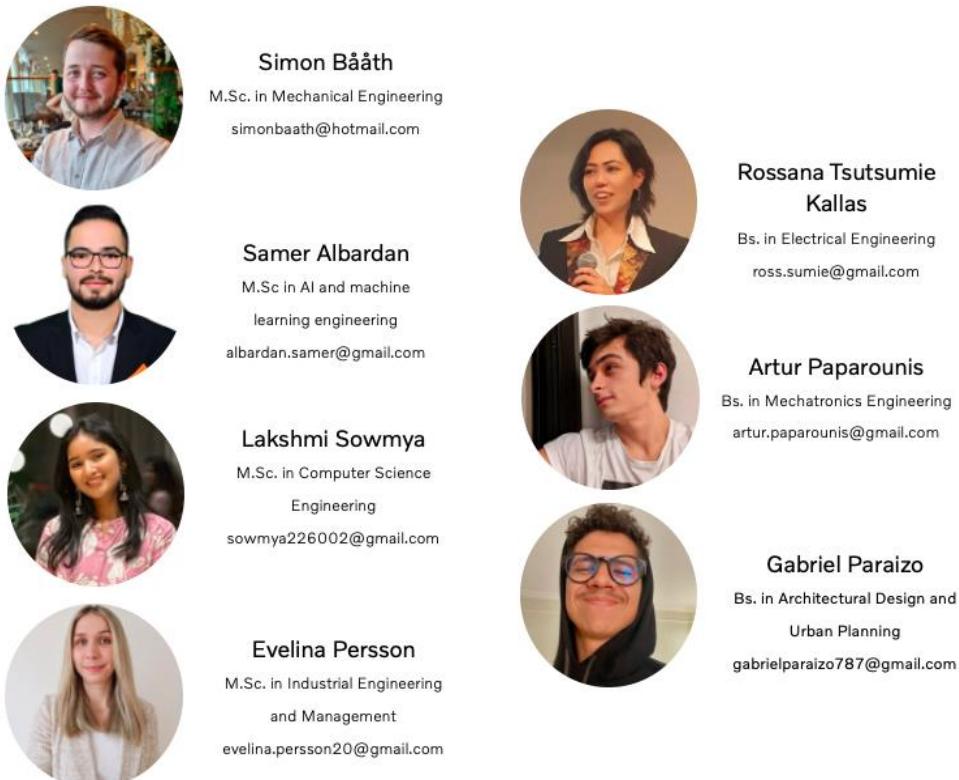


Figure 1. Members of the team, the Swedish students to the left and the Brazilian students to the right.

The prompt

The introduction to the problem space was given through the prompt presented below. By interpreting this based on the findings, the aim is to develop a product service system fulfilling both the needs of Volvo CE and its customers.

Volvo CE wants to explore...

...continuous evaluation of the actual through-life customer needs to support sales of site solutions that are tailored to provide higher value to the customer continuously through the lifecycle of the construction equipment.

We envision...

...a construction equipment Product-Service System that capitalizes on historical and real-time data to satisfy customer needs.

We want you to...

...within the context of the construction machine explore enabling technologies (e.g., IoT, AI, Machine Learning) for the application of a Digital Twin to support through life support of customers' construction fleet ...explore technologies to be able to update legacy- as well as competitor's machines to integrate them into a site-wide solution.

The initial understanding of the prompt revolved around developing a construction equipment Product-Service System that continuously evaluates and supports customer needs, tailor solutions to provide higher value throughout the lifecycle of the equipment, and includes integration of legacy and competitor machines into site-wide solutions. During the initial phase, the emphasis was predominantly placed on the sales process, in the end the attention shifted towards life cycle support which provides a broader scope and more opportunity to provide value to the customer. Initially there was no clear customer provided and therefore analyzing the different roles at a construction site became a crucial research area.

Methods

Interviews

The interviews performed throughout this project all followed a similar layout, differentiation slightly depending on the interviewee. Thorough preparation was done before each occasion to ensure the visit and interview yielded accurate and usable data, and the interview material was modified based on who was interviewed. The interviews were structured in a manner based on the needfinding interview structure presented by Lewrick et al. (2018) and included the following steps:

1. The first order of business is to introduce the interviewers and the purpose of the interview, clearly communicating that no right or wrong answer exists and asking permission to record the

interview for further analysis. This introduction aims to invite the interviewee into a safe space where they feel comfortable enough to answer the questions in the best possible way.

2. After opening the interview, general questions about the problem space are introduced to establish a simple reference, again emphasizing building comfortability and trust between the involved parties.
3. Simple questions about the interviewees' day-to-day operations are asked to find a recent example that matches the problem space to bring the person closer to the subject. Once again, focus is put on assuring and accepting the answers, even if they might not match the problems or critical experiences, and asking further questions if more depth is required.
4. When a general understanding and a discussion have started, the interview opens up to the Grand Tour, the critical element of the interview. If the previous steps were successful, the interviewee would feel trust and comfort and could open up to share exciting experiences that would have remained secret otherwise.
5. Once the discussion ends, a pause for reflection is taken, and gratitude is expressed toward the interviewee for taking the time to answer the questions. The summarized main findings are presented to allow for one last push of important information, and the interviewee gets a chance to remember additional things of interest and to point out any inconsistencies, giving an additional moment to dig deeper or discuss the subject more generally.
6. With the interview ending, gratitude is once again expressed for the opportunity, and the gained insights and the opportunity for the interviewee to ask questions are also given. In this step, much emphasis is put on expressing the value of the information and creating a connection with the interviewee to allow further meetings in the later stages of the project.

Personas

Throughout the project, several personas were created, which are essentially profiles of typical users, framed as real persons with real interests, careers, and hobbies (Lewrick et al., 2018). These personas aimed to provide insights into the users by creating a sketch and validating it with real potential users. By developing these personas, the project team can step into the users' shoes and understand their needs better (Lewrick & Link, 2015).

Creating the personas involved data analysis from various sources, including observations, interviews, and user interactions. The key characteristics and behaviors of different user groups were identified, which helped to build a more accurate and detailed picture of the target audience. Once the personas were validated through further interaction, they were used to narrow the scenario and aid the storytelling of the prototypes.

Prototypes

Throughout the project, different prototyping strategies were employed to suit the developing needs of the project, starting with quick and simple prototypes, moving into diverging prototypes, and closing with a functional concept.

Critical Experience Prototype

The primary objective of the Critical Experience Prototype (CEP) is to determine whether the proposed concept has the potential to add value to the user (Domingo et al., 2020). The CEP is a prototype that simulates the user experience using a well-defined story and available technology, allowing the user to experience the final concept without having to spend time on development. The prototype is typically created using rough, low-fidelity mockups with faked or scripted elements that emulate the final outcome.

Critical Function Prototype

The primary objective of a Critical Function Prototype (CFP) is to identify the core functional component of a system and build prototypes to test its feasibility before investing resources into other subsystems (Elverum et al., 2016). The CFP aims to provide valuable insights into the feasibility of the concept and help determine whether it is worth exploring further.

Dark Horse Prototype

Dark Horse Prototypes (DHP) aims to diverge the solutions by exploring new and risky directions that otherwise would not have been taken (C.S. Durão et al., 2018). This approach provides the opportunity to see the problem from a new angle and the potential to deliver the breakthrough idea.

The term "dark horse" is often used to describe something that embodies an element of surprise and unpredictability, originating from horse racing, where it represents the unknown horse that was expected to lose but would result in a significant payoff if successful (Merriam-Webster, 2024). The DHP is typically developed outside the traditional development processes, allowing for greater freedom and flexibility in exploration and encouraging risk-taking and experimentation, often challenging established norms and pushing the boundaries of possibility (Bushnell et al., 2013). By doing so, DHP promotes creative thinking without limitations, enabling new insights and directions for exploration that may not have been available otherwise (C.S. Durão et al., 2018).

Due to the nature of prototyping, all prototypes could, in some regard, be considered dark. Therefore, the DHP requires a previously established idea of what is possible to depart from this and reach for the impossible to uncover hidden opportunities and pave the way for transformative change.

Funky Prototype

The third prototype phase included a Funky Prototype. This iteration was aimed to bring together all the insights and feedback gathered from the previous stages and create a comprehensive system concept (Schindlholzer et al., 2010).

The primary objective of the Funky Prototype is to develop the critical functional elements that would significantly impact the functions to be developed in the later iterations and to define the goal of the final prototype (Domingo et al., 2020).

The Funky Prototype is created by piecing together a system built on the previous prototypes as subcomponents (Schindlholzer et al., 2010). As a result, the prototype system is made up of some parts that are functional and others that are not. This process helps identify specific components that need more development, should be defined better, scaled back, or completely missing (Domingo et al., 2020).

Functional Prototype

The Functional Prototype is made with functionality as the primary goal (Schindlholzer et al., 2010). Therefore, simulated aspects are kept to a minimum, and the prototype is designed to provide a more tangible and practical solution (Domingo et al., 2020). As a result, this prototype represents the final version of the product, providing an easily understandable and functional concept that can be presented to the stakeholders for further evaluation and feedback.

Initial Needfinding

The initial needfinding phase involved conducting interviews with Volvo CE experts and users/clients, who are also key stakeholders in the process. These interviews were aimed at gaining a broad understanding of the journey and identifying the pain points from both perspectives. Additionally, a field visit was conducted at Tracbel, one of the largest Brazilian dealerships of Volvo CE products, to gain insights into the marketing and sales strategies employed by industry professionals. The detailed interviews can also be found on appendix B.

Expert Interviews

The initial experts interviews focused on personnel related to the sales process of construction equipment. The findings were used to create the initial two personas for developing the prototypes: the Salesperson and the Volvo Sales Representative presented in appendix B.

The Interviews, Key takeaways and learnings

Table 1. Expert interviews report.

| Interviewee Info | Role and Responsibilities | Key takeaways and learnings |
|---|--|---|
| Sales Representative - California LA | Represent the company for 5 years Traditional Salesman, like to build a close relationship with the clients Daily routine involves scheduling meetings, visiting construction sites, sending messages and emails | The sales process is highly relationship-driven, with a focus on networking and personal interactions within specific industries like demolition, recycling, and waste management. This emphasizes the importance of building trust and maintaining close contact with potential customers. There is a high degree of customization available, which requires detailed discussions and face-to-face meetings to tailor machines to customer needs. This involves, in the traditional method adopted by the salesman, mainly creating spreadsheets with options, pricing, and quotes, which can be time-consuming but necessary for a personalized approach. Managing extensive documentation and ensuring all customization requests are met without overwhelming the customer with unnecessary details. The sales process is complex, involving multiple steps, including finance and service agreements, and requires careful coordination. Useful Insights: The need for streamlined tools to handle extensive customization and documentation could lead to the development of digital solutions that simplify the sales process. Enhancing communication between sales, dispatch, and after-sales teams could improve efficiency. |
| Sales Solution Manager at Volvo CE, Eskilstuna, SE | Focus on selling solutions for new productivity services, primarily through direct sales to key accounts in Europe. | Volvo is transitioning from traditional sales methods to more direct customer engagement, reflecting a broader industry shift. This transformation is essential for adapting to new market demands and enhancing customer relationships |

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| | <p>Provided insights into Volvo's sales process and its approach to enhancing customer experiences</p> | <p>The sales process is complex, and decisions are often influenced by emotional factors rather than purely rational analysis. Understanding this dynamic can help sales teams tailor their approach to better align with customer motivations.</p> <p>There is a growing need to consolidate customer data and communications into a single platform. Tools like CPQ (Configure, Price, Quote) and visualization aids are seen as the future, helping customers and sales teams visualize solutions more effectively.</p> <p>Useful Insights: The focus on emotional decision-making and the integration of advanced digital tools highlight the importance of personalized, customer-centric approaches. Future sales strategies could benefit from investing in technologies that simplify complex processes and provide clear visualizations of customer solutions.</p> |
| Internal Sales Representative at Volvo CE | <p>Emerged as a crucial persona into the initial needfinding phase</p> <p>Primary role involves supporting distributors, ensuring they have the necessary machines and information to represent Volvo effectively</p> <p>Deals more with administration than direct sales, with direct communication from vendors requiring interaction with their manager before engaging with him for discussions on pricing reductions and discounts.</p> | <p>One of the biggest challenges is configuring the right machine for the customer, especially given the vast array of options and potential customizations. This requires a deep understanding of customer needs and the ability to navigate complex configurations.</p> <p>There is a need for more intuitive tools that help salespeople configure machines accurately and efficiently. Current reliance on Excel and manual processes can be cumbersome, and a more streamlined approach could enhance the sales process.</p> <p>The emphasis on better configuration tools and clearer customer interaction suggests that digital solutions, such as automated configurators and enhanced CRM systems, could play a significant role in improving sales efficiency and accuracy.</p> |
| Triple Interview: Technical Consultant, Application Instructor and Product Support & Technical Interface between Sales and Engineering | <p>1^o: Consulting and training for the entire Volvo CE network, portfolio management, and product quality</p> <p>2^o: Manages the sale of services, a heavily explored area for the company nowadays, including machine hours counters, co-pilot, and other performance-enhancing services</p> <p>3^o: Translates customer needs to sellers and works by aligning more with the project's theme and having his expertise explored in this conversation</p> | <p>Technical assistance is performed in the field, but there are challenges with remote diagnostics due to a lack of integrated systems. Augmented reality tools and better diagnostic integration could improve maintenance efficiency.</p> <p>Services like Caretrack, which provides real-time machine data, are critical for ongoing maintenance and support. However, the current diagnostic process is labor-intensive, requiring technicians to interpret extensive data manually.</p> <p>There is a gap between ideal training scenarios for new sellers and the reality of on-the-job learning, which can lead to inconsistencies in how Volvo's values and products are represented.</p> <p>Useful Insights: There is a need for better integration between diagnostic tools and service delivery. Developing more user-friendly diagnostic systems and enhancing training programs for sales and technical staff could significantly improve service quality and consistency.</p> |
| B2B Service Sales | <p>Oversees Interviewee 2</p> <p>Gave insights about how the Volvo CE approach on becoming a umbrella company, acquiring</p> | <p>Useful Insights: The need for better integration between diagnostic tools and service delivery is evident. Developing more user-friendly diagnostic systems and enhancing training programs for sales and technical staff could significantly improve service quality and</p> |

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| | smaller companies changed the way they make sales | <p>consistency.</p> <p>Understanding customer needs, especially regarding costs and emissions, is crucial. Decisions are often emotionally driven, so framing the sales process in a way that resonates emotionally with customers can be effective</p> <p>Useful Insights: The emphasis on integrating customer data and enhancing visualization tools indicates a clear path forward for Volvo. Developing platforms that consolidate information and provide intuitive, user-friendly interfaces will be key to future success in B2B sales.</p> |
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User Interviews

The goal with the initial user interviews was to obtain insight into how the process of acquiring equipment looked from the user side, both on the relationship between the dealership and the purchaser. The focal point was the identification of needs of the new equipment and the processes surrounding those decisions.

The Interviews, Key takeaways and learnings

Throughout this phase, several interviews were conducted with different people from different companies to gain a diverse look into the process. The major interviews that provided the initial insights and a diverse view are listed here, additional interviews were conducted with similar personnel, but the results from those are just confirming the previous.

Table 2. User interviews report.

| Interviewee Info | Role and Responsibilities | Key takeaways and learnings |
|---|--|---|
| Swerock Syd Regional Manager | <p>Company that supplies input materials for construction.</p> <p>Has been in this position for 5 years.</p> <p>Worked as purchaser at the same company for 10 years</p> <p>Has some close connection with purchasing department</p> | <p>Procurement Process: Understanding that the procurement of new machinery is a multi-step process involving economics, depreciation, and site manager input. The Investment Council plays a crucial role in final decisions, highlighting the importance of aligning site needs with budget approvals.</p> <p>Challenges: The time-consuming nature and the financial stakes involved in acquiring new equipment are significant concerns. This led to the insight of possible tools or processes to streamline decision-making.</p> <p>Some other useful insights were: Developing a clearer understanding of equipment benefits could aid in faster and more efficient decision-making.</p> |
| Head of Purchasing at Peab | <p>One of the largest companies in Scandinavia.</p> <p>Veteran in their field and had decades of</p> | Cultural Differences: The interview highlighted the impact of cultural differences on procurement processes, especially between countries like Germany and Sweden. Understanding these nuances can help in tailoring approaches to different regions. |

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| | experience. | <p>Importance of Ergonomics and Total Cost of Ownership: Ergonomics, working environment, and total cost of ownership are critical factors in equipment selection.</p> <p>Challenges and Tools: The lack of a system to track equipment usage more accurately and the need for simulation tools to determine the best machine for a job suggests potential areas for technological improvement.</p> |
| Owner of a small family-owned contracting company | <p>Owner of 7 machines and five employees</p> <p>Is a owner-operator</p> <p>Small company makes the process of procurement and deciding the machine easier than the big companies</p> | <p>Rental Strategy: The company's shift from owning to renting machinery highlights a cost-effective approach that could be useful for other firms, especially those dealing with fluctuating demand.</p> <p>Partnerships and Trust: Partnerships with rental companies reduce the need for advanced technology or investment in finding equipment.</p> <p>Technology in Equipment: The minimal use of technology, relying on tablets for basic operational data, suggests that advanced technological solutions might not always be necessary or preferred, especially in small to mid-sized companies.</p> |

Field Visit

Tracbel (1st of February, 2024)



Figure 2. Picture of the Brazilian team visiting Tracbel, Volvo's dealer in São Paulo

Tracbel has 40 units and employs about 1,500 workers, demonstrating its broad presence and operational capacity. Throughout its journey, it has attracted 200 million in investments. The company reached R\$ 3.4 billion in revenues and 100,000 SKUs in its catalog.

Its commitment to quality is evidenced by the awards and recognition received in service innovation. Although the company has previous experience with leasing services, it has chosen not to continue in this line of business, adjusting its focus to better meet market demands and its customers' needs.

Currently, the company's platform includes 20,000 pieces of equipment, of which 10,000 are actively monitored. This monitoring not only ensures operational efficiency and effectiveness but also underlines the company's commitment to innovation and providing high-quality services to its customers.

The service planning process includes understanding the customer, understanding the customer's business, and finally, how the equipment will contribute to the enhancement of the customer's business.

The objectives in the partnership between VCE and Tracbel focus on creating new products and services to monetize all the intelligence being generated, as well as to enhance sales in the customer service processes.

Activities carried out remotely include machine monitoring, remote diagnostics, remote maintenance, and the preparation of performance reports. Regarding the management of salespeople, Tracbel seeks to optimize service routes and enhance sales along these optimized routes. The systems in operation at Tracbel include strategic CRM (under development), operational CRM (implemented), "No Code" tools, moove for fault prediction, SENAI algorithm for lead forecasting, indicium for data products development, COPILOT to suggest the best way to operate the equipment, Matrix that downloads equipment telemetry for maintenance management and direction of active sales, Uptime for real-time monitoring of equipment and technicians. It directs preventive maintenance, Care Track, a hardware and software system that manages equipment information, Active Care Direct: a service that uses data from Care Track to produce indicators, generate reports, and direct commercial and maintenance actions, and the Tracbel platform with a focus on the first digital equipment sale.

Key Findings of the visit

After the dealership visit, the main discoveries made were related to the relationship between the dealership and Volvo and between the dealership and the customers. These relationships permeated all parts of the machine's lifecycle, from sales, to aftersales, maintenance and end-of-life of the machines.

From the sales perspective, we understood the processes and key aspects of the machine sales, relying heavily on established contacts, dealer personnel expertise and personal relations. This enabled us to focus some of our efforts and prototypes on trying to improve the dealership experience and make sales more consistent and less reliable on specific skills from the salesperson.

From the aftersales and maintenance perspective, we got a glimpse of the role dealers play on tracking machine breakages, selling aftersales programs and actually performing maintenance on machines. This mainly gave us a better understanding of the current maintenance process, enabling us to start the ideation to improve this very costly and critical activity. Simultaneously, understanding this dealership role made us take them into consideration as stakeholders in our after sales and maintenance ideas, making for more realistic and complete business models and systems, understanding which functions would and could be performed by the dealers and by Volvo itself.

Prototypes

In the first round of needfinding the project was sectioned into four different areas of research, critical experience prototype (CEP), critical function prototype (CFP), interviewing experts and interviewing users. The experts, as previously stated, consisted of people related to the process of selling services that add value to a product, and the users consisted of the customers of Volvo CE that are purchasing or are using the service and product provided.

Critical Experience Prototype

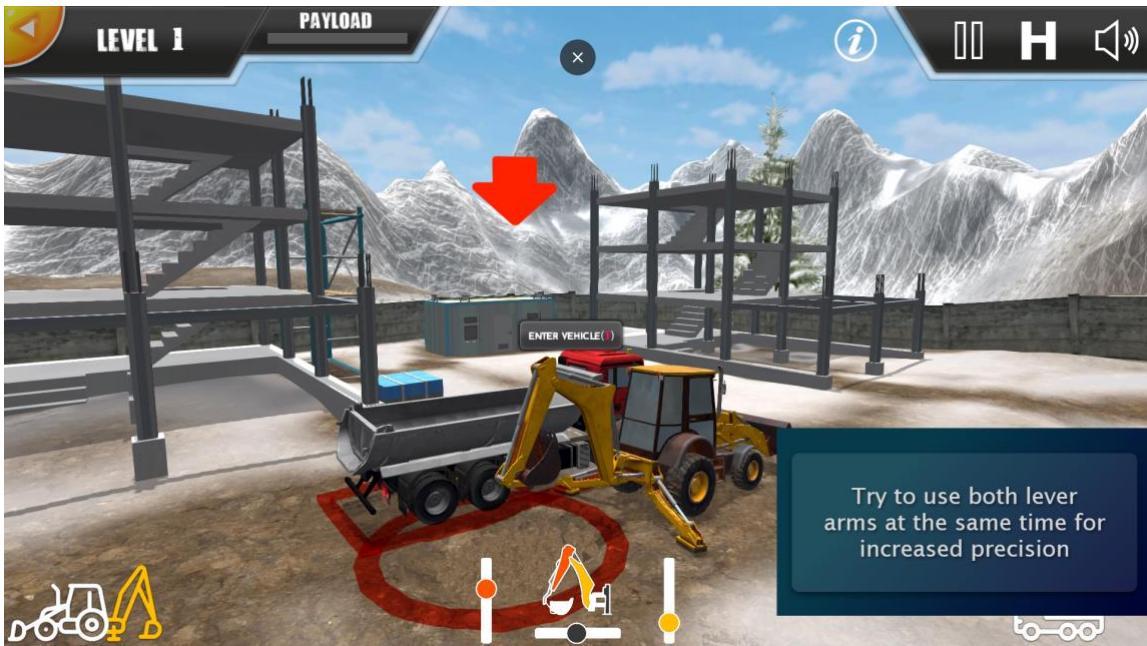


Figure 3. Screenshot of the single screen version of the CEP

The Critical Experience Prototype (CEP) is designed to test an idea to improve operator productivity and safety through the use of augmented reality and digital twin technologies. This prototype focuses on the most critical aspects of the user experience to validate key concepts and interactions. The CEP was conceptualized to tackle inefficiencies in construction equipment operation. The aim was to enhance productivity, safety, and machine uptime for operators and construction companies. Using Augmented Reality (AR) or other screen-based interfaces, we introduced live data analysis, machine learning, and digital twin technologies to provide operational guidance for operators.

The Prototype



Figure 4. Critical Experience Prototype storyboard

A prototype was built to simulate the operation of construction machinery using existing virtual simulators like 'Demolish and Build 3: Excavator Playground'. The prototype included an overlay system that provided real-time data and recommendations to the equipment operator. Various interfaces like keyboard and joystick controls were used to interact with the simulator, while recommendations were presented on a separate screen or we put these recommendations on handwritten papers in the corner of the screen.

Testing

The evaluation of the prototype was designed to measure its influence on operators' behavior and task efficiency.

Adherence to Recommendations: We monitored how consistently operators complied with the system's recommendations. This involved a quantitative analysis of the number of guidelines followed and the precision with which they were executed.

Productivity Metrics: Productivity was evaluated by estimating the output in tangible metrics, such as the volume of materials moved (tons), within a given timeframe. This allowed for an objective measure of work completed with and without the assistance of our system.

Efficiency Analysis: We looked for variations in efficiency by comparing the amount of commands on the excavator arms and the distance moved to estimate fuel consumption. The idea was to determine if the assistance provided led to the completion of tasks with more efficient movement without compromising quality or safety.

Operator Performance Feedback: To gather qualitative data, we collected feedback from the operators. This helped us to understand the practical implications of our system on their work. It highlighted the perceived benefits or drawbacks, particularly focusing on whether the operators found the guidance distracting or supportive.

The results were drawn from a contrast between two distinct groups:

- Group A (Control Group): Operators who used the construction equipment simulator without any additional guidance or recommendations, relying solely on their skills and experience.
- Group B (Test Group): Operators who performed the same tasks while receiving real-time recommendations and guidance from the prototype.

This comparative analysis offered insights into the behavioral changes prompted by the prototype, the efficiency gains that could be attributed to following the provided recommendations, and the overall acceptance of such a system by the operators in a simulated work environment.

Feedback and learnings

The experiment revealed a 60% increase in efficiency and decreased the time to complete the task by 25% for players who followed the guidelines. Most guidelines were followed, albeit with varying degrees of accuracy, and there was a noted decrease in adherence over time. Players found the prototype's guidelines helpful and not distracting.

Critical Function Prototype

The Critical Function Prototype (CFP) aims to personalize user behavior understanding and aid project managers and equipment purchasers. This prototype tests specific functionalities crucial to the system's performance. The CFP focused on addressing the challenges faced by project managers and equipment purchasers in the construction industry, specifically the difficulty in understanding personalized user behavior and answering their unique queries effectively. The problem is the lack of a streamlined, intuitive process for these users to easily find and understand the best equipment for their specific needs, leading to a reliance on time-consuming consultations with sales representatives. Our aim was to simplify this process by providing a digital solution that adapts to individual user preferences and requirements, thereby enhancing the decision-making process for construction equipment selection.

The Prototype

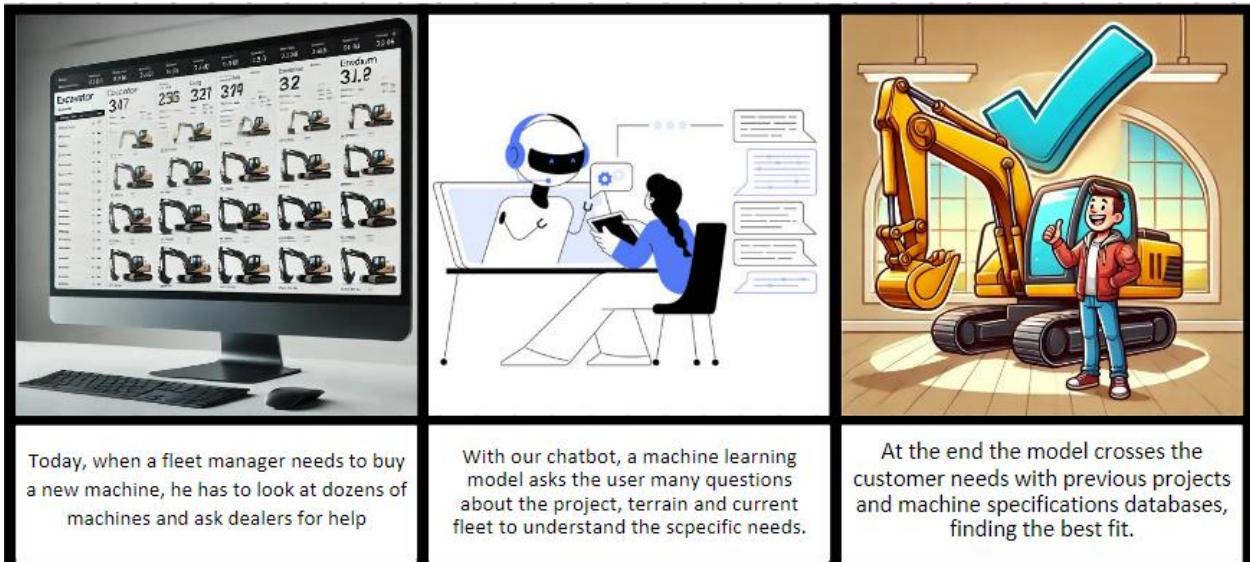


Figure 5. Critical Function Prototype storyboard

The AI-driven chatbot prototype was envisioned to revolutionize customer support at Volvo CE. Positioned as a central communication hub, it leverages advanced technologies like OpenAI's Large Language Models and the Langchain framework, enhancing conversational capabilities and offering precise support. This tool enriches the customer experience by:

- **Personalized Advice:** Serves as the go-to source for real-time, personalized interactions.
- **Product Inquiry:** Provides in-depth information on Volvo CE's product lineup.
- **Product Recommendation:** Offers suggestions tailored to the users' specific requirements.
- **Machine Comparison:** Enables users to compare different Volvo models effectively.
- **Navigation Help:** Assists users in finding information swiftly on Volvo's website.
- **Usage Tips:** Shares best practices for optimal use of Volvo products.
- **Dealer Locator:** Helps users locate the nearest dealer or showroom with ease.
- **Warranty Information:** Answers questions regarding warranty coverage and claims.
- **Sustainability Efforts:** Educate users about Volvo's sustainability initiatives.
- **Troubleshooting Guidance:** Offers solutions for product-related issues or queries.

Testing

We conducted experiments and initiated user testing sessions to observe real-time interactions, using both structured scenarios and open-ended explorations to cover a broad range of potential customer inquiries. This approach helped us assess the chatbot's effectiveness in understanding complex queries, providing detailed product specifications, and offering comparative analysis with competitor models.

User Feedback Highlights:

- Appreciation for the chatbot's ability to understand complex queries and learn from interactions, enhancing its proficiency over time.
- Suggestions emphasized the need for expanding the knowledge base to include service bookings, maintenance, and technical support, alongside streamlining the collection of user feedback for more tailored responses.
- Calls for extending support across the entire customer journey, from initial inquiries through to post-purchase services, were notable.

Identified Opportunities:

- There's a clear pathway for integrating more advanced, personalized interactions. This includes the potential for incorporating enhanced virtual demonstrations of equipment through 3D model integrations and other digital tools.
- These insights highlight the critical need for ongoing improvements in our chatbot's functionality, emphasizing the expansion of its knowledge base, refinement of response strategies, and enhanced integration within Volvo CE's comprehensive service offerings. Such advancements are key to delivering a seamless, fully integrated customer journey.

Dark Horse Phase

Dark Horse Prototypes represent unconventional and innovative ideas that challenge the status quo. These prototypes explore creative solutions that may initially seem impractical but have the potential to yield significant breakthroughs. The dark horse phase aimed to analyze potential solutions that may not be feasible for full development given the current technological limitations, but would provide significant information and knowledge for further developments. By exploring alternative solutions, key components solving the issue at hand can be found.

Mac



Figure 6. Mac's screen mockups for validation of the idea

During the Dark Horse phase, one of the concepts that were built, tested, and evaluated, was Mac, short for Macgyver, a solution focusing on predictive maintenance that would solve the issues in the equipment before they caused mechanical failure. The idea behind the creation of the Mac stemmed from the realization that diagnosing and repairing equipment failures is a process that can be both time-consuming and disruptive. When equipment failure occurs, a diagnosis is required, a spare part must be ordered and delivered, and a technician needs to be scheduled before arriving to perform the repair.

The intention with Mac is to streamline this process by performing predictive maintenance and sending alerts before a critical failure occurs. With the help of machine data and some guidance from the operator, Mac can narrow down the issue and order the necessary spare parts. Mac also schedules a technician for the repair and informs the operator to what extent the equipment can continue to operate while waiting for repairs. Mac's primary interaction is with the operator, taking agency in the repair process, thus alleviating the managers, technicians, and dealerships.

The Prototype

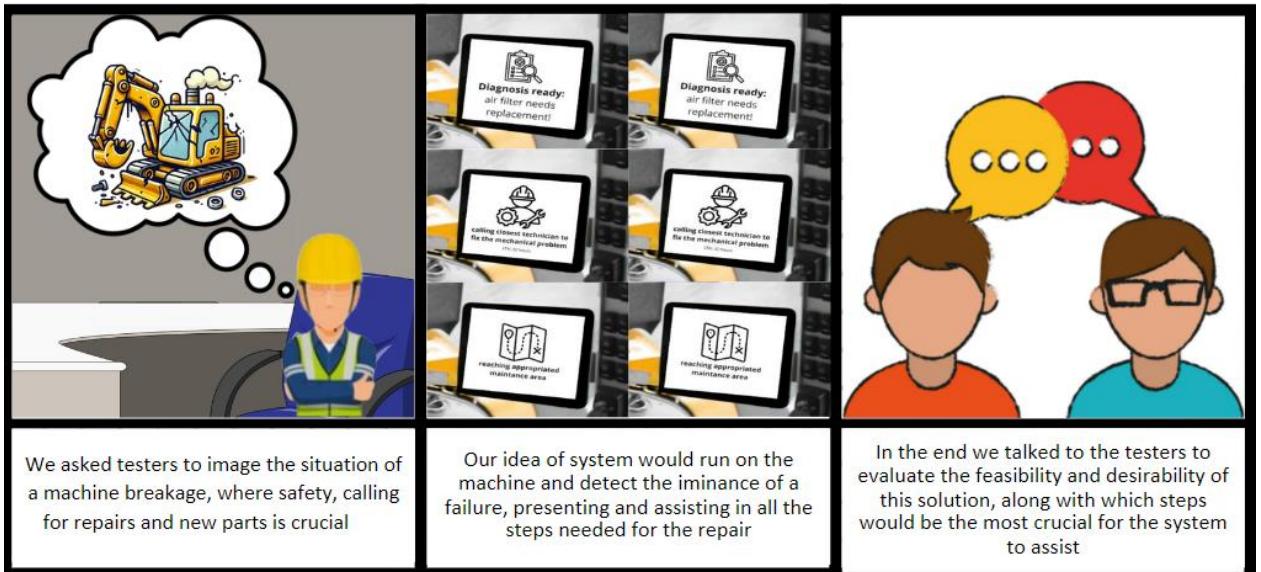


Figure 7. Mac's storyboard

The prototype of Mac was an application aimed to demonstrate how the interface would look when used by an operator. With intuitive buttons and informative pop-ups, Mac provides basic information regarding the issue and guides the operator step-by-step throughout the troubleshooting process.

A prototype story was crafted, in an attempt to guide the test subject into the scenario shown in the application. This story includes some backstory on how the problem is solved today, what the current operation is looking like, and how Mac would work in the background.

Testing

An initial test of the concept was held at Volvo CE in Braås. The background and goals of the prototype were presented and followed by a discussion. Testing of the prototype was performed with three stakeholders, one site manager, one equipment operator, and one owner-operator. The prototype and the story were introduced similarly to all three, with slight adjustments to better suit the listener, more emphasis on what happens outside the machine for the manager, and more on the troubleshooting guidance for the operator. After introducing the story and the prototype, the testers looked at the different responses and provided feedback. Additionally, several questions concerning the concept and the surrounding operation were asked and answered.

Feedback and Learnings

Initially, the solution was aimed at the construction site, and to be used by the operator. After the initial tests, concerns regarding the operators' ability and knowledge of the equipment arose, and after testing with operators in both developing and developed countries, this concern was validated. From this, it became clear that while some operators have the skill and trust to perform certain activities, others would need simple instructions or assistance from someone on-site with more knowledge and responsibility, and then would perform as good as any.

Overall, the need to expedite the process of repairing sudden failures was confirmed throughout the tests and presentations of the concept. Additionally, the potential ability to know what is wrong and what tools and parts are needed before the technician arrives was well-liked.

It was also expressed by some that depending on location and equipment, certain technicians might be desired, and not tying it to the Volvo brand. Additionally, the information provided to the technician before arriving and while reading the codes from the machine is limited, and often not enough to pinpoint the error.

The findings and learnings from this prototype heavily influenced the development of our final service. The concept of having a predictive maintenance tool on-site, integrated with the operator and accessible to all stakeholders in the process chain, served as the initial guiding principle for the Volvo HS development.

Blue

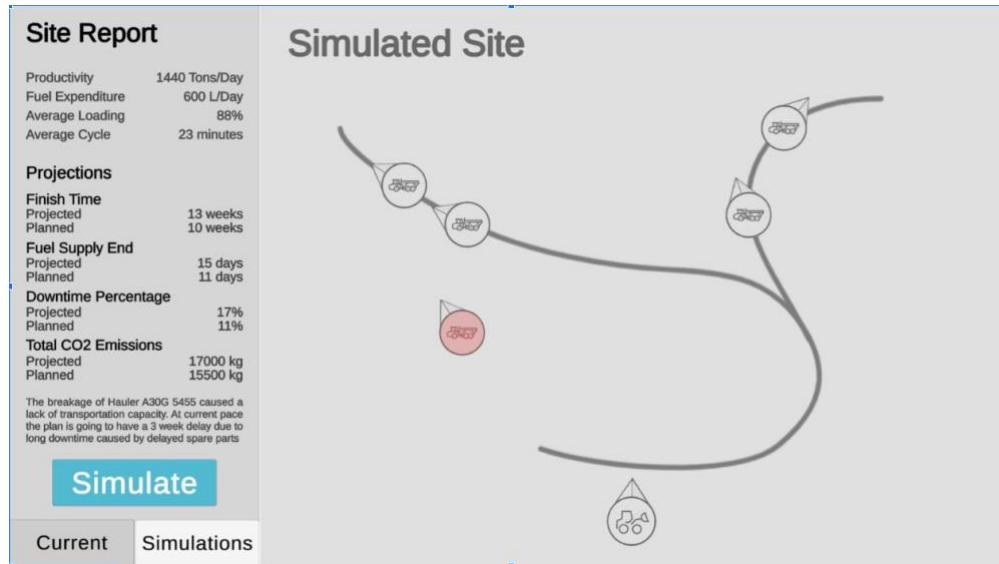


Figure 8. Blue's site manager platform prototype made in Unity

During the beginning of the ideation phase, the idea of a robot that could concentrate all the expertise and knowledge about the construction site came up. This robot, named Blue, would be able to help all managers and workers on the construction site. This prototype was made in 2 phases, one initial concept for the Volvo factory visit, at Braås, and another one incorporating the feedback from it. The latter became software that could concentrate and analyze all data about the machines on a site, understanding the problems encountered and deviations from plans, and giving suggestions based on real-time simulations.

Blue aims at solving the problems site managers have of tracking everything that is happening in an operation. The amount of different operators, machines, problems, and metrics to be aware of is very demanding for them, making really broad analysis more difficult and missing issues more common.

It also helps them in the hard decision-making process that happens on the day-to-day of an operation, when multiple factors influence efficiency and productivity and human expertise might be insufficient to make hard operational decisions. In those scenarios site managers may be weary of making big changes as unforeseen problems may arise, Blue capability of simulating the possible changes to the site actually backs up decisions with actual numbers, minimizing risk.

The Prototype



Figure 9. Blue prototype storyboard

We built a simple interface for the prototype using Unity, emulating how it would operate for a specific scenario. The scenario imagined involves a quarry with 4 articulated haulers and 1 wheel loader, but 1 of the haulers is broken. This situation is simple enough for understanding the functions of the prototype, but also presents difficulties, as managing load-moving units and dealing with downtime problems are real issues faced by site managers.

The interface showed information about the individual machines, like fuel percentage, load carried, map position and who is operating it. Also, on the side was data about the operation in general, giving important metrics to track the performance on site. On top of that there is a section with projected metrics, these projections are compared to the planned numbers, being able to give insights on possible future problems that would go unnoticed. Below the comparison an analysis done by Blue is shown, demonstrating that the software will have the ability to understand the situation and give a textual overview that summarizes the data and the current situation.

The main part of the prototype is the simulation tab, where the site manager can choose to simulate the current situation, receiving different recommendations of changes to do, their benefits and downsides, being also able to see how the site would operate under such new conditions and the projected metrics with those changes.

Testing

An initial test of the concept was held at Volvo CE in Braås, at which the aim of the prototype was communicated and discussed with the attendees. The tests made with the prototype were mainly based on evaluating the desirability, use cases, how they deal with the problems solved by Blue now, and how much would site managers trust and use software like the one shown.

The testing process involved giving a basic 5-sentence context for the site manager to understand what type of operation is being shown on screen and then letting them use the software for around 5 minutes. Then 6 basic questions are asked to the site manager, mainly trying to probe them for how and why they

would or would not use this application. The focus of the questionnaire is on their current and ideal day-to-day work life and if Blue would add value or be forgotten/untrusted easily in their current environment.

Feedback and learnings

The feedback gained from the visit to Braås helped us narrow down the more open and idealized version of Blue into a concrete site managing aid that can solve more concrete problems and have clearer use cases. Other findings from that occasion were the lack of simulations done with the real-time situation of the site, being mainly restricted nowadays to the planning of the operation, not on possible live changes that could bring benefits. Another insight is the site managers need of ways to understand and be more aware of the situation of the site, being very overwhelmed by all the tasks being done on site and spending a lot of mental energy on making sure everything is running according to plan. With those insights, the data visualization and automatic analysis of it is an important focus for the following ideas, along with enabling real-time simulations using real-time data and operation situations.

Volvogotchi



Figure 10. Printed cartoon machine's on cardboard to explain Volvogotchi's concept

During the ideation phase, we tried to find out what was the difference between an operator whose machinery belongs to them, and a contracted operator, who doesn't. By doing that, we noticed a great lack of emotional and financial connections between machines and operators. If a machine breaks, the operator might just use another one, once there are mainly no consequences for not taking good care of it. This difference in the care and value put on the machines and how it affects the decision making-process when using the machines can be related to the Endowment Effect as analyzed by Guo (2024).

Having the motivation in place, Volvogotchi was created to focus on developing this emotional connection. The prototype aimed to address how the operator cares for a machine that doesn't belong to them. The initial idea was to build a digital twin using machine sensors to monitor the current state of the machine and display this information on an interface. By doing so, we imagined that the worker would take more care if they knew how each of their actions affects the current and future state of the machine. The "emotional state" of the machine on the interface, whether happy or sad, could potentially influence the real-life emotional state of the operator.

As for the beneficiary, the operator would be directly affected, but the one who stands to gain the most is the fleet manager since their machines would look much cleaner and last longer, with less maintenance.

The prototype

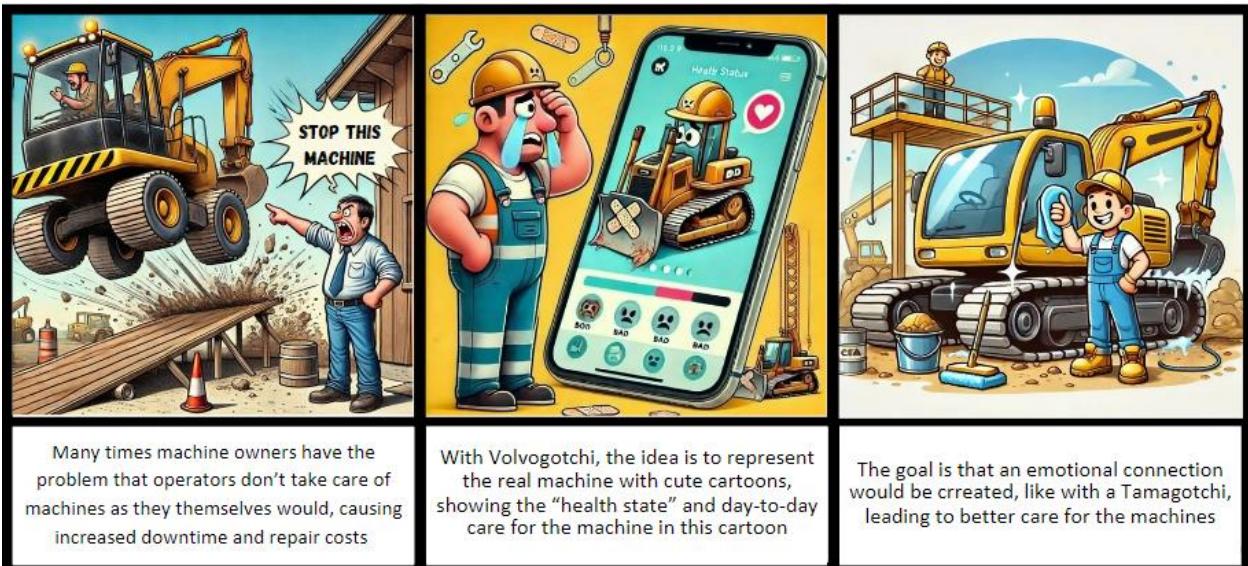


Figure 11. Volvogotchi prototype storyboard

We created a physical model of what the interface would look like, in the form of a triangular prism, to demonstrate what the operator would see in their day-to-day use of Volvogotchi and what visual impact the prototype aimed to cause. Each side contained a state of the machine (happy, sad, broken), along with a miniature version that helped us illustrate how the machine's states impact the model in the application.

Testing

The initial idea was tested with Volvo employees in Braås, during a presentation of all the work developed up to that point. We received some positive feedback, but the main point was that tracking all the workers' information is illegal, as it could be used against them by a site manager or their boss. In the following days, we discussed extensively how to keep the idea working towards a similar goal, but everything seemed to make the Volvogotchi too similar to other prototypes already developed (an app with lots of useful information for the site manager, but which doesn't add anything to the emotional connection with the workers themselves, as continuous information about the machine was necessary for the app's

functioning). Therefore, we decided to discard the idea and pursue others that seemed less inconsistent, but keeping in mind the things we learned during Volvogotchi's construction and presentation processes.

Feedback and Learnings

Creating an emotional connection can be good and helpful, even though tracking people's data isn't the best way to do it. This is because the operators feel like they are being traced which is an invasion of privacy. How much longer will it last: giving an expiration date to a product will probably the interest in fixing things, as people actually know how much longer a machine will last if it keeps being affected by a determined problem.

Key Findings

The key findings and problems found during the three months of early needfindings, prototyping and testing.

Sales and Procurement

- A personified AI is perceived as helpful when providing information on equipment specifications and optimized utilization of said equipment.
- The relationship between sales personnel and customers affects the nature of the purchase. A lot of trust is put into the salesperson.
- Sales personnel have a hard time knowing about all the different options and what fits best for the diverse amount of applications.
- There is a lack of support when deciding what equipment to buy, and when planning new projects what equipment to assign to the task.
- Gauging the condition of second-hand equipment is difficult and often becomes a gamble

Maintenance and Equipment

- The view on the operators' involvement in troubleshooting requires further evaluation but taking a load of the managers, dealerships, and technicians during this process was seen as a good thing. However, managers would need to be involved in the final decision.
- There is a need to offer automatic updates on project progress and issues, both real and potential ones using a visual tool. This could be done using the AI chatbot to share further knowledge on the site and potential optimizations.
- Creating an emotional connection with the machine could lengthen the life of the machine, but poses issues regarding tracking the operator.
- There is a clear need and desire to speed up the repair process before and after machine failure.
- Technicians showing up with the wrong spare part or missing the correct tools is an issue, and information provided to the technician is often very limited.
- Time is spent waiting for parts to be delivered since keeping them in stock is expensive

Site Management

- The setup of different machines affects the usage of services on-site.
- Getting an overview of the current phase of the project and what machine is where and doing what is difficult.
- Choosing the best option for improvement or in case of unplanned events and calculating the outcome is difficult.
- Especially when the equipment is rented, or when the operator is hired to drive another machine for a short duration, the general opinion is that the equipment takes more beating than usual.

Key Findings for the Final Solution

After three months of early needfinding, prototyping, and testing, the team, along with the Teacher Team and Volvo CE Stakeholders, determined that the following topics should form the foundation of our final solution, as their value was proven to be key findings from our testing.

- Supporting the selection of equipment during sales and project planning
- Maintenance and equipment condition for higher uptime
- Predictive maintenance tool for on-site solutions
- Site overview, management, and optimization in operation

Refined Personas

After conducting additional interviews and gathering more information about the user, as identified during the functional prototype development phase, four new personas were created to refine the final solution proposition. Since the functional prototype stage and moving forward, we have centered our focus on the operator as our primary user. This approach has been consistent in our development process. The personas were differentiated not only by the distinction between owner-operators and non-owner-operators but also by the distinct behavioral characteristics observed among Brazilian and Swedish operators, which were identified as crucial for understanding our final user, the operator. The final personas included a Brazilian machine owner, a Brazilian company operator, a Swedish machine owner, and a Swedish company operator. For the proper development of the personas, eight characteristics were established: their role and career, how they function, their background, needs, desires, pain points, tone of voice, and their typical approach to business dealings.

1st Persona: Elliane Macedo, 38 years old, the Brazilian owner-operator



Figure 12. Representation of Elliane

Role and Career:

- Owner and operator of a medium sized (14T) Caterpillar backhoe loader
- Have been operating machines till her childhood, uses the machine as part of her body

How she function:

- Have a simple mind and love mechanical work
- Like to have her own moment with the machine at work

Background:

- Mother of two
- Has the driving force of her life as her family
- Currently living in the interior of São Paulo, as there's more job to be done and less competition than the big cities.

Needs:

- Reminders to perform certain tasks
- Reduce risk of sudden failures to reduce the extra stress from this risk
- Overview of long term machine health

Desires:

- Get the work done quick and easy
- Have a functioning machine with minimal effort
- A little freedom at work but also directions

Pain Points:

- Fear of mechanical breakage and loss of income
- Maintenance, service & unexpected failures

2nd Persona: Altair Tavares da Silva, 43 years old, the Brazilian company-operator



Figure 13. Representation of Altair

Role and Career:

- Operator for a big contractor for 15+ years
- Basic education, learned everything of the machine on the site

How he function:

- Have a simple mind and love mechanical work
- Work on the site to provide for himself and his family

Background:

- Father of a family of four
- Has three Brown mixed-breed
- House owner in São Paulo, capital of the state
- Work for the same company for years, loyal and trusted by his bosses

Needs:

- Freedom to work at his own pace but also directions
- Reduce risk of sudden failures to reduce potential problems from this risk
- A more instructed mechanical technician to provide solutions to machine problem he don't understand

Desires:

- Having support when dealing with his bosses once a machine has a problem
- Have a minimal effort during work
- A comfortable place to work

Pain Points:

- Working for other people can be a pain in the ass
- Can't decide the aspects of the machine he'll drive

3rd Persona: Aston Mårten , 35 years old, the Swedish machine-owner



Figure 14. Representation of Aston

Role and Career:

- Owner and Operator of a medium sized Volvo excavator
- Started working as hauler-driver at 20 years old, moved to excavators at 25
- Started her own company and bought her first excavator at 30

How he function:

- Need instant gratification to perform boring tasks
- Mind is full of thoughts and ideas, menial things are often forgotten

Background:

- Mother of two
- Has a Bearded collie
- House owner in the suburbs of Kristianstad

Needs:

- Reminders to perform certain tasks
- Reduce risk of sudden failures to reduce the extra stress from this risk
- Overview of long term machine health

Desires:

- Get the work done quick and easy
- Have a functioning machine with minimal effort
- Instructions but freedom to work independently

Pain Points:

- Fear of mechanical breakage and loss of income
- Lack of time for the telematics
- Maintenance, service & unexpected failures

4th Persona: Rolf Roj Svensson, 40 years old, the Swedish company-operator



Figure 15. Representation of Rolf

Role and Career:

- Operator of a medium sized Volvo excavator for a construction firm
- Only uses the machines owned by the company, has operated different machines over the years

How he function:

- Likes to do his job and then leave and go home
- Mind is full of things he wants to do outside of work

Background:

- Father of two
- Has a Bearded collie
- House owner in the suburbs of Sölvesborg

Needs:

- Have clear instructions
- "Leave the work at work"
- A functioning machine to do his job
- Easy access to the services

Desires:

- Get the work done quick and easy
- Have a functioning machine with minimal effort
- A little freedom at work but also directions

Pain Points:

- Maintenance, service & unexpected failures
- The technology and machine as a whole seem complicated, it easier to just drive instead of owning and caring for it.

The Final Solution

The tests and feedback indicated that the Dark Horse Prototypes (DHP) had the potential to add significant value to the sector. After discussing the possibilities and the identified problems, Mac was selected as the concept with the most promise for further development in the next phase to alleviate the issues of maintenance and uptime. However, upon investigating how to bring the idea back from the future to what is currently feasible, it was discovered that not only this concept but all of the DHPs faced the same issue if they were to retain their core value-adding aspect. Although the concepts were desirable and viable, they all lacked feasibility, indicating a need for the solution and its potential marketable value, but technical constraints were hindering their realization. To realize the concepts, more data would be needed from the equipment to build machine-learning models capable of providing the input they require. Adding additional sensors was however found to not be a good option due to the added complexity and the increased risk of malfunction that comes with it. Identifying this constraint moved the focus, and instead of creating a system that only presents and uses data, the focus shifted to developing a system that enriches the data through the collection of contextual data from the operator to supplement the existing data.

During further visits to construction sites, it was discovered that at the beginning of every day, the operators would go through the equipment and perform a daily checkup to ensure that the machine has no severe malfunctions. These checkups are, however, rarely documented for further use and are forgotten unless something requiring immediate action is discovered. This insight, combined with insights gained during the visit to Braås regarding how not having an operator affect the approach to data management and troubleshooting issues, sparked the idea of giving the operator a more central role in the equipment health monitoring.

The Concept

The final solution is designed to tackle the problem of unplanned downtime caused by data lacking context. It primarily aims to improve overall awareness of equipment health and implement predictive maintenance to prevent unexpected equipment failures. To address the challenge of insufficient equipment data, the solution enables the operator to act as a sensor, providing additional data that multiple stakeholders can use.

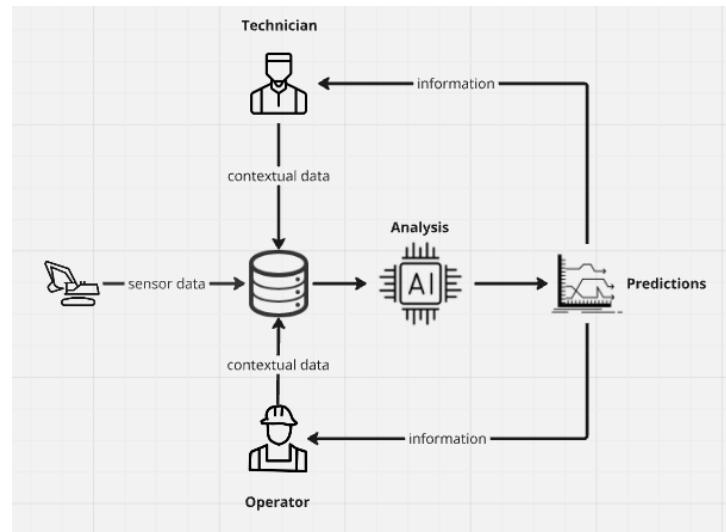


Figure 16. System diagram of the final solution

Operators can use the solution to collect data for assessing equipment health. They are required to record the daily checkup using an app, reducing additional tasks and enhancing their ability to provide accurate data. The app prompts operators to input information about the machine, including the operating environment, weather conditions, and tasks to be carried out. Operators can also input more details if they notice anything unusual, such as strange vibrations, sounds, or odors. The ability to report additional symptoms is always available to ensure they are documented as soon as they are noticed, ensuring that relevant data is captured and included in the report. Additionally, operators are asked to take pictures throughout the process as a security measure to confirm that the checkup is performed. These pictures are saved for future use and analyzed for any visible issues that the operator might have overlooked.

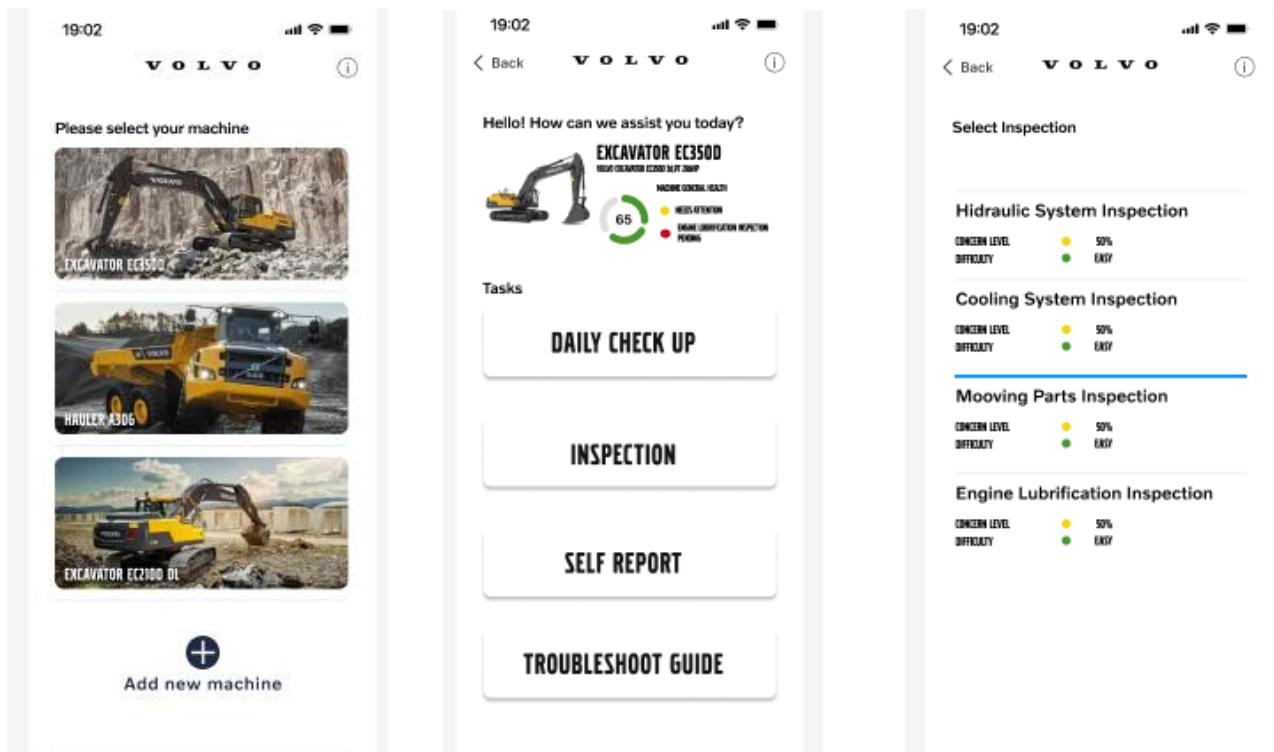


Figure 17. Application screens for the first version of the operator's app

Despite the fact that the extra collected data gives more context to the machine data for predicting failures, the ML model might require additional information to minimize false positives. As a result, the operator may need to conduct further inspections of specific machine parts to help identify potential issues. These inspections might involve areas or tasks that the operator is not familiar with, so the app would assist the operator through the inspection using both AR and AI to ensure the information gathered is as accurate as possible.

A substantial amount of data is gathered during each process. This data is then combined with the machine's existing data to update the virtual model. By employing ML algorithms, prediction models are developed to anticipate future failures. These models take into account various factors such as the type of machine, the nature of the task, environmental conditions, and the machine's historical data. By analyzing this combined data, the ML model can recognize patterns and trends that aid in predicting potential failures and issues in the future. This proactive approach helps in preventing potential downtime and ensuring smooth operations.

In case the machine malfunctions or requires regular maintenance, a technician's assistance may be necessary. If such a situation arises, the technician will be granted access to all the information collected by the system through an interface similar to the operator's. This will allow them to gain a comprehensive overview of the machine's condition and more efficiently identify the root cause of the issue. Furthermore, the technician will be required to input additional information throughout the entire repair or maintenance process, contributing to continuous improvements in the system's accuracy and effectiveness.

The additional data is initially meant to improve understanding of the machine's condition by adding contextual data and enabling the logging of additional data when prompted by the operator. Contextual data refers to information that complements the existing machine data by providing data that cannot be collected through sensors or tracked by the currently installed sensors. Access to potential workloads, project tasks, geographical data, and failure data improves the ability to understand how different excavator models perform in various scenarios. This additional information not only provides better support in guiding sales but also offers better insight into the usage of different equipment and could highlight areas for improvements in both product and service development.

Scenario without and with Volvo HS

Scenario Without Volvo HS:

Before the integration of the Volvo HS system, construction projects often encountered significant unplanned downtime due to equipment failures. For instance, consider the case of Elliane, an excavator operator working on a critical construction project. One day, despite a routine checkup indicating no immediate issues, Elliane notices an overheating warning on her excavator's dashboard. Uncertain about the severity of the problem and lacking detailed diagnostic tools or immediate support, she decides to continue working, hoping it is just a minor issue influenced by the day's high temperatures.

As the day progresses, the excavator's performance diminishes, ultimately leading to a complete breakdown. Smoke begins to billow from the engine compartment, forcing Elliane to stop the machine entirely. The nearest technician, located hours away from the remote job site, cannot arrive for three days. When the technician finally assesses the excavator, it is discovered that a coolant leak led to severe engine damage. Replacement parts are needed, but they will take two months to arrive, further delaying the project. In the meantime, Elliane must lease another machine to keep the project on track, significantly increasing costs due to the lease, delayed project timeline, and additional technician fees.

Scenario With Volvo HS:

With the implementation of Volvo HS, the approach to maintenance and equipment monitoring transforms. In this new scenario, Elliane conducts her daily checkup using the Volvo HS app, which prompts her to enter specific information about the excavator's performance, environmental conditions, and any unusual observations. This day, she notes a slight decrease in coolant levels and follows the app's guidance to conduct a focused inspection using augmented reality tools.

The app, integrating data from the machine's sensors with Elliane's inputs, detects subtle signs of a potential coolant system issue before it becomes critical. It advises her to inspect the cooling system more closely. During this inspection, Elliane discovers a small crack in one of the coolant lines. The Volvo HS system predicts that with daily coolant top-ups and a slight reduction in workload, the excavator can continue operating safely for another week.

Simultaneously, detailed information about the issue and the predictive diagnostics are shared with a local technician, who prepares the necessary parts for a precise and efficient repair. The parts needed are less numerous and less critical, allowing for a faster delivery. The technician schedules a visit within a week, during a planned downtime, minimizing the disruption to the project.

Impact of Volvo HS:

This proactive maintenance approach provided by Volvo HS not only prevents severe damage to the equipment but also significantly reduces the downtime and associated costs. Predictive maintenance ensures that minor issues are addressed before they escalate into major failures, thus maintaining continuous project momentum. The integration of operator-driven data collection enhances the machine's data context, making diagnostics more accurate and maintenance more timely.

Operators become a crucial part of the equipment health monitoring process, empowering them with tools to understand and influence the operational readiness of their machines. This shift not only improves operational efficiency but also fosters a sense of ownership and responsibility among operators, enhancing their engagement and satisfaction at work.

The proactive, data-enriched approach of Volvo HS transforms traditional reactive maintenance paradigms into a strategic asset management practice, thereby reducing unplanned downtime, lowering operational costs, and boosting overall productivity on construction sites.

Prototype Evaluation

The prototype was taken to construction sites in Sweden, where the idea and the concept were presented to operators, who received a brief explanation of the issue and scenario. They were then provided with the app and could follow the steps in the prototype to conduct the machine checkup. The feedback gathered during these tests was predominantly positive, with users seeing the app as a useful tool rather than an additional responsibility or burden. However, some testers mentioned that holding the phone during checkups could be awkward, especially in winter when gloves are typically worn. Machine owners

found great value in the additional assistance with documentation and the overview provided. The manager of a large project, which involved machines operated by different individuals, was also introduced to the idea and tested the prototype; they expressed how this concept would facilitate issue discovery, as it would make it easier for operators who felt no personal attachment to the machine to report issues.

Overall, the results of user testing and stakeholder feedback reflect positively on the concept. It would offer advantages and address an existing issue in the construction industry without being overly intrusive or obstructive for operators.

The App

We can analyze the final prototype from two perspectives: the aspects related to the software component involving user interaction (frontend) and the aspects related to the software component involving the database (backend) and integration with other technologies used for the complete functioning of the system, such as the predictive models and image analysis AI developed by the team.

User Interaction

With a solution aimed at having the operator act as a "human sensor," one of our top priorities was to validate a user interaction that was intuitive, feasible, and accessible. To achieve this, using the operator's own smartphone was a solution that met these prerequisites. Our main challenge then became creating an interface that would encourage the operator to use the system and guide them to produce coherent and relevant data for Volvo CE.

The code for the final prototype's front end can be found at <https://github.com/RossSumie/VolvoHS.git> (03/07/2024).

Timeline and Validations

Initially, with the aim of validating the proposal with as many people as possible (including operators, fleet managers, and Volvo workers), we developed a responsive website using TypeScript and Next.JS. This responsive website could be accessed by scanning a QR code or through a link we sent to individuals relevant to our validation process. The app flow was guided with glowing green boxes indicating where the operator should tap on their first run of the app, and for this demo there were also green text books around the app with the developing team comments. This approach ensured that test users could experience the application on their own mobile devices without needing to download or configure the app, streamlining the validation process and encouraging more people to participate in our research.

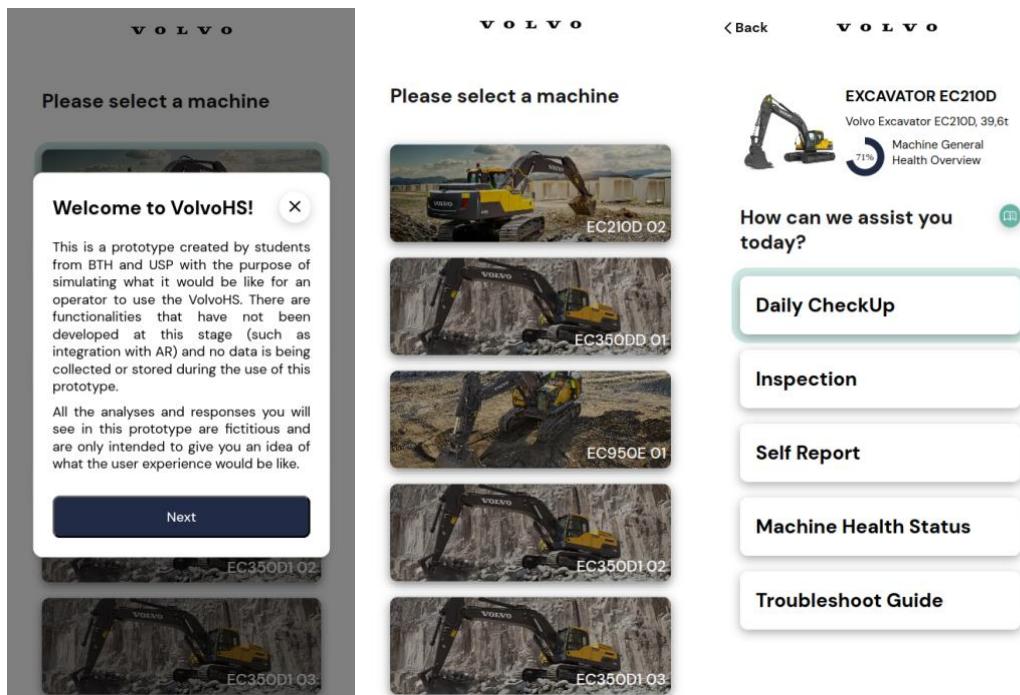
In this first version of the application as a responsive website, we were able to validate the user flow we envisioned based on their role, the functionalities we believed would add the most value to the product, and the technologies we intended to implement.

We realized that options needed to always have clear and intuitive text, and that open response fields were not appropriate due to previously identified written communication difficulties by the Volvo CE Brazil team. We also noted that operators, unlike technicians, do not necessarily have knowledge about the parts and components of the machines they operate. Therefore, even simple inspections require intuitive instructions. Lastly, we discovered that there is a daily inspection routine that operators are instructed to perform, but currently, its conclusions are not recorded anywhere.

Another important validation and feedback we received during this first prototype was the potential to create different user types for the application. This would allow not only operators but also technicians and fleet managers to provide contextual data to the system.

Each user type would have a different user journey, with questions customized by category (for instance, more technical questions for technicians compared to operators) and varied access to information from the database. This ensures VolvoCE has complete control over who accesses what information.

With all these insights from the validations of this first prototype, we moved on to developing a second prototype to validate new aspects and implementations of the application.



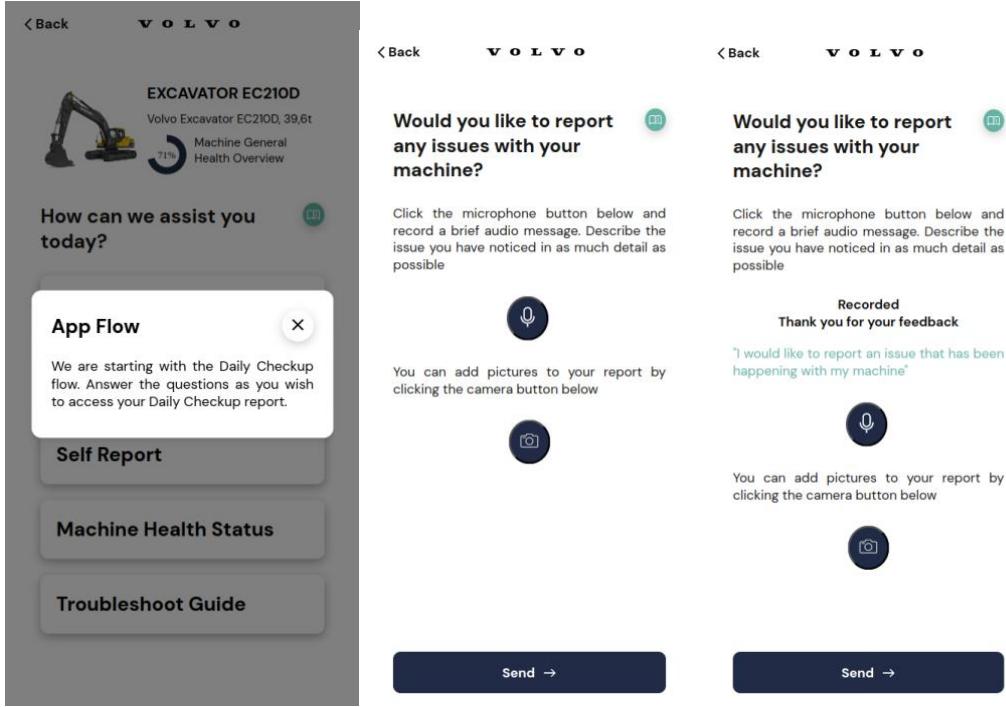


Figure 18. Application screens for the final version of the operator's app

This first prototype can still be accessed through <https://macgyver-mocha.vercel.app/> (25/06/2024) and the code can be found at <https://github.com/RossSumie/macgyver.git> (03/07/2024)

Technologies

The second and most recent version of the Volvo HS prototype was developed in **TypeScript** using the **React Native** framework (which is specifically designed for mobile app development).

To test the integration of the application with augmented reality, we migrated the platform development to React Native to enable interactions with the device's camera. We researched various ways to integrate augmented reality with mobile applications and, aiming to develop the application as quickly as possible to validate this feature, we used the **ViroMedia** libraries.

All the code for the prototype can be found in a [GitHub](#) repository (excluding the node_modules folders and the Java/Gradle configurations to save space).

About React Native

[React Native](#) is an open-source framework developed by Facebook that enables the development of mobile applications using JavaScript, TypeScript and React. With React Native, developers can create native applications for iOS and Android using a single codebase, significantly reducing development time and costs. The main applications of React Native include building mobile apps that require a rich and responsive user interface, with the ability to access native device functionalities such as the camera, GPS, and push notifications.

About ViroMedia

[ViroMedia](#) is an open-source development platform for creating augmented reality (AR) and virtual reality (VR) experiences in mobile applications. Using frameworks like React Native, ViroMedia allows developers to easily integrate AR and VR elements into their apps, providing rich and immersive interactions. Its main applications include creating interactive experiences such as AR product visualizations, immersive games, and educational apps that leverage augmented reality to enhance learning.

In this prototype, it is important to note that the identification of machine parts occurs through specific images recognized by ViroMedia. These images are located in the "assets" folder within "src," and when the camera is pointed at these specific images, it returns the markings as manually programmed.

**** It is important to note that using ViroMedia for launching the application in production is **highly discouraged**, as it is an open-source tool with no concrete maintenance guarantees. The platform was used specifically for this prototype to validate the use of augmented reality as a way to add value to the product-service developed to guide the user during their inspections.

Data Bank

After setting up the first prototype of UI as mentioned above with next js and vercel, we have uncovered many challenges and got a lot of feedback. Considering all of these we started working on the final version which uses react for frontend and express, flask for backend.

Flask Server

First we have created a backend server for the image analysis yolo model we implemented for inspection to identify and detect potential failures in machine parts. This backend server is implemented using 'Flask' and deployed on 'Digital Ocean'.



Figure 19. Backend activity dashboard

Using the trained model best.pt from the image analysis yolo, we did predictions on the input images. And by abstracting these detections on the input images we have hardcoded a python file to draw bounding

boxes and display identified labels, which are sent to the server by deploying it on a digital ocean platform. So when a post request is made to the server it will analyze the input image and will give the detected image back. To run the code use command 'flask run'

In this process the main challenge we faced was slower output responses, it was initially taking more than 30 seconds to return the analyzed images which was long enough. This issue was due to the high data quality of images sent. We tried to fix this problem by decreasing the quality to a higher extent and resizing images sent on request, then we started seeing the wrong detections completely. We did some testing and in the end figured out that was to to the yolo model which was trained on high quality images and so analysis on lower quality images using that model will end up giving wrong detections. The we did some trial and error adjusting the quality of images sent on request by keeping it not to low and not to high, for ensuring quick output responses of analyzed images and also to give correct detections.

Final code is accessible here 'https://github.com/sowmyamillapalli/macgyver_ml_backend'

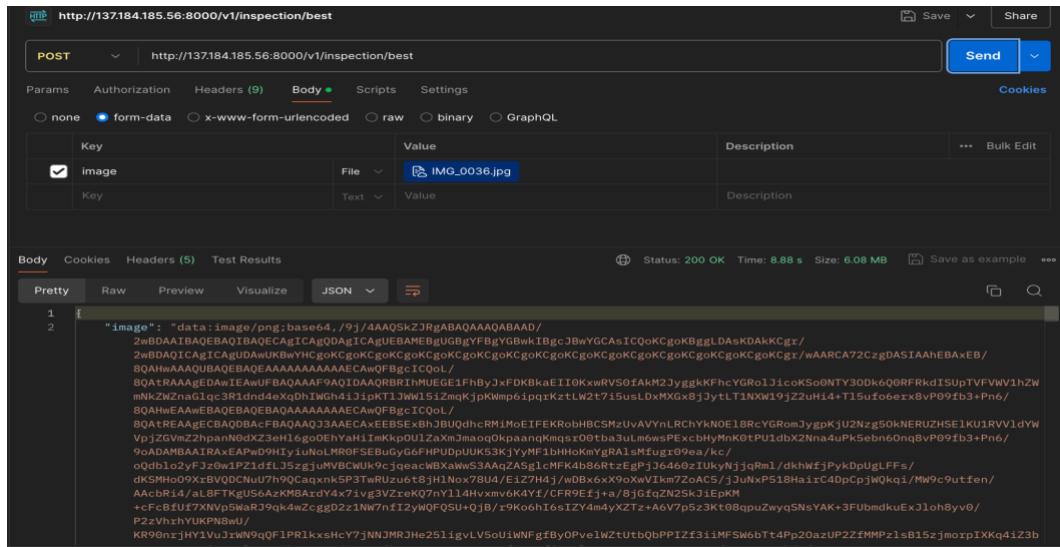


Figure 20. Backend POST request with base64 encoded image

Technologies Used

Flask

Flask is a lightweight Python web framework used in this project to build the backend server. It manages HTTP requests and serves the outputs of the YOLO model, enabling rapid prototyping and straightforward deployment of the web services necessary for interfacing with the machine learning model.

Digital Ocean

Digital Ocean offers scalable cloud infrastructure services, used here to host the project's Flask server on a virtual private server (Droplet). It provides an accessible, cost-effective, and reliable platform, ensuring stable performance for the AI-driven application and its web-based interactions.

Express Server

The main backend server is implemented using node framework ‘Express’, database utilized is ‘MongoDB’ and for storing images ‘Aws S3’ is used . First we started off with setting different routes for both DailyCheckUp page and InspectionPage. Then we connected to mongodb by creating a new cluster and collection under it. We wrote separate codes for both daily checkup and inspection by creating a model.js files, of how the data variables are stored, in which formats etc.

The screenshot shows the MongoDB Atlas interface. On the left, there's a sidebar with sections like Overview, Deployment, Database, Services, Security, and a Goto link. The Database section is active, showing databases like 'macgyver', 'sample_airbnb', 'sample_analytics', 'sample_geospatial', 'sample_guides', 'sample_mflix', 'sample_restaurants', 'sample_supplies', 'sample_training', and 'sample_weatherdata'. Under 'test', there are two collections: 'dailycupreports' and 'inspectionreports'. The 'dailycupreports' collection has documents listed. One document is expanded, showing fields such as '_id', 'weather_state' (with values 'hot' and 'cold'), 'kind_of_operations' (with values 'NA' and 'N/A'), 'working_ground_image_before' (with a URL), 'check_coolant_level' (with values 'no' and 'N/A'), 'was_coolant_refilled' (with values 'no' and 'N/A'), 'check_coolant_leaks' (with values 'no' and 'N/A'), 'abnormal_sounds' (with values 'no' and 'N/A'), 'anything_else' (with values 'no' and 'N/A'), 'Date' (with value '2024-05-27T23:04:06.930+00:00'), and '_v' (with value '0').

Figure 21. API requests documentation for our backend integration

By exporting those model.js files we created controllers to initiate all the other actions server is responsible for. Example, in inspectionController.js we first wrote a function to call external image detection services using the api endpoint we created to the flask server which is '<http://localhost:8000/v1/inspection/best>', then we wrote a function to collect the input images uploaded as a file, preprocess it, detect images by calling above function in this and also uploading the analysed images to the s3 bucket. using this function we return the url of raw images and also analyzed images. Then we created three controllers, one is to create an inspection report, another is to get all inspection reports of a particular user, the last one is to get an inspection report by particular id or of that session by using the exported InspectionModel.js file. Similarly for DailyCheckupController.js also we did the same thing, uploading initial images to S3 bucket, creating and calling functions if there is analysis and returning the final urls. Also creating controllers for creating daily checkup reports, getting all dailycheckup reports of a user and by particular id or session.

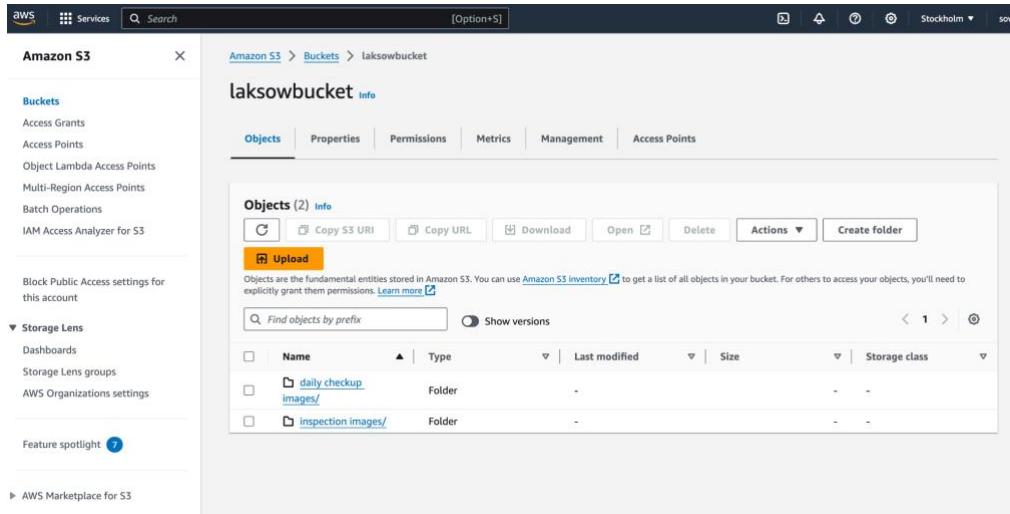


Figure 22. Backend folders for daily checkup and inspection images

Finally we exported all these controllers in the initial routes created for both dailycheckup page and inspection page. And exported those routes in the index.js file where we created initial routes and started server.

And after successfully executing this on local server we deployed it on render and extracted the new api end points which are used on frontend side to store data and extract responses for requests made.

Final code is accessible here 'https://github.com/sowmyamamillapalli/macgyver_express_backend'

This is the postman doc's to test the backend"

The screenshot shows a Postman interface with the following details:

- Request URL:** https://macgyver-express-backend.onrender.com/api/inspection/create-inspection-report
- Method:** POST
- Body:** form-data (selected)
 - Key: coolant_image_before, Value: File (IMG_0036.jpg)
- Response Headers:** Status: 201 Created, Time: 49.44 s, Size: 1.43 KB
- Response Body (Pretty JSON):**

```

3   "check_coolant_level": "NA",
4   "check_fan_blades_wear": "NA",
5   "check_fan_function": "NA",
6   "coolant_leaks": "NA",
7   "odd_water_pump_sound": "NA",
8   "fan_spinning_correctly": "NA",
9   "Analysed_coolant_label": "radiator fins bent",
10  "Analysed_radiator_label": "Unknown",
11  "radiator_image_before": "",
12  "coolant_image_before": "https://laksowbucket.s3.eu-north-1.amazonaws.com/inspection%20images/1719847570277_IMG_0036.jpg",
13  "radiator_image_analyzed": "",
14  "coolant_image_analyzed": "https://laksowbucket.s3.eu-north-1.amazonaws.com/inspection%20images/
    1719847576482_analyzed_coolant_IMG_0036.jpg",
15  "extra_image": null,
16  "_id": "6682ca996b3c211323687bee",
17  "Date": "2024-07-01T15:26:17.170Z",
18  "__v": 0

```

Figure 23. Backend POST request for engine overheating inspection

This is final document'<https://documenter.getpostman.com/view/34831199/2sA3QsAXcf>' to test the backend on postman.

Technologies Used:

Express Server

Express is a fast, unopinionated web framework for Node.js used in this project to handle routing and server-side logic. It efficiently manages communication between the frontend and the backend services, processing API requests that interact with the MongoDB database and AWS S3 storage, orchestrating the flow of data and server responses.

AWS S3

AWS S3 (Amazon Simple Storage Service) is utilized in this project for storing and retrieving images efficiently. It acts as a robust, scalable object storage for the application, handling large volumes of data with high availability, which is crucial for maintaining the performance and scalability of the image analysis features.

MongoDB

MongoDB is a NoSQL database used here for its flexible document structure, which is ideal for handling varied and complex data sets typical in web applications. It stores data in JSON-like documents that provide a rich and dynamic schema, facilitating the quick integration of data from various sources and speeding up the application development process.

Image Analysis

As described above we have implemented image analysis to detect the potential failures in machine parts using ‘you only live once-yolo model’. First we wanted to start working on a particular problem so we choosed ‘machine overheating’ as our scenario. Later we listed out all the parts that needs to be analysed which eventually leads to failures, if shows unusual behaviour. So we choose to check two machine parts and analyze them using yolo which are

- 1) Radiator
- 2) coolant tank

Data Collection

With the help of our supervisors we were also able to gather pictures of clean machine parts, of both radiator and coolant tank. Apart from that we also got pictures of both these machine parts in dirty state from the most beaten up machine in germany.

Data preprocessing

Using the gathered images we performed preprocessing which is data augmentation and annotations. By doing data augmentation we did increase the data set by doing rotations and scaling to make the dataset diverse with different angles and intensities. For annotations we used an open source tool called LabelMg (Jose et al., 2024). So for each machine part we included several classifications and gave labels for all of the pictures in the dataset. For example with radiator we included these classifications:

- 1) Radiator fins bent
- 2) Radiator Clogged
- 3) radiator clean

And we also tried to increase the dataset by photoshopping some clean radiator images to potrey clogged radiator. We added some dust into fins and was able to train on that dataset.

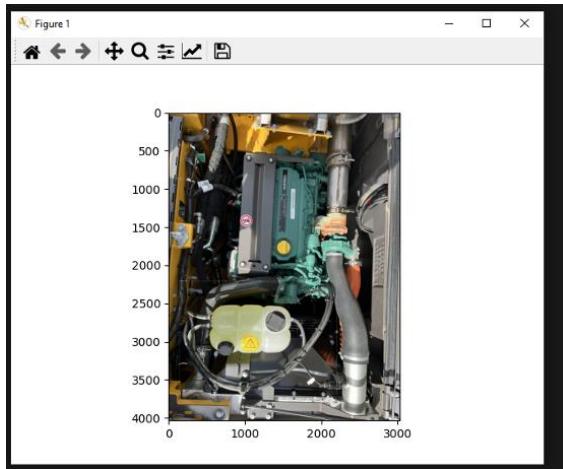


Figure 24. Engine image for analysis

Model Training

The model is trained using the YOLOv5 framework (Horvat & Gledec, 2022). Data is split into 80% training, 10% validation, and 10% test sets, and configurations are set in a YAML file. Training is initiated with train.py, adjusting parameters like batch size and epochs according to the system's capabilities. The model uses distributed data parallelism for efficiency and dynamically adjusts training parameters based on performance metrics. Checkpoints are saved periodically to capture model states, with the best performing model preserved at the end of training for deployment which is the 'best.pt'.

Command for training 'python train.py --img 640 --cfg yolov5s.yaml --hyp hyp.scratch.yaml --batch 32 --epochs 100 --data road_sign_data.yaml --weights yolov5s.pt --workers 24 --name yolo_road_det'.



Figure 25. Labeled images for model training

Testing and Performance Evaluation

Post-training, the model's accuracy is assessed using the detect.py script, which applies the best weights to the test dataset. The script processes each image, marking detections with bounding boxes and confidence scores, and outputs these visualizations alongside text files containing detailed detection data. This phase evaluates key metrics like precision and recall, ensuring the model performs well on new, unseen data and confirming its readiness for practical deployment.

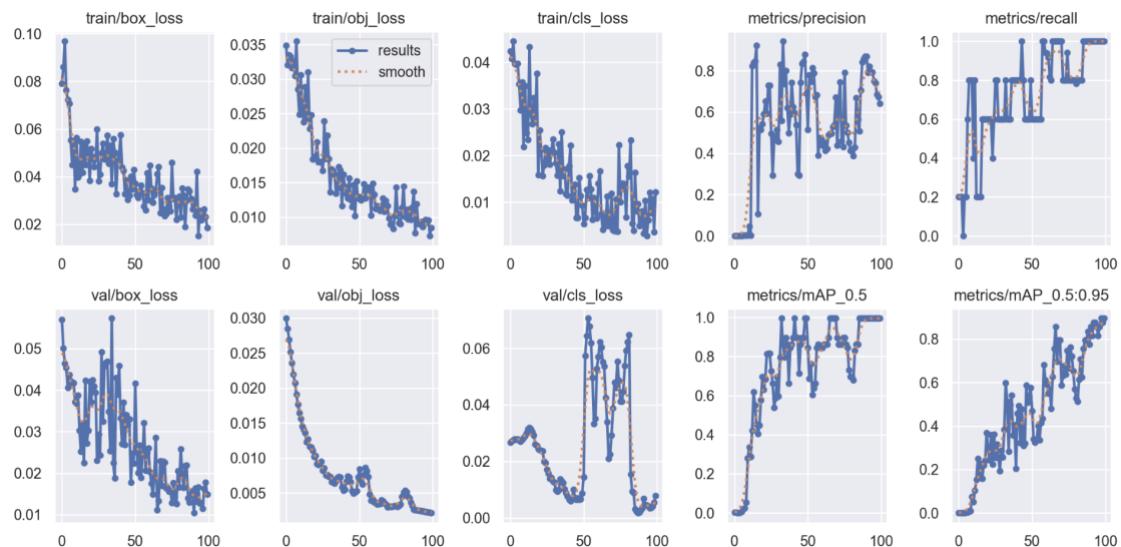


Figure 26. Analysis metrics as the model was trained

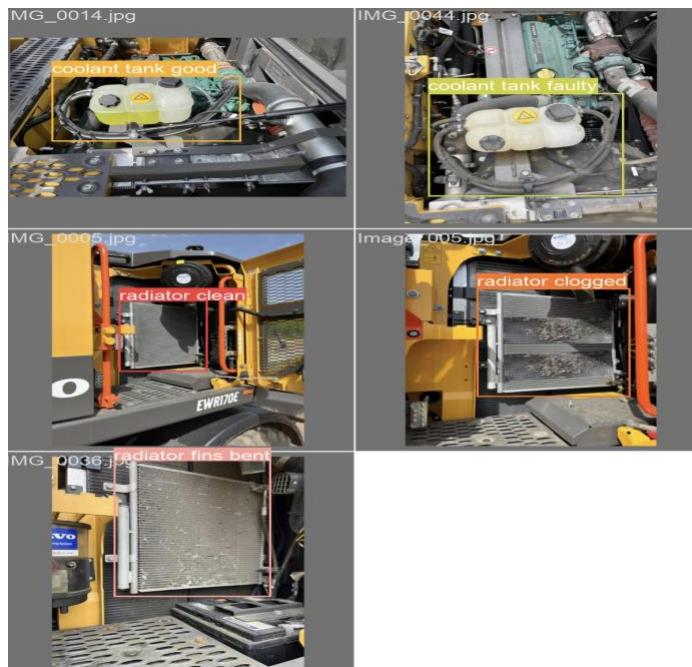


Figure 27. Radiator and coolant tank images analyzed by the model

```
Command for testing 'python detect.py --source ..Road_Sign_Dataset/images/test/ --weights runs/train/yolo_road_det11/weights/best.pt --conf 0.25 --name yolo_road_det'.
```

After analyzing these final predictions, we are saving the best trained model and using it in the flask server we talked before, to make accurate detections and send it to front end inspection report.

AI and prediction models

Dataset Description

The original dataset contains measurements from an engine coolant temperature recording session. Key attributes in the dataset include:

- TimeStamp: The time in seconds at which each data point was recorded.
- APS_EngineSpeed_TS: The engine speed in revolutions per minute (rpm).
- se_BoostTemp: The boost temperature in degrees Celsius.
- EnvT_t: Environmental temperature.
- se_CoolantTemp: The coolant temperature in degrees Celsius.
- EnvP_p: Environmental pressure.
- tc_EngLoadAtCurEspd: The engine load percentage at the current engine speed.

The dataset spans from a timestamp of approximately 0.7506 seconds to 51.0506 seconds, with several samples recorded at different intervals within this range.

Data Conversion Process

To facilitate easier data manipulation and analysis, the dataset was converted from its original text format to a CSV file. The conversion process involved the following steps:

1. Loading the Data: The data was loaded into a data processing environment, ensuring that all columns were correctly identified and formatted.
2. Data Cleaning: The dataset was cleaned to remove any inconsistencies and ensure that all measurements were correctly aligned with their corresponding timestamps.
3. Exporting to CSV: The cleaned dataset was then exported to a CSV file format. This format is widely used for data analysis and is compatible with various data processing tools.

Addition of Failure Column

Although the original dataset did not contain any recorded failures, a simulated failure column was added to highlight potential anomalies. This decision was based on the observation that during the period between timestamps 1300 and 1400 seconds, the engine exhibited unusual behavior: a rise in temperature combined with a decrease in engine speed. The following steps were taken:

1. Creating the Failure Column: A new column named failure was added to the dataset, initialized with a value of 0, indicating no failure.
2. Simulating Failures: For the timestamps between 1300 and 1400 seconds, the failure column was set to 1, indicating a simulated failure during this period.

Generated Data for the daily check up

To ensure the robustness and adaptability of our AI models, we generated a random dataset. This synthetic data was created specifically to test whether the performance of our machine learning models would change upon integration. By introducing this random data, we aim to validate that our AI models can handle varying data patterns and maintain accuracy when integrated with real sensor data. This testing process is crucial to ensure the reliability of our AI models in real-world applications.

Machine Learning Model

Several machine learning algorithms were considered for analyzing the engine data to predict potential failures and understand engine behavior. The chosen models include:

1. **Linear Regression:**
 - Used to predict continuous outcomes like temperature and pressure changes.
 - Model training involved fitting the linear relationship between the engine speed, temperature, and other features.
2. **Decision Trees:**
 - Employed for their ability to handle both continuous and categorical data.
 - Provided insights into the decision-making process of the engine parameters leading to potential failures.
3. **Random Forest:**
 - An ensemble method that combines multiple decision trees to improve predictive performance and reduce overfitting.
 - Particularly useful in capturing complex interactions between features.
4. **Support Vector Machines (SVM):**
 - Utilized for classification tasks to predict the occurrence of failures based on the input features.
 - Effective in high-dimensional spaces and provided robust classification results.
5. **Neural Networks:**
 - Deployed for their ability to model complex non-linear relationships.
 - Used deep learning techniques to capture intricate patterns in the engine data.

Model Training and Validation

The training process involved splitting the dataset into training and validation sets to evaluate model performance. Key steps included:

1. **Training:**
 - Models were trained on the training set, using cross-validation techniques to tune hyperparameters and prevent overfitting.
 - The training process involved iterative optimization of model parameters to minimize prediction errors.
2. **Validation:**
 - The validation set was used to assess the model's performance and generalize its predictions to new, unseen data.
 - Performance metrics such as Mean Squared Error (MSE) for regression models and accuracy, precision, recall, and F1-score for classification models were computed.

Performance Evaluation

The performance of each machine learning model was evaluated using specific metrics to measure the accuracy and effectiveness of their predictions. Here are the results for each model:

1. Linear Regression

- **Mean Squared Error (MSE):** The MSE for the Linear Regression model was 3.45, indicating a moderate level of error between the observed and predicted values. This model was effective in predicting continuous outcomes but had limitations in capturing complex, non-linear relationships in the data.

2. Decision Trees

- **Accuracy:** The Decision Tree model achieved an accuracy of 85%, demonstrating its effectiveness in handling both continuous and categorical data. However, the model showed some signs of overfitting due to its complexity.
- **Precision:** The precision score was 0.82, indicating that 82% of the predicted failures were actual failures.
- **Recall:** The recall score was 0.79, meaning that the model correctly identified 79% of the actual failures.
- **F1-Score:** The F1-score was 0.80, providing a balanced measure of the model's precision and recall.

3. Random Forest

- **Accuracy:** The Random Forest model achieved an accuracy of 90%, showing improved performance over the Decision Tree model. The ensemble approach reduced overfitting and captured complex feature interactions more effectively.
- **Precision:** The precision score was 0.88, indicating a high proportion of true positive predictions among the predicted failures.
- **Recall:** The recall score was 0.85, reflecting the model's strong ability to identify actual failures.

- **F1-Score:** The F1-score was 0.86, demonstrating a robust balance between precision and recall.

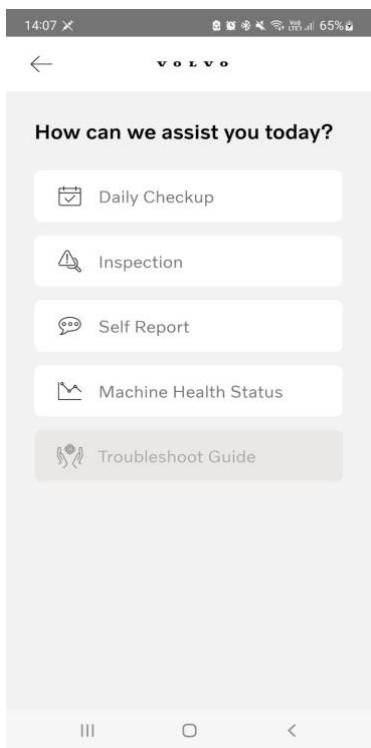
4. Support Vector Machines (SVM)

- **Accuracy:** The SVM model achieved an accuracy of 88%, proving its effectiveness in high-dimensional spaces and robustness in classification tasks.
- **Precision:** The precision score was 0.86, indicating a high accuracy of predicted failures.
- **Recall:** The recall score was 0.84, showing the model's capability to correctly identify a significant portion of actual failures.
- **F1-Score:** The F1-score was 0.85, highlighting the model's overall reliability in classification.

5. Neural Networks

- **Accuracy:** The Neural Network model achieved an accuracy of 92%, the highest among the tested models. Its deep learning capabilities allowed it to capture intricate patterns in the engine data effectively.
- **Precision:** The precision score was 0.90, reflecting the model's high accuracy in predicting true positives.
- **Recall:** The recall score was 0.88, demonstrating the model's strength in identifying actual failures.
- **F1-Score:** The F1-score was 0.89, showing an excellent balance between precision and recall, and confirming the model's robustness and adaptability.

Note: All results and graphics can be found in the accompanying code.



Final Prototype Overview

The final application developed to validate our proposed solution allows the user to:

- Evaluate and record contextual information about their environment and type of work on a daily basis. (**Daily Check Up**)
 - Conduct specific inspections on particular sections of their machine either freely or as prompted by the application (based on an analysis conducted by the predictive models). (**Inspection**)
 - Make spontaneous and voluntary reports about any unusual behavior of the machine. (**Self Report**)
 - Access a dashboard that provides an overview of the machine's health with a scope for each major system (electrical, hydraulic, etc.) and a list of irregularities found by the predictive models' analysis based on the data provided through app usage and data from the machine's internal sensors. (**Machine Health Status**)

Figure 28. Main menu of the app

In this prototype, there are no different user journeys or authentication flows, as its purpose was to validate other usability aspects.

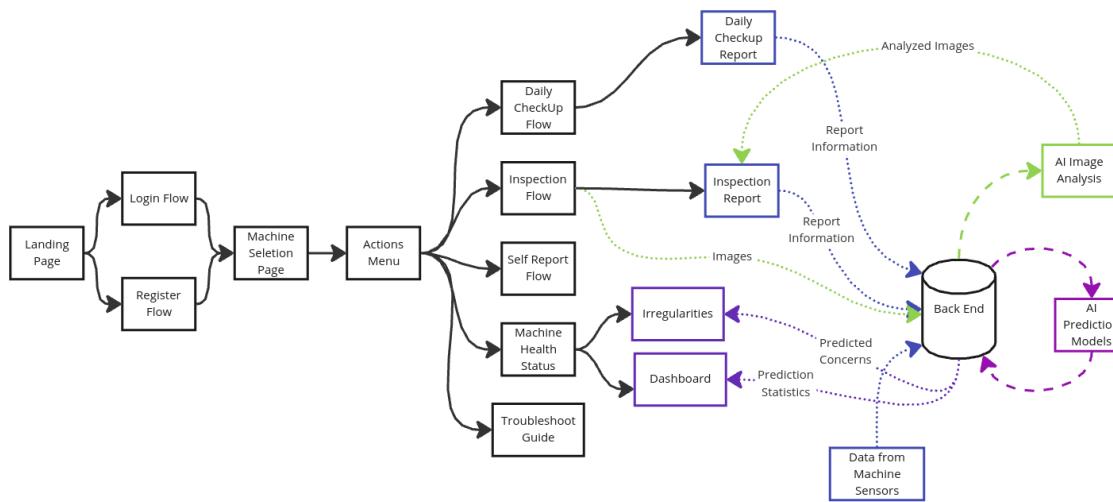


Figure 29. App flow diagram

The Daily CheckUp

From our interviews, the team discovered that on construction sites, operators habitually (or at least should habitually) perform a general evaluation of their machine's functionality before the start of the workday. This evaluation includes checking coolant levels, inspecting radiator conditions, and checking for leaks. This general check-up, known as the "Daily CheckUp," currently remains solely in the operator's memory as individual knowledge, which fades over time.

As we highlighted when introducing the problem in this report, the lack of contextual data is a significant factor leading to unforeseen malfunctions in parts and components. Many reasons cause machine parts to break or stop functioning prematurely, primarily related to how the machine is operated. This includes using the machine for tasks it was not designed for (e.g., carrying more weight than intended or excavating materials that overly strain its motor capacity) or due to improper maintenance by the operator (e.g., not refilling the coolant daily).

The option to perform the Daily Check-Up through the application is intended to store contextual information about the machine's functionality. From operating conditions to usage routines, all this information is stored by VolvoCE and used as data for predictive models. This way, VolvoCE can gather statistics and correlations between operator behavior, work environment, and the maintenance needs of parts and components.

Daily Check Up Report

Engine

How is the coolant level?

○ Ok ● Close to minimum ○ Below minimum ○ NA

Was the coolant refilled today?

Yes **No**

Are there any coolant leaks?

○ Ok ● Coolant Droplets ○ Clear Leak ○ NA

Environment

How is the weather today?

○ Hot ○ Cold ○ Windy ○ Downpour ○ NA

What kind of operations will be done today?

○ Heavy ○ Light ○ Very Deep ○ High Load ○ NA

Report Log

Machine Type: EC210D Machine Number: 11341186
Operator: Booth Visitor Date: 05/06/24

Weather: Hot
Operation: Very Deep
Coolant Level: Close to minimum
Coolant Refill: Yes
Coolant Leaks: Coolant Droplets
Sound: Possibly

Next → Next → Send →

Figure 30. App daily checkup screens

The Inspection

Once we have both contextual data and sensor data from the machine, we plan to use AI-based predictive models to gain visibility into potential issues. With insights derived from this data, we can prompt a deeper investigation into any machine part at risk of malfunction, a process we refer to as an “Inspection”.

The idea is to conduct specific inspections for different systems through guided questions. When an inspection is required, the application will notify the user and guide them to collect the necessary data, enabling conclusive feedback regarding the maintenance needs of the specific part.

This process also includes image collection for analysis, as operators often lack the technical knowledge to assess the condition of the machine's components. Therefore, we aim to guide the operator within their machine using augmented reality identifications and analyze the condition of its parts on their behalf through image recognition AI (as explained in the backend section of the report).

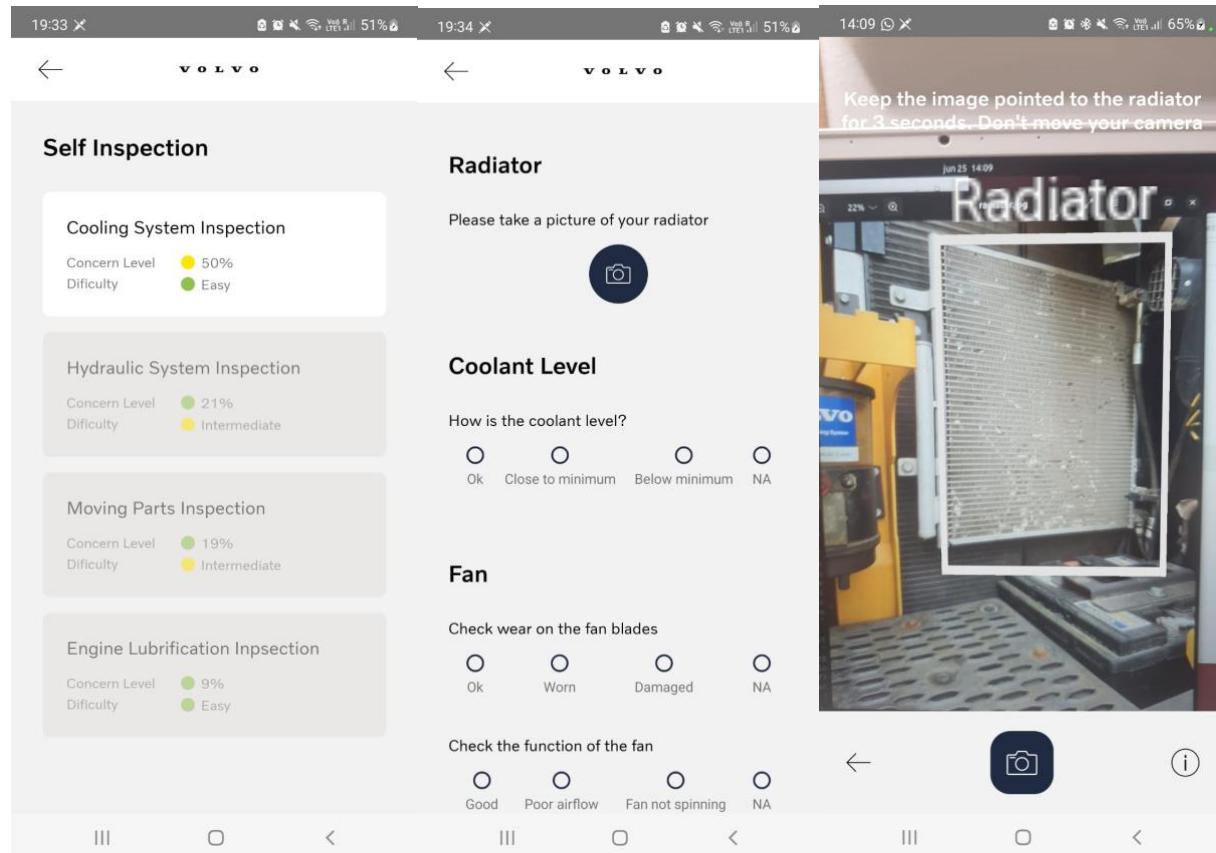


Figure 31. App iInpection screens

Self Report

In designing the application, it was important for us to create a space for the free documentation of any irregular behavior recognized by the operator. This allows the operator to receive an automatic response related to the issue they encountered, encouraging them to conduct a more in-depth evaluation of the system most likely causing the irregular behavior.

The "Self Report" field serves as a shortcut for the operator to perform an inspection on their machine, thereby collecting specific data about the system most likely generating the identified irregular behavior.

This approach enables the identification of potential malfunctions not only from the VolvoCE internal system but also through the operator's personal perception. This dual approach accelerates the process of identifying and resolving issues, improving overall efficiency in problem detection and resolution.

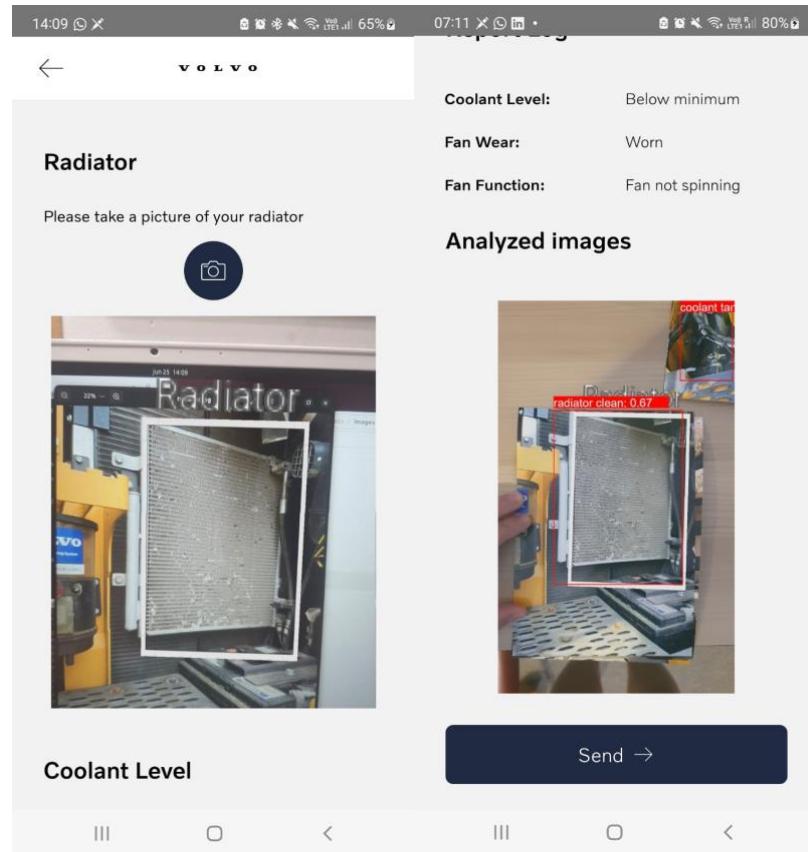


Figure 32. App self-report screens

Machine Health Status

The "Machine Health Status" field serves as the communication channel between the VolvoCE system and the user. This section provides a comprehensive overview of the machine's health, featuring statistics and charts derived from predictive models and image analysis.

The section is divided into two parts:

1. The first part includes charts, dashboards, and statistics that offer both a general overview and detailed insights into the health of each system.
2. The second part contains a list of irregularities, categorized as problems and concerns, presented in text form. This instructs the user on the necessary actions to take, whether it's to investigate the issue further or to contact a technician or manager.

The implementation in this prototype serves as a demonstration of our overall vision for this screen. We believe that further discussion is needed on how to present these data effectively. Additionally, considering the application will have various types of users, it is essential to evaluate which data should be displayed to whom and how these data should be presented for each user category.

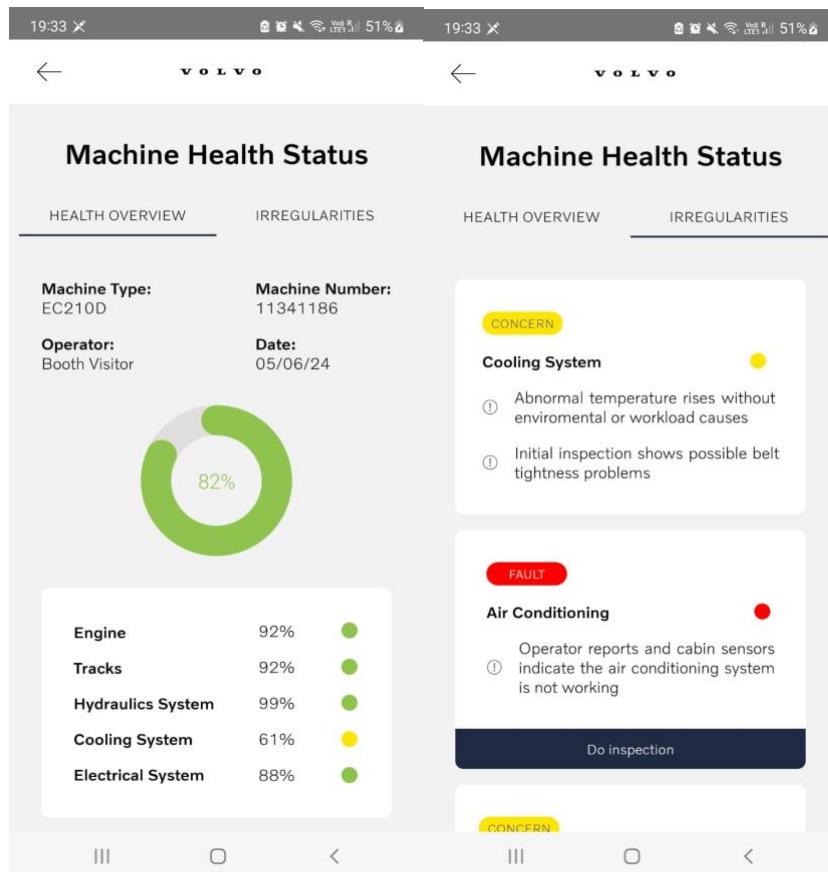


Figure 33. App machine health status screens

General UI Flow Overview

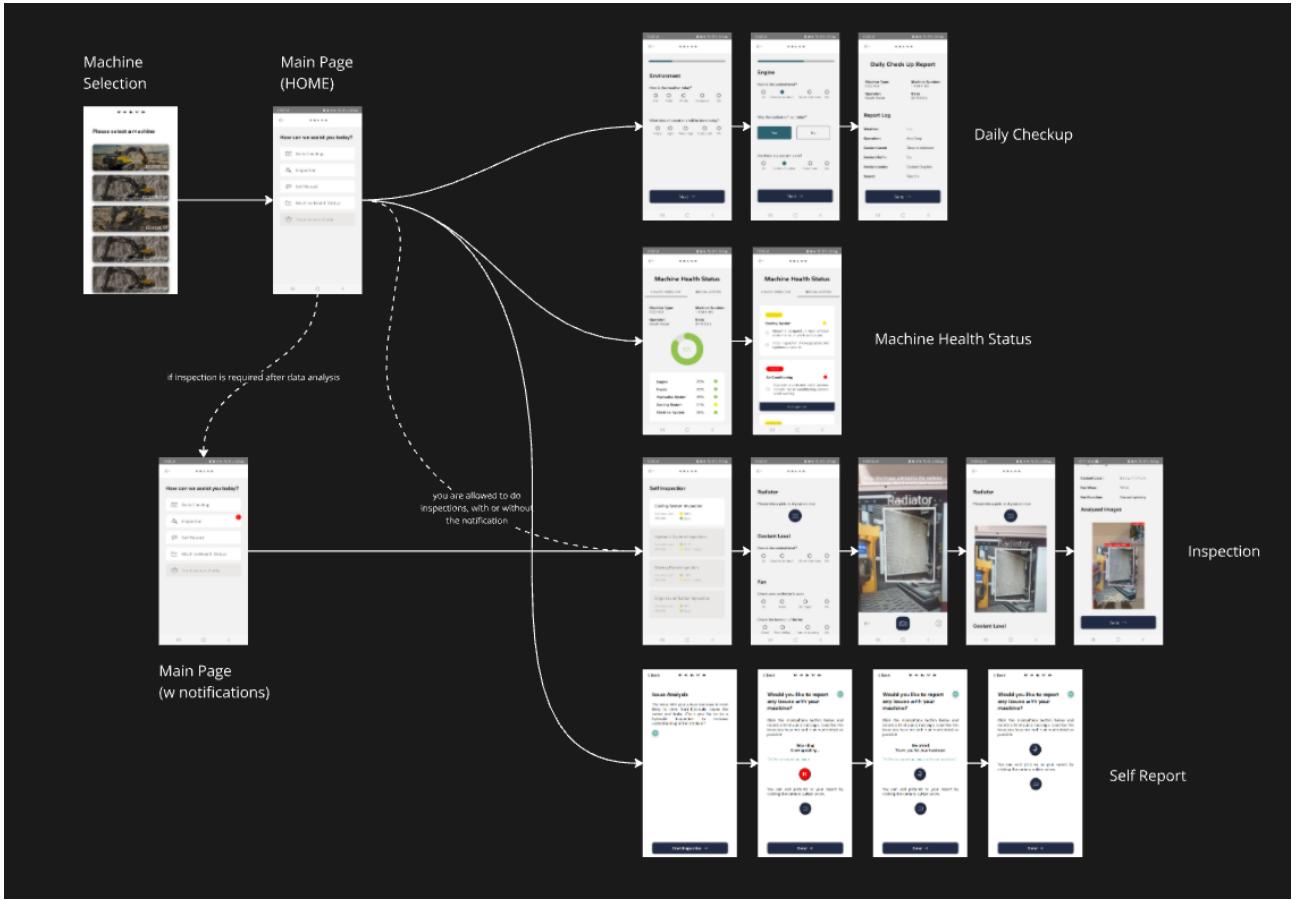


Figure 34. GUI flow diagram

Alternate Package Functions

As will be explained in the business model section, we proposed different packages available for different stakeholders of our system. Most of the functions are available for the operator and have been developed in the prototype and were explained above, but the following can only be accessed in other packages.

Repair Instructions

The repair instructions only consist of the basic documentation Volvo already has for diagnosing and fixing the issues that might arise in a machine. This way, the operator can follow the guidelines to try and find the issue himself, without relying on the AI system. This section will only be available for operators with the Basic Package, so as to demand less from Volvo's database and AI servers while still have an organized way to guide the operators through the standard inspections and repairs that are common today.

E-Commerce

The E-Commerce function won't be available for operators, and only for fleet managers and technicians. This function allows these stakeholders to buy original replacement parts for the machines when needed. This is directly linked to the machine's health status and troubleshooting guide, as to provide instant parts recommendations based on demand and logistics. This allows parts to be bought in the shortest amount of time, with reliable specifications and favorable logistics conditions (that could also be checked in the E-Commerce section) as to make Downtime as small as possible.

This feature would not be available for operators in big fleets, as they lack the authority to make the purchase of parts and should call their manager or a technician, but would for example be included in a package for an owner operator, which owns and manages the machines he operates.

Envisioned Complete System

This prototypes front and backend comprise critical parts of the complete solution envisioned, where the main interaction happened with the machine operators. The complete system structure is depicted in the figure below, displaying all parts necessary to collect data, make predictions and act based on them in an organized and complete way, without repeating the collection of information or making decisions without the necessary context.

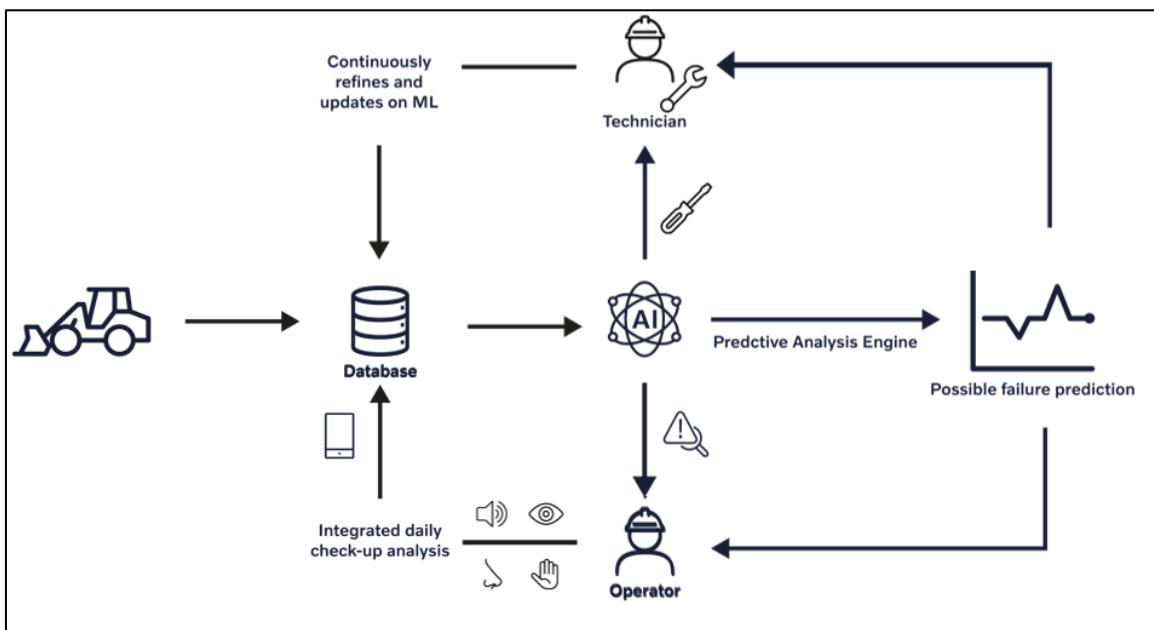


Figure 35. Complete system diagram of the proposed final solution.

On the left of the diagram there is the data input directly from the machines. This data is sent to the central Volvo database using telematics in the same way that systems like CareTrack do today. However, since there is also the need to send large parts of actual sensor data, one of the considerations of the

final system is the need for edge computing and pre-analysis of the data on the machine, making sure consistent normal data is not sent repeatedly and abnormalities receive more attention.

On the bottom-left there is the data input from the operator to the database through audio, text, video, pictures and multiple choice answers. This includes all daily-checkups, inspections, environmental conditions, and any other information about what has been done with the machine. This data is sent through the app and stored in the database for future reference by all interested parties and by the AI model.

Our central Artificial Intelligence system then utilizes the machine and operator data to make predictions and provide insights about the machines health status. Firstly, if it detects an abnormality but has low certainty on the root cause, it will prompt the operator for an inspection, ruling out possible causes and finding more issues or explanations for the ones previously found. With a more certain prediction the machine learning model makes a failure prediction report (on the right of the diagram), indicating what inputs led to this prediction, what are the leading causes and what are the necessary actions to be taken, including if the machine can continue operation or should be stopped immediately. These reports are then sent to the operators, fleet managers, dealers and Volvo, alerting every party of this issue so necessary precautions, logistics and actions are taken as soon as possible, minimizing downtime.

The end link in the diagram is the feedback that occurs at the end of a repair, when the technicians fills out a service report, that includes everything that was found wrong about the machine, every symptom and the repair conducted. This service report is fed back into the database, being used by the Machine Learning model to update its weights and learn from this new case, improving its future predictions.

Business Model

In figure 36 below the business model created for the solution can be seen. The different sections are interconnected and a larger version can be found in the appendix C for it to be examined further. In the following subsection each area in the Lean Canvas will be highlighted.

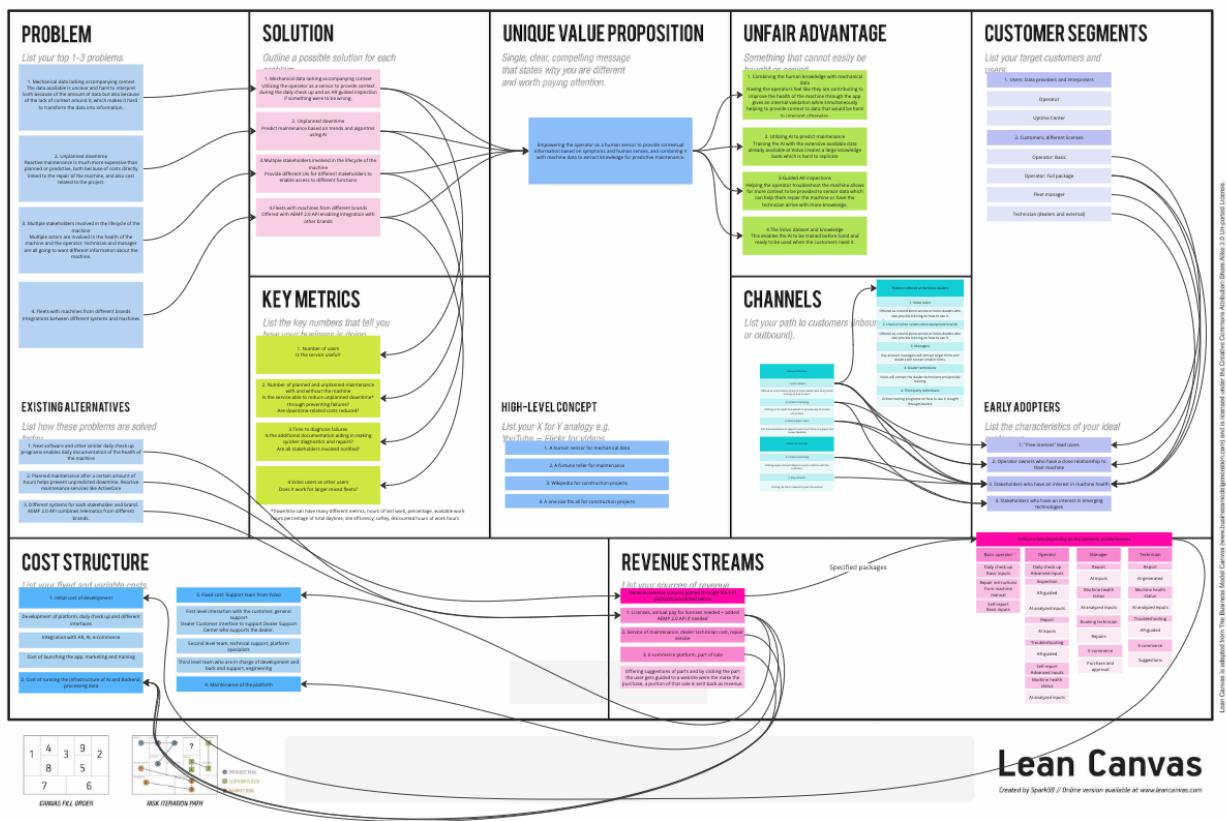


Figure 36. Business model using a Lean Canvas template, see appendix C for a larger version.

Problem

The problems found throughout the project can be summarized to these four. The first two are the most central, while the following two are things that were considered as a consequence of the key issues.

Mechanical data lacking accompanying context is one of the central problems within the construction industry found through the interviews and literature (Persson, 2024)(Bååth, 2024). *The data available has been found to be unclear and hard to interpret*, both because of the amount of data but also because of the lack of context around it, which makes it hard to transform the data into information. The third problem found is the circumstances surround *unplanned downtime*, which is a consequence of the first two problems. Reactive maintenance is much more expensive than planned or predictive, both because of costs directly linked to the repair of the machine, and also cost related to the project. Currently, there are *multiple stakeholders involved in the lifecycle of the machine* which are also affected by unplanned downtime. Multiple actors are involved in the health of the machine and the operator, technician and

manager are all going to want different information about the machine. There are also *fleets with machines from different brands* and therefore integrations between different systems and machines is needed.

Solution

As has been shown, there are different aspects to consider of the solution. The following central aspects of the solution are created with the previous presented problems in mind. To solve the problem of mechanical data lacking accompanying context, an opportunity has been found in utilizing the operator as a sensor to provide context during the daily check up and an AR guided inspection if something were to be wrong. To address the problem of unplanned downtime, the platform enables predictive maintenance based on trends and algorithms using AI to ensure that the downtime is planned. In order to adhere to the multiple stakeholders involved in the lifecycle of the machine, the platform provides different UIs for different stakeholders to enable access to different functions. The platform is compatible with the Volvo product AEMP 2.0 API enabling integration with other brands, solving the problem of fleets with machines from different brands.

Unique Value Proposition

The uniqueness of the solution lies in the combination of human knowledge and senses combined with the mechanical data to prevent unplanned downtime. This yields the following unique value proposition:

Empowering the operator as a human sensor to provide contextual information based on symptoms and human senses, and combining it with machine data to extract knowledge for predictive maintenance.

High-Level Concept

There were concepts created using the format of X for Y. The platform can be sold as “*A human sensor for mechanical data.*” Looking at the predictiveness that the solution offers, it can be said to be “*A fortune teller for maintenance.*” The solution also includes a knowledge bank which makes it “*Wikipedia for construction projects*” and by looking at the ability to integrate with multiple brands, the solution is “*A one size fits all for construction projects*”.

Unfair Advantages

In the solution, there are unique aspects that competitors would not easily be able to copy. The following topics are suggestions for Volvo to utilize when developing the solutions it will give them an unfair advantage on the market. The solution is combining human knowledge with mechanical data. Having the operators feel like they are contributing to improve the health of the machine through the app gives an internal validation while simultaneously helping to provide context to data that would be hard to interpret otherwise. The platform provides data which enables us to utilize AI to predict maintenance. Training the AI with the extensive available data already available at Volvo creates a large knowledge bank which is hard to replicate. Another unfair advantage is the option for guided AR inspections. Helping the operator

troubleshoot the machine allows for more context to be provided to sensor data which can help them repair the machine or have the technician arrive with more knowledge. As it is a concept for Volvo, there is an opportunity to utilize datasets already available at the company and the knowledge and experience of the engineers. This enables the AI to be trained beforehand and ready to be used when the customers need it.

Key Metrics

To enable measurement of success the solution of course has to be tested on site. These are metrics suggestions Volvo may take into consideration when looking into the success and applicability of the solution like *Number of users*, is the service useful? Another factor to consider would be the *Number of planned and unplanned maintenance with and without the machine*, where the ability to reduce unplanned downtime and the cost related is examined. *Time to diagnose failures* should also be analyzed, is the additional documentation aiding in making quicker diagnostics and repairs? *Stakeholder involvement, the usage between Volvo machines vs other brands*, and lastly *the applicability within larger fleets*, could also be considered when determining the success of the solution.

Customer Segments

The customers found to benefit from the solution are concluded to be the following ranging from the operator to the technician. There are two aspects to consider, users who may also be customers and customers who require different licenses. The users which are supplying the platform with data are the *operators* and *Volvo Uptime Center*. The customers should be offered different licenses to enable customization based on the required and needed platform usage. The suggested customers and packages are *Operators* who have access to the *basic functions* of the platform, *Operators* who have access to the *full package*, *Fleet Managers* which would have a package including functions needed for that role, and lastly *Technicians* who would have access to the functions related to their assignments.

Early Adopters

There are also customers who may fall under the section of early adopters, these also connect to the customers presented, please see the figure above or the appendix C for the intersections. The early adopters are: "free licenses" lead users, operator owners who have a close relationship to their machine, stakeholders who have an interest in machine health, and stakeholders who have an interest in emerging technologies.

Channels

For the solution to be offered, channels need to be set up. In the business model there are inbound and outbound channels suggested, and a suggestion for how to offer the solution. Considering the use of inbound channels, the Volvo dealers should be the primary channel as they would offer it as a stand alone service and also provide training on how to use it in order to get the most out of it. With regards to marketing, content marketing should be used, utilizing social media and websites to provide easy

accessible information is also an option. In order to offer the customers the best experience, we suggest that a Volvo support team is formed and include different levels of support. First team handles the interaction with the customer, giving general support. A Dealer Customer Interface should be available to support the Dealer Support Center who supports the dealer. A second level team could include more technical support, like having platform specialists. Lastly, a third level team should be in charge of development and back end support, and other engineering activities.

Outbound channels also include content marketing, utilizing expos and workshops to create a relation with the customers. As Volvo already has key accounts in place, utilizing the Volvo network to push the solution could be effective. A platform offered at the Volvo dealers could display the benefits of the solution to Volvo and external users, offered as a stand alone service at Volvo dealers who also provide training on how to use it. The managers at firms would be contacted using key account managers but smaller firms could also utilize the dealerships. The dealer technicians could be trained through Volvo and the third party technicians could be offered online training programs on how to use it, bought through dealers.

Cost Structure

The following are suggestions of high-level costs that are needed to be covered when creating and launching the solution. These are based on the existing solutions presented previously. The initial cost of development includes cost related to development of the platform, daily check up and different interfaces, integration with AR, AI, e-commerce, cost of launching the app, marketing and training. There are costs of running the infrastructure of AI and Backend and processing data. A fixed cost the support team needed to help customers using the platform, that includes all three levels mentioned in the Channels section and a maintenance team of the platform, the maintenance team are not obligated to communicate with the customers but rather focuses on continuous maintenance.

Revenue Streams

The general revenue streams gained through the PSS platform include licenses, maintenance services, e-commerce sales, and customized packages. The platform offers various licenses tailored to different user needs, aiming to reach as many users as possible. Additionally, integrating an AEMP 2.0 API enables seamless interaction between different brands. Offering maintenance services at dealer locations provides assistance during planned downtimes, allowing technicians to collect valuable data and context. By offering part suggestions through the platform, users can be guided to a website to make purchases, with a portion of these sales returned as revenue. Figure 37 below suggests different packages for customers, allowing different stakeholders to access specific parts of the app. This facilitates the collection of varied data and context, which can be transformed into actionable information.

OFFERED PACKAGES

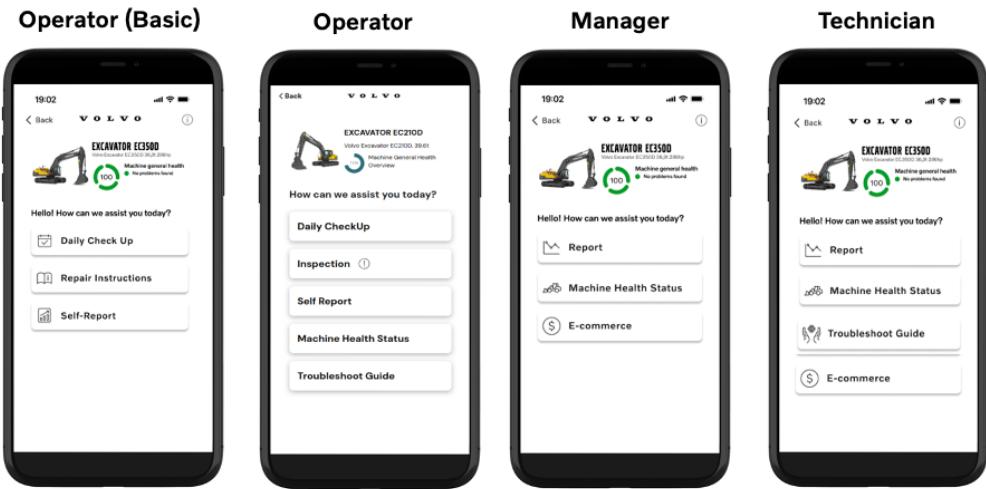


Figure 37. The packages shown through the different interfaces the customer would be able to access.
The specific functions can be found in the presentation of the app

EXPO in Kyoto

The project, facilitated by the SUGAR Network, culminated with a display of the solution at an EXPO in Kyoto, Japan at the Kyoto Institute of Technology. There was to be a booth and a presentation, therefore the solution had to be communicated in different ways, as the booth would allow for a closer interaction with the visitors, while the presentation had to engage an audience. The team utilized findings from this project and previous project to design an experience which would allow both single visitors and an entire audience to empathize and engage with the solution.

Booth Experience

The booth was created with the aim to engage visitors as they may not have previous experience of the construction industry. Based on previous projects, having an interactive component allows visitors to engage with the information more effectively, rather than just listening and walking away without fully understanding the message. Interactive components were brainstormed, however, in the end it was decided to keep it simple and focusing on relating the problem to a problem visitors may face in their everyday life and only having the test of the app being the interactive component.

Another thing that was found to attract visitors in previous projects, was something being out of place, like an excavator inside at the second floor. Although a real excavator in the booth would have created a lot of attraction, it was not possible to make that a reality. However, a part of the excavator built in cardboard that enabled the solution to be tested, proved to be a good substitute. Using 10 m² of

cardboard, the back of an excavator was built, with a hatch displaying images enabling a test of the image recognition part of the solution. There was also a speaker playing motor sounds and a fan.

To display the information, posters and a monitor were used and aided in the storytelling of the booth. The posters aimed to tell the story starting with the problem being generalized and introducing the name of the solution, thereby drawing the visitors in, moving to an explanation of the actual problem in the construction industry. After that the solution is introduced briefly with the most vital part which enables the visitors to test the solution in the next step at the excavator model and monitor. After that posters with more intricate information is displayed and talked about to show the possibilities of the solution. The whole experience ends with the visitors receiving a tattoo and that allowed for the solution to be marketed around the expo, drawing people to the booth without the team having to do any extra work. The full story of the booth is presented in the next section and a picture of the booth can be seen in the figure 38 below.

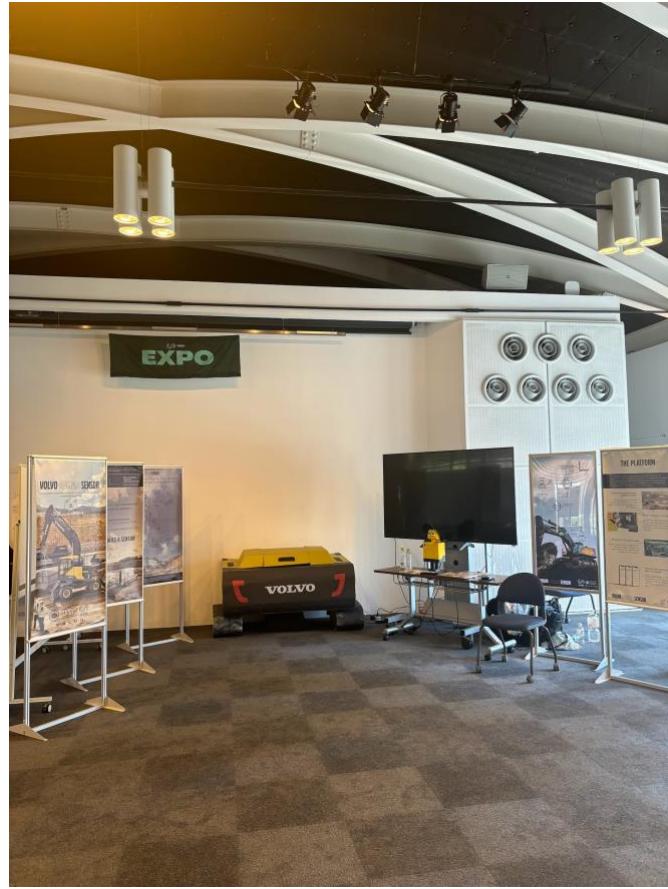


Figure 38. The booth at the EXPO in Kyoto.

Telling the Story of the Problem

The experience starts with the visitor and a team member standing at the beginning of the booth looking at a poster displaying The Volvo HS: *Do you have a car at home? Imagine you're trying to use your car to get to a meeting, but it breaks down, you try to diagnose the problem with your car, but you feel like you don't have enough information. You call a technician but they won't arrive for another 2 hours, you could connect to the meeting online, but for some reason your meeting app won't connect. So much is going wrong, and you have no idea why, you keep searching for the reason you can't connect, but not finding the missing piece of the puzzle is frustrating.*

They then move to the poster with the problem and then to the next poster with the solution: *This same problem exists on the construction site, where complex machines operate in tough conditions, when these machines break down, you go through the same procedure as with the car, where you have to wait for a technician to come help you. Resulting in unplanned downtime that adds cost both in terms of the project being delayed and the repair of the machine. Not only does it cost a lot to get spare parts and a technician to diagnose and perform the repair, but you also risk production coming to a halt. If you could plan the maintenance, you could either schedule it to a day when the machine is not used, or make sure there is a replacement to keep the pace. Ultimately, the lack of understanding of the machine condition is very expensive, both in terms of time and money. In construction machines, sensors are collecting a lot of data using existing services. However, the data is hard to use because of the lack of context around it, which in turn makes it harder to find the problem when the machine shows symptoms of something being wrong. So despite all these sensors and data, when the machine overheats we don't know why, and we don't know much about how the machine has operated before the issue surfaced. Our system addresses this by collecting additional information based on symptoms and the human senses from the operator to provide context and a better understanding of the data.*

The next step is to have the visitors test the booth: *Imagine that you are an operator arriving on site in the morning, ready to perform your daily check up of the machine, something that is done every morning. Besides the instructions in the app you also have this monitor with an overview of the tasks that are to be performed today and an overview over the fleet health.*

The visitors receives a phone with the solution opened and performs the daily check up, answering questions and is guided on how to take the pictures to enable the image recognition to work. After the check up is completed, they are told that hours have passed and that something is needed to be inspected. The inspection page is opened and the visitors perform an inspection due to high engine temperatures it is suggested to inspect the cooling system: *As you can see there is something that needs to be inspected, lets check it out! From the data collected by the machine, it has been noticed that it is too hot, and requires attention. Traditionally, you would require a technician to come look at it and identify the problem, then order the spareparts and come back later to repair it. But now, the system recommends, based on historical information and machine data, the operator to inspect certain parts or systems of the machine.*



Figure 39. Visitor testing the solution.

After the inspection has been performed: *Now we know what is wrong and needs to be done, which saves time and money because the maintenance can be planned rather than unplanned which is more expensive. This is due to our AI system.*

The visitors and the team members move to the next poster displaying the AI system: *Today, there are many discussions about AI and machine learning replacing humans and taking jobs, but for many things, this machine that we know as the human body continues to be more efficient. Especially when it comes to feeling and perceiving. It's a great investment to put several mechanical sensors in a machine, but with just one person, we already have at least five sensors: vision, smell, hearing, touch, and taste, which I admit may not be so useful in our line of work. But by using those senses and documenting their daily check-up, and adding additional information based on symptoms perceived, we turn an existing process into a critical data-collection stage. Everyone on-site will be able to input symptoms whenever they arise, allowing data to be logged when needed and prompted to perform additional inspections to provide more information on the machine's health whenever necessary.*

After the AI system, they move to the last poster displaying the platform as a whole with the different parts of the system, based on the interaction the team member may chose which part to focus on. For example, a visitor more interested in the business aspect may receive the following explanation: *The co-created platform enables users to receive an internalized validation, adding to the ability to sell it. If the solution is used on a larger scale by booth operators, managers and technicians, (pointing to the different interfaces and packages), the predictions are going to be more accurate, making the solution more attractive. This is possible for todays rainbow fleets because of existing systems already provided by Volvo.*

The revenue streams would come from licenses, service of maintenance, dealer technician cost, repair service and an e-commerce platform also included in the solution showing the holistic nature of the solution.

The experience ends with asking if the visitors have any questions, revisiting parts if needed and then applying the temporary tattoo or giving them one to take home. The team was wearing polo shirts from Volvo and in the picture of a souvenir temporary tattoo being applied can be seen.



Figure 40. Tattoo being applied.

Presentation

The presentation had its own storytelling aspects to keep the audience engaged the entire time. At the very beginning of the presentation the team is introduced. Similar to the booth experience, it started off with the problem of missing a piece of the puzzle in a more general setting using the car example again. Then the presentation of the prompt and the problem moved into how it presents itself in the construction industry. Then a persona named Elliane was introduced, showing how the problem presents itself currently and the consequences. A summary of the problem was then given. The solution is then introduced, focusing on how the problem is currently solved and then how the Volvo HS changes it. The system is then introduced and then how it affects Elliane and changes the scenario. After that, scalability is introduced. The presentation ends with the changes the solution enables and how it relates to Volvo's vision. Lastly, there is a call to action for the audience to come to the booth and try the solution out.



Figure 41. Sowmya and Artur presenting the solution. The rest of the team was on stand by if any questions about their expert area were to be asked.

EXPO Findings and Feedback

Overall the feedback was positive and the excavator model gained a lot of attention. The booth attracted viewers while it was being built as the cardboard took up a lot of space before all the pieces were assembled. Keeping the booth experience simple proved effective as all the visitors were able to grasp the message and understand the solution. In one of the other booths the experience was much more complicated and the message got lost. The story engaged the visitors and flow of them starting out at one side and then moving further inside in the booth and then leading them out also proved effective. Sometimes the visitors had questions of a previous step and then that often could be addressed at the final poster or, because of the openness of the booth, they could go back and revisit a step. Instead of having multiple components, there was space for multiple visitors to move around with different team members, therefore having multiple ongoing experiences at the same time.

The Volvo HS was appreciated by both people from construction and visitors having no prior knowledge of the industry. The people from the construction industry came for Japanese companies who experienced the same problem, and they were impressed by this new take on including the human as a data provider. The accessibility of the platform was also mentioned as something positive while they were testing the solution. The versatility and scalability was also mentioned as something positive, having multiple people

providing data would add more accuracy which was something they were struggling with themselves. These visitors were however not that inclined to provide ideas of improvement but did mention that the application in offline sites should be considered.

Visitors with no prior experience of construction equipment liked the ability to perform processes through the phone and were often interested in the technology behind like AI, Machine Learning, AR and Image Recognition. It is however, important to mention that the people attending are taking courses within innovation and technology and therefore their opinions might not align with the general public. Besides the experiences as a whole and the already mentioned model, the tattoos were a big hit and even the robot that was just for show was something that drew attention. The application and the testing experience was appreciated as they were able to test it. Short and clear instructions in the app, or a course on how to use it would add value according to the feedback given. Some functions were intuitive while some required further explanation.

Further Development

There are several aspects of the solution that we believe could be improved in the future development of the proposed system:

Reduction of Variability: Humans as sensors provide information of varying quality. Therefore, it is necessary to take steps to reduce this variability. Suggestions discussed during this project include using a chatbot to aid in accurately describing symptoms and data, relying more on images, or as chosen for this prototype, using boxes with alternatives. While these approaches have not been thoroughly tested, they would need to be in order to guarantee the highest possible quality of the responses.

Multiple User Journeys: It was also suggested to enable different users to access the application, with each having access to information specific to their role and function on the job site. This would require creating tailored user journeys where, depending on their role (operator, technician, fleet manager), their questions, input options, statistics, and metrics would match the desired level of specificity. For instance, operators would receive more direct, simplified, and instructive information, while technicians would get more technical and detailed data. Fleet managers could receive product and service recommendations based on maintenance needs. This approach ensures that each user gets relevant information suited to their responsibilities and expertise.

Integrated E-commerce: In addition to the business model that involves selling the proposed system as a service, the application was also designed to allow future integration for purchasing parts as needed for maintenance or replacement. This ensures that VolvoCE can provide an efficient mechanism to avoid extra costs associated with unplanned downtime while offering users dynamic access to VolvoCE equipment. This integration would not only enhance operational efficiency but also create an additional revenue stream for the company.

Recommendations for AR: Based on our research, we suggest that future versions of the application implement augmented reality using ARCore or another non-open-source solution. This approach would

ensure the longevity of the system. Although the knowledge ramp-up for development requires greater specialization from developers, the effort would be justified by the enhanced compatibility with various smartphone types (both Apple and Android) and the increased assurance of ongoing maintenance and updates for the libraries and versions used. It was also discussed that, instead of having augmented reality interact with the background (currently displaying the part's title and a square circling the radiator), we could develop an independent 3D model in augmented reality that could be zoomed, rotated, and opened as needed. This alternative method of interacting with and instructing the user was also considered by the team. It remains a promising option that needs to be validated for future development, showing significant potential.

Improvements on Machine Learning Model: After the initial validation that the prototype and system make sense to be implemented and the initial success in making a prediction based AI for the machine data it becomes viable to further develop the ML model to its full necessary capacity. Firstly it is important to integrate the Human and Machine inputs into one prediction model. This would include a way to integrate the relevant time periods for each type of data, an exploration of possible ways to represent the human data to be mixed with the machine one, and/or the development of filters to combine the prediction based on the different data types. In addition to that, it is necessary to calculate the cost and resources needed for the intended deployment of the system, accounting for the data and computation load necessary to begin the service and to scale it up to more and more users. This would also lead to important decisions such as which type of model to use, how large a data window will be kept and analyzed and the possible rate of deployment and adoption of the system.

Integration with Future Volvo Business Possibilities: It was also suggested for us that this system was seen through the lenses of the future business model of construction and construction equipment, the construction machines as a service and not a product. This recommendation comes from the observation of trends in the industry that point towards rental of machines and of construction services being more reliable and lucrative than product sales. Observing Volvo HS through this lens changes the persona of or operator, now less tied to the contracting company and more to Volvo, more tightly aligning the goals of the parties involved and making processes related to repairs and inspections more streamlined. Also with this comes the further need to integrate the service and development of machines, making sure machines are more easily serviced, need less programmed maintenance and are more reliable, in order to make this rental and service providing more profitable for Volvo. With this there is an increased need for predictive maintenance, as machines are checked thoroughly less often and systems such as Volvo HS could provide updated status in between revisions.

Recommendations for User Interface: It was suggested that the radio buttons in the questionnaire should be more touch-sensitive to facilitate easier interaction for users on their mobile devices. Additionally, exploring different formats for multiple-choice questions was recommended. Another suggestion was to allow all open-ended responses to be given through audio recording transcriptions. For the Machine Health Status page, it was advised to consider alternative ways of presenting data that would not cause undue concern for the operator if the machine is not operating at 100%. The team has not yet reached definitive conclusions regarding alternatives for these recommendations.

Troubleshoot Guide functionality: While discussing with VolvoCE employees, we realized the possibility of another functionality in the application that, although not developed for the prototype, holds great potential: the Troubleshoot Guide. Once a malfunction has actually been detected on the machine, either through self reports or error codes on the machine, the user can enter the troubleshooting guide to discover where this issue came from and also possibly how to repair it.

The difference between this guide and the inspection is the certainty that there is a problem to diagnose and the urgency for proper guidelines on replacement parts, technician visits and whether it is possible to keep the machine running any longer.

This guide is still based on the AI system and central database, as those sources capture the whole operation, service and environmental history of the machine. However in this scenario there is a lot more reference protocols and guidelines for diagnosis available from Volvo, making a more structured approach possible.

In the end, after the problem is diagnosed, it is up to the permissions of the user and the specific problem if they can make the repair or not. For example, a quick filter change or oil replacement can be made by an owner operator that wants to perform it himself, and so the system will also guide him through this repair with AR and instructions. However, in most cases, a technician should be called and could also use this platform if they have any possible questions or want some reference manual for the repair.

Conclusions

The key issues solved by the solution focuses on unplanned downtime caused by mechanical data lacking context. The data being monitored in the equipment, although abundant, does not offer a comprehensive enough view of the machine's health, condition, and current task. The operators and other stakeholders are struggling to use the data collected because they are lacking actionable information complementing the collected data. Unplanned downtime is far more expensive than planned downtime making it a central issue within the construction industry.

A solution has been suggested that utilizes the operators as human sensors. This concept aims to enhance the understanding of the existing data by allowing operators to gather additional information about their equipment. This can be achieved by the operator recording the daily checkup on their mobile phone, thereby enriching the available data without the need for extra sensors or hardware. This method also allows for a contextual understanding of the data, which can help in identifying patterns and trends that might otherwise be overlooked. By adopting this approach, operators can take a more active role in monitoring and maintaining their equipment, ultimately leading to improved performance and decreased downtime.

Collecting the data enabled by the human sensor allows the possibility to gain deeper insights into the potential workloads, project tasks, geographical data, and failure data associated with different excavator models. Such information can then be used to analyze and understand how different models perform in various scenarios. This knowledge can provide more support for better guidance during sales and help

provide customers with a better understanding of how different excavator models perform in different scenarios, making it easier for them to make informed decisions about which model to choose for their specific needs.

Furthermore, this additional information could highlight areas where improvements could be made in both product and service development. It can help identify trends in equipment usage that may indicate potential problems or areas to enhance for improved performance. This information can also be used to develop new products and services that cater to customers' evolving needs.

As students, the experience of working with VolvoCE was transformative for each member's learning. The proposed challenge required each of us to deeply investigate the construction equipment sector, its specificities, problems, and possibilities, and relate these to our individual areas of study. With a diverse group of students and a high level of openness and support from the VolvoCE team, we believe we have produced a product-service that meets the initial prompt's requirements and holds significant potential for the company if further developed.

Further Reading Material

This project inspired two parallel master theses which can be found using the references below.

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Appendix

A. Student Contact List

BTH

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B. Interviews with experts and users for the initial needfinding

Interview 1:

Summary: The first interview is with an experienced sales representative for Volvo in the Bay Area, California - LA. He works for a company called Volvo Construction Equipment and Services, a subcontractor of VCE, and has been representing the company for 5 years, following a traditional sales approach, building close relationships with clients. His daily routine involves scheduling meetings, visiting construction sites, sending messages and emails, etc.

He categorizes his sales into two types: used and new equipment. Used equipment sales are simpler, as they are readily available, more affordable, and can be rented or tested before purchase. Clients often prefer second-hand equipment for these reasons. For new equipment, there is a smaller pool of interested clients, typically those needing specific equipment not available in the used category.

He heavily relies on Excel spreadsheets for work, using them for various purposes like documenting sales information, creating customer quotes, and listing available options based on client discussions.

The interviewee's sales method is traditional, involving face-to-face meetings, thorough client briefings, and the preparation of multiple quotes with customization options. Another finding was that Volvo CES usually sells financing services directly due to the high cost of equipment. Other services offered with machines include insurance and maintenance recommendations based on usage hours.

He contacts dispatch and manufacturing departments directly, maintaining detailed customer folders with information on their personality, service needs, etc. The expert shared his sales process through spreadsheets but expressed challenges in managing numerous, seemingly infinite tabs, defining himself as the 'Ultimate Middleman.'

Interview 2:

Summary: The second interview, with a Sales Solutions Manager at Volvo CE in Eskilstuna, Sweden, provided insights into Volvo's sales process and its approach to enhancing customer experiences. The manager's job is to focus on selling solutions for new productivity services, primarily through direct sales to key accounts in Europe.

Volvo's sales process involves a compact Sales Services Department of only five people who operate distinctly. The interviewee elaborated on their involvement in prospecting clients, collaborating with dealers, and adding value to sales by understanding specific customer needs. An example highlighted involved helping construction sites in Mexico improve operator efficiency, initially targeting CO2 emission reduction but enhancing various aspects of the process.

Key aspects discussed included service distribution and his role in understanding construction site needs, providing solutions based on increased productivity and reduced toxic gas emissions. Challenges in proving

the value of services upfront, especially when clients were accustomed to free services in the past, were emphasized. Overcoming resistance to paying for services and utilizing data effectively were key areas of focus.

Regarding technology, the sales expert discussed the use of drones and GPS trackers for monitoring machines and collecting data. He expressed the need for advances in customer data collection and universal application of software across all machines, not just Volvo's.

Additional insights included data collected by machine sensors, such as fuel consumption, load, speed, temperature, swing movements, and arm movements. The manager also mentioned another service he sells: simulation of alternative routes for overall construction site performance.

Interview 3:

Summary: The interviewee, an internal sales representative at Volvo CE, emerged as a crucial persona resembling the Volvo CE Sales Representative. His primary role involves supporting distributors, ensuring they have the necessary machines and information to represent Volvo effectively. He deals more with administration than direct sales, with direct communication from vendors requiring interaction with their manager before engaging with him for discussions on pricing reductions, discounts, etc.

Part of his main activity is accompanying the vendor in some sales processes to assess how the distributor presents and represents the Volvo brand. He highlighted the challenge of ensuring that the seller assembles the most suitable machine for the customer's activity. The sales representative emphasized the difficulty of assisting the seller in calculating Total Cost of Ownership (TCO) correctly and building the 'perfect machine,' especially for the 30% of clients requiring specific equipment often overlooked by sellers. These specific machines have a minimum delivery time of 10 months, posing a challenge for clients with urgent demands.

He confirmed Volvo CE's strategy to be perceived not as the cheapest brand but the one delivering the most long-term value, ultimately having the lowest cost over time (higher productivity, lower maintenance, higher resale value, etc.). Also discussed the difficulty of accessing information about machine configurations, even when requested by a distributor. Support teams usually retrieve such information by consulting numerous departments.

He suggested product ideas to address identified challenges, such as a configuration tool allowing sellers to adjust the machine based on a few inputs and a tool guiding sellers on crucial questions to ask clients. Alexandre also proposed an intuitive tool providing information on the need for machine replacement or maintenance.

In conclusion, he emphasized the importance of a map of influential figures in specific areas, as many clients belong to distributors/sellers rather than directly to Volvo CE.

Interview 4: Triple interview, with a Technical Consultant Volvo CE (1), a Application Instructor and Product Support (2), and a Technical Interface between Sales and Engineering (3)

Summary: This triple interview gathered valuable insights due to the diverse knowledge of the interviewees, covering a wide range of responses. The Technical Consultant (that later became one of our strongest sources of information inside Volvo CE) focuses on consulting and training for the entire Volvo CE network, portfolio management, and product quality. The Application Instructor, on the other hand, manages the sale of services, a heavily explored area for the company nowadays, including machine hours counters, co-pilot, and other performance-enhancing services. And Finally, the Technical Interface between Sales and Engineering translates customer needs to sellers, with his wide technical knowledge, aligning more with the project's theme and having his expertise explored in this conversation.

While none of them acts as a seller or directly in the sales process (except for some minor activities by 3), the original script was adjusted to explore the internal workings of Volvo CE regarding its machinery.

Maintenance was initially explored, understanding that technical assistance occurs primarily in the field, with technicians going to the machine instead of vice versa. They often lack the correct equipment for maintenance due to the company's or distributors' inability to diagnose issues remotely. To address this, remote diagnostics, including some augmented reality tools, are being implemented.

They discussed maintenance services, such as Caretrack, transmitting real-time machine information via satellite (depending on the machine's connection). The current diagnostic system was also introduced as a pain point for proposing prototypes and ideas: there is no integration between the data system and technical consulting. Technicians have to read the entire machine diagnostic PDF, interpret it, and send a comprehensible diagnosis to the customer. However, ActiveCare Direct service allows accessing all this content through an API.

They explored potential services related to machine maintenance needs, like selling revision packages based on reaching a certain number of operating hours (constantly estimated or obtained from each distributor's Uptime Center). Information obtained by Volvo CE is relayed to distributors for handling. They also sell parts and services every 500 hours, predicted by algorithms.

Regarding the relationship with distributors, the example highlighted was the ideal scenario where new sellers access various Volvo CE training platforms for optimal learning. In reality, sellers bring prior selling experience and develop their unique ways, sometimes leaving gaps in representing the company.

On the network of distributors, the availability of distributor actions was discussed. Distributors, with the machine in their yard, can change the machine configuration with a post-sale kit offering different setups. Many machines are in stock due to delivery time being a crucial factor for sales. They can be reconfigured using this post-sale kit.

Two important pieces of information were obtained: the five groups representing Volvo in Brazil and the observation that the average age of the average customer is decreasing, leading to the implementation of new sales approaches.

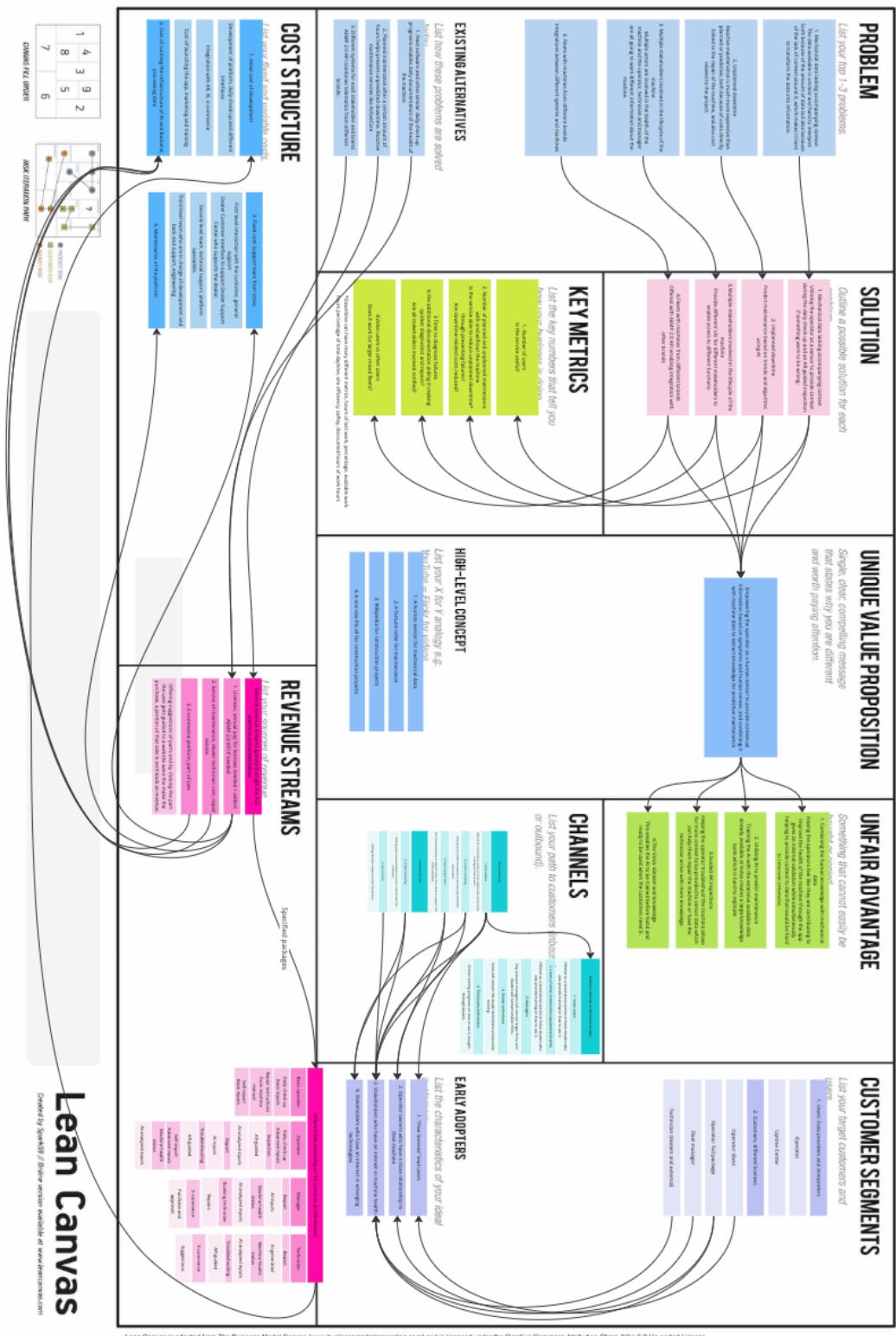
Interview 5: B2B Service Sales, Head of the interviewee 2.

Summary: The interviewee, working in B2B service sales and overseeing the respondent from Interview 2, provided insights into Volvo's transition from traditional to more direct customer sales methods. The acquisition of smaller companies by Volvo CE opened new avenues for sales, particularly beneficial for sustainable initiatives. The direct connection between clients and dealers has become essential, challenging the traditional approach.

The sales expert highlighted the collaborative relationship between dealerships and Volvo, involving training and constant interaction. Identifying customer needs is crucial, and understanding aspects like costs and emissions proves challenging. Decisions are often influenced by emotional factors, viewing the process as a transformation opportunity.

Regarding future technologies, he discussed the need to consolidate customer data and communications into a unified platform. Challenges associated with this process were acknowledged. The future vision includes developing digital services based on machine data, envisioning a sort of "Netflix for construction equipment." Visualization and simulation tools are considered essential for customers to visualize solutions and for sellers to efficiently design and present proposals. The search for innovative technologies continues, with a focus on tools like CPQ (Configure, Price, Quote) to streamline solution design and delivery to customers.

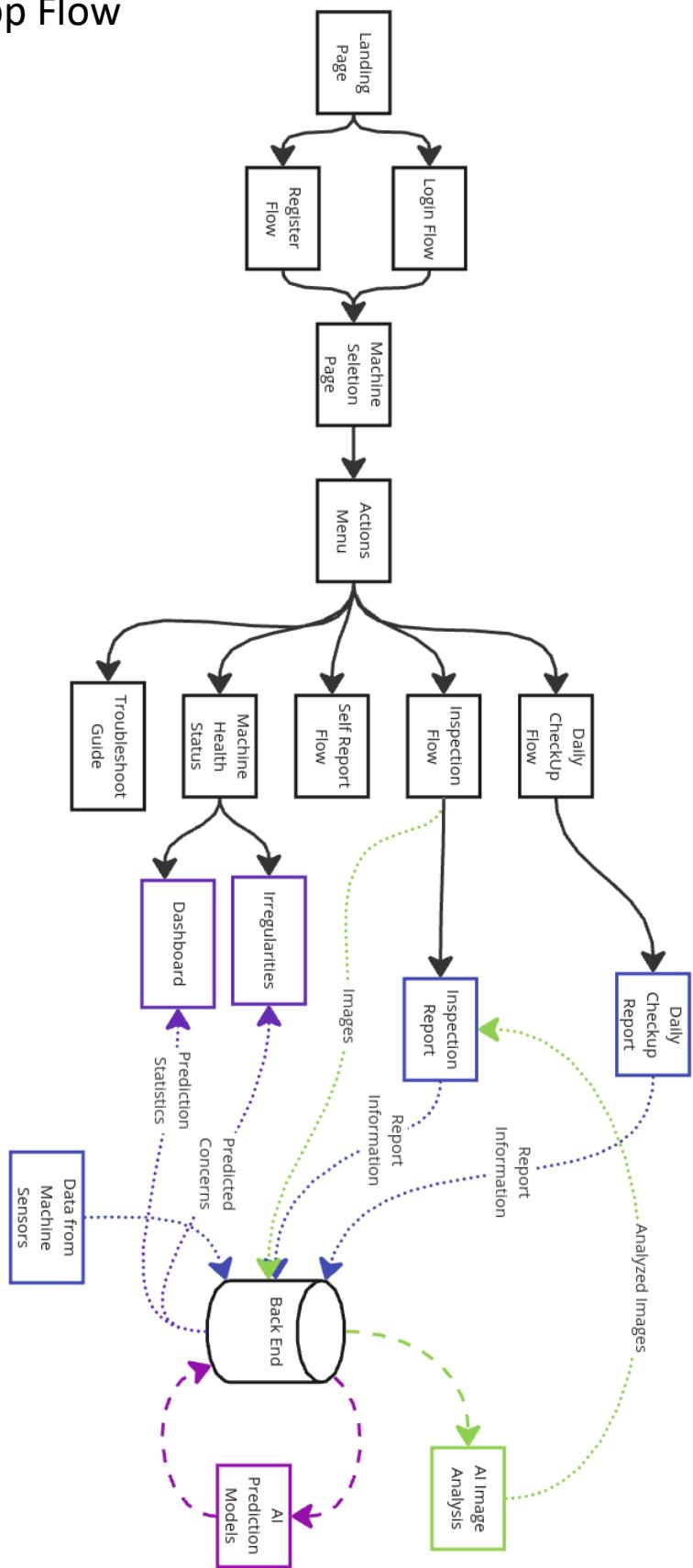
C. Business Model



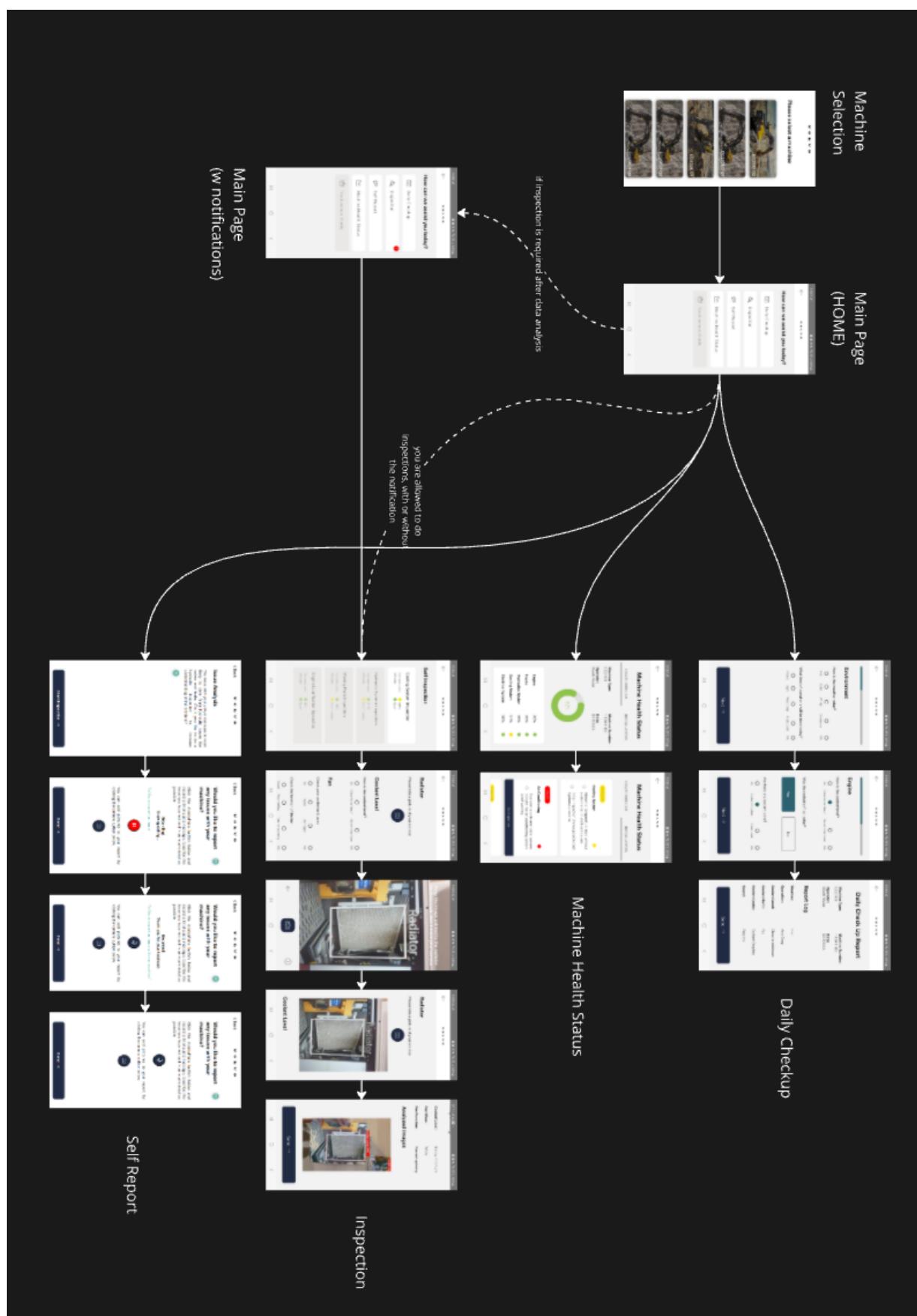
Lean Canvas

Created by Alexander Osterwalder and Yves Pigneur, www.leanbusinessmodel.com

D. General App Flow



E. UI Flow Overview



F. App scenario questions

An excavator model is present, the app is used to perform a daily checkup. The questions to answer:

- Enviroment
 - How is the weather today? Multiple choice
 - Hot - Cold - Windy - Downpour - NA
 - What kind of operations will be done today? Multiple choice
 - Heavy - Light - Very deep - High offloading - NA
- Engine
 - **Take a picture of the radiator**
 - Check the radiator
 - Clean/Undamaged - Dirty/Damaged
 - Check Coolant Level
 - Ok - Close to Minimum - Below Minimum- NA
 - Was the coolant refilled today?
 - Yes - No
 - Check for Coolant Leaks
 - Ok - Coolant Droplets - Clear Leak - NA
- "Engine start up" (Bring a speaker?)
 - Are there any abnormal sounds?
 - No - Possibly - Yes - NA

After the checkup is done, the checkup report is shown

*****Tell the user that a couple hours has passed*****

When to the main page, there is a notice on the inpection page, due to high engine temperatures it is suggested to inspect the cooling system.

If radiator, the analyzed image is shown. Or a "coolant tank" (we can swap from full to low between checkup and inspection)

- Check the radiator
 - Clean - Dirty - Damaged - Undamaged
- Check coolant level
 - **Take a picture of your coolant tank**
 - Ok - Close to Minimum - Below Minimum- NA
- Check the fan (**Get a small fan to blow air?**)
 - **Take a picture of the fan blades**
 - Check wear on the fan blades
 - Ok - Worn - Damaged - NA
 - Check the function of the fan
 - Good - Poor Airflow - Fan not spinning - NA

F.2 Presentation and Developed materials

Presentations (PDF and video), Posters, Images and Marketing Designs

Presentations can be found by [this link](#) (including video of the sugar final presentation at Kyoto), as well as [Posters, Images and Marketing Designs](#).

Application: Backend, Frontend, Ai prediction system and Image Classification

They can all be found on this links: Backend ([express](#) and [main](#)) , [Frontend](#), [Ai prediction system](#) and [Image classification](#)

The Android Application Pack (APK) itself can be found here: [Application Relea](#)

G. Image Analysis (YOLO model)

YOLO, which stands for "You Only Look Once," is a state-of-the-art, real-time object detection system. The model has been specifically trained to identify various machine parts, such as radiators and coolant tanks, and classify their conditions. This section provides an overview of the key scripts used to train and deploy the model, namely `train.py` and `detect.py`.

G.1 `train.py`: Overview and Key Functions

Purpose:

The `train.py` script is used to train the YOLOv5 model on a dataset of construction equipment parts. The script allows for both single-GPU and multi-GPU training. It includes various functions and configurations to handle data loading, model configuration, training, and saving the trained model. Below is an overview,

Key Functions:

- **Data Loading:**
 - The script uses a YAML configuration file (`coco128.yaml`) to specify the dataset path and other related parameters. This includes loading images and annotations for training.
- **Model Configuration:**
 - The script can loads pre-trained YOLOv5 models (`yolov5s.pt`).
- **Training Process:**
 - Training involves a loop where the model's predictions are compared against ground truth labels, and the loss is calculated. The optimizer then updates the model weights to minimize this loss. The script includes various options for adjusting the learning rate, batch size, and number of epochs.
 - The script also supports distributed training across multiple GPUs for faster processing.

- **Output:**
 - The script saves the trained model weights, logs the training process. The final trained model can be used for inference on new images.

G.2 `detect.py`: Overview and Key Functions

Purpose:

The `detect.py` script is designed to run YOLOv5 detection inference on different formats of image data using the trained YOLOv5 model .

Key Functions:

- **Model Loading:**
 - The script loads the YOLOv5 model weights (`yolov5s.pt`) in various formats, such as PyTorch, TorchScript, ONNX, and OpenVINO. This allows for flexibility in deploying the model across different environments.
- **Image Preprocessing:**
 - Before running inference, the script preprocesses the input by resizing, normalizing, and converting images to the required format. This ensures compatibility with the model's input requirements.
- **Detection Process:**
 - The model processes the input images or video frames, identifying objects by predicting bounding boxes, class labels, and confidence scores. The script then applies non-maximum suppression to refine the results.
- **Output:**
 - The detection results, including bounding boxes and labels, are displayed on the input images frames. These can be saved to disk or directly streamed for real-time applications. The script supports saving the results in various formats like images, videos, or even JSON files for further processing.