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Integrating operators and enabling technologies in construction equipment to enhance lifecycle value and future-proof business models

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Abstract

This research investigates the application of enabling technologies within the construction equipment industry. The primary challenge addressed is enhancing customer value across the entire equipment lifecycle. Through iterative exploration, creation, and validation phases, the research developed and tested various prototypes to optimize sales processes, maintenance procedures, and equipment management. The findings highlight the potential of advanced data collection from operators for predictive maintenance, enhancing machine learning models by integrating human and machine data for more accurate predictions, reducing downtime, and boosting operational efficiency to align construction equipment maintenance with the demands of future business models.

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1. Introduction

Product-Service Systems (PSS) is a specific aspect of servitization that integrates services with products [1] as a broad intentional response to a complex customer need [2]. Currently, supporting services in the construction industry are emerging, focusing on product customization and digital twins [3, 4]. However, [5] highlight a lack of advanced supporting services in this sector and emphasize the need for their implementation at various stages of construction development.

The rapid evolution of digital technologies and their integration into the construction equipment industry have driven the need for new approaches to optimize processes and maximize value throughout the product lifecycle [6]. However, the systematic application of data-driven and machine learning (ML) methods in this sector still faces significant challenges, particularly in effectively incorporating artificial intelligence into design and innovation processes.

This study explores the convergence between Design Thinking and Data-Driven approaches to enhance the development of solutions for construction equipment. Unlike purely technical approaches, this work seeks to integrate machine learning methods and analytical tools into a structured model that balances user-centered innovation with data-driven operational optimization.

To achieve this objective, this study aims to answer the following research questions:

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1. How can the combination of Design Thinking and machine learning improve the development and lifecycle management of construction equipment?

2. What are the challenges and opportunities in implementing ML-based solutions to optimize predictive maintenance and reduce downtime?

3. How can different data modalities (sensors, operators, operational context) be integrated into an analytical model that adds value to business decisions?

The research follows an iterative process of exploration, creation, and validation, combining multiple phases of prototyping and testing in real operational environments. Thus, this work does not merely propose technical solutions for the construction equipment sector but also contributes with a framework to integrate artificial intelligence into innovative processes, facilitating the adaptation of business models to the industry's future.

2. Methods

The project was developed within a design network. This network is an international alliance of over 25 universities where students collaborate in teams on product design and development projects. In each project, a multidisciplinary group of 3 to 5 students from one university teams up with a similar group from a second university, forming a global team, along with a corporate sponsor that presents a challenge to be solved [7]. Over the course of approximately nine months, these global teams research the problem space, reframe their challenge, and produce multiple prototypes of design concepts.

The teams follow the Design Thinking method, a creative design engineering approach in which participants generate, evaluate, and specify concepts for devices, systems, or processes that meet clients' objectives and users' needs while satisfying a defined set of constraints [8].

Five cycles of development were conducted, each including the convergent and divergent phases inherent to the Design Thinking approach. Each cycle expanded from diverse needfinding, involving visits to observe and interview workers at construction sites, construction equipment dealers, and several of the corporate partner's development sites. Interviews followed a consistent structure [9]. For the synthesis, distinct personas and user journeys were created to represent typical users and stakeholders, validated through real interactions to understand their needs better [10]. Finally, each cycle incorporated creative activities to generate ideas for addressing the refined challenges identified [11].

Distinct prototyping strategies were employed in each iteration to enhance creativity, relevance, and utility, beginning with simple prototypes and culminating in a functional concept. Using low-fidelity prototypes, the Critical Experience Prototype (CEP) simulated the user experience to test the concept's value without full development [12]. The Critical Function Prototype (CFP) tested core functionality to evaluate feasibility before developing subsystems [13]. The Dark Horse Prototype explored risky, unconventional solutions to identify breakthrough ideas [14]. The Funky Prototype consolidated insights from previous phases to develop a comprehensive system concept [15]. Finally, the Functional Prototype focused on delivering a practical, functional solution for stakeholder evaluation [12].

3. Results

This section presents the most relevant results of the complete innovation development project, considering all the phases described in the previous section.

3.1. Initial Needfinding

The initial needfinding phase involved immersion in the working environments of users, clients, experts, and other relevant stakeholders from the industry partner. Initial interviews aimed to gain insights into the equipment acquisition process from the user's perspective, particularly focusing on the relationship between the dealership and the purchaser, forging a comprehensive understanding of the user journey to identify pain points considering multiple perspectives. Interviews also focused on the selling process of construction equipment, emphasizing services sold to add value to the product and the resulting user experience throughout the product lifecycle of the provided goods and services. Field visits were conducted to gather insights into the various processes employed by industry professionals. The focus was identifying the needs associated with new equipment and the processes surrounding those decisions. Key observations revealed that the process relies heavily on established personal relationships, highlighting opportunities to improve the dealership experience and make sales more consistent.

Throughout the project's development, personas were created, tested, and refined to justify the development of the final solution. The personas consist of various construction workers and machine operators with different experience levels and responsibilities. One of them even owns their equipment, which leads to a heightened sense of responsibility for the machine's reliability.

The first persona is a 38-year-old Brazilian female backhoe loader operator working in the interior of Brazil, where she finds more opportunities and less competition than in larger cities. She has operated machines since childhood and views them as extensions of herself. Her primary goal is to work efficiently with minimal downtime, and her main concerns are mechanical breakdowns and income loss due to equipment failures. The second persona is a 43-year-old Brazilian male machine operator with 15 years of experience seeking greater autonomy in his work. He looks for clear instructions and mechanical support but is frustrated by his lack of control over his operating machines. The third persona is a 35-year-old Swedish female owner-operator who transitioned from being a hauler driver to owning her own excavator business. She faces challenges in maintaining her equipment and needs reminders for routine tasks, focusing on maintaining efficiency and independence. The final persona is a 40-year-old Swedish male operator who works for a construction firm and values efficiency and clear instructions. He prioritizes leaving work behind at the end of the day and prefers to concentrate on operating machines rather than dealing with maintenance or technical complexities.

3.2. Intermediate Prototypes

The Critical Experience Prototype (CEP), presented in Figure 1, was designed to improve operator productivity and safety applying augmented reality and digital twin technologies. A virtual simulator was used to test real-time data and recommendations, evidencing increased efficiency and reduced task completion time for operators who followed the proposed guidelines. While the guidelines were generally followed and considered helpful, adherence decreased over time.

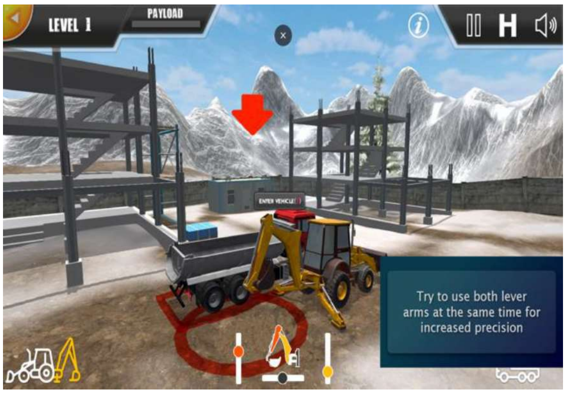

Figure 1 – Critical Experience Prototype

The Critical Function Prototype (CFP), presented in Figure 2, was a chatbot aimed to help project managers and equipment purchasers by simplifying the process of selecting construction equipment through a personalized digital solution. User testing showed the chatbot trained on the industrial partner's online product catalog, effectively understood complex queries, and provided detailed product specifications. Users who tested the prototype suggested expanding the knowledge base to include post-purchase services. Some identified opportunities include integrating 3D model demonstrations and refining the chatbot's functionality to enhance the customer journey within the industry partner's service offerings.

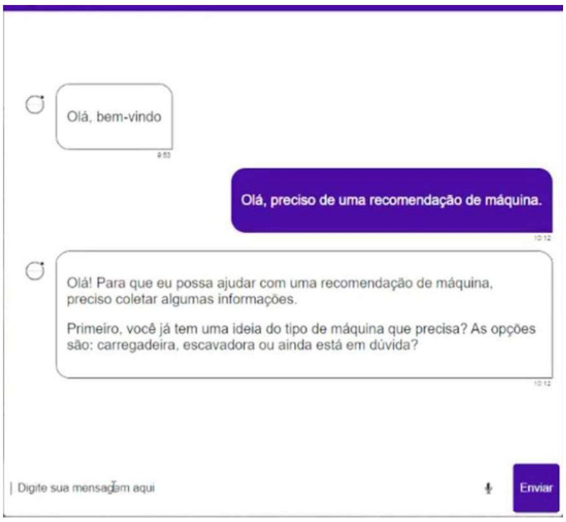

Figure 2 – Critical Functional Prototype

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.

Presented in Figure 3, the first Dark Horse, Mac, a predictive maintenance solution, was developed to address equipment failures by diagnosing issues and ordering spare parts before mechanical breakdowns occur. Testing with various stakeholders revealed that while some operators can effectively engage with the solution, others require more guidance, leading to refinements in how the system supports operators with varying skill levels. The feedback highlighted a need for faster repair processes and the importance of technician preferences and better pre-arrival diagnostics, influencing the design of the final maintenance service prototype.

Figure 3 –Dark Horse Prototype 01

Presented in Figure 4, the second Dark Horse concept, Blue, was designed to centralize construction site expertise and data to aid managers in tracking operations and making informed decisions. It evolved into a software solution that analyzes machine data, identifies problems, and provides real-time simulations to support decision-making, helping site managers handle complex variables and minimize risk. Initial testing revealed a strong need for real-time simulations and better data visualization, emphasizing the importance of clear use cases and aiding overwhelmed managers with live insights and recommendations.

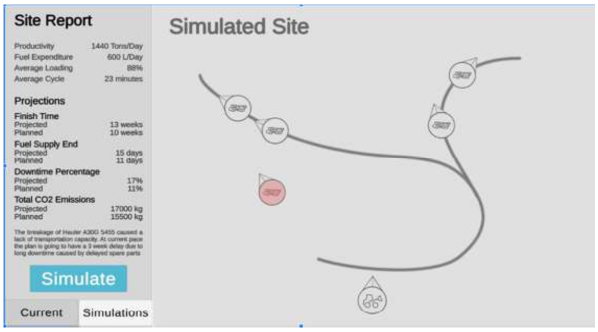

Figure 4 –Dark Horse Prototype 02

The final Dark Horse concept, presented in Figure 5, was a prototype to foster an emotional connection between operators and machines. It used a digital twin to gauge and display the machine's status and how the operator's actions impact it in a user-friendly way. Feedback highlighted that while creating emotional connections is beneficial, tracking operators' data felt invasive, and giving machines an "expiration date" could motivate better care and maintenance.

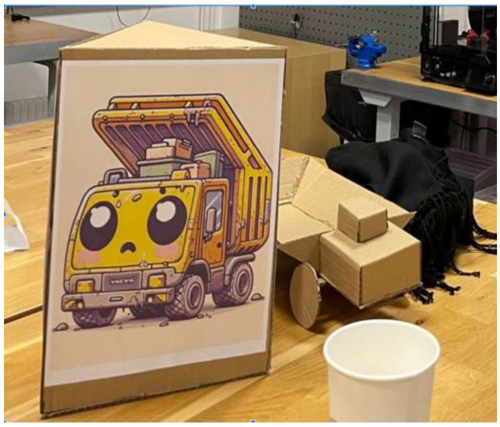

Figure 5 –Dark Horse Prototype 03

3.3. The Final Prototype

The tests and feedback revealed that the Dark Horse Prototypes (DHP) could add significant value to the sector. After evaluating the possibilities, the concept "Mac" was selected for further development to address maintenance and uptime issues. However, adding more sensors was deemed impractical due to complexity and increased malfunction risks. This led to a shift in focus towards developing a system that enriches existing data by collecting contextual data from the operator.

Further visits to construction sites revealed that daily checkups on equipment are only documented if immediate issues are found. This insight highlighted the potential of making operators central to equipment health monitoring, enhancing data collection and troubleshooting.

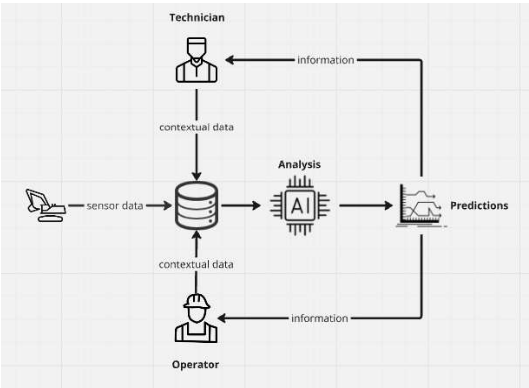

Figure 6 - System diagram of the proposed final solution

Figure 6 presents the complete system diagram of the proposed final solution. Operators use an app to record daily machine checkups, providing information about the equipment, environment, and tasks while reporting unusual signs like sounds and vibrations. The app prompts operators to take photos as a security measure, ensuring thorough documentation. The collected data enhances machine learning (ML) models for predicting failures. However, operators may need further inspections with assistance from augmented reality (AR) and artificial intelligence (AI) tools. The data, combined with machine history, helps build virtual models to predict potential issues. Technicians can access the data for maintenance and repairs, contributing to system improvements. The additional contextual data provides a better understanding of machine performance in different scenarios and informs product and service development. The prototype was tested on construction sites, with positive feedback from operators who found it useful and non-intrusive. Some testers noted challenges using the app in cold weather. Machine owners valued the documentation support, and project managers highlighted its potential for improving issue reporting. Overall, the solution was well-received and addressed key industry challenges.

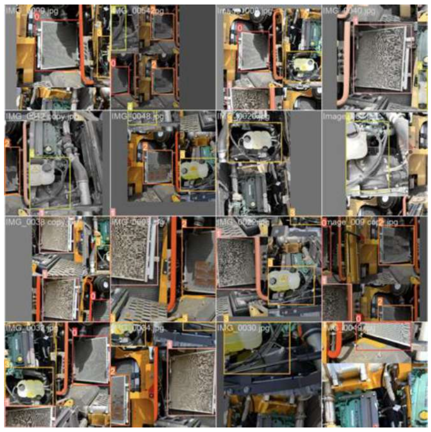

Figure 7 - Model training using the YOLOv5 framework

The model is trained using the YOLOv5 framework [16] (see figure 7). 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'.

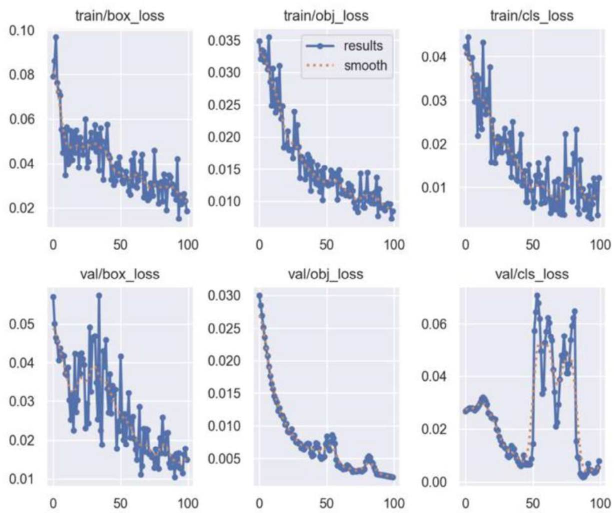

Figure 8 - Testing and perfomance evalutaion

Post-training, the model's accuracy is assessed using the detect.py script, which applies the best weights to the test dataset (see Figure 8). 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. Several machine learning algorithms were considered for analyzing the engine data to predict potential failures and understand engine behavior. The chosen models include Linear Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and Neural Networks

4. Discussion

During three months of early needfinding, prototyping, and testing, several key findings and challenges emerged across sales, procurement, maintenance, and site management. In sales and procurement, it was observed that a personified AI can help provide information on equipment specifications and optimized utilization. However, the trust between sales personnel and customers heavily influences purchasing decisions. Sales staff often need help knowing all the available options and finding the best fit for diverse applications, and there is a lack of support in deciding what equipment to buy or assign to new projects. Additionally, gauging the condition of second-hand equipment remains a gamble, highlighting the need for better assessment tools.

In terms of maintenance and equipment, the role of operators in troubleshooting is seen as beneficial for relieving pressure on managers, dealerships, and technicians. However, final decisions still require managerial input. There is a desire for automatic updates on project progress and potential issues through a visual tool, possibly integrated with an AI chatbot, to provide further site knowledge and optimization opportunities. Creating an emotional connection between operators and machines may extend the lifespan of equipment but poses challenges in tracking the operators. The need to speed up repairs before and after machine failure is also evident, as technicians often arrive without the right parts or tools, and parts delivery delays add to downtime due to the high cost of keeping parts in stock.

Regarding site management, the configuration of machines affects on-site service usage, and it is difficult to gain an overview of the project's current phase or the location and tasks of each machine. Choosing the best option for improvement or addressing unplanned events is challenging, especially when equipment is rented, or operators are temporarily assigned to unfamiliar machines, often resulting in damaging equipment.

These findings led the teams to focus on key areas for the final solution. The solution aims to support equipment selection during sales and project planning, improve maintenance processes for higher equipment uptime, provide predictive maintenance tools for on-site solutions, and offer better site overview, management, and operational optimization. The final solution addresses unplanned downtime by enriching mechanical data with contextual insights from operators, who act as "human sensors." While current equipment data lacks actionable information, operators can enhance it by recording daily checkups via mobile devices, providing a more complete view of machine health. This system identifies patterns and reduces downtime without the need for extra hardware. The collected data also offers deeper insights into workloads, project tasks, and equipment performance, enabling customers to make informed decisions and providing sales teams with better guidance. Additionally, it informs product and service improvements, aligning with evolving customer needs and identifying areas for enhanced performance.

5. Conclusion

The results of this study demonstrate the transformative potential of integrating Design Thinking and machine learning in the construction equipment sector. The proposed approach not only optimized maintenance and equipment management processes but also structured a data-driven innovation model that adds value for operators, managers, and manufacturers.

The application of ML models, including YOLOv5, proved to be promising but also highlighted the need for continuous refinement to integrate contextual data and improve prediction accuracy. Furthermore, the multimodality of data—including sensors, operator feedback, and maintenance records—emerged as a critical factor in enhancing the effectiveness of the solution

However, this study represents an initial step within an emerging field. For future research, we suggest:

- Deepening the analysis of multimodal data integration, exploring new techniques for fusing sensor information and operational records.
- Expanding testing and validation across different operational environments, ensuring greater robustness and generalization of the developed models.
- Investigating hybrid artificial intelligence approaches, combining symbolic and statistical techniques to improve the interpretability and reliability of predictions.

The convergence of Design Thinking and Machine learning opens new opportunities for the sector, enabling construction equipment manufacturers and operators to adopt more agile and adaptable strategies. This work underscores the importance of an integrated approach to innovation, combining human and digital intelligence to develop more efficient and sustainable solutions for the industry.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Open AI - Chat GPT to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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