BACHELOR' S THESIS / BIOMEDICAL ENGINEERING 2024

Market Analysis and Prototype Validation for TransCOR

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Bachelor's Thesis UPF 2023/2024

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Dedicatory

To my friend, for her unconditional support and patience.

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Acknowledgments

I'm deeply grateful to my supervisors, Sergio Sánchez and Bart Bijnens, for giving me the chance to work on this project. Your consistent guidance and support throughout the year have been invaluable, and your assistance in overcoming obstacles has been crucial to my progress. To my friends, thank you for your encouragement and support. Finally, to my family, I am deeply grateful for your unwavering support, patience, and for allowing me to pursue my passion. Your faith in me has been my greatest source of strength.

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Summary/Abstract

TransCOR, a research tool developed by PhySense (UPF), is a web-based platform crucial for collaborative research in ultrasonography. It facilitates high-quality image management and analysis through rigorous quality checks, manual labeling, and AI-powered image evaluation, vital for generating ground-truth data and automating cardiac measurements. With a cloud-based infrastructure and privacy-by-design approach, TransCOR ensures global clinical collaboration while maintaining data security and compatibility with diverse ultrasound equipment. The main objective of this Bachelor's Thesis, motivated by positive feedback from users of TransCOR, is to help it transition from its status as a research tool to an attractive product in the market, which is a process known as technology transfer. To do so, a dual approach with a market analysis and prototype validation of TransCOR using qualitative and quantitative methods was performed. Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA) were used to assess competitor positioning. Results indicated TransCOR excels in data acquisition and feature extraction but revealed opportunities to enhance interpretation and decision support functionalities. Qualitative validation highlighted user demand for advanced decision support functionalities, guiding future development priorities. In conclusion, this study provides strategic insights into TransCOR's market positioning and incorporates valuable feedback from industry experts. The integration of market analysis with expert opinions highlights critical factors for a successful go-to-market strategy. Together, these insights will guide the development of a comprehensive roadmap for effectively positioning TransCOR in the market.

Keywords

TransCOR, market analysis, prototype validation, technology transfer

Preface or prologue

TransCOR, developed by PhySense (UPF), is an innovative platform designed for collaborative research in ultrasound imaging. This study aims to transition TransCOR from a research tool to a commercial product through a process of technology transfer, utilizing a comprehensive market analysis and prototype validation. The findings highlight TransCOR's strengths in data acquisition and feature extraction while identifying opportunities for enhanced decision support functionalities. By combining market insights and expert feedback, this research provides key strategies for a successful go-to-market approach.

Index

List of Figures

List of Tables

1 Introduction

1.1 TransCOR

TransCOR is a web-based software platform developed by the *Sensing in Physiology and Biomedicine* (PhySense) group of Universitat Pompeu Fabra (UPF), currently used as a tool in different collaborative research projects where ultrasonography image management and analysis are needed. This tool connects to data sources and allows the collection of high-quality images through rigorous quality checks (manual labeling and image quality evaluation) and the generation of ground-truth data essential for artificial intelligence (AI) model development, such as segmenting anatomical structures and delineating Doppler signals. Additionally, its AI-automated extraction of relevant clinical measurements from images significantly reduces the time needed to read imaging studies, standardizing reports and minimizing diagnostic errors. With a cloud-based infrastructure and privacy-by-design approach, TransCOR fosters global collaboration among clinical teams while ensuring data security. Furthermore, its vendor-neutral design ensures compatibility with a wide array of ultrasound imaging equipment, making it versatile and easily integrated into real-world clinical practice [5]. These features of TransCOR are aimed at helping clinicians during the process of decision-making.

Regarding how machine learning can support the clinical decision-making process, there are four main steps involved in the process: data acquisition, feature extraction, interpretation, and decision support, which have an increasing risk for the patient (Figure 1) [11].

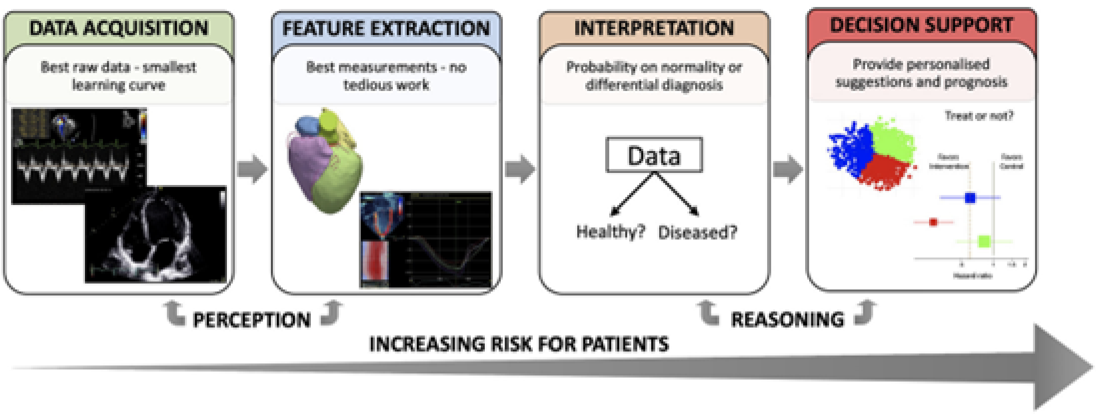

Figure 1: Different tasks where machine learning (ML) can support clinical decision-making (extracted from [11]).

In this summary, the main tasks are outlined [11]:

1. Data acquisition: This stage involves gathering comprehensive data, such as clinical history, patient demographics, physiological measurements, electrocardiogram results, imaging findings, and laboratory test outcomes.

2. Feature extraction: Following data acquisition, the focus shifts to analyzing images and extracting relevant features through quantitative information.

3. Interpretation: This process involves contextualizing information with population-based rules and understanding the patient's current health status.

4. Decision support: Based on the interpreted data, informed decisions about patient management are taken, which may include gathering additional data or recommending specific interventions.

The current version of TransCOR excels in data acquisition and feature extraction. It ensures high-quality image collection through rigorous quality checks, and provides tools for generating ground truth data. Additionally, its advanced tools for automated measurements, enhance the efficiency and accuracy of ultrasound imaging analysis. Therefore, it can be said that the current TransCOR excels at the first two steps of the decision-making process described above: data acquisition and feature extraction.

1.2 Motivation

The medical landscape is marked by the high incidence of cardiovascular diseases, which contribute to approximately 30% of all recorded deaths and 37% of premature deaths in the world [10], underscoring the significant impact these conditions have on public health and healthcare systems. Ultrasound is widely used in cardiology for diagnostic purposes, helping clinicians assess cardiac structure and function non-invasively. This technology provides detailed images of the heart, aiding in the detection and monitoring of various cardiovascular conditions such as coronary artery disease, heart valve abnormalities, and cardiomyopathies. Moreover, ultrasound's role extends beyond cardiology; it is also a cornerstone in obstetrics for assessing fetal development and monitoring pregnancies. Its convenience, non-invasive nature, and ability to provide immediate results make it invaluable in both fields, contributing to improved patient care and outcomes [2].

This highlights the need for precise image analysis. The integration of AI for assisting in clinical decision-making by automating manual tasks in medical imaging, particularly in cardiology, has demonstrated growth potential [11] which triggered the breakthrough of image analysis products such as TransCOR.

Transitioning TransCOR from its current status as a research tool to a practical healthcare solution presents a formidable challenge for this Bachelor's Thesis (BT). As highlighted in the previous paragraph, TransCOR, while currently serving as a valuable research instrument, is not yet positioned for widespread use within clinical settings and is not market-ready. Therefore, helping the integration of TransCOR into the global ultrasound imaging software market is the primary motivation of this BT.

1.3 Technology transfer

Following the identification of this motivation, the focus shifts to addressing it through the process of technology transfer. Technology transfer refers to the process in which an idea does not remain inside an institution or a university, instead, it is exploitable, usable, and accessible by a large number of users [8]. When talking about technology transfer, it is important to mention the concept of Technology Readiness Level (TRL), which is a scale from 1 to 9 for quantifying the technical maturity of a technology during its acquisition phase [14], and acknowledging the research stage of TransCOR, which has a TRL of 2-3.

Technology transfer begins with researchers conducting studies to generate new knowledge and innovative solutions. When researchers identify commercially viable innovations, they undergo an assessment to evaluate market potential, analyze competitors, and review intellectual property considerations. If deemed suitable for commercialization, strategies are developed to protect these innovations through patents or copyrights. Innovations are then marketed to potential industry partners to find collaborators who can further develop and bring them to market. Partnerships are formed with existing companies or through startups to advance the development of these innovations. Once partnerships are established, rights to commercialize innovations are licensed to these partners, who take responsibility for developing and selling products based on the innovation. Throughout the commercialization phase, support is provided to partners through funding facilitation, networking, and technical assistance. Successful technology transfer leads to impactful innovations, including improved outcomes, economic development, and revenue generation, benefiting society and advancing global innovation [7]. Steps of a typical technology transfer process discussed above can be observed in Figure 2.

In the context of this BT, the stage where the work plays a big role is the

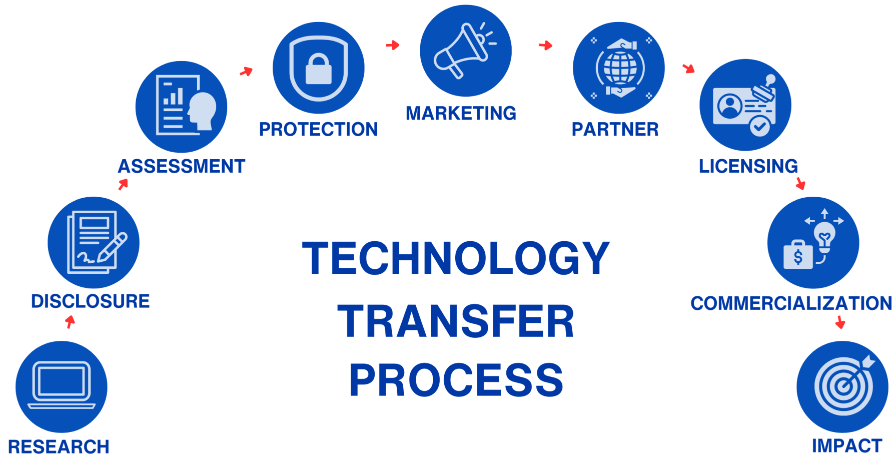

Figure 2: Steps of a typical technology transfer process (extracted from [7]).

assessment of the market and the potential of TransCOR to access this market.

1.4 Objectives

The general goal of this BT is dedicated to facilitating the integration of TransCOR into the global market for ultrasound imaging. As mentioned above, after acknowledging TransCOR's current status as a research product in TRL 2-3, the general goal is to mature it for market readiness. Initial screening interviews with platform users have suggested that TransCOR could be highly beneficial. Users particularly praised its collaborative and web-based features, highlighting its potential to enhance connectivity and cooperation among clinical teams globally (see Section 3). This positive initial feedback underscores the importance of conducting a comprehensive market analysis. By understanding market needs and the competitive landscape, we can refine TransCOR to meet industry standards and user expectations effectively. The insights gained from this analysis will guide how to properly shape TransCOR, ensuring that it evolves from a promising research tool into a valuable end product.

The approach involves a dual focus: firstly, conducting a thorough market analysis to understand the competitive landscape. In parallel, the validation phase entails rigorous testing of TransCOR's usability and clinical relevance. Expert feedback, gathered from healthcare professionals and AI companies will be used to guide iterative refinement, aligning the tool with evolving end-user (clinicians) and industry needs.

The obtained insights from market analysis and prototype validation will hint at potential modifications in the product/business proposition and refine TransCOR to meet market demands, and therefore, help to propose a strategic go-to-market strategy that accommodates both market tendencies and user needs.

Therefore, we can say that the specific objectives of this BT are the following:

1. The first objective is to conduct a comprehensive market analysis to identify potential niches and the competitive landscape, considering TransCOR's current status as a research product not yet mature for the market. Understanding market needs, competitive landscape, and potential barriers is crucial to refine TransCOR and ensure it meets industry standards and user expectations effectively.

2. The second objective is to validate TransCOR's efficacy, clinical relevance, and usability through rigorous testing and customer discovery. This involves gathering expert feedback from healthcare professionals and AI companies to refine the tool and align it with evolving market needs. This part is interconnected with the marketing analysis into a continuous refinement cycle, which means that it will help to reorient it, ensuring that the development of TransCOR is guided by real-world requirements and expectations.

2 Methods

For clarity, Figure 3 displays a conceptual map of all the steps performed in this BT.

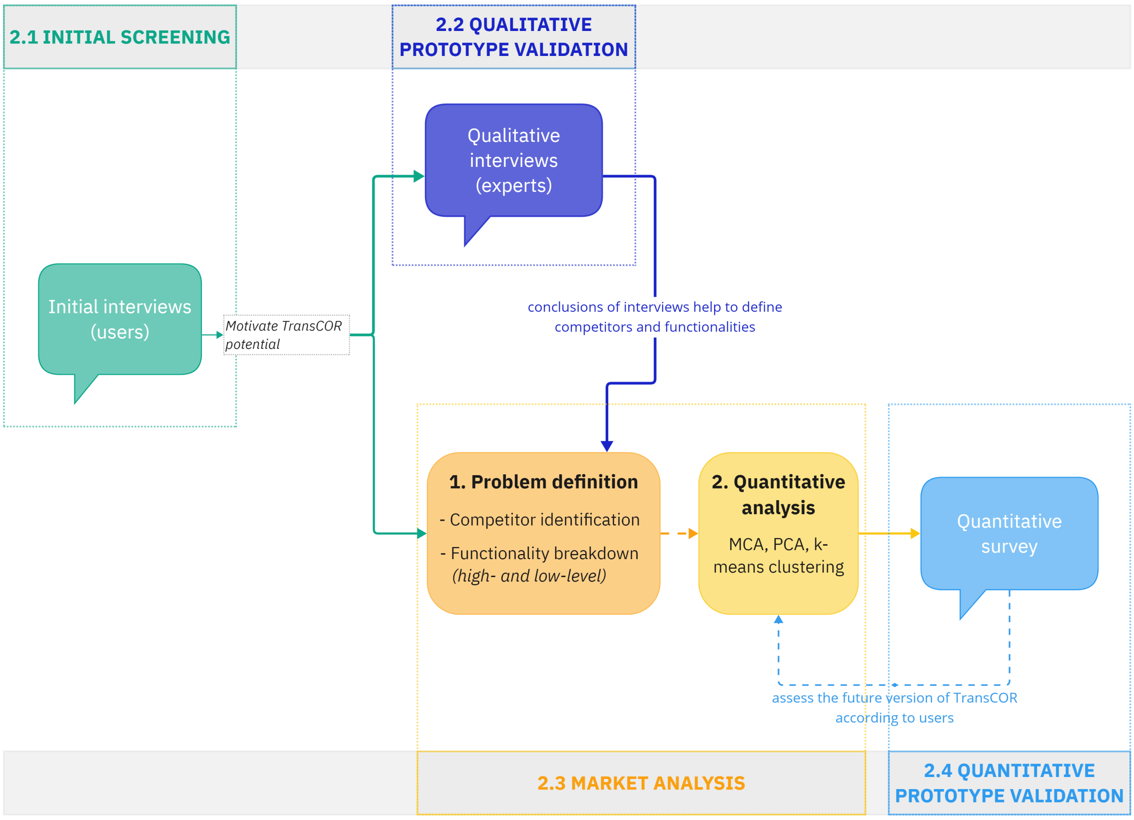

Figure 3: Conceptual map illustrating all stages performed in this work.

2.1 Initial screening interviews

Two initial screening interviews have been conducted with clinicians in collaborative research projects using the TransCOR platform to assess its potential and determine if it would be worthwhile to develop it into a marketable product. These interviews were carried out informally, without specific guidelines or a strict script. Instead, clinicians were asked to provide their spontaneous feedback, focusing on what they found most beneficial about the platform and what aspects could be improved. They were also asked to give their overall opinion on the platform.

2.2 Qualitative prototype validation

The qualitative validation has been performed through a series of structured interviews, where it was aimed to explore and understand key aspects including customer discovery, problem discovery, problem validation, product discovery, product validation, and product optimization. Here is a brief explanation of these categories:

- Customer discovery: Consists in understanding better the background and knowledge of the interviewee.
- Problem discovery: Understanding the problems and issues that the interviewee faces during their work.
- Problem validation: Understanding whether the problem that TransCOR is intended to solve is relevant.
- Product discovery: Presenting the current version of TransCOR and its main features.
- Product validation: Understanding whether the solution that TransCOR provides is relevant, adequate, and efficient.
- Product optimization: Trying to gather any other potential functionalities to TransCOR that according to interviewees are currently missing.

Two versions of this questionnaire, depending on the type of interviewee (clinician or AI expert) have been drafted based on these categories. The questionnaires can be found in Tables 4 and 5, located in the Additional information section.

A total of six interviews have been conducted: three with clinicians and three with experts within the context of AI experts, taking into account the different backgrounds of potential stakeholders. The received feedback serves as a foundational step, providing a starting point for subsequent market analysis. Specifically, it helped to understand not to focus only on competitors who provide products in the area of cardiology and also to give more detail to decision support functionalities during the functionality breakdown. This will be reviewed in more detail in the subsequent sections.

2.3 Market analysis

2.3.1 Competitor identification

The first step of the market analysis consisted of identifying potential competitors of TransCOR and understanding their products. For this market analysis, a top-down approach has been performed, where first a more general criterion (AI in healthcare) has been used to screen competitors, and then, the obtained list has been refined by focusing only on those whose imaging modality is ultrasound and the therapeutic area was cardiology or obstetrics/fetal medicine.

The strategy to find competitors has included both a manual search in various sources and a more automated one by performing web-scraping techniques (using UiPath, a Robotic Process Automation (RPA) tool) and filtering by keywords in sources with potential innovative products, such as medical trade shows or fairs (MEDICA 2023, Arab Health 2023 and Digital Health World Congress 2023).

2.3.2 Functionality breakdown

A crucial step in this BT is to define a robust way of studying the products that the different competitors are offering. To do so, a breakdown by functionalities (different features, for example, raw data acquisition) and implementations (how to execute these features, for example, in case of raw data acquisition this can be manual and/or AI-enhanced) has been performed following a top-down approach, which involves an initial high-level perspective refining toward identifying specific implementations. This high-level perspective is based on the four steps involved in clinical decision-making explained during the introduction. The general idea was to think of it as a continuous process where after each main step there is an output which is then used as the input of the next step.

The first step is data acquisition, where there is the integration of diverse data sources—from ultrasound scans and maternal health records to laboratory results—into a centralized data warehouse, which is the output of this step. Then, feature extraction follows, focusing on deriving a clinically relevant set of features from the amassed data. Once we have this set of features, they can be either reported (documentation) or served as input for the next step, which is interpretation. This step merges the set of features and integrates them with knowledge, which can be summarized in guidelines or AI-based exploration of populations, in order to determine the state of the patient, which can be also documented or used as the input for the next step: decision support. This step, similarly to the previous one, uses the state of the patient and integrates it with knowledge in order to produce a decision, which like in the previous case, can also be documented. Each of these steps includes several high-level functionalities which are instrumental in making these steps work. The schematic view of this process can be seen in Figure 4.

In addition to these four steps, there are also management functionalities, such

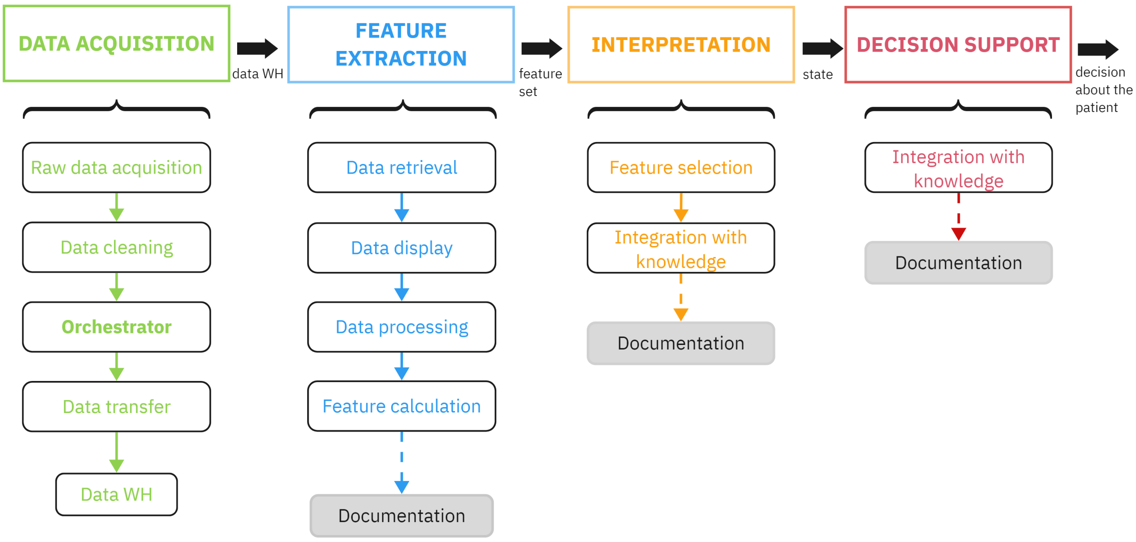

Figure 4: High-level functionalities during the process of clinical decision making.

as the implementation of informed consent management, data management plan (DMP), and audit trails. Finally, the inclusion of data pseudo-anonymization/encryption and data sharing between controller and processor are also part of these management functionalities. These functionalities, which make sure that the product is compliant with regulations, and other overarching functionalities are not part of any specific step but are crucial for creating an end product. This schematic can be observed in Figure 5.

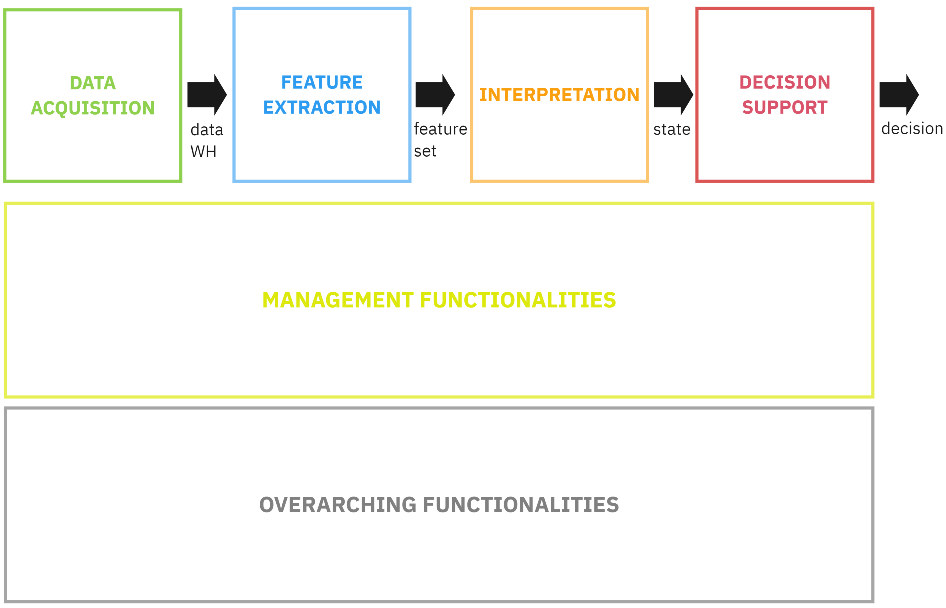

Figure 5: All main steps required for an end product.

In order to understand how this functionality breakdown is defined, we can identify three levels of hierarchy:

1. The four main steps in clinical decision-making, management functionalities and overarching functionalities.

2. Different high-level functionalities that constitute these main steps. For example, data retrieval, data display, data processing, feature calculation, and documentation which are part of feature extraction are all high-level functionalities.

3. Different low-level implementations that constitute the high-level functionalities. For example, quality control can be considered as one of the parts of data processing. Then, this quality control can be either binary, rule-based, or deep learning-based. In this case, for example, rule-based quality control for data processing is one of the low-level implementations present in the analysis.

For the subsequent analysis of competitors, the following approach has been used:

1. Implementations at the lowest hierarchical level have been studied based on whether TransCOR and the different competitors have that implementation in their product or not. Binary values have been assigned (1: Yes, 0: No).

2. Scores for each high-level functionality have been computed as the average of the low-level implementations that constitute that functionality.

3. Remarks: For the sake of simplifying the analysis, all implementations had the same weight for the computation of the scores for the functionalities, despite not necessarily being at the same hierarchical level. In addition to that, some of the information regarding the implementations was not directly present in the product descriptions, so they had to be inferred based on a qualitative contextual imputation and own judgment. This means that the analysis may contain some errors or uncertainty. Again, for the sake of simplicity, this uncertainty has not been taken into account for the analysis.

The table containing all the information regarding competitors, and the information about high-level functionalities and low-level implementations can be found in Tables 6 and 7, located in the Additional Information section.

2.3.3 Multiple Correspondence Analysis

Understanding the data being studied is crucial for effective analysis. For reducing the dimensionality of the dataset and understanding the relationships between the different implementations of the functionalities, Multiple Correspondence Analysis (MCA) [1] has been employed to reduce the dimensionality and analyze the low-level implementations. To do so, the Python Prince library [1] has been used. MCA allows for the exploration of relationships between categorical variables and aids in identifying underlying patterns within the data.

In this part, this approach has been chosen because it allows to work with binary values, which is helpful to perform a study based on all the different low-level implementations discussed in the previous section. The idea of doing this is to take into consideration all the possible implementations and map the competitors based on them without losing information.

2.3.4 Principal Component Analysis

In an alternative approach, to find a different perspective from the MCA approach (see section Results), Principal Component Analysis (PCA) [9, 6] has been used to understand the dataset by aggregating the low-level implementations into high-level functionality groups (see section 2.3.2) into numeric variables. The idea of performing this analysis was to have a complementary to the MCA approach view of the competitors from a different perspective, having a more general/high-level point of view without looking so much into specifics. However, the drawback of this kind of approach is the fact that some implementations that are potentially game-changers are diluted, meaning that some information may be lost.

Using the Python scikit-learn library [2], PCA has been applied to these variables to capture underlying patterns and reduce dimensionality. PCA transforms correlated variables into linearly uncorrelated principal components, ordered by the amount of variance they explain. The objective is to select a subset of principal components that collectively capture a substantial portion of the overall variance while minimizing dimensionality [6].

After evaluating the cumulative explained variance ratio, 4 principal components have been retained, explaining almost 80% of the total variance (Figure 6). This decision strikes a balance between capturing significant patterns of variance and reducing dimensionality, facilitating further analysis and interpretation of the dataset.

[1] https://github.com/MaxHalford/prince
[2] https://scikit-learn.org/stable/

The inputs of the PCA and also of the MCA from the previous section, and the code used to generate the results can be found in the following GitHub repository[3].

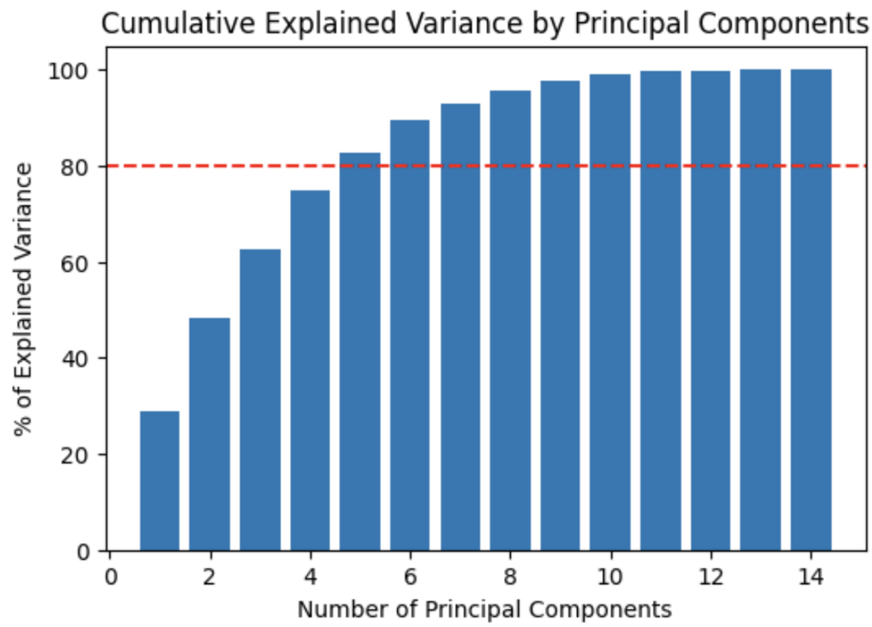

Figure 6: Plot showing the cumulative explained variance of the Principal Component Analysis (PCA) components.

2.3.5 k-Means Clustering algorithm

Following the PCA, the subsequent step involved conducting k-means clustering [12] to identify groups among competitors. The idea of examining the clusters in the PCA-reduced space, despite having lost some information after aggregating the low-level implementations, consists of identifying different groups of competitors based on their products viewed from a high-level perspective, and highlighting market niches, indicating unmet needs or opportunities for innovation. By doing this, it will be easier to classify different competitors with potentially different ways of implementing some functionality into groups or segments in the market landscape.

In order to perform it, scikit-learn library[2] has been used. The elbow method, a heuristic technique used to determine the optimal number of clusters in a dataset for clustering algorithms like k-means, initially suggested four clusters [3] (Figure 7).

[3] https://github.com/germananashkin001/TFG_TransCOR

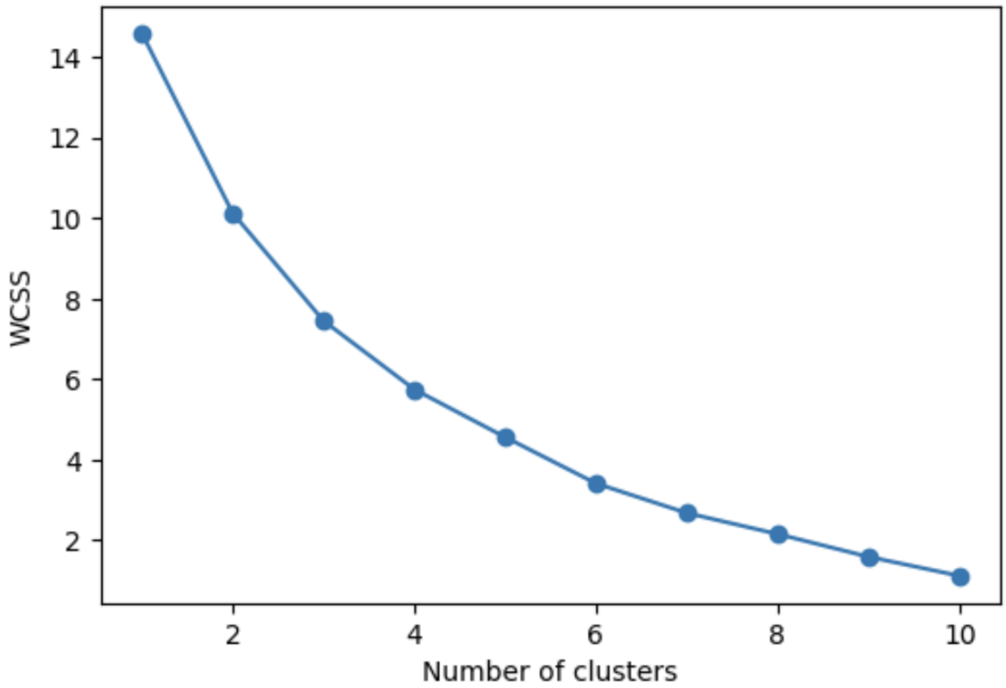

Figure 7: Results of the number of clusters within the data against the within-cluster sum of squares (WCSS).

It involves plotting the number of clusters against the within-cluster sum of squares (WCSS), which measures the compactness of the clusters. As the number of clusters increases, the WCSS typically decreases because each cluster becomes smaller and more tightly packed. However, beyond a certain point, adding more clusters does not significantly reduce the WCSS, resulting in a less pronounced decrease in the plot [3].

2.4 Quantitative prototype validation

Quantitative prototype validation in the context of TransCOR involves assessing the importance of its functionalities and specific implementations through a survey designed to gather user feedback. The survey begins with a brief introduction to TransCOR, outlining its purpose and providing context for respondents. Each functionality and its specific implementations are then presented with concise descriptions, detailing their intended use and benefits. Participants are asked to rate each functionality on a scale from 0 to 5, where higher ratings indicate greater perceived importance, meaning that if added to the current version of TransCOR, they could help to create the 'ideal product'. The created questionnaire can be found in the Additional information section.

This approach allows for a systematic evaluation of user preferences and priorities regarding TransCOR's features. By collecting quantitative data through ratings, the survey aims to identify which functionalities resonate most with users and which implementations are perceived as crucial for enhancing usability and effectiveness. Insights gathered from this validation process further inform the development and refinement of TransCOR, ensuring that future iterations align closely with user expectations and maximize utility in real-world applications.

To do so, the table functionality table of TransCOR has been updated to consider the 'ideal version' of TransCOR according to users and has been positioned again in the competitor maps after performing again the MCA approach. The idea of doing this consists of seeing how the 'ideal TransCOR' is located in the competitor map in comparison to the current version of TransCOR and thus understanding which are the most critical functionalities that are essential to implement in order to get there.

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3 Results

3.1 Initial screening

The initial feedback underscores several key insights about the TransCOR platform, emphasizing its collaborative and web-based functionalities as significant strengths. Users appreciate the platform's robust image quality and calibration features, which are noted as superior to other tools available. Suggestions for improvement include enhancing workflow efficiency by allowing the use of the same image for multiple measurements and incorporating decision support capabilities. There is a clear demand for expanding the platform's applicability across various trimesters in fetal ultrasound and adapting it for gynecology and obstetrics.

Users also highlight the platform's potential for both commercialization and research applications, while pointing out the importance of features such as automatic image annotation and validation.

Overall, the feedback that users provided regarding TransCOR is positive, and they clearly highlighted that they see potential in it to become an end product. Therefore, these results give the green light to further study the market landscape.

3.2 Qualitative prototype validation

After performing qualitative interviews with different stakeholders several results have been obtained. In order to arrange them, they have been broken down into different categories and distinguished between the backgrounds of the interviewees (experts from AI companies and clinicians). The main insights from the qualitative interviews can be found in Table 1.

Category	Insights AI companies	Insights clinicians
Product Features	• Importance of being vendor-neutral and SaaS for competitive advantage. • Shift towards interpreting the patient's condition and creating decision support systems.	• Limited automation in pediatric cardiology due to heterogeneity. Big players aren't in that market yet. • Opportunity for a tool handling heterogeneous cases through phenogrouping. Decision support.
Data Integration and Accessibility	• Challenges in accessing diverse and annotated datasets. • Emphasis on the importance of data quality control. • Universities are the main source of data. Generation of ground truth.	• Need for robust data aggregation and validated risk scores. • A desire for a user-friendly tool for easy integration, especially in smaller clinics.
Product Impact	• Certification processes (FDA, CE) can be quite complex. (business impact) • Quick and agile certification methodologies are crucial for a successful business.	• Assessment of congenital heart diseases in pediatric patients is very difficult but could also save a lot of money, a potential but very specific niche. • Improved longitudinal assessments for patient monitoring are crucial.

Table 1: Insights from qualitative interviews.

3.3 Market analysis

3.3.1 Competitor identification and functionality breakdown

The tables containing all identified competitors, along with a comparison to TransCOR, and information about functionalities and implementations, are constructed according to the methodology described in Section 2.3.2. The table with information related to high-level functionalities is presented in Table 2. Information regarding low-level functionalities is provided in Tables 6 and 7, located in the Additional information section.

Companies	DATA ACQUISITION			FEATURE EXTRACTION				INTERPRETATION			DECISION SUPPORT		MANAGEMENT FUNCTIONALITIES	OVERARCHING FUNCTIONALITIES
	Raw data acquisition	Data cleaning	Data transfer	Data display	Data processing	Feature calculation	Documentation	Feature selection	Integration with knowledge	Documentation	Integration with knowledge	Documentation	Compliance with regulations	Overreaching functionalities
Intelligent Ultrasound	0.33	0.67	0.00	0.43	0.67	1.00	0.00	0.50	0.50	0.25	0.17	0.25	0.83	0.33
US2.ai	0.17	0.67	0.50	0.43	0.67	0.83	0.33	0.00	0.25	0.50	0.50	0.25	0.67	0.67
ULTROMICS	0.17	0.67	1.00	0.29	0.67	0.83	0.33	1.00	0.75	0.25	0.67	0.25	1.00	0.33
Caption Health	0.17	1.00	0.00	0.43	1.00	0.83	0.33	0.50	0.50	0.25	0.67	0.25	0.67	0.67
HeartLab	0.17	0.50	0.50	0.43	0.50	1.00	0.00	1.00	0.50	0.25	0.50	0.00	0.67	0.67
VIZ.ai	0.17	0.67	0.50	0.71	0.67	1.00	0.00	0.50	0.75	0.25	0.83	0.25	0.67	1.00
Dyad Medical	0.17	0.50	0.50	0.43	0.50	1.00	0.33	0.50	0.50	0.50	0.17	0.25	0.67	0.33
Ligence	0.17	0.67	0.50	0.29	0.67	1.00	0.00	0.50	0.50	0.00	0.00	0.00	0.67	0.33
DiA Imaging Analysis	0.33	0.67	0.50	0.43	0.67	0.83	0.67	0.50	1.00	0.50	0.50	0.25	0.67	0.33
Ultrasight	0.33	0.83	0.00	0.14	0.83	0.33	0.33	0.50	0.00	0.00	0.00	0.00	0.67	0.33
Echo IQ	0.33	0.83	1.00	0.43	0.83	1.00	0.00	0.50	0.75	0.25	0.50	0.25	1.00	1.00
ThinkSono	0.33	1.00	0.00	0.43	1.00	0.50	0.33	1.00	0.25	0.25	0.00	0.00	0.67	1.00
VentriPoint	0.17	0.50	0.50	0.43	0.50	1.00	0.33	1.00	0.75	0.25	0.50	0.25	0.67	0.33
Caas Qarcia (Pie. Med. Imaging)	0.17	0.50	0.50	0.43	0.67	1.00	0.33	1.00	1.00	0.00	0.00	0.00	0.67	0.67
IntelliSpace (Philips)	0.67	0.50	1.00	0.86	0.67	1.00	0.33	1.00	0.75	0.25	0.00	0.00	1.00	1.00
Xcelera (Philips)	0.33	0.17	0.50	0.57	0.33	0.17	0.33	1.00	0.50	0.25	0.00	0.00	1.00	1.00
EchoPAC (GE)	0.50	0.50	1.00	0.71	0.67	1.00	0.33	1.00	0.75	0.25	0.00	0.00	1.00	1.00
Syngo Dynamics (Siemens)	0.67	0.50	1.00	0.86	0.67	1.00	0.67	1.00	0.75	0.50	0.17	0.25	1.00	0.67
Aplio a550 (Canon)	0.50	0.33	0.50	0.43	0.33	1.00	0.00	0.00	0.25	0.00	0.00	0.00	0.83	0.33
Aplio i900 (Canon)	0.50	0.33	0.50	0.43	0.33	1.00	0.00	0.00	0.25	0.00	0.00	0.00	0.83	0.33
TransCOR	**0.17**	**1.00**	**0.50**	**0.57**	**1.00**	**1.00**	**0.33**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**1.00**	**1.00**
Trice	0.33	0.67	0.50	0.57	0.83	0.33	1.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Sonio	0.50	1.00	0.50	0.57	1.00	1.00	0.67	1.00	0.00	0.00	0.00	0.00	1.00	0.67

Table 2: Competitors and their high-level functionalities with scores.

3.3.2 Multiple Correspondence Analysis

The results of the approach using MCA can be seen in Figure 8. It is seen that there two clear groups: most of the AI startups are situated in the left part of the plot whereas big players (General Electric, Philips, and Siemens) are grouped in the right part. TransCOR, along with a few other competitors, is placed between the two groups. In the Discussion section, this will be reviewed in more detail.

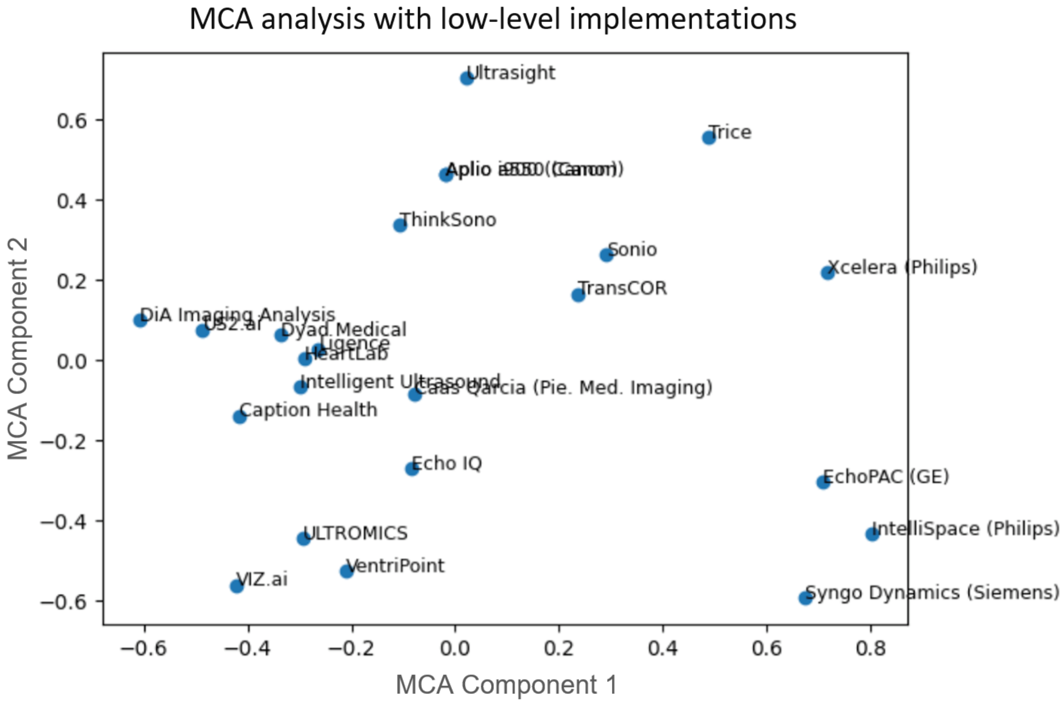


Figure 8: Multiple Correspondence Analysis (MCA) results.

3.3.3 Principal Component Analysis and k-means clustering

The outcomes of employing the PCA and k-means clustering approach are shown in Figures 9 and 10. Figure 9 illustrates two two-dimensional plots with principal components (Component 1 vs Component 2 and Component 2 vs Component 3) as axes. Figure 10 illustrates a three-dimensional representation with the first three principal components. The clusters are visually indicated within these plots, providing insights into the grouping patterns of the competitors, as well as where TransCOR is positioned among these competitors. We can see a clear discretization in the first principal component, which is driven by the 'Overarching Functionalities' high-level functionality, which has only three possible values.

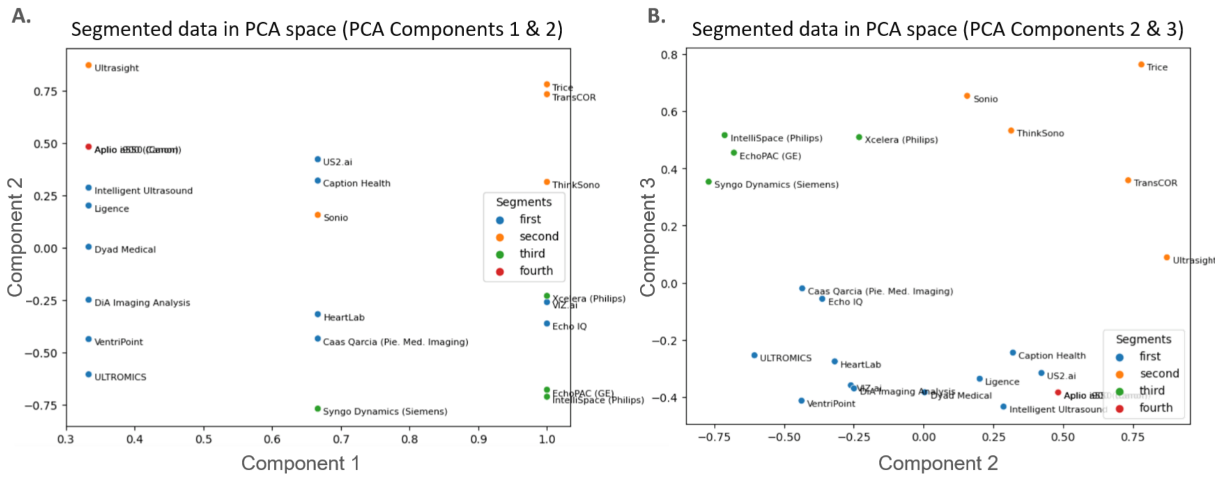


Figure 9: Projection of the segmented data in the Principal Component Analysis (PCA) space, in a 2-dimensional plot with PCA Components 1 Vs 2 (A), and Components 2 vs 3 (B).

3.3.4 Interpretability of clusters

Once competitors are clustered, it is vital to comprehend the significance of each cluster to ensure the interpretability of the results. To achieve this, the scores of functionality groups have been examined to identify commonalities among competitors within each cluster:

- **Cluster 1:** This is the cluster that contains the biggest amount of competitors. Overall, they are very strong in data processing and feature calculation and also have decent scores in integration with knowledge for interpretation and decision support.

- **Cluster 2:** This group contains products that similarly to the previous group, have high scores in data processing, feature calculation, and data cleaning. However, in this case, these products have much lower scores for functionality regarding interpretation and decision support. The current version of TransCOR is part of this group.

- **Cluster 3:** This cluster contains all the 'big players' (General Electric, Philips, Siemens). These products also excel at feature extraction, but in this case, they are also very strong at raw data acquisition, due to the fact that these products are aimed to be integrated within imaging equipment. They also have decent scores in interpretation functionalities.

- **Cluster 4:** This cluster contains only the two versions of Aplio (Canon). This product is different from the rest due to the fact that it is a scanner with some

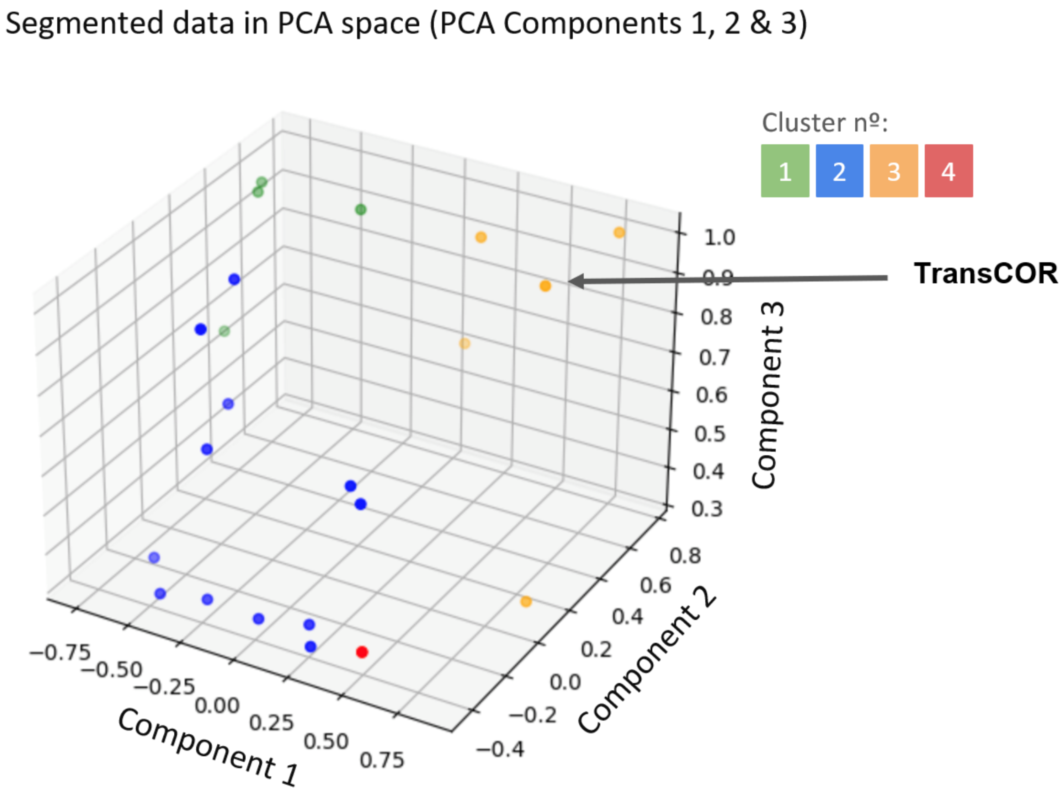


Figure 10: Projection of the segmented data in the Principal Component Analysis (PCA) space, in a 3-dimensional plot with Component 1 vs Component 2 vs Component 3.

image processing and feature extraction capabilities.

3.3.5 Quantitative prototype validation

Three responses have been obtained for the functionality assessment survey. In the following table (Table 3), the scores for each of the functionalities assessed in the survey are displayed.

Functionality	Score (Out of 5)
AI-based raw data acquisition	4.33
Compatibility with different types of data	4.67
Clinical data entry	4.33
Rule-based quality control	4.33
DL-based quality control	4.67
Data cleaning/preprocessing	4.33
Interoperability with RedCap	5.00
Interoperability with a PACS system	4.67
Manual data processing tools	5.00
Automatic/AI-enhanced data processing	4.33
Manual data entry for reporting	1.33
Pre-filled templates	5.00
Automatic reporting	5.00
Integration with clinical guidelines (interpretation)	5.00
Automatic (ML-based) exploration/interpretation	4.33
Alerts on critical findings (interpretation)	5.00
Integration with clinical guidelines (decision support)	5.00
Automatic (ML-based) decision support	4.00
Information about patient outcome	4.33
Information about required action	4.00
Alerts on critical findings (decision support)	4.67
Collaborative approach	4.67
Data filtering sorting/options	5.00

Table 3: Results of the functionality assessment survey. The list of functionalities and their given score (0-5) are displayed.

Once gathered the quantitative feedback, those functionalities/implementations that have a high rating (3 out of 5 or above) have been updated in the functionality breakdown table, and the MCA approach has been repeated. The reason for choosing this approach relies on the fact that it enables us to preserve more information than the PCA approach, which in this case is crucial as we are dealing with quite specific questions.

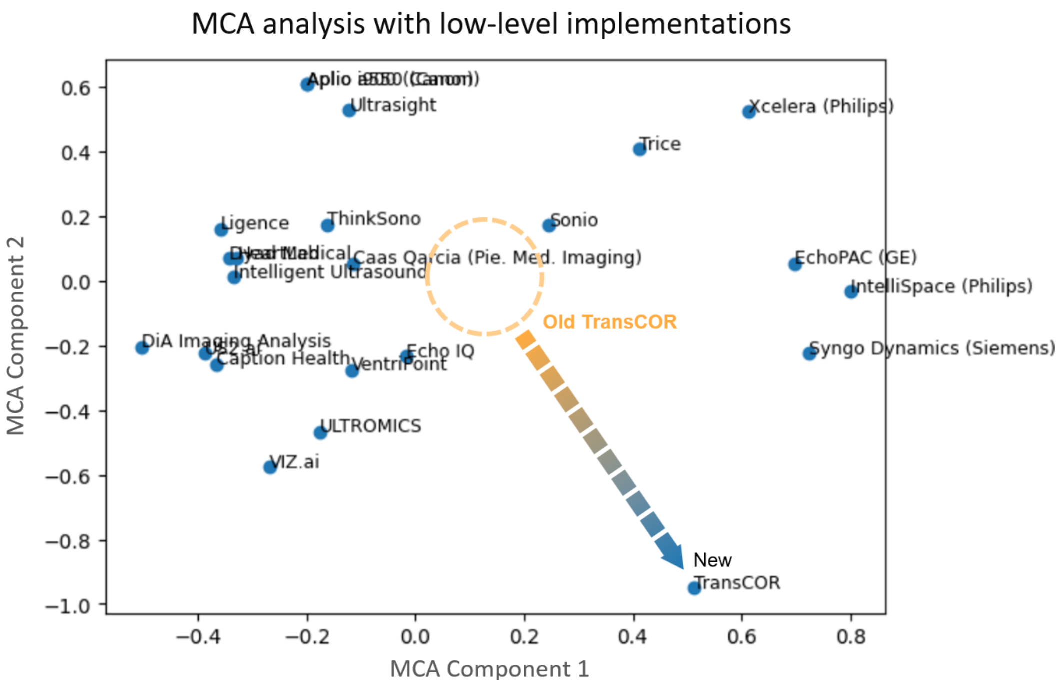


Figure 11: Multiple Correspondence Analysis (MCA) results with the 'ideal version' of TransCOR. Dashed circle and arrow display the region where the original TransCOR was located.

4 Discussion

4.1 Overview

This study employed a multi-faceted approach to evaluate the TransCOR platform and its competitive positioning within the ultrasound imaging market. The methodology comprised four main components: initial screening interviews with users, qualitative prototype validation, market analysis, and quantitative prototype validation. Each component offered unique insights, with conclusions from earlier sections guiding the direction and emphasis of later parts. This approach contributed to a thorough understanding of TransCOR's current capabilities and areas for enhancement.

The initial screening interviews with TransCOR users were conducted informally, to gauge spontaneous feedback on the platform. These interviews highlighted both the strengths and weaknesses of TransCOR, setting the stage for more structured evaluations.

After the screening, the qualitative prototype validation involved structured interviews with a diverse group of stakeholders, including clinicians and experts in the AI field. This phase focused on understanding key aspects such as customer and problem discovery, product validation, and optimization. The feedback gathered was instrumental in identifying critical areas for development, particularly in enhancing decision support functionalities.

The first step of the market analysis involved defining the problem through competitor identification and functionality breakdown. The competitor identification utilized a top-down approach to screen and refine potential competitors, focusing specifically on AI in healthcare with an emphasis on ultrasound imaging within cardiology and obstetrics/fetal medicine. A combination of manual searches and web-scraping techniques facilitated a thorough competitor analysis in which 22 competitors and TransCOR were considered. The functionality breakdown was based on the clinical decision-making process, specifically following the steps proposed in [11] (Figure 1), which include data acquisition, feature extraction, interpretation, and decision support. This framework was used to analyze how competitors' products integrate and implement various features or functionalities.

The second step involved a quantitative analysis of these competitors based on their functionalities, utilizing dimensionality reduction techniques. All detailed functionalities (low-level), categorized with binary values, were used to perform MCA. Meanwhile, high-level functionalities were averaged into broader features for PCA, as shown in Figure 2 where the values display a linear distribution between 0 and 1. Following this, the data was clustered using the k-means algorithm.

By clustering the data, we identified TransCOR's position relative to other companies and assessed its proximity to them. We also identified gaps in the plot, highlighting functionalities absent in other companies that could serve as differentiation opportunities for TransCOR. We then conducted quantitative prototype validation to envision an improved version of TransCOR and reapplied MCA.

The following subsections provide a detailed discussion of MCA, PCA, and qualitative prototype validation, each requiring careful technical examination.

4.2 Market Analysis

4.2.1 Multiple Correspondence Analysis

Regarding the MCA plot, as briefly mentioned in the Results section, it can be observed that the major industry players are clustered on the right side, indicating high values of MCA Component 1. In contrast, most AI startups are positioned on the opposite side, with lower values of this component. Notably, TransCOR is situated in the middle of the plot, along with a few other competitors. Empirical observation reveals that companies on the right side are particularly strong in image acquisition, often integrating their products directly with imaging equipment. On the other hand, most AI startups tend to focus less on data acquisition functionalities. TransCOR, however, distinguishes itself by offering advanced data acquisition features such as robust quality control and ground truth generation, providing a clear competitive advantage over many of its competitors.

Regarding the MCA component 2 axis, it can be observed that most AI startups and major industry players are clustered in the lower part of the axis, while TransCOR and a few other companies are positioned above. This distribution suggests that those in the lower part, including big players and companies like Ultromics, excel in interpretation and decision support capabilities. In contrast, TransCOR appears to be less developed in these areas. This observation aligns with feedback from the qualitative prototype validation, where several interviewees highlighted the need for TransCOR to enhance its decision support functionalities.

4.2.2 Principal Component Analysis and k-means clustering

The PCA combined with k-means clustering approach complements the insights from the MCA analysis. Cluster 1, which includes a significant number of competitors, shows a strong focus on feature extraction functionalities, along with decent capabilities in knowledge integration for interpretation and decision support. This group represents a balanced approach to both data handling and higher-level decision-making functionalities, similar to the right side of the MCA plot where major players dominate due to their strength in data acquisition and integration.

In contrast, Cluster 2, which includes the current version of TransCOR, shares high scores in data processing and feature calculation but falls short in interpretation and decision support functionalities. This is consistent with the MCA observations where TransCOR, positioned centrally, indicates robust data acquisition features yet lacks advanced interpretative capabilities. This highlights a critical area for development as noted in previous qualitative feedback. The clustering analysis reinforces this, underscoring that while TransCOR excels in data management, its competitive edge would significantly benefit from enhanced decision support functionalities.

Cluster 3, encompassing major industry players like GE, Philips, and Siemens, excels in both feature extraction and raw data acquisition, reflecting their integration with imaging equipment as observed in the MCA's right-side positioning. These companies also possess substantial interpretation capabilities, showcasing their comprehensive market approach. This places them in a dominant position, underscoring the gap that TransCOR needs to bridge to compete effectively, especially in terms of not only data acquisition functionalities but also decision support.

Lastly, Cluster 4's unique positioning, including only Canon's Aplio versions, highlights specialized products focused primarily on scanning with some image processing and feature extraction capabilities.

Overall, the alignment between the PCA clustering and MCA results illustrates TransCOR's current market positioning as strong in feature extraction but needing significant improvements in decision support and interpretative functionalities. Addressing these gaps could be very beneficial for TransCOR to enhance its competitive edge and align more closely with the comprehensive solutions offered by other competitors.

4.3 Prototype Validation

4.3.1 Qualitative prototype validation

The qualitative validation of TransCOR revealed a critical need for advanced decision support functionalities, a trend mirrored by the market where not only AI startups but also big players are starting to focus on these technologies. Another significant insight from interviews was the challenge of accessing high-quality, annotated datasets. This can be seen as a potential competitive advantage for TransCOR, as it has the capability to generate ground-truth data, which addresses this issue. Additionally, feedback emphasized the importance of expanding beyond cardiology to include applications in obstetrics and fetal medicine. This feedback has refined our market analysis and reinforced the strategic direction for the further development of the tool.

4.3.2 Quantitative prototype validation

In the quantitative prototype validation section, several key insights were gathered, providing valuable feedback on the current capabilities and future directions for TransCOR. Despite the advancements in AI-based measurement tools, it seems like users still place a very high value on manual measurement tools. This preference underscores the importance of maintaining and possibly enhancing manual functionalities alongside the development of AI-based features, ensuring the product remains versatile and user-friendly. Feedback also highlighted the potential benefits of incorporating interpretation and decision support capabilities into the product. This aligns with previous discussions and observations from the qualitative interviews and MCA analysis, which suggested that the lack of robust decision support features was a notable gap in TransCOR's offerings.

If we look at the new MCA map after updating TransCOR's functionalities based on the feedback, we can see that TransCOR has shifted down and to the right. The rightward shift on the MCA map signifies an increase in the product's data acquisition strengths, placing TransCOR closer to the major industry players who excel in integrating their solutions with imaging equipment. The downward movement on the MCA component 2 axis, underscores the continued need for development in interpretative and decision support functionalities. This positional change in the MCA map is consistent with the previously discussed interpretations of the components: the rightward position indicates strong data acquisition, while the lower position suggests a need for enhanced interpretative and decision support capabilities. Therefore, the feedback from the prototype validation and the movement in the MCA map both point to the same conclusion. From a practical point of view, a potential roadmap for getting an end product from TransCOR may be going more toward the direction of AI startups such as Ultromics, as going in the direction of the big players may be unrealistic in terms of data infrastructure

In addition, it is worth mentioning that now TransCOR is more isolated on the MCA map, distinguishing itself with a unique blend of strengths and areas for development. Its enhanced data acquisition and processing capabilities set it apart, providing several competitive advantages that it already possessed, such as robust quality control and ground truth generation. Additionally, the potential to integrate decision support features presents a new opportunity to further differentiate the product from the competition.

4.4 Limitations

One of the significant limitations encountered in this BT was the challenge of acquiring comprehensive and accurate competitor information from their websites. Often, the information available on these platforms is incomplete or lacks the necessary detail to fully understand the functionalities and capabilities of their products. This issue is particularly problematic when trying to evaluate and compare features across different competitors, as the absence of detailed information can lead to an inaccurate representation of their offerings.

Another limitation pertains to the complexity of categorizing various implementations and functionalities. Many competitors offer a wide range of features that do not fit neatly into predefined categories or levels of functionality. Additionally, there are often different levels of hierarchy within a product's capabilities that are difficult to account for in a straightforward scoring system. In this analysis, the hierarchical nature of these functionalities was oversimplified. This could potentially obscure nuances and lead to a less accurate comparative analysis of competitor strengths and weaknesses.

Then, another important limitation is the fact that in the market analysis stage, only different functionalities and implementations have been taken into account, but no other relevant information such as specifics about the competitors' products (target population, target disease) that could help to better understand the market landscape. In addition to that, performance Key Performance Indicators (KPIs) of those competitors, such as estimated revenue or employee growth have not been assessed either. By incorporating this information into the analysis, it will be easier to draft a market strategy as we will have a picture of which market trends are more successful.

Regarding the dimensionality reduction stage of this work, a key area for future development is a more detailed analysis of the clusters formed after applying the k-means algorithm. In future work, computing the loadings [4] will be essential to better understand the principal components and how the original variables contribute to them.

Finally, another important limitation is the fact that the quantitative validation approach includes only three answers to the questionnaire, which may not be enough to draw conclusive insights.

These limitations underscore the need for more detailed and structured data collection methods in future studies to ensure a more comprehensive and accurate evaluation of competitor products.

5 Conclusions and Future work

5.1 Conclusions

One of the conclusions that are worth noting is the fact that the MCA and PCA approaches complement very well each other. While the MCA approach has been used to take into consideration more information, it can also produce noisier results, possibly due to the challenge of high dimensionality [13], PCA emerged as a valuable tool, as it effectively differentiated various categories of products, offering insights that could prove instrumental in several ways complementing the ones from the qualitative prototype validation and the MCA approach.

As a more general conclusion, this BT has provided a strategic overview of TransCOR's positioning within the competitive landscape, highlighting both its strengths and areas for improvement. Despite the challenges in obtaining comprehensive competitor information and the complexities involved in categorizing product functionalities, the analysis using MCA and PCA with k-means clustering has delivered critical insights. These methodologies, paired with opinions from experts during the prototype validation phase, have clarified how TransCOR stands out in feature extraction, while also pointing to the significant potential in enhancing its interpretation and decision support capabilities.

This study has thus achieved its objective of providing a deeper understanding of the market and offering strategic insights that can guide TransCOR in refining its competitive approach and achieving sustained market success. With all this, we can draft some main points to be considered in the implementation roadmap:

- Focusing on adding interpretation and decision support capabilities for the platform, and also keeping on staying up to date in feature extraction functionalities and automated reporting.
- Related to feature extraction capabilities, do not limit the platform to cardiology but focus also on fetal and pediatric measurements, as according to user feedback, this area is much less explored.
- As pointed out in the Results section, the certification process is essential and can be difficult. Therefore, focusing on this after having validated the product is crucial.

5.2 Future work

As for future work, there are several key areas for exploration and refinement to improve the understanding and strategic approach for TransCOR. Firstly, refining the hierarchies of different functionalities will provide a more detailed and accurate assessment of competitor capabilities, enhancing our comparative analyses. Secondly, incorporating additional metrics such as performance KPIs, therapeutic area relevance, and disease-specific applications will offer deeper insights into product performance and market fit across diverse contexts. Moreover, expanding data collection efforts from quantitative prototype validation surveys will yield richer feedback on usability, performance, and feature preferences. These efforts will not only validate current findings but also inform iterative improvements to meet evolving market demands effectively.

6 Additional information

This section contains the following supporting information:

- Questions for qualitative interviews (pages 32-33).
- Table with competitors and their high- and low-level functionalities (pages 34-35).
- Questionnaire for quantitative prototype validation (pages 36-47).

Category	QUESTION
00. Customer segmentation	How long have you been practicing cardiology? In your clinical practice, do you specialize in adults, children, or others (e.g., rare diseases)? Do you just work in the public healthcare system, or do you also have private consultations?
00. Customer segmentation	Do you work with echocardiography? Do you work with other imaging modalities? How often do you use echocardiography in your daily practice? Are you frontline and therefore do more echocardiography, or are you more specialized in another imaging modality, and do you receive referred patients?
1.1. Problem discovery	Do you see many patients? How much time do you have per patient on average?
00. Customer segmentation	If you use echocardiography, who does the imaging study?
1.1. Problem discovery	What is the process from when you do the study until you issue a diagnosis?
1.1. Problem discovery	Do you obtain the measurements extracted from the image automatically, or do you have to calculate them manually?
1.1. Problem discovery	If manual: What difficulties do you encounter when performing clinical measurements on echocardiographic images?
1.1. Problem discovery	Is there a critical factor, what you always measure first, to diagnose? Do you measure it, or do you know it only by visual inspection? What is the average time until a diagnosis is issued, and the minimum/maximum?
1.1. Problem discovery	How long does it usually take to get accurate measurements from an echocardiogram? Is it a laborious process? What are the most laborious / cumbersome measurements to obtain? Why?
1.1. Problem discovery	What are the biggest challenges you face when interpreting echocardiograms to diagnose cardiac pathologies?
1.2. Problem validation	Are the measurements about the study made at the moment, or in the tranquility after the consultation? Do you use all the information generated only for clinical purposes, or do you also participate in research studies?
1.1. Problem discovery	Is precision important in the annotation of clinical parameters, or is there usually a lot of inter-subject variability? From what moment does variability represent a problem for you in terms of standardizing subsequent diagnosis?
1.1. Problem discovery	Do you know if the image is good at the moment or do you realize later and have to repeat the test? Of every 100 images, how many do you discard? And would knowing the value of the clinical measurement in real time add value to you?
1.1. Problem discovery	What happens if the echocardiography image is suboptimal, do you discard it, or use it?
1.1. Problem discovery	To monitor patients, do you need to compare measurements from different time points? How are images of the same patient stored and retrieved in your current practice?
1.1. Problem discovery	Do you need to share information with other doctors from another service, or even connect with cardiologists from other institutions in any case? If yes, how do you do it?
1.2. Problem validation	What tools or software do you currently have to perform clinical measurements in echocardiography (manual or automatic), do you use it?If not, why? If yes, what does it give you?
1.2. Problem validation	What aspects do you consider most important when evaluating or choosing a platform/software to assist in the extraction of clinical measurements in echocardiographic images?
1.2. Problem validation	What specific functionalities would you like to see in a platform/software to facilitate the extraction of clinical measures?
1.2. Problem validation	How do you imagine a clinical measurement extraction tool integrated into your daily workflow would impact your practice?
1.2. Problem validation	What features should this platform have to make it intuitive and easy to use in your daily life?
1.2. Problem validation	Do you think that the implementation of a clinical measurement extraction tool would improve the accuracy of your diagnoses?
1.2. Problem validation	How do you think this tool could influence the quality of care you provide to your patients? What do you value most? Speedup of the consultation, time until you issue the diagnosis?
2.1. Product discovery	Present the TransCOR solution – product value proposition – what aspect of the value proposition are you most excited about?
2.2. Product validation	Does the product that we have presented to you seem relevant to you or not?
2.3. Product optimization	What would you add, what would you change?
04. Ending interviews	Is there anything that you think I have left out and you want to tell me because it may be relevant?
04. Ending interviews	Do you have any contact or know someone I could talk to to get more points of view?
04. Ending interviews	What would be the prioritization of features, from most important to least?

Table 4: Qualitative questionnaire for clinicians.

CATEGORY	QUESTION
00. Customer segmentation	What is your role, responsibility, and functions performed within the company?
00. Customer segmentation	How long have you been working in MedTech, software or pharmaceutical companies?
00. Customer segmentation	Do you work with medical imaging? And specifically cardiovascular image? How far do you know the problem?
00. Customer segmentation	What specific tasks do you perform in relation to the development of AI models for the diagnosis of cardiac pathologies?
1.1. Problem discovery	What are the biggest challenges you encounter when working with data sets to train cardiac diagnostic models?
1.1. Problem discovery	Where do you get the image databases, how do you annotate them (who annotates?)? Or do you have previously annotated datasets?
1.1. Problem discovery	What is the size of your databases? Have you ever bought? At what price?
1.1. Problem discovery	Training the models (in which populations, with which scanners?)
1.1. Problem discovery	What are the main difficulties in accessing adequate and annotated data sets for diagnosis?
1.1. Problem discovery	What percentage of your time do you spend finding and validating data for training compared to the time spent developing the AI model itself?
1.1. Problem discovery	Do you implement an evaluation of the quality of the images that you use to train cardiac diagnosis models?
1.1. Problem discovery	What are the main problems you encounter regarding the quality and validity of annotations available in image databases?
1.1. Problem discovery	What do you like least about your current dataset? And what else? What flaws do you see and what things work well?
1.1. Problem discovery	Do you think that the quality of the images and their annotations has an impact on the accuracy and credibility of your models?
1.1. Problem discovery	What programming language do you use? What libraries? Where do you deploy your services? Do you develop your own models, or do you use known models/architectures and limit yourself to re-training (fine-tuning) and adapting with your data?
1.1. Problem discovery	How do you certify products? What classification of medical device?
1.2. Problem validation	How do you think a large-scale database with cardiologist-validated annotations would facilitate or improve your process of developing diagnostic AI models?
1.2. Problem validation	What aspects do you consider most important when evaluating the usefulness of a data set for model training?
1.2. Problem validation	Sample size (sex, age, ethnicity, ...), different teams represented in the database, different populations, different clinical care contexts
1.2. Problem validation	How much do you think having an optimized and validated database would impact the efficiency and accuracy of your cardiac diagnostic models?
1.2. Problem validation	What features should a database (images + annotations) have so that it integrates easily into your workflow?
2.1. Product discovery	Introduce the TransCOR solution – mainly image classification, quality control and annotation functionality
2.2. Product validation	Does the product that we have presented to you seem relevant to you or not?
2.3. Product optimization	What would you add, what would you change?
04. Ending interviews	Is there anything that you think I have left out and you want to tell me because it may be relevant?

Table 5: Qualitative questionnaire for AI-experts.

Functionalities / Companies	DATA ACQUISITION													
	Raw data acquisition						Data cleaning						Data transfer	
	Automation			Data in scope			Quality control			Collaborative approach	Automation		Pathway through RedCap	Access to a PACS server
	Manual	AI-enhanced	Real-time	Imaging (US, CT, MRI)	eCRF form	Clinical data	Rule-based	Binary (yes/no)	DL-based	Multiple users	Manual	AI-enhanced	-	-
Intelligent Ultrasound	0	0	1	1	0	0	1	0	1	0	1	1	0	0
US2.ai	0	0	0	1	0	0	0	0	1	1	1	1	0	1
ULTROMICS	0	0	0	1	0	0	0	1	1	0	1	1	1	1
Caption Health	0	0	0	1	0	0	1	1	1	1	1	1	0	0
HeartLab	0	0	0	1	0	0	1	0	1	1	0	0	0	1
VIZ.ai	0	0	0	1	0	0	0	0	1	1	1	1	0	1
Dyad Medical	0	0	0	1	0	0	1	0	0	0	1	1	0	1
Ligence	0	0	0	1	0	0	1	0	1	0	1	1	0	1
DiA Imaging Analysis	0	0	1	1	0	0	1	1	1	0	0	1	0	1
Ultrasight	0	0	1	1	0	0	1	1	0	1	1	1	0	0
Echo IQ	0	0	1	1	0	0	1	0	1	1	1	1	1	1
ThinkSono	0	0	1	1	0	0	1	1	1	1	1	1	0	0
VentriPoint	0	0	0	1	0	0	0	0	1	0	1	1	0	1
Caas Qarcia (Pie. Med. Imaging)	0	0	0	1	0	0	0	1	1	0	1	0	0	1
IntelliSpace (Philips)	0	1	0	1	1	1	0	0	0	1	1	1	1	1
Xcelera (Philips)	0	0	0	1	0	1	0	0	0	1	0	0	1	0
EchoPAC (GE)	0	0	0	1	1	1	0	0	0	1	1	1	1	1
Syngo Dynamics (Siemens)	0	1	0	1	1	1	0	1	0	0	1	1	1	1
Aplio a550 (Canon)	1	0	1	1	0	0	1	0	0	0	0	1	0	1
Aplio i900 (Canon)	1	0	1	1	0	0	1	0	0	0	0	1	0	1
TransCOR	**0**	**0**	**0**	**1**	**0**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**
Trice	0	0	0	1	1	0	0	1	0	1	1	1	0	1
Sonio	0	0	1	1	1	0	1	1	1	1	1	1	0	1

Functionalities / Companies	FEATURE EXTRACTION																						
	Data display							Data processing						Feature calculation						Documentation		
	Data in scope			Comments		View		Quality control			Collaborative approach	Automation		Functional measurements	Anatomical measurements	Segmentation	Delineation		Data in scope	Reporting		
	Imaging (US, CT, MRI)	eCRF form	Clinical data	Comment box	Messaging	Anatomical alignment	Signal alignment	Rule-based	Binary (yes/no)	DL-based	Multiple users	Manual	AI-enhanced	Automation (manual/AI-enhanced)	Automation (manual/AI-enhanced)	Automation (manual/AI-enhanced)	Data in scope (Doppler, M-mode)	Automation (manual/AI-enhanced)	Imaging (US, MRI, CT)	Manual data entry	Templates	Automatically generated reports
Intelligent Ultrasound	1	0	0	0	0	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0
US2.ai	1	0	0	0	0	1	1	0	0	1	1	1	1	1	1	0	1	1	1	0	0	1
ULTROMICS	1	0	0	1	0	0	0	0	1	1	0	1	1	1	0	1	1	1	1	0	1	0
Caption Health	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0
HeartLab	1	0	0	0	0	1	1	1	0	1	1	0	0	1	1	1	1	1	1	0	0	0
VIZ.ai	1	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0
Dyad Medical	1	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1
Ligence	1	0	0	0	0	1	0	1	0	1	0	1	1	1	1	1	1	1	1	0	0	0
DiA Imaging Analysis	1	0	0	0	0	1	1	1	1	1	0	0	1	1	0	1	1	1	1	0	1	1
Ultrasight	1	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	1	0	1	0	1	0
Echo IQ	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0
ThinkSono	1	0	0	1	0	1	0	1	1	1	1	1	1	0	0	0	1	1	1	0	1	0
VentriPoint	1	0	0	0	0	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	0
Caas Qarcia (Pie. Med. Imaging)	1	0	0	0	0	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0
IntelliSpace (Philips)	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0
Xcelera (Philips)	1	0	1	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0
EchoPAC (GE)	1	1	1	0	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0
Syngo Dynamics (Siemens)	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0
Aplio a550 (Canon)	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0
Aplio i900 (Canon)	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0
TransCOR	**1**	**0**	**0**	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**	**1**
Trice	1	1	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	0	0	1	1	1
Sonio	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1

Table 6: Table showing the assessed companies and the high- and low-level functionalities from the processing topics of: data acquisition and feature extraction.

Functionalities / Companies	INTERPRETATION										DECISION SUPPORT										MANAGEMENT FUNCTIONALITIES						OVERARCHING FUNCTIONALITIES		
	Feature selection		Integration with knowledge				Documentation				Integration with knowledge						Documentation				-						-		
	Automation		Guidelines	Calculation			Reporting				Guidelines	Calculation			Type of decision		Reporting				Compliance with regulations						Collaborative approach	Customizable dashboards	Filtering/sorting options
	Manual feature selection	Automatic feature selection (dim. red. techniques, MKL)	-	Manual calculator	Automatic calculator	ML model	Manual data entry	Templates	Automatically generated reports	Alerts on critical findings	-	Manual calculator	Automatic calculator	ML model	Patient outcome	Action required	Manual data entry	Templates	Automatically generated reports	Alerts on critical finding	Informed consent management	DMP implementation	Audit trails	User activity tracking	Role-based permissions	Data pseudo anonymization and encryption	Collaborative approach	Customizable dashboards	Filtering/sorting options
Intelligent Ultrasound	0	1	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1	1	1	0	1	1	0	0	1
US2.ai	0	0	0	0	1	0	0	1	1	0	0	0	1	0	1	1	0	0	1	0	1	1	1	0	0	1	1	0	1
ULTROMICS	1	1	1	0	1	1	0	0	0	1	1	0	1	0	1	1	0	0	0	1	1	1	1	1	1	1	0	0	1
Caption Health	0	1	1	0	1	0	0	0	0	1	1	0	1	0	1	1	0	0	0	1	1	1	1	0	0	1	1	0	1
HeartLab	1	1	1	0	1	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	1	1	1	0	0	1	1	0	1
VIZ.ai	0	1	1	0	1	1	0	0	0	1	1	0	1	1	1	1	0	0	0	1	1	1	1	0	0	1	1	1	1
Dyad Medical	0	1	1	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	1	0	1	1	1	0	0	1	0	0	1
Ligence	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	0	1
DiA Imaging Analysis	0	1	1	1	1	1	0	1	1	0	0	0	1	0	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1
Ultrasight	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	0	0
Echo IQ	0	1	1	1	1	0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1
ThinkSono	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1
VentriPoint	1	1	1	0	1	1	1	0	0	0	1	1	0	1	0	0	0	1	0	0	1	1	1	0	0	1	0	0	1
Caas Qarcia (Pie. Med. Imaging)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	0	1	1
IntelliSpace (Philips)	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Xcelera (Philips)	1	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
EchoPAC (GE)	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Syngo Dynamics (Siemens)	1	1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1
Aplio a550 (Canon)	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	0	1	0
Aplio i900 (Canon)	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	0	1	0
TransCOR	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Trice	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
Sonio	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0

Table 7: Table showing the assessed companies and the high- and low-level functionalities from the processing topics of: interpretation, decision support, management functionalities, and overarching functionalities.

TransCOR functionality assessment

Welcome to the TransCOR functionality assessment survey!

TransCOR is a web-based software platform developed at PhySense (UPF), whose current status is as a research tool used in different collaborative research projects where ultrasonography image management and analysis are required. This tool utilizes a cloud-based architecture, ensuring consistent data management and sharing among healthcare professionals. Its user-friendly interface caters to the needs of multiple stakeholders, including
both data scientists and clinicians. It has features such as manual labelling and image quality
evaluation, paired with automated image analysis, which can help users generate detailed and
accurate reports, facilitating the diagnosis of different clinical conditions.

The idea of this survey is to assess the potential functionalities that could be added to the current version of the TransCOR platform in order to make it more attractive as an end product. These
functionalities were derived from the multiple steps of clinical decision-making which ranges from the acquisition of high-quality data ("Data Acquisition"), to the extraction of features from the obtained data ("Feature Extraction"), to then aggregate these features to interpret the state of the patient ("Interpretation"), to ultimately be able to take a decision on this patient ("Decision Support"). (see image 1)
These steps can be broken down into more refined functionalities that could be implemented in
a potential product. This functionality breakdown is the stepping stone for the list of the different functionalities/implementations asked in this survey. (see image 2)

Additionally, management functionalities (compliance with regulations) and other overarching
functionalities that don't fall under any specific step are also part of this breakdown.
Based on that, a list of **different functionalities** with a brief description will be provided. Reflect on
whether each functionality would enhance your experience, improve efficiency, or meet a critical
need. Based on that, **rate** the importance of each functionality on a scale from 0 to 5 following
these criteria:

- 0: Not important at all or I don't know what it is.
- 1: Very low importance.
- 2: Low importance.
- 3: Moderate importance.
- 4: High importance.
- 5: Essential.

* Indicates required question

1. Email *

Image 1. Steps in clinical decision making.

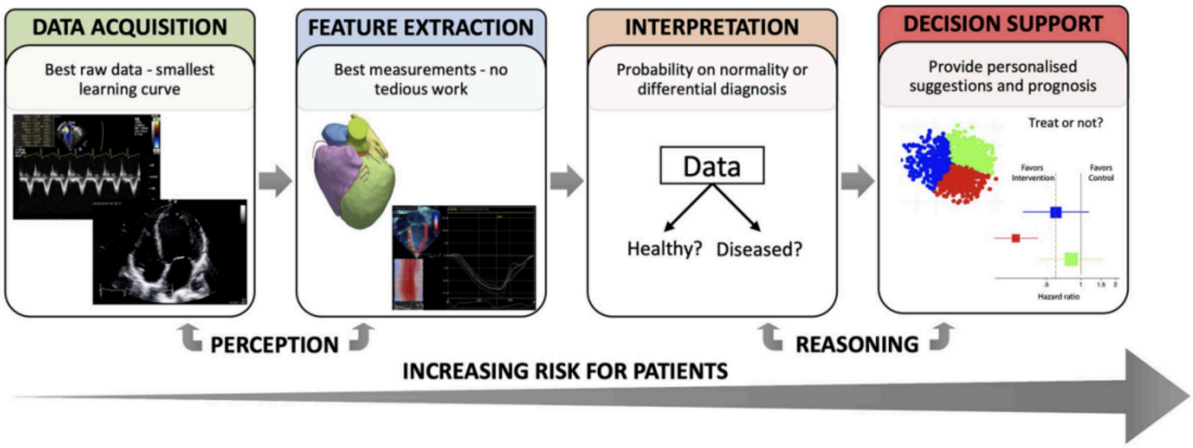
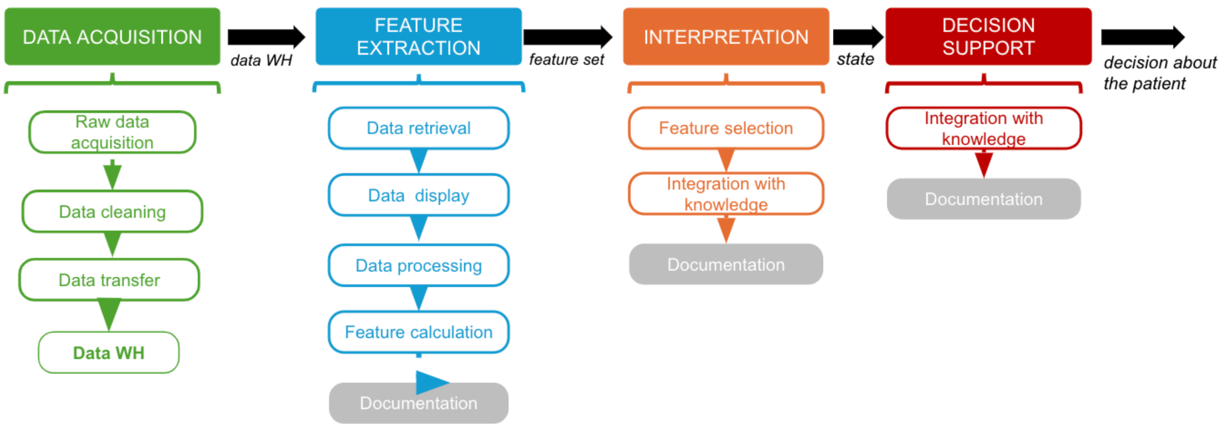


Image 2. Detailed view of steps in clinical decision making.



Data acquisition

This step goes from extracting raw data, cleaning and structuring such data, to then store it in a data warehouse (WH).

2. **AI-based raw data acquisition:** this feature would enhance the acquisition of high-quality medical images by guiding users to capture standard planes critical for accurate diagnosis, ensuring consistency and reducing human error. Could also include real-time image acquisition for subsequent analysis. *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

3. **Compatibility with types of data:** this feature consists of the type of data that is being used. For example, a potential platform could not be limited to imaging but also include signal data (e.g. ECG) or clinical data (e.g. laboratory tests). *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

4. **Clinical data entry:** functionality consisting on an eCRF form to enable the user to collect and manage clinical data directly in the platform. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

5. **Rule-based quality control:** a user fills out a form evaluating different parameters of the data (e.g., contrast, gain, anatomical alignment, etc.). This functionality ensures that next steps of the decision-making process only use high-quality data. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

6. **DL-based quality control:** this feature would speed up/automate the quality assessment of an image through the use of a DL model trained to automatically evaluate the quality of the data. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

7. **Data cleaning/preprocessing:** this feature would aim to enhance the quality of the dataset based on the results of the quality control. That could be removing low-quality data/duplicates or correcting data (noise reduction, binarization, etc). *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

8. **Interoperability with RedCap:** refers to the process of connecting and synchronizing a database coming from RedCap (Research Electronic Data Capture) system. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

9. **Interoperability with a PACS system:** refers to the ability to connect to a PACS, which is a medical imaging technology used for storing, retrieving, managing, and sharing medical images within healthcare environments. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

Feature extraction

The output of this step consists in getting a set of features from the data.

10. **Manual data processing tools:** would include manual options for analyzing/measuring data. For example, the ability to make anatomical measurements through a caliper tool, or the ability to segment different structures or Doppler tracings. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

11. **Automatic/AI-enhanced data processing:** in this case, the manual tasks performed in the previous point (manual measurements or delineations) would be performed automatically, which would potentially save a lot of time for the users. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

12. **Manual data entry for reporting:** most basic reporting functionality. The user would have to manually enter the data based on the obtained measurements/features. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

13. *

Pre-filled templates: here, some of the fields would be already filled in or would be offering drop-down options, potentially saving a lot of time and avoiding human errors during data entry.

Mark only one oval.

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◯	◯	◯	◯	◯	◯

14. *

Automatic reporting: here, reports would be generated automatically (e.g. AI-based) after performing a certain analysis, reducing the time, and potentially human error, even more.

Mark only one oval.

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◯	◯	◯	◯	◯	◯

Interpretation

This step involves determining the state of the patient based on a set of features.

15. *

Integration with clinical guidelines: this functionality consists of integrating risk calculators or decision-tree based diagnostic schemes, which allow interpreting the state of the patient based on the expert consensus gathered in clinical guidelines.

Mark only one oval.

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◯	◯	◯	◯	◯	◯

16. **Automatic (ML-based) exploration/interpretation:** the patient's state would be determined automatically using a ML model trained on a comparable population. This feature would be more exploratory (e.g., comparing a new patient to a previously known population), and could not set the basis for a diagnosis, unless properly certified. *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

17. **Alerts on critical findings:** notification in case of abnormal patient state for taking further actions. *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

Decision support

This step involves assisting the clinician in making a decision.

18. **Integration with clinical guidelines:** this functionality consists of integrating risk calculators or decision-tree based diagnostic schemes, which allow making a decision based on the expert consensus gathered in clinical guidelines. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

19. **Automatic (ML-based) decision support:** the decision would be taken automatically using a ML model trained on a comparable population. This feature would be more exploratory (e.g., comparing a new patient to a previously known population), and could not set the basis for a prognosis or action to take, unless properly certified. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

20. **Information about patient outcome:** this feature would enable the prediction of the future (prognosis) of the patient. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

21. **Information about required action:** in addition to what has been mentioned in the previous functionality, a suggestion on the next steps (e.g. treatment, drug to use, etc) is provided. *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

22. **Alerts on critical findings:** notification in adverse outcomes (e.g. bad prognosis, urgent action) is provided. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

Overarching functionalities

Other functionalities that don't fall under any specific steps but improve the overall product.

23. **Collaborative approach:** functionality or set of functionalities that enable collaboration between multiple users. For example, including the option of sending messages, commenting on specific parts of the data, tagging users, or implementing different roles depending on the type of user, etc. *

Mark only one oval.

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◯	◯	◯	◯	◯	◯

24. **Data filtering sorting/options:** options to refine and organize data by the user to better analyze and visualize the information according to specific criteria. *

Mark only one oval.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

25. Is there any other important functionality that hasn’t been mentioned in this survey?

Survey finished

Thank you very much for your time and help!

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