

Using Visual Patient Heart to improve anaesthesia professionals' ECG Interpretation and Arrhythmia Situation Awareness: A Quantitative Study

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Abstract

Background

The Visual Patient concept is a patient monitoring technology that transforms numerical and waveform data into an intuitive, avatar-based representation of the patient's condition. Previous studies have shown that it enhances care providers' situation awareness compared to conventional monitoring alone. Rapid recognition and response to cardiac pathologies are essential in acute care settings. Visual Patient Heart (VPH) expands this concept by integrating an established algorithm-based rhythm and ischemia analysis into a novel visual model for cardiac monitoring.

Methods

In this computer-based study, 75 anaesthesia care providers from four academic university hospitals in Central Europe assessed randomised sequences of standardised 12-lead ECG displays and corresponding VPH visualisations. Each sequence was presented for six seconds, reflecting the average glance duration observed in perioperative settings and simulating real-time constraints in clinical decision-making. The VPH representations were based on detections made by the Philips "*ST/AR algorithm*", an automated system for arrhythmia and ST-segment analysis. Quantitative outcomes included diagnostic correctness, self-rated decision confidence and perceived workload, measured using a modified NASA Task Load Index (NASA-TLX) questionnaire.

Results

VPH significantly improved diagnostic correctness compared to conventional 12-lead ECG interpretation (78% vs. 42%, $p < 0.001$), with an odds ratio of 6.06 (95% confidence interval, 4.79–7.66) from the mixed logistic model. It also increased decision confidence and reduced perceived workload (both $p < 0.001$).

Conclusion

This study demonstrates that the VPH concept may enhance healthcare providers' ability to recognise cardiac pathologies with greater confidence and lower cognitive burden. The findings support the potential of avatar-based visualisation as a complementary tool in patient monitoring.

Introduction

Background

Advancements in medical technology have significantly improved patient care, particularly in perioperative [1] and critical care environments [2]. Modern patient monitoring systems provide

continuous streams of physiological data, offering clinicians dynamic insights into a patient's condition. However, as the volume of available information increases, so does the cognitive burden on healthcare providers, making it more challenging to quickly extract and interpret meaningful insights [3, 4]. This cognitive overload can impair situation awareness, a critical factor in clinical decision-making, as it is linked to up to 80% of treatment errors in anaesthesia and intensive care [5]. Traditional monitoring systems present vital signs as separate numerical values or waveforms in a single-sensor, single-indicator format, requiring clinicians to process multiple parameters simultaneously and synthesise complex information mentally [6]. Research in human factors suggests that visual elements such as colours, shapes and motion are processed more efficiently than numbers or text [7, 8]. Situation awareness-oriented designs provide integrated visualisations that consolidate multiple parameters into a single, intuitive display, thereby reducing cognitive load and improving decision-making efficiency. One example of such innovation is the Visual Patient concept, developed at the University Hospital Zurich, Switzerland, and now commercially available as the Philips Visual Patient Avatar product. This technology translates vital signs into an intuitive, dynamic, animated avatar that reflects real-time physiological changes [9]. The technology was found to enable clinicians to perceive significantly more vital signs at a glance, increasing diagnostic confidence and reducing workload, and has been evaluated in a variety of situations, for example, under distraction [10], with peripheral vision [11], in high-fidelity simulation [12], and real-life use [13–15].

Cardiac events, including arrhythmias and ST-segment deviations, pose a particular challenge in anaesthesiology and critical care, as they require rapid recognition and intervention to prevent deterioration [16, 17]. While interpreting a standard 12-lead ECG remains a fundamental clinical skill, it can be cognitively demanding and time-consuming, particularly in high-pressure settings where clinicians must manage multiple critically ill patients, such as in emergency rooms, intensive care units, or postoperative care units [18, 19]. For instance, perioperative atrial fibrillation is a common perioperative complication, with incidence rates reported to vary widely in the literature, from approximately 0.4% to as high as 20–40% [20, 21]. The highest rates are observed following cardiac and oesophageal procedures, underscoring the need for heightened awareness and improved detection of rhythm disturbances in the perioperative setting [22]. The Philips “*ST/AR (ST and Arrhythmia) algorithm*” supports cardiac assessment by automatically analysing multi-lead ECG signals to detect arrhythmias and ischemic changes [23, 24]. It is widely integrated into Philips monitoring systems and is the basis for many clinical alarms. This study extends the Visual Patient concept by integrating “*ST/AR*”-detected cardiac pathologies into a newly developed avatar-based visualisation system called Visual Patient Heart (VPH). This model uses intuitive graphical cues in an animated heart icon to represent real-time cardiac rhythms and ischemic changes.

Objectives

This study aims to evaluate the impact of Visual Patient Heart on anaesthesia providers' ability to accurately identify cardiac pathologies, as detected by the Philips “*ST/AR algorithm*”, compared to

conventional 12-lead ECG interpretation. In addition to diagnostic accuracy, we assessed participants' self-reported decision confidence and perceived workload using the NASA Task Load Index (NASA-TLX) questionnaire.

Methods

Ethics

This study was conducted in compliance with the Helsinki Declaration for medical research involving human participants. We obtained written informed consent from all participants, ensuring the confidentiality of the data. The study received a declaration of non-jurisdiction from the Cantonal Ethics Commission of Zurich, Switzerland (BASEC-Nr. : Req-2024-00353), and obtained positive ethical approval from all additional participating sites in Germany (Munich: 2024-383-S-CB, Bonn: AZ 2024-209-BO, Frankfurt: #2024 – 1760).

Study Design

This multi-method, comparative study evaluated anaesthesia providers' diagnostic accuracy, confidence, and perceived workload when exposed to simulated cardiac scenarios using two different display modalities: the novel VPH system and conventional 12-lead ECG displays. Before testing, all participants attended a standardised educational session, either individually or in groups of two participants. These sessions included a 9-minute training video explaining the purpose and design of the VPH technology. Participants were also familiarised with the layout of the conventional ECG simulation display. We provide the training video on VPH and an overview of the 12-lead ECG scenarios (Fig. 1, **Supplementary Figures S1-4, Supplementary Material 1**). Participants completed a demographic questionnaire and reported their prior experience and confidence with ECG interpretation. Participants were allowed to ask questions to ensure a full understanding of the study procedures. The order of scenarios and the corresponding modalities (VPH or conventional ECG) were fully randomized using computer-generated random assignment. Participants were unaware that they saw each cardiac state twice, which helped minimise potential learning or order effects. After each scenario, participants were asked to identify the ECG diagnosis, rate their diagnostic confidence, and perceived workload using the NASA Task Load Index (NASA-TLX) [25]. The items assessing ECG diagnosis and diagnostic confidence were specifically developed for this study, whereas perceived workload was assessed using the previously published and validated NASA-TLX questionnaire.

Data Collection

Participants were randomly assigned to one of two groups (Group A or Group B, **Supplementary Figure S5**). The 22 cardiac states were distributed between the groups so that each participant viewed 10 or 11 distinct cardiac conditions, each presented twice (once in each modality). One additional visualisation –

representing an ambiguous “*unknown*” state (e.g., due to lead disconnection) – was shown to both groups using VPH only. Scenario allocation is illustrated in **Supplementary Figure S5**. All study data were collected digitally on an iPad using the iSurvey application (Harvest Your Data, Wellington, New Zealand). Each video simulation was displayed for 6 seconds following a countdown and was viewed on a MacBook Air (2020, M1 chip). A 6-second display period was chosen based on average glance durations in perioperative settings, reflecting real-time constraints in clinical decision-making. All videos were rendered in 1080p resolution and created using Final Cut Pro X (Apple Inc.). After each simulation, participants were given unlimited time to complete the questionnaire.

Study Centres

This study was conducted at four academic medical centres: the University Hospital Zurich (USZ), Switzerland, the University Hospital Bonn (UKB), Germany, the University Hospital Frankfurt am Main (UKF), Germany, and the TUM University Hospital in Munich, Germany.

Study participants

A total of 75 anaesthesia care providers were enrolled, representing a range of clinical roles and levels of experience. Eligible participants included resident anaesthesiologists, staff anaesthesiologists, and nurse anaesthetists (one student nurse anaesthetist). They all had routine exposure to patient monitoring and spent a substantial portion of their working hours in the operating theatre. Participation was voluntary and uncompensated. All participants received written information about the study and provided informed consent before enrolment. Detailed participant demographics and experience levels are presented in Table 1 and visualised in **Supplementary Figure S6**.

Table 1

The study and participant characteristics in detail. USZ (University Hospital of Zurich), UKF (University Hospital of Frankfurt am Main), TUM (Technical University Hospital of Munich), UKB (University Hospital of Bonn). Group A and B represent the randomisation groups for modalities and scenarios.

	Group A (n = 38)	Group B (n = 37)	Overall (n = 75)
Clinic			
USZ	11 (28.9%)	10 (27%)	21 (28%)
UKF	9 (23.7%)	10 (27%)	19 (25.3%)
TUM	10 (26.3%)	9 (24.3%)	19 (25.3%)
UKB	8 (21.1%)	8 (21.6%)	16 (21.3%)
Age			
Mean (SD)	35.6 (9.68)	33.5 (6.90)	34.5 (8.43)
Median [Min, Max]	33 [22, 60]	33 [22, 60]	33 [22, 60]
Gender			
Male	15 (39.5%)	18 (48.6%)	33 (44%)
Female	23 (60.5%)	19 (51.4%)	42 (56%)
Job			
Nurse (training)	-	1 (2.7%)	1 (1.3%)
Nurse	13 (34.2%)	8 (21.6%)	21 (28%)
Resident	17 (44.7%)	22 (59.5%)	39 (52%)
Specialist	8 (21.1%)	6 (16.2%)	14 (18.7%)
Experience (yrs.)			
Mean (SD)	9.05 (9.96)	6.62 (6.34)	7.85 (8.41)
Median [Min, Max]	5.5 [0, 38]	5 [0, 28]	5 [0, 38]
ECG / week			
Mean (SD)	23.2 (50.5)	23.8 (25.4)	23.5 (39.9)
Median [Min, Max]	10 [0, 300]	10 [0, 80]	10 [0, 300]
Skill			
Mean (SD)	46.8 (26.4)	52 (20.7)	49.7 (23.8)
Median [Min, Max]	51.5 [0, 85]	51 [30, 90]	51 [0, 90]

Statistical Analysis

Based on a power calculation using McNemar's test for paired data, a sample size of 49 participants was determined to be sufficient to detect a meaningful difference in diagnostic accuracy with 90% power at a significance level of $\alpha = 0.05$. Descriptive statistics are presented as means, standard deviations (SD), medians, interquartile ranges for continuous variables (IQR), and counts and percentages for categorical data. The number of correctly identified cardiac conditions was analysed overall and per pathology as the primary outcome. Paired binary outcomes between modalities were compared using McNemar's test. We applied a mixed-effects logistic regression model with a random intercept for each participant to account for within-subject variation. This model was adjusted for the presentation order of modalities and for participants' self-reported experience with ECG interpretation, quantified as the number of standard ECGs interpreted per week. Secondary outcomes—decision confidence and NASA-TLX scores—were analysed using linear mixed-effects models, including a random intercept for each participant and adjusting for modality order and weekly ECG exposure. To further explore the NASA-TLX subcategories, we employed a Wilcoxon signed-rank test with Bonferroni correction. With five tests, the adjusted significance level was set at 0.01. Statistical analyses were conducted using R version 4.4.2 (R Foundation for Statistical Computing, Vienna, Austria), and figures were created using MATLAB R2023a, Update 8 (MathWorks, Natick, MA, USA).

Standardised 12-lead ECG displays

We created custom digital 12-lead ECG displays to resemble standard patient monitors' layout and visual style. These artefact-free simulations were based on real-life ECGs retrieved from publicly available teaching cases from ECG Wave-Maven (Beth Israel Deaconess Medical Centre and Harvard Medical School) [26]. Each display was a dynamic animation simulating real-time monitoring in an operating room or intensive care unit. This approach was chosen to approximate the conditions under which providers would encounter such data in clinical practice. Displays were designed using Procreate (Savage Interactive, Hobart, Tasmania, Australia), and a complete overview of the ECG scenarios is provided in **Supplementary Figures S1-4**.

Philips "ST/AR Algorithm" for Cardiac Monitoring

The Philips "*ST/AR (ST and Arrhythmia) algorithm*" is an established technology integrated into Philips patient monitoring systems and has been clinically used for decades. It operates independently of the VPH tool and is the real-time basis for routine arrhythmia and ST-segment monitoring alarms. This algorithm continuously analyses ECG signals from a single, user-selected channel, following a five-step sequence: (1) ECG signals are initially sampled at 8000 Hz to capture pacemaker activity, then downsampled to 500 Hz for rhythm analysis. (2) Two digital filters are applied to reduce baseline wander and muscle artefacts. (3) QRS complexes are identified while P-waves, T-waves, and noise artefacts are filtered out. Beats are analysed by amplitude, duration, area, and timing and then classified as normal, ventricular ectopic, paced, or questionable. Beats with recurring morphology are grouped into template

families. (4) Irregular rhythms and premature ventricular contractions are detected using R-R intervals and QRS morphology. Notably, the algorithm does not analyse P-waves directly. A separate ventricular fibrillation module detects fibrillatory patterns lasting over 4 seconds. (5) Based on the severity of the detected abnormality, alarms are triggered, with higher-priority alarms overriding lower-priority ones [27]. The algorithm's ST-segment monitoring feature identifies deviations suggestive of myocardial ischemia. It calculates a baseline ST value at the start of monitoring and continuously compares real-time data, using lead-averaged values to minimise false positives before issuing alarms [23, 24]. The Philips "*ST/AR algorithm*" can detect 23 distinct cardiac pathologies, including Asystole, Ventricular fibrillation, Ventricular tachycardia, Supraventricular tachycardia, Atrial fibrillation with a variable ventricular response (indicated as irregular heart rate), Bradycardia, Tachycardia, Ventricular bigeminy, Ventricular trigeminy, Ventricular couplets, Ventricular beats, Run of ventricular beats, Missed beats, Pacer not pacing, Pacer non-capture, Pacer non-sensing, Pacer artefact, ST-segment elevation, ST-segment depression [23]. The following conditions were not visualised in the current version of the VPH prototype: pause, multifocal ventricular beats, R on T, and irregular heart rate.

Designing Visual Patient Heart (VPH)

The development of VPH was grounded in the output of the Philips "*ST/AR algorithm*". In consultation with cardiac anaesthesiologists from the University Hospital Zurich, we selected a subset of pathologies deemed most clinically relevant for the prototype visualisation. Our team refined VPH designs through an iterative process, guided by principles of situation awareness-oriented design [27], and supported by expert feedback, including consultations with the original developers of the "*ST/AR algorithm*" at Philips to inform our understanding of the system. The design philosophy followed the established principles of the Visual Patient concept: simplicity, intuitiveness, and enhanced visual situation awareness [28].

Testing decision confidence and workload (NASA-TLX)

Participants completed a standardised NASA-TLX form after each monitoring scenario. The dimension "*physical demand*" was excluded from the analysis, as it was not relevant to the computer-based, seated task environment. The five remaining dimensions assessed were mental demand, temporal demand, performance pressure, cognitive effort, and frustration. Each was rated on a continuous scale from 0 (lowest score) to 100 (highest score), providing a subjective measure of perceived cognitive load. In addition, participants were asked to rate their decision confidence for each scenario on a separate continuous scale from 0 (no confidence) to 100 (certainty).

Results

Quantitative analysis

Primary Outcome: Correct identification (ECG vs VPH)

We analysed 1,651 simulated monitoring scenarios to compare diagnostic accuracy between conventional 12-lead ECG displays (788 scenarios) and the VPH visualisation tool (863 scenarios). With standard ECG monitoring, only 42% (332 scenarios) of cases were correctly identified, while 58% (456) were misinterpreted (Fig. 2A). The use of VPH resulted in better recognition: 78% (677) were correctly classified, only 22% (186) were incorrect (Fig. 2B). Across both modalities, correctness was 61%, with 39% of cases answered incorrectly (Fig. 2C). McNemar's test indicated very strong evidence for a difference between the two modalities ($p < 0.001$). The adjusted odds ratio from the mixed logistic model was 6.06 (95% confidence interval, 4.79–7.66, $p < 0.001$). This suggests that participants' odds of correctly identifying a cardiac condition were over six times higher when using VPH than conventional ECG monitoring in the simulated setting. There was no evidence for an effect of the additional variables, self-reported ECG interpretation per week and the presentation sequence (Fig. 3A, **Supplementary Table 1**). We also analysed accuracy by individual pathology (Fig. 3B). VPH outperformed conventional 12-lead ECG in most cardiac conditions, including: Atrial Fibrillation, Bigeminy, Irregular Rhythm with Missed Beat, No Pacemaker, Sinus Bradycardia, Sinus Tachycardia, ST-Segment Elevation (anterior, inferior, posterior, and extensive), Supraventricular Tachycardia (SVT), Ventricular Rhythm, Ventricular Fibrillation, Ventricular Tachycardia, and Proper Pacemaker Function. For several pathologies, including Non-Sustained Ventricular Tachycardia (NSVT), Trigeminy, Ventricular Ectopic Couplet (VES-Couplet), and Sinus Rhythm, no evidence for a difference in correct identification was observed between the two modalities. The only condition in which ECG slightly outperformed VPH was asystole, with 92% versus 89% (**Supplementary Figure S7**).

Influence of Visual Patient Heart (VPH) on confidence and workload

The linear mixed model showed that confidence was, on average, 24 points higher with VPH than with ECG. Confidence also increased moderately by 0.23 points per scenario, while the prior experience had no significant effect. Baseline confidence was 50 [46, 55] (Fig. 3C). Similarly, for NASA-TLX, workload was perceived as 25.5 points lower with VPH, with no evidence for an impact of other variables. The baseline NASA-TLX score was 55 [51, 59] (Fig. 3D). Further analysis of self-assessment items comparing VPH and ECG showed strong evidence of differences across multiple dimensions (Fig. 4), as indicated by the Wilcoxon Signed-Rank Test: temporal demand ($p < 0.001$), performance pressure ($p < 0.001$), cognitive effort ($p < 0.001$), mental demand ($p < 0.001$), and frustration ($p < 0.001$), see **Supplementary Figure S8**.

Discussion

This study assessed the diagnostic performance of anaesthesia providers using a novel, avatar-based monitoring technology, Visual Patient Heart, in comparison to conventional 12-lead ECG displays. In a simulated setting, VPH significantly enhanced the recognition of cardiac pathologies, increased decision confidence, and lowered perceived cognitive workload, measured by the NASA-TLX. These findings

highlight the potential of visualized monitoring to support clinical decision-making and reduce cognitive demands.

Patient monitoring is critical in clinical decision-making, particularly in high-acuity settings such as the operating room (OR), post-anaesthesia care unit (PACU) [1], and intensive care unit (ICU) [24]. As with all technologies, the effectiveness of cardiac event detection systems is inherently dependent on the clinical decisions guiding their use. Consequently, despite technological advances, rhythm disorders such as perioperative atrial fibrillation may still go undetected if monitoring strategies do not align with the temporal pattern of arrhythmia onset [20]. Maintaining situation awareness is key in a time-sensitive setting, which has been extensively studied in aviation [29, 30], critical care, and anaesthesiology [31–33]. Situation awareness involves three stages that shape the foundation for every informed decision: perception of relevant data, comprehension of its meaning, and projection of future status based on current trends [27, 34]. Cardiac pathologies can emerge rapidly and compromise hemodynamic stability. Accurate and timely recognition of arrhythmias or ischemic signs is therefore vital. While interpreting 12-lead ECGs is a standard part of medical education and respective algorithms [35, 36], it remains cognitively demanding, particularly under pressure. The VPH system was designed to support rapid perception and comprehension by transforming algorithm-based signal analysis into intuitive visual representations. Importantly, VPH is not a diagnostic algorithm, but a novel visualisation tool based on the clinically established Philips *“ST/AR algorithm”*, which continuously analyses the ECG signal, including lead-based ST-segment deviations and rhythm abnormalities, and detects 23 distinct cardiac pathologies. In designing the VPH visualisations, we aimed to reflect pathophysiological mechanisms while preserving the visual identity of the existing Visual Patient concept. A sinus-originating rhythm was visualised via an arrow emerging from a sinus node, whereas ventricular-origin beats originated from the apex. All visualisations are described in detail in **Supplementary Material 1**.

Our results demonstrated that anaesthesia care providers were significantly more accurate in identifying cardiac pathologies using VPH than standard ECG. Despite their greater familiarity with conventional 12-lead ECG interpretation, participants achieved a correct classification rate of 78% with VPH, compared to 42% with 12-lead ECG ($p < 0.001$). A mixed logistic regression model yielded an odds ratio of 6.06 (95% confidence interval, 4.79–7.66, $p < 0.001$), indicating a more than sixfold increase in correct identification when using VPH. VPH improved accuracy in most arrhythmias and ST-related conditions. Asystole was the only condition identified more accurately using conventional ECG (92% vs. 89%). This finding is likely attributable to the highly distinctive and alarming appearance of asystole on conventional ECG, which all anaesthesia providers are trained to recognise immediately. In contrast, the corresponding VPH visualisation was newly learned and may have required more deliberate cognitive processing, slightly hindering correct identification. Decision confidence was significantly higher ($p < 0.001$) and perceived workload significantly lower ($p < 0.001$) with VPH. We used a modified NASA-TLX, which was validated previously by our group for use in patient monitoring tasks [25]. Our findings are consistent with earlier visualization work, which has shown benefits in detecting critical vital sign deviations [8–15, 37]. Reducing cognitive burden is especially valuable in high-workload or cognitively saturated environments where decision errors are more likely [26]. While 12-lead ECGs remain indispensable in clinical

diagnostics, they are not inherently optimised for fast visual recognition. VPH provides an at-a-glance representation of key rhythm disturbances designed to support situation awareness at the bedside, particularly in environments such as the OR, PACU, or ICU, where clinicians may be simultaneously responsible for multiple patients. The underlying Visual Patient concept has previously demonstrated benefits in enhancing situation awareness in such settings [38].

Participants reported that Visual Patient Heart was intuitive and easy to learn, offering rapid access to situational overview. While hospitals currently use different strategies for telemetry monitoring of non-critical patients, ranging from centralized to decentralized systems, the future holds significant potential with innovations like the Visual Patient Heart. This technology could greatly enhance telemetry monitoring even for patients on normal wards, offering a more intuitive and rapid way to assess vital signs and cardiac function. Our findings suggest that VPH may be a valuable complementary tool to existing monitoring technologies, potentially improving efficiency and safety in acute care settings.

Limitations

This study has several limitations.

Methodical

We used simulated 12-lead ECG displays, which may not fully capture the variability and complexity of real-world clinical ECGs. Each scenario was limited to six seconds of viewing time, aiming to evaluate the initial perceptual phase of situation awareness rather than in-depth ECG interpretation skills. VPH is not intended to replace 12-lead ECG analysis but to offer anaesthesia providers a quick, intuitive, and reliable first indication of cardiac rhythm and function changes, consistent with Endsley's situation awareness model. The Philips *"ST/AR algorithm"*, at the base of VPH, is widely implemented in current Philips patient monitoring systems. However, it has not been extensively validated in large-scale randomised controlled trials or clinical cohorts, and its performance in diverse patient populations remains to be further established. Nevertheless, given its widespread use, developing a dedicated visualisation interface could improve the algorithm's usability by providing clinicians with an intuitive and easily interpretable model.

Participant recruitment and analysis

Participants were recruited from four university anaesthesiology departments rather than selected through random sampling. While we ensured a balanced distribution across study centres, gender, and professional roles—including physicians and nurse anaesthetists—it is possible that those who chose to participate were more technically inclined or open to new technologies. We adjusted for prior ECG experience by accounting for the number of ECGs participants reported interpreting weekly and controlled for the randomised order of modality presentation to reduce potential confounding effects.

Conclusion

This study investigates the impact of the Visual Patient Heart, a novel visualisation tool based on the Philips “*ST/AR algorithm*”, on the ability of healthcare providers to identify cardiac pathologies in simulated monitoring scenarios. Compared to conventional 12-lead ECG display simulations, VPH significantly improved diagnostic accuracy while increasing participants’ decision confidence and reducing perceived workload, as measured by the NASA-TLX questionnaire. These findings support the potential of avatar-based visualisation models to enhance clinical situation awareness and may contribute to improved decision-making and patient safety in acute and critical care environments. Particular value may also lie in settings where non-expert staff monitor multiple patients simultaneously, such as in telemedicine or central monitoring applications.

Abbreviations

AF

Atrial fibrillation

AR

Arrhythmia

BASEC

Business Administration System for Ethics Committees (Switzerland)

ECG

Electrocardiogram

Hz

Hertz

ICU

Intensive care unit

IQR

Interquartile range

NASA-TLX

National Aeronautics and Space Administration Task Load Index

NSVT

Non-sustained ventricular tachycardia

OR

Operating room

PACU

Post-anaesthesia care unit

QRS

QRS complex

R–R interval

Interval between successive R waves

SD

Standard deviation

ST

ST segment

ST/AR

ST and Arrhythmia

SVT

Supraventricular tachycardia

UKB

University Hospital Bonn

UKF

University Hospital Frankfurt am Main

USZ

University Hospital Zurich

VPH

Visual Patient Heart

VES

Ventricular ectopic beat

Declarations

Ethics approval and consent to participate

This study was conducted in compliance with the Helsinki Declaration for medical research involving human participants. We obtained written informed consent from all participants, ensuring the confidentiality of the data. The study received a declaration of non-jurisdiction from the Cantonal Ethics Commission of Zurich, Switzerland (BASEC-Nr.: Req-2024-00353), and obtained positive ethical approval from all additional participating sites in Germany (Munich: 2024-383-S-CB, Bonn: AZ 2024-209-BO, Frankfurt: #2024-1760).

Consent for publication

Not applicable.

Availability of data and materials:

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing Interests:

CAH and ME are a registered inventors of Visual Patient Heart technology. TRR is an inventor of Visual Patient Predictive and Visual Blood, with intellectual property held by the University of Zurich and Philips. TRR receives research funding, honoraria, and travel support through joint development and licensing agreements from Philips. DWT is an inventor of Visual Patient, Visual Patient Predictive, Visual Blood,

Visual Clot, Visual Hemofilter, and Visual Patient Heart with intellectual property held by Philips and the University of Zurich. DWT receives research funding, honoraria, royalties, and travel support through joint development and licensing agreements. Instrumentation Laboratory–Werfen, the Swiss Foundation for Anaesthesia Research, the International Symposium on Intensive Care and Emergency Medicine have provided additional honoraria and travel support. DWT serves on the Philips Patient Safety Advisory Board.

All other authors declare no conflict of interest.

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Authors' contributions:

CAH: Conceptualization, Technology Development (Visual Patient Heart), Data Collection, Data Curation, Investigation, Visualization, Writing: Original Draft

ME: Conceptualization, Data Collection, Data Curation, Methodology, Investigation, Visualization, Writing: Original Draft

TRR: Data collection

AR: Data Collection

AD: Data Collection

FP: Data Collection

FJR: Data Collection

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Figures

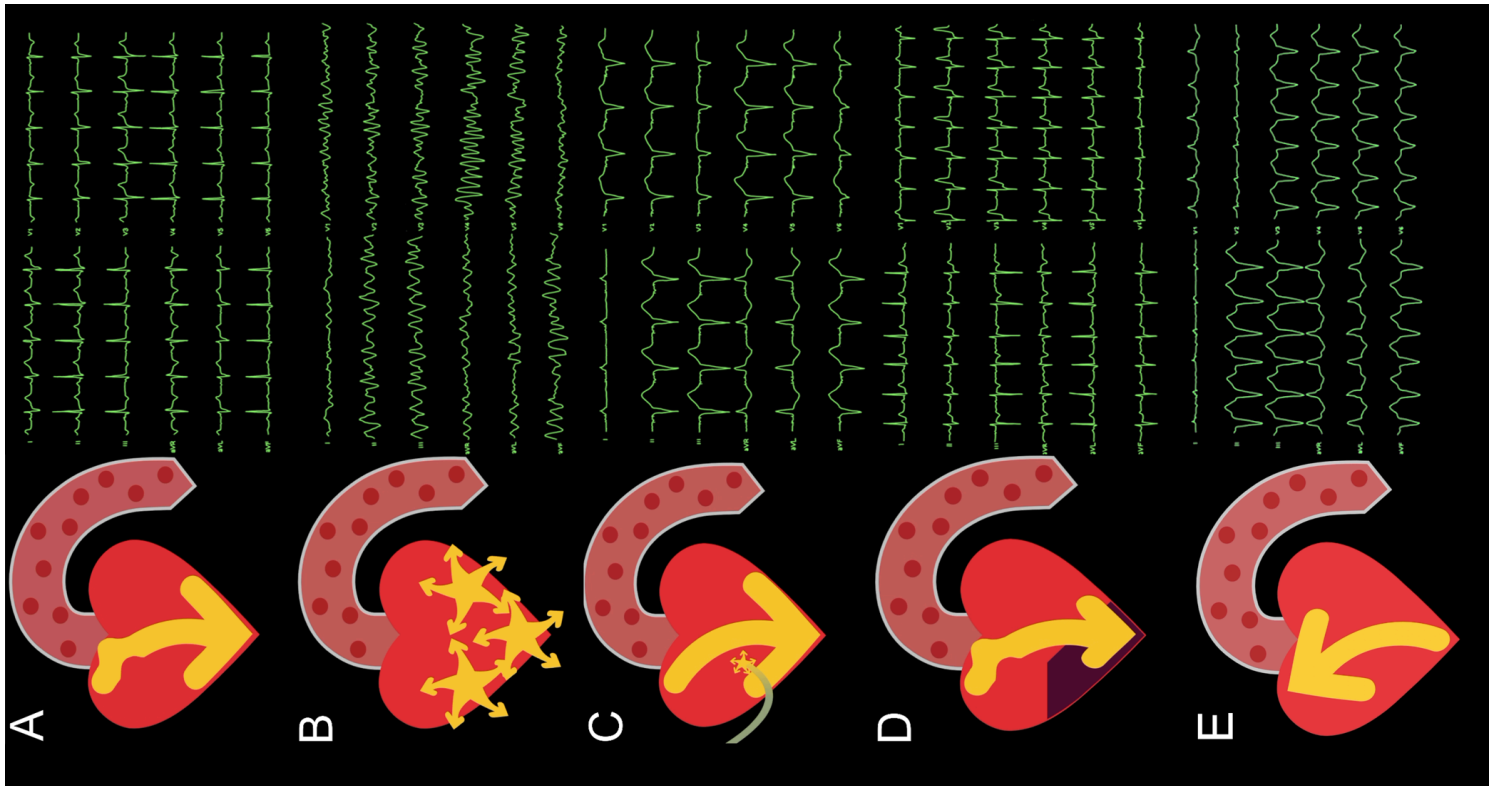


Figure 1

Four examples showing 12-lead ECG visualisations next to corresponding Visual Patient Heart designs. The yellow 'arrow visualisation' represents a simplified version of the heart's electrical conduction system and integrates the new heart visualisations. As part of the original Visual Patient concept, the aorta visualisation displays cardiac output by showing varying erythrocytes expelled with each pulse.

A sinus rhythm

B ventricular fibrillation

C pacemaker functional

D STEMI posterior

E Ventricular rhythm

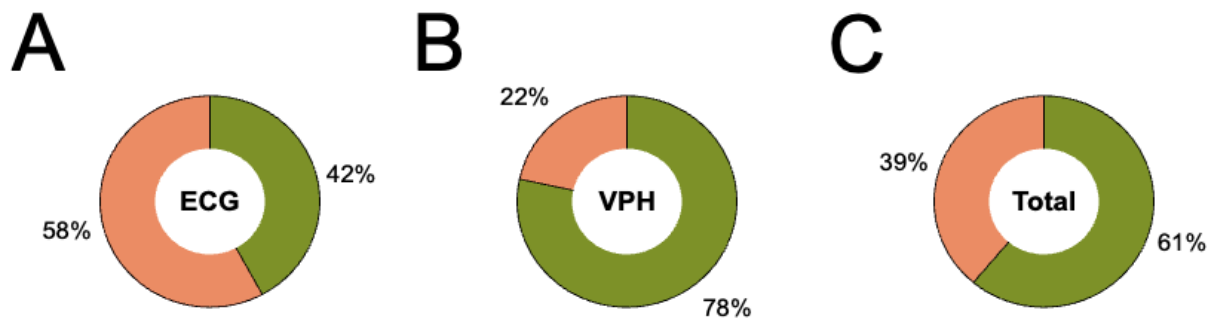


Figure 2

Pie charts showing participants' diagnostic decisions based on modality. The graphs illustrate the percentages of correct (green) and incorrect (red) diagnoses cumulatively over all participants (n=75) and all pathologies (mean).

A ECG

B Visual Patient Heart (VPH)

C Overall (both modalities)

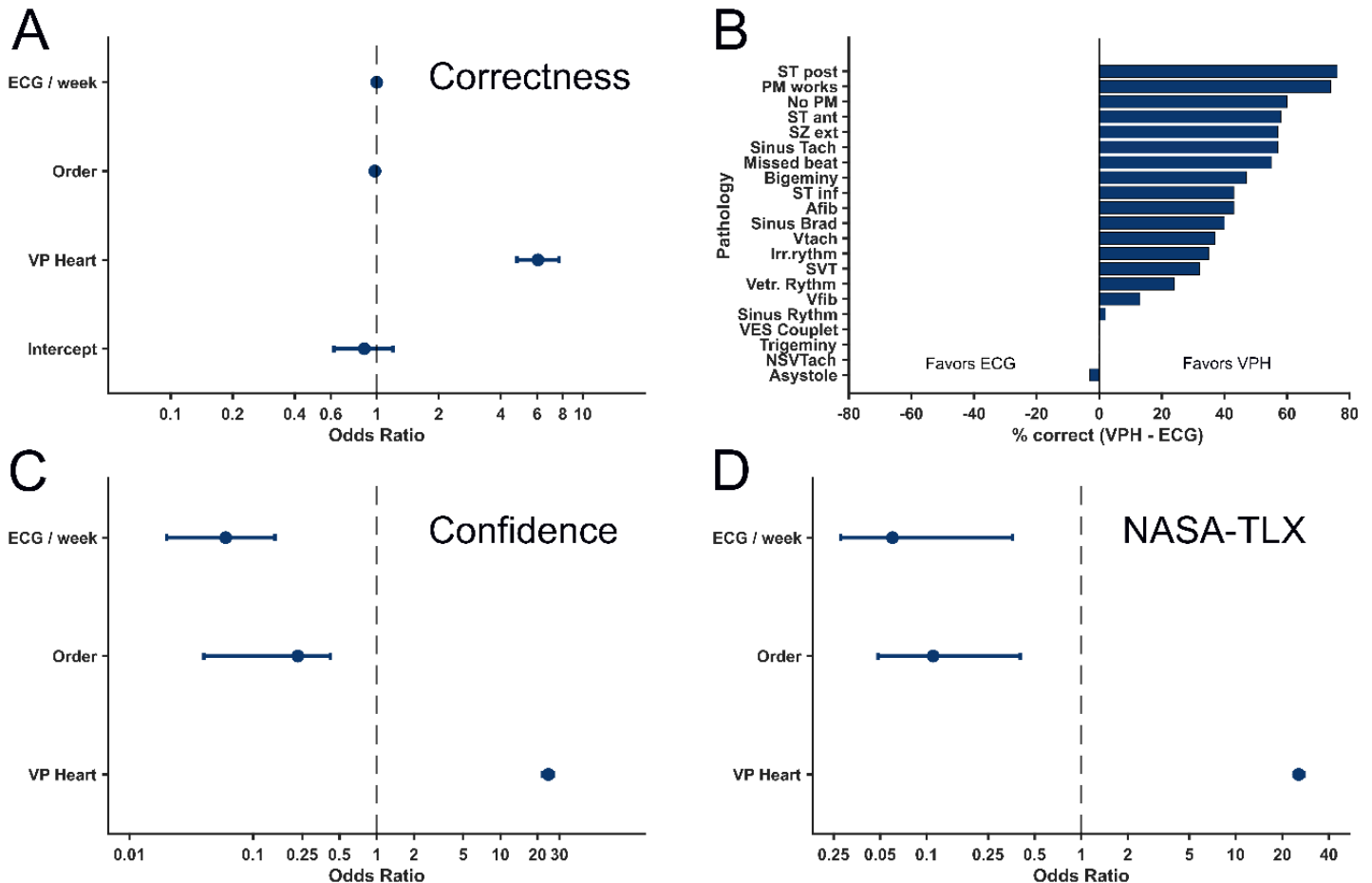


Figure 3

Odds Ratios for correctness, confidence and NASA-TLX, Percentages of Correctly Identified Pathologies by both modalities.

An odds ratio of 1 indicates no significant effect on the variable.

A Results for mixed logistic regression model for correct identification.

B Bar chart indicates the difference in percentage of correctly identified pathologies for Visual Patient Heart (VPH) minus 12-lead ECG; the pathologies are ranked with descending differences in the percentages, i.e., the top pathology shows the highest superiority for correctness of VPH. The lowest (Asystole) indicates superiority of conventional 12-lead ECG identification (92% ECG vs. 89% VPH).

C Graph showing results from a linear mixed model for confidence

D Graph showing results from a linear mixed model for NASA-TLX

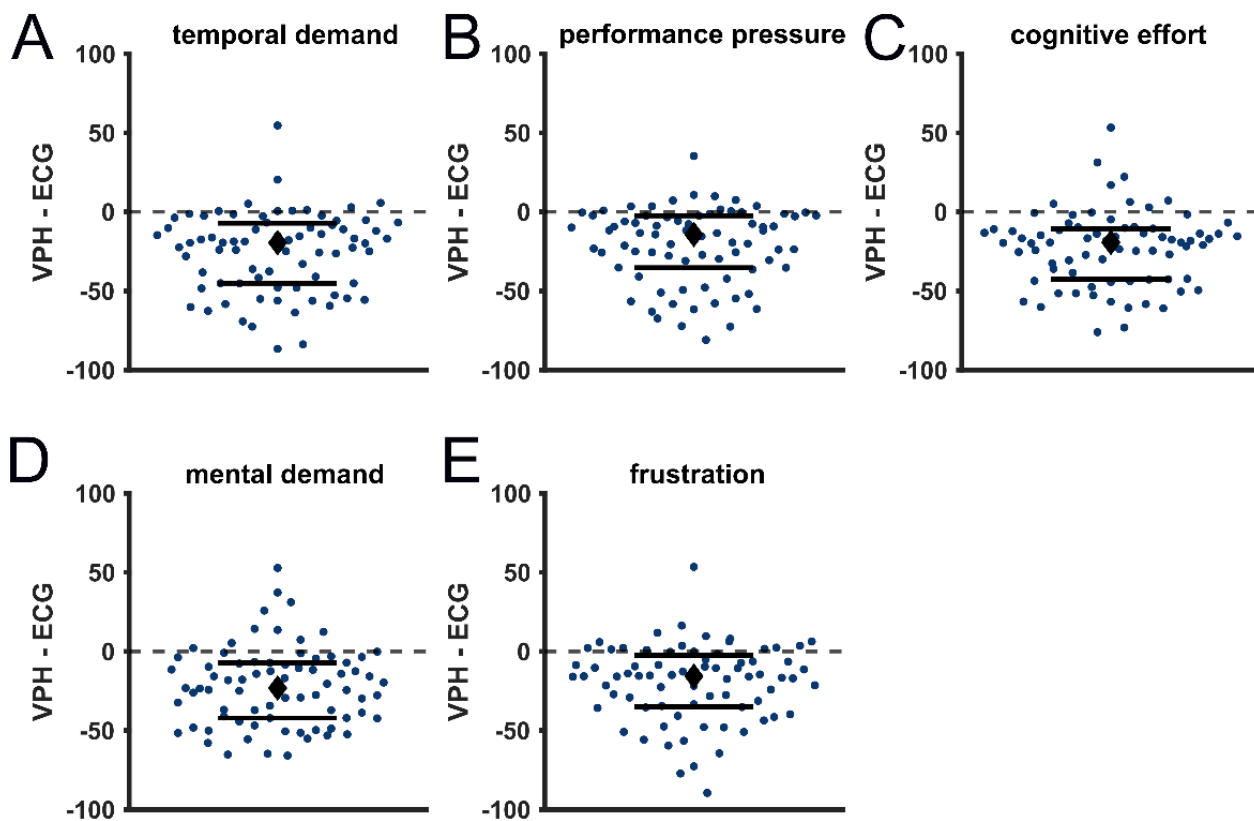


Figure 4

Secondary outcomes for ECG and Visual Patient Heart (VPH)

We present the data as one mean score per participant for each modality (Visual Patient Heart minus 12-lead ECG). Dots below zero indicate a lower perceived workload using VPH. Diamonds indicate the

median; horizontal ticks mark the 25th and 75th percentiles.

A temporal demand

B performance pressure

C cognitive effort

D mental demand

E frustration

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [VPHQUANTISupplementaryMaterial1.docx](#)