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Research Article

Non–invasive Vital Signs Monitoring in the Adult Population in Clinical Settings — Current State of the Art and Beyond

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Abstract. The aim is to delineate the current state of the art in non–contact red-green-blue (RGB) camera–based heart rate and rhythm monitoring in adult populations in the clinical setting. In addition, the challenges that still exist for more widespread use of this technology are outlined, as well as potential ways to overcome them. A search using Boolean operators was carried out in PubMed, Google Scholar, IEEE Xplore, CINAHL and Cochrane databases using predefined inclusion and exclusion criteria. Studies within hospital settings that extract heart rate data from videos of adult patients were identified and their successes and limitations were analysed from a clinical perspective. Fifteen studies were identified that fit the inclusion criteria. Many of these studies took place in emergency department settings, with the postoperative care unit being another environment that was investigated. Although good correlation between gold standard measurements and camera-based values were obtained overall, there are still challenges related to patient movement, changes in illumination and standardisation of techniques. This may be the reason that the use of this technology is not yet commonplace. Although a lot of valuable work has been performed highlighting the advantages and feasibility of using camera-based photoplethysmography to extract heart rate data in clinical scenarios, challenges still need to be overcome before these systems can become more mainstream in clinical practise. Therefore more research needs to be conducted in the field of non-invasive vital signs monitoring in the clinical setting.

Keywords: Non–Contact Vital Signs Monitoring, Camera–Based Photoplethysmography, Contactless Heart Rate Monitoring, RGB-based monitoring

1 Introduction

Non–contact vital sign monitoring (NCVSM) is a relatively new scientific methodology in which health–related parameters are extracted from patients in a non–contact manner without the use of any leads or wires. Most commonly, this is done by means of cameras, namely red–green–blue (RGB) or thermal imaging cameras, or more sophisticated equipment such as various types of radar (). The most commonly extracted vital signs include heart rate and rhythm, respiratory rate, oxygen saturation and, less commonly, blood pressure (). These are parameters that are part of many early warning scores and are crucial in helping healthcare workers determine patient stability and prioritise care (Patel et al., 2015). This review will focus on the extraction of heart rate and rhythm data in real–world scenarios using videos taken by RGB cameras. This is because RGB cameras are very easy to acquire, they are not particularly large or bulky, and good quality videos can be obtained with minimal expense and personnel training. Therefore, such vital sign extraction should be easily reproducible by research teams around the globe.

NCVSM has gained increasing interest in the clinical setting in recent years due to its advantages to patients and healthcare workers in different clinical settings. NCVSM systems offer increased comfort to patients who can be monitored without wires constantly attached to them, enabling more freedom of movement and less discomfort. In theory, it can also allow monitoring during periods of time like interventions or physiotherapy, when traditional monitoring is impractical (Malasinghe et al., 2019).

In the case of patients with vulnerable skin such as burns patients or the very elderly and frail, this can translate to actual medical benefits in terms of reduced irritation, skin

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damage and pain. Transmission of infectious organisms, which are often resistant to multiple drugs and pose a great problem in healthcare systems at present, is also reduced between patients. This is because the risk of leads and wires being inadequately disinfected between subsequent patient uses is eliminated ().

For healthcare workers, using NCVSM means that there is a reduced need to be constantly checking that leads and wires are appropriately attached, disconnecting and reconnecting them every time that patients need to move from their bed or every time these leads get inadvertently dislodged. This saves time in already busy clinical scenarios. The advent of the COVID–19 pandemic has highlighted this even more, since healthcare workers need to fully don and doff every time that they need to enter the patient's area of a COVID positive individual. Apart from this being very time consuming, it also leads to wastage of personal protective equipment, which is expensive, detrimental to the environment and is often in short supply ().

NCVSM also allows patients to be monitored in remote locations such as their homes or quarantine facilities. This is another need that has come to the forefront during the pandemic. With overwhelming numbers of patients becoming infected with a disease about which little was initially known, many needed close monitoring since, although their health situation might be stable at the time of presentation to medical services, it could quickly and unpredictably deteriorate especially in patients with underlying comorbidities. The possibility of close monitoring while the patient remains at home is very useful in this scenario since it allows hospital beds to be reserved for patients who need active medical intervention. However it is obviously impractical for patients to be wearing leads at all times, and help may not always be available to troubleshoot leads that have come off or become tangled or displaced ().

The principle by which heart rate and rhythm data is extracted from videos taken using RGB cameras is termed photoplethysmography (PPG). Haemoglobin present in the blood vessels located underneath the surface of the skin will absorb wavelengths of visible light within the green spectrum, reflecting those in the red spectrum. These absorption peaks correspond to the fresh influx of oxygenated blood from the heart that happens with each beat, and may be enhanced and extracted by the application of various filters and algorithms ().

Videos taken using RGB cameras usually include areas of the skin from where PPG signals may be extracted, most commonly the face or a part of it, and sometimes limbs and neck regions. The selected area for signal extraction is termed the region of interest (ROI), and was traditionally manually selected by the data analyst from video segments or images to yield the best results. Newer algorithms are able to select the best ROI automatically and track it throughout the video sequence, using methods such as, for example, the Kanade–Lucas–Tomasi algorithm commonly referred to as KLT ().

Green filters applied to the images in a video frame can help enhance the signal and multiple algorithms are used to recognise the pulsatile waveform associated with heart rate activity (Tamura et al., 2014). Some examples include: the Fast Fourier transform (FFT), which can break down the noisy PPG signal into its component parts and extract the parts of interest in terms of heart rate (C., 2022); Eulerian Video Magnification (EVM), which decomposes the sequences in videos and magnifies the parts of interest to the operator; and Principal and Independent Component Analysis (PCA and ICA respectively), which seek to extract individual components and differentiate them from other signals which are considered unnecessary noise ().

The most recent algorithms are based on a machine learning paradigm, termed convolutional neural networks (CNN). These are machine learning algorithms that may be trained to recognise particular components from videos and images, in this case the PPG signal, using training data where the ground truth corresponding values are also provided. Once trained, CNNs are able to extract the signals they have been trained to recognise, from new video clips presented to them. These networks have great potential in the field of NCVSM and they are becoming increasingly complex ().

This clinical review aims to describe studies published within the last decade that deal with RGB video camera use in extracting heart rate and rhythm data in real world clinical and hospital scenarios, while delineating some of the more significant limitations which prevent their widespread use at present and possible directions for improvement.

2 Methods

A systematic search was carried out on academic search engines including PubMed, Google Scholar, IEEEXplore, CINAHL and Cochrane. In the case of Google Scholar, the first 200 results returned were analysed. The search term used was "(hospital OR patient) AND (RGB) AND (vital signs OR heart)". The following inclusion and exclusion criteria were predetermined for the articles encountered during the search.

Inclusion criteria included studies with patients above 18 years of age, that took place within hospital or clinical settings, recruited patients with documented pathology or symptoms of pathology, include the use of RGB cameras, measured heart rate or rhythm as vital signs and have been published in peer–reviewed journals in the English language since 2012.

Exclusion criteria were the following: studies including only participants below eighteen years of age or who were healthy without symptoms or documented pathology outside clinical or hospital environments; if the focus is on screening for diseases in general; if the studies did not make use of RGB cameras, did not include extraction of heart rate or rhythm data.

3 Results

The PRISMA diagram depicts the results of the search criteria (figure 1). Fifteen papers met all inclusion criteria and were included into the final analysis of data for this review.

The most common clinical areas where NCVSM was implemented include the emergency department and the post–operative care unit, however other interesting settings such as general medical wards and haemodialysis units are also represented (). The studies included in this review were divided according to the environment in which they were undertaken in order to enable analysis of the limitations encountered in each setting.

One of the identified papers for inclusion in this review is a systematic review itself, and will be described separately since it does not fit into any specific category (Antink et al., 2019). It focused on NCVSM between the years 2016 and 2018. It included 116 studies, however only 16 of these included patients with actual medical conditions, and most of these studies recruited small groups of participants of 20 persons or less. These are small sample sizes, however over the years it is noted that study cohorts have increased in size as well as in the variety of diseases and environments studied. Most camera–based studies included in that systematic review used more sophisticated cameras as opposed to consumer grade equipment, thereby potentially increasing complexity and hiking costs. Although results obtained in terms of accuracy were acceptable, Antink et al. (2019) noted the lack of standardisation available for determining what is in fact an acceptable level of accuracy for NCVSM monitoring in the clinical setting. Another issue is the lack of data and algorithm sharing between different teams, which would enable one team to build further on what another has achieved. Issues that prevent this include the often-sensitive nature of videos that show vulnerable patients and institutional data access regulations.

NCVSM in the Triage of Infective Patients

The COVID-19 pandemic has brought with it surges of patients presenting to the Emergency Department with suspected symptoms, not all of whom required immediate medical care, or indeed any medical care at all. Triage of patients according to the severity of their medical conditions will allow prioritisation of care, however it is often time consuming and requires a lot of resources which may be in short supply in a time of crisis. The idea of triaging of patients who present with symptoms of potentially contagious viral illness, however, precedes the COVID–19 pandemic, with influenza being the typical yearly culprit that makes these services necessary ().

Three teams of researchers applied camera–based PPG to infectious disease screening, including patients with documented pathology or symptoms thereof, in the study cohort (). Negishi et al. (2020) included forty–one subjects, among whom were 22 patients with seasonal influenza, focusing on screening them for elevated temperatures but adding in respiratory rate and heart rate to increase the sensitivity of detection. This is because elevated temperature can easily be masked by simple anti–pyretic medication, which is one of its main criticisms as a screening test for contagious illness. Increased heart rate and respiratory rates, which are also common markers of viral illness, are much more difficult to hide. Tapered window and signal reconstruction were used to reduce the effect of background noise, with MUSIC algorithm used to extract heart rate values, obtained a root mean square error (RMSE) value of 5.93 beats per minute (bpm) (Negishi et al., 2020).

Huang et al. (2022) as well as Malmberg et al. (2022) focused on patients presenting with COVID symptoms to emergency settings. In the case of (Huang et al., 2022) an RGB camera was incorporated into a robotic device named Dr Spot, which was able to navigate rough terrain to cross over to a tent where potentially contagious patients were being triaged. Healthcare workers were able to operate Dr Spot remotely, reducing potential exposure and wastage of personal protective clothing. The forehead and cropped parts of the face were used as the ROI since they yielded the most accurate results, providing a mean absolute error (MAE) of 7.5 bpm. POS algorithm was used enabling the distinction between the pulsatile PPG signal and surrounding noise sources. The system was successfully used for triage being able to read heart rates of between 50 and 160 bpm (Huang et al., 2022).

Malmberg et al. (2022) similarly extracted heart rate data from a cohort of suspected COVID-19 patients, with the study sample comprising 214 individuals, mostly female and of Caucasian skin tone. Videos of the patients' faces were obtained under ambient lighting as well as under red lighting using an LED and using near–infrared detection. An unspecified AI algorithm was used to extract PPG signals and comparison with ground truth data obtained a MAE of 1.4bpm, making this method the

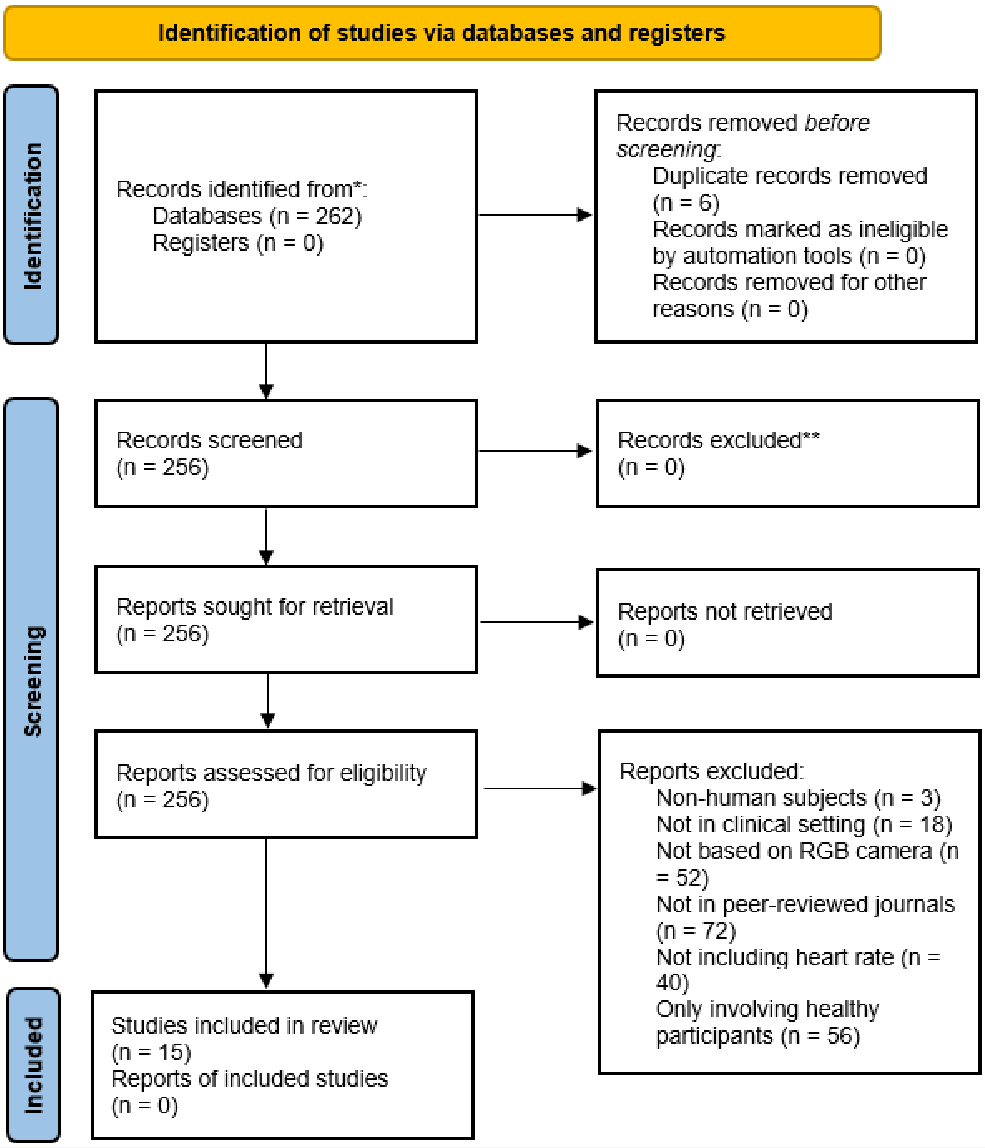

Figure 1: PRISMA diagram, detailing included and excluded papers and the reasons for their exclusion from data analysis.

most accurate of the identified studies in this section (Malmberg et al., 2022).

NCVSM in the Operative and Post-Operative Setting

The post–operative care unit is an ideal setting for the study of NCVSM, since the lack of leads and wires will enhance patient comfort. The relatively high patient turnover also means that inadequate disinfection of leads and wires will result in infection of several individuals.

Trumpp et al. (2018) were the only team identified for this review who tackled the issue of NCVSM in the operating theatre. This environment is ideal for the study of such new technologies because patients are immobile and most sources of noise such as ambient illumination are controlled. Access to an adequate ROI, however, may be problematic in cases where surgical drapes cover most of the patient's face and neck, highlighting the need to explore further ROIs. Trumpp et al. (2018) successfully extracted heart rate data from 41 intra-operative patients using RGB and near infrared cameras for 95% of the time that videos were taken, using Bayesian classifiers to segment and track the relevant ROIs over subsequent video frames. Application of a green filter enhanced the signal although constant ambient illumination over the ROI was still required for successful results. Ten second delays were experienced in obtaining PPG values, which may be significant in the case of unstable patients and complex surgeries. The quality of signal obtained reflects on the adequacy of microvascular perfusion and therefore could potentially be used to provide information to anaesthetists to titrate vasoactive infusions (Trumpp et al., 2018).

The effects of several vasoactive agents in the post-op cardiac care unit were also investigated in a separate study (Trumpp et al., 2017). PPG signals were obtained from patients who were on different infusions to maintain blood pressure and their effects on pulse pressure signals were obtained. Not surprisingly, the effect on PPG was related to the vasoactive effects of the drug, with patients on glyceryl trinitrate (GTN) with higher haemoglobin levels showing better PPG extraction due to increased dermal microvascular perfusion. Noradrenaline proved to have the opposite effect due to its vasoconstrictive effects (Trumpp et al., 2017).

Post-op cardiac surgical patients were also monitored for extraction of PPG signals in two separate studies (). Between both studies, 88 patients were included, the majority of who were still intubated and mechanically ventilated. Several algorithms were used to extract PPG data from videos which were mostly around 30 minutes long with manually selected ROIs to optimise the obtained signal. Blind source separation (BSS) was used to distinguish the heart rate signals from other sources of background noise as well as PCA and ICA. A mean absolute error (MAE) of 5bpm was obtained for 83% of videos, however, changes in illumination, patient motion and hypotension negatively impacted results ().

NCVSM in the general medical ward

General medical wards are adequate environments for testing NCVSM technologies since patients admitted there often present with multiple complaints and underlying comorbidities, are often mobile and able to consent to participation and the environment is relatively uncontrolled. This allows for proper real–world testing of various conditions.

Several teams of researchers focused on different general ward settings in extracting heart rate data from RGB videos of patients. Ge Xu et al. recruited 38 patients with an average age of 40 years who had been suffering from diabetes and ischaemic heart disease for a period of three to five years (Xu et al., 2022). PPG signals proved harder to obtain from patients who had less well controlled disease, most likely due to the sclerotic effects that these conditions have on dermal microvasculature. Chrominance (CHROM) was used for denoising of the signal and bandpass filtering allowed selection of the frequencies of interest (Xu et al., 2022). Patients in atrial fibrillation, defined as an irregularly irregular heart rhythm, proved harder to extract PPG signals from. Similar issues were observed by Couderc et al. (2015) who recruited 11 patients with known atrial fibrillation presenting for elective cardioversion. Ventricular ectopic beats were missed on PPG signals when compared to ground truth ECG data, however, with a 20% error rate for the overall heart rate, the team postulated that this technique was feasible for monitoring of atrial fibrillation and identification of patients at risk of adverse sequelae such as cerebrovascular accidents (Couderc et al., 2015).

The accuracy of consumer grade mobile applications that use non-contact PPG to estimate the user's heart rate was investigated (Coppetti et al., 2017). A total of 108 patients were recruited to trial these applications (namely "What's My Heart Rate?" and "Cardioversion") from a chest pain unit, obtaining respective correlation coefficients of 0.62 and 0.60 with pulse oximetry and gold standard ECG, respectively. These values were even lower when variation in illumination was observed or when tachycardia was present, and highlight the need for further standardisation and upgrades in relation to accuracy prior to these methods being made use of for medical purposes (Coppetti et al., 2017).

Elderly patients had multiple comorbidities including diabetes mellitus, hypertension and atrial fibrillation. In one particular study, the KLT algorithm was used for ROI tracking during periods of time when patients were moving (Yu et al., 2020). Recordings were obtained just before and after physiotherapy sessions, obtaining a root mean square error (RMSE) of 3bpm. However, monitoring during the actual physiotherapy session was not performed. Near infrared cameras were also used in this study and were considered to be good options for the geriatric populations since they do not require additional light sources for proper functioning, especially in dim light conditions and darkness. Adding a light source could worsen delirium in at–risk populations since their circadian rhythm could be interrupted (Yu et al., 2020).

Sun et al. included a cohort of 11 subjects in a rehabilitation hospital obtaining PPG data via a robotic device termed Vital SCOPE that also included respiratory rate and temperature (Sun et al., 2018). Interestingly, the ROI chosen for this study was an area close to the carotid artery in the neck. Pearson correlation coefficient values of 0.91 were obtained when compared with ECG data (Sun et al., 2018).

Another study focused on a group of 46 patients receiving haemodialysis, also with no restrictions to patient movement or ongoing procedures (Tarassenko et al., 2014). In this case, autoregressive modelling and pole cancellation was used to extract PPG signals obtaining MAE of 3bpm in segments where patients were still. However, motion and ambient illumination changes negatively impacted the results (Tarassenko et al., 2014).

One small but interesting study was performed by Lin et al. (2019), who studied extraction of PPG signals in a series of three patients undergoing radiotherapy for uveal melanoma. Part of their thermoplastic mask was removed to uncover the cheek to be used as an ROI. Eye movement was also allowed to be monitored by this technique that used a camera and a dedicated LED light source above the patient. Manual ROI selection was performed and the KLT algorithm was used to track the ROI over time, although movement during a radiotherapy session needs to be minimal to allow targeted treatment and prevent collateral damage to nearby structures. MATLAB software based on FFT was then used to extract the final PPG signal. With this technique, MAE of 2.37bpm was obtained with the ground truth data being obtained from pulse oximetry. This is indeed a very accurate value (Lin et al., 2019).

Table 1 summarises the salient points of the studies included in this review. The studies are arranged in chronological order and details pertaining to the environment they were conducted in, the included study cohort and the best results obtained are provided.

Year	Author	Population Studied	Environment	Best Results Obtained
2014	Tarassenko et al.	46 end stage kidney disease patients	Haemodialysis Unit	MAE 3bpm
2015	Couderc et al.	11 atrial fibrillation patients	Electrophysiology Laboratory	20% variation from ground truth data
2016	Rasche et al.	70 post-cardiac surgery patients	CICU	Variation of 5bpm from ground truth data
2017	Trumpp et al.	70 post-operative patients	PACU	Correlation of 0.73 with ground truth value in GTN cohort
2017	Coppetti et al.	08 patients	Chest Pain Unit	Correlation values of 0.6 and 0.62 for two mobile phone applications compared to ground truth data
2017	Wedekind et al.	18 post cardiac surgery patients	PACU	Comparison between PCA and ICA outputs on datasets — PCA performed better for homogenous inputs and ICA was better for heterogenous inputs
2018	Trumpp et al.	41 patients intra–operatively	Operating Theatre	88% of time with less than 5bpm variation from ground truth
2018	Sun et al.	11 patients	Rehabilitation Hospital	Pearson Correlation Coefficient 0.91 compared to ECG data
2019	Hoog Antink et al.	16 reviews involving non-healthy subjects	Several different locations	Variable results obtained
2019	Chen Lin et al.	3 uveal melanoma patients	Radiotherapy Suite	MAE 2.37 bpm and RMSE 2.76 bpm
2020	Negishi et al.	40 influenza patients	Clinic	RMSE 5.93bpm
2021	Yu et al.	10 geriatric patients	Geriatric Ward	RMSE 3bpm
2022	Ge Xu et al.	38 general medical patients	Cardiology Department and Diabetes Centre	Accuracy value of 88.43% in heart disease patients and 82.12% in diabetes patients
2022	Hen Wei Huang et al.	Not specified for heart rate data	Accident and Emergency Department	MAE 7.5bpm
2022	Malmberg et al.	214 potential COVID patients	Accident and Emergency Department	MAE 1.4bpm

Table 1: Summary of populations and environments studied and best results obtained for PPG data for the studies included in this clinical review. CICU = Cardiac intensive care unit; PACU = Post-anaesthesia care unit; MAE = Mean Absolute Error; GTN = Glyceryl Trinitrate; PCA = Principal Component Analysis; ICA = Independent Component Analysis; RMSE = Root Mean Square Error.

4 Discussion

The use of NCVSM is advantageous to patients and healthcare workers alike, due to its ability to increase patient comfort and reduce risk of transmission of multidrug resistant organisms between patients (). In a time of crisis such as the ongoing COVID pandemic, when healthcare resources are overwhelmed, the ability to monitor patients remotely and identify those patients who require actual admission and those others who can be treated at home, will enable better allocation of resources. NCVSM also allows for reduced direct contact between healthcare workers and potentially infective patients, as demonstrated by several studies that devised robotic equipment capable of obtaining vital signs from patients while healthcare workers control it from a safe distance (). This is beneficial both in reducing the risk of contagion of healthcare workers and the use of personal protective equipment which healthcare workers must don every time they approach infected patients, including the replacement of displaced monitoring leads. Such protective clothing is expensive, detrimental to the environment and is also often scarce ().

As evidenced by the studies included in this review, camera–based PPG monitoring of cardiovascular parameters is capable of being performed to adequate standards in many different real world clinical scenarios. In some cases variations from ground truth data considered as the current gold standard was of less than 2bpm (Malmberg et al., 2022). However, these excellent results only apply to situations where the videos are obtained under idealised conditions with constant illumination, patients who are not moving, and ROIs which are fully visible. Delays in obtaining values still exist, and this can be an issue in critical scenarios when patient deterioration occurs within a matter of seconds (Trumpp et al., 2018). Once conditions start to become less than ideal, which is the usual situation in the real world, the accuracy of results starts to deteriorate. This highlights a need for further advancements in the algorithms (Tarassenko et al., 2014) such as to address these sources of error and unsatisfactory performance.

Many of these systems also require to be physically close to patients in order to be able to extract PPG data from videos. In one study, the robotic device was placed specifically two metres away from patients. While this is often not an issue, in cases where there is clinical equipment surrounding the patient's bed, it may be a problem to find adequate space for the monitoring equipment too (Huang et al., 2022). Overhead setups may overcome this problem especially when the patient is confined to a bed, but will incur costs of the infrastructural changes necessary to enable the attachment of cameras. When the patient is not in bed, such as during mobilisation to the armchair, the issue of the face (which is the most commonly used ROI) not being visible will come into play, highlighting the need for more ROIs to be available for data extraction.

There is also a notable lack of standardisation of techniques and sharing of datasets which would allow teams to build on each other's work, thereby accelerating improvements (Antink et al., 2019). This is understandable since videos of patients taken with RGB cameras are considered sensitive data and patients featured in them are easily identifiable. Therefore sharing of data needs to be governed by strict laws such as the General Data Protection Act in Europe and corresponding legislation in other geographical parts of the world (Mondschein & Monda, 2019). However, new frameworks could be set up that would allow such data sharing to take place between accredited institutions with patients' consent.

Over the years, the number of studies that consider real world clinical scenarios have increased in number as well as in the size of the recruited cohorts. This is beneficial since the sample of pathologies that patients present with and their underlying comorbidities are being increasingly represented, with common conditions such as diabetes, ischaemic heart disease and atrial fibrillation being increasingly included (Xu et al., 2022). The irregularity of microvasculature caused by these diseases has been noted to cause issues in obtaining accurate PPG signals, and this begs the question of what will be the effects of further comorbidities such as skin conditions and other diseases on PPG signals (Climie et al., 2019).

Although this review deals specifically with patients in hospital settings, interesting applications for NCVSM exist also for long term remote monitoring at home, for patients with chronic disease or the elderly who live alone in the community (). This could provide peace of mind to many patients who would feel reassured that healthcare workers are monitoring them and will be able to help them should they become unable to call for help themselves. It would also allay the burden of outpatient work which often involves simply following up otherwise stable patients. Obviously, issues of privacy and transmission of sensitive data would need to be tackled. Such technologies are already being trialled in some instances, such as for the detection of falls in the community ().

5 Conclusion

In this review, there is an outline of the current state of the art in camera–based PPG for heart rate and rhythm monitoring in real world clinical scenarios. Although many significant advances have been made in the past several years, obtaining reasonably good results in idealised video segments, there is still more to be done in terms of accuracy in non-ideal conditions and in pathological cases before these technologies can be rolled out for widespread use in clinical practise.

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7 Competing Interests

The authors have no relevant financial or non–financial interests to disclose.

8 Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, analysis and write-up of the first draft were performed by N.G. All authors read and reviewed all the previous versions of the manuscript and approved the final manuscript.

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