INTI JOURNAL | Vol.2025, Issue 5, No.21
eISSN:2600-7320

AI-Enabled Mobile Application for Surgical Safety Checklist Automation and Wrong-Patient Surgery Prevention

Siva Sathya S[1*], Santosh Sateesh[2], Shaoni Mukherjee[1], Bharat H Sharma[1]

[1]Department of Computer Science, Pondicherry University, India
[2]Department of Cardiology, JIPMER, India

***Email:** ssivasathya@pondiuni.ac.in

Abstract

Wrong Site, Wrong Procedure and Wrong Patient adverse events (WSPEs) rank among the most alarming and catastrophic errors in surgical practice. Although such incidents are relatively rare, their impact becomes significant in highly populated countries like India, where the sheer volume of daily procedures amplifies the risk. The wrong procedure and wrong patient adverse event anomaly occur when the surgery is being done on the wrong person, often due to name similarities, leading to unwanted surgery that could cause a lot of damage. Although standardized surgical checklists are implemented to prevent such errors, high surgical volumes often make strict compliance challenging for healthcare teams. The increased workload can lead to oversight, reducing the effectiveness of manual verification processes. To address this issue, this paper presents an AI-driven mobile application employing FaceNet architecture to streamline checklist completion and enhance patient identification accuracy. By automating critical verification steps, the solution minimizes human error and reinforces adherence to safety protocols, ensuring more reliable and efficient surgical procedures. Experimental validation proves that the FaceNet achieved 100% detection and 98.33% recognition accuracy. Hospitals can integrate this technology to strengthen patient safety measures and reduce the incidence of preventable adverse events.

Keywords

WSPEs [Wrong Site, Wrong Procedure, and Wrong Patient adverse events], Machine Learning, Android Studio, Face Detection

Introduction

Surgical adverse events involving wrong-patient, wrong-side, and wrong-procedure incidents remain significant challenges in healthcare safety. In consultation with medical professionals, we developed a mobile application designed to mitigate these risks through enhanced patient

Submission: 28 September 2025; **Acceptance:** 29 December 2025; **Available online:** December 2025

identification and streamlined completion of the surgical safety checklist. While the World Health Organization's surgical safety checklist, subsequently adapted by JIPMER (World Health Organization, 2009), provides a robust framework, its implementation often falters in high-volume clinical settings due to time constraints and administrative burdens, resulting in incomplete documentation. The solution proposed in this work addresses these limitations through three integrated modules: i) Surgical Safety Checklist Module: This component prevents wrong-procedure errors by presenting role-specific checklist items to nurses, doctors, and anesthetists, thereby reducing cognitive load while ensuring compliance. The system employs mandatory field completion, automatically records surgical details (including time and location), and generates alerts for incomplete pre-operative documentation; ii) Facial Recognition Module: To eliminate wrong-patient errors, we implemented a deep convolutional neural network (Deep-CNN) based verification system. Patient photographs captured during pre-operative admission are stored with unique identifiers and verified against live images prior to incision, providing a robust identity confirmation mechanism; iii) The application's architecture specifically accommodates the workflow requirements of three primary users: operating nurses, surgeons, and anesthesiologists. By integrating these technological interventions, we aim to significantly reduce preventable surgical errors while maintaining compliance with established safety protocols. In short, this work proposes a mobile based application for surgical safety checklist by employing a Deep-CNN-based FaceNet algorithm thereby minimizing human errors in the process.

This paper is organized as follows: Section 2 discusses related work in surgical safety, Section 3 details the system architecture and methodology, Section 4 presents the performance evaluation, and Section 5 concludes the work.

Background and Related Work

WSPEs represent one of the most critical yet underdiscussed challenges in surgical safety. In a highly populated country like India, even a small percentage of these errors poses significant damage. Wrong-patient errors typically stem from name similarities, while wrong-site surgeries often result from ambiguities involving paired organs or patient positioning and wrong procedure also may be due to patient name confusion. Current preventive measures rely on manually completed checklists from WHO (World Health Organization, 2009) and other organizations. To enhance accuracy and efficiency, we propose digitizing this process through a mobile application incorporating facial recognition technology.

Recent research demonstrates significant progress in facial recognition algorithms. (Azam, 2013) enhanced traditional Local Binary Pattern methods with advanced image processing techniques, achieving robust real-world performance. Similarly, (Wang et al., 2018) obtained improved recognition accuracy through Large Margin Cosine Loss (CosFace) in deep learning models. In (Chen et al., 2018) the authors present a class of extremely efficient CNN models, MobileFaceNets, which use less than 1 million parameters and are specifically tailored for high-accuracy real-time face verification on mobile and embedded devices. To ensure optimal performance of our facial recognition module, a comprehensive comparative analysis was conducted on four state-of-the-art algorithms: FaceNet (Schroff et al., 2015), Eigenfaces (Turk & Pentland, 1991), Fisherfaces (Anggo & La Arapu, 2018), and LBPH (Jothi Shri et al., 2019).

Rigorous testing across varying sample sizes (50-200 images) demonstrated FaceNet's consistent 100% recognition accuracy, significantly outperforming alternative approaches which showed accuracy fluctuations between 63-91%. This empirical validation led to FaceNet's selection as our core recognition engine. The results of the comparison are tabulated in Table 1 and its visual depiction is displayed in Figure 1.

Table 1. Comparative Analysis of different Algorithms

#Samples	FaceNet	Eigenfaces	FisAnherfaces	LBPH
50	100%	82%	76%	77%
100	100%	80%	82%	82%
150	100%	75%	85%	85%
200	100%	63%	89%	91%

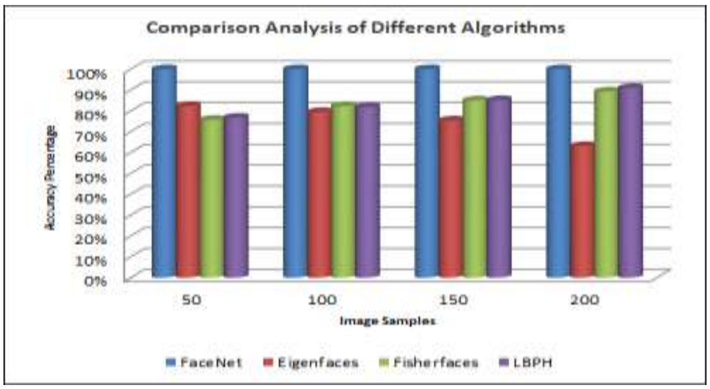

Figure 1. Comparative analysis of algorithm

Proposed System

This research proposes an Android based application, to streamline the surgical safety checklist process and ensure correct patient identification using a Deep-CNN-based FaceNet algorithm. The system aims to minimize human errors such as Wrong Site, Wrong Procedure and Wrong Patient adverse events (WSPEs) by combining digital checklists with real-time face recognition. Figure 2 depicts the proposed system workflow.

System Architecture & Workflow

The application operates through five key phases; each aligned with a specific point in the surgical process. These phases include user-specific digital forms and facial verification tasks, completed sequentially by doctors, nurses, and anesthetists. Identity verification using FaceNet is integrated in the first three phases before the skin incision.

Face Recognition Module: FaceNet maps patient facial images into a Euclidean space using deep CNN, trained via triplet loss, ensuring identity verification through comparisons between anchor, positive, and negative image embeddings.

Barcode Integration: Patient details are fetched from the Hospital Information System (HIS) via barcode scanning, ensuring accurate and consistent data association.

Enforced Compliance: The system uses force functions and automated alerts to ensure form completion before surgery steps. Email and device notifications remind users to complete pending forms and confirm patient details. Also, the surgeon will receive an email notification on the day of surgery having details of the patient and the scheduled surgery.

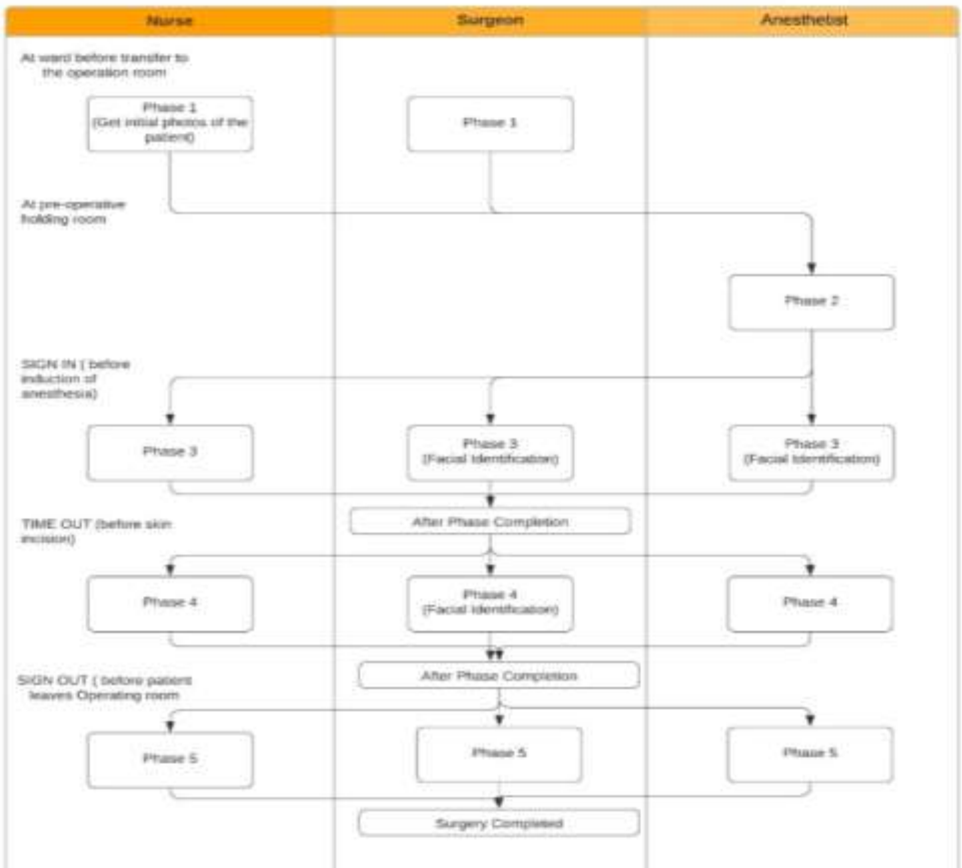

Figure 2. Proposed system workflow

Working Principle of the Application

The application is designed to ensure that all essential information is systematically collected from the respective medical personnel for every surgical procedure. This approach helps minimize errors like WSPEs by following a structured checklist format for recording surgical details and incorporates a machine learning-based identity verification mechanism. The identity verification process employs the FaceNet algorithm, which generates unified embeddings suitable for clustering, recognition, and verification. It maps facial images into a Euclidean space such that similar faces are positioned closer together. For instance, multiple images of the same individual will appear nearer to each other than to those of different individuals. Once embeddings are generated, standard domain-specific techniques can be used for various facial recognition tasks. FaceNet utilizes a Deep Convolutional Neural Network (CNN), trained using Stochastic Gradient Descent (SGD) with AdaGrad and standard backpropagation. Input images are preprocessed through scaling, transformation, and tight cropping around the facial region. A key component of FaceNet is the triplet loss function, which compares three images: anchor, positive, and negative. It ensures that the distance between the anchor and positive images (same person) is smaller than the distance between the anchor and negative images (different persons), thereby enabling accurate face similarity assessment. Table 2 provides a summarized overview of the five-phase workflow implemented in the proposed system, outlining the location, responsible users, key activities, and the role of facial recognition at each stage of the surgical process.

Table 2. Description of different phases in the proposed system

Phase	**Location & Responsibility**	**Key Activities**	**Facial Recognition Role**
Phase 1 – Admission	Ward (Doctor & Nurse)	Patient admission and entry of surgical details; initial data collection	Anchor image of the patient captured for later facial recognition; anesthetist not involved
Phase 2 – Pre-operative	Pre-op Holding Room (Anesthetist & Nurse)	Anesthetist obtains consent and assesses patient’s condition, allergies, etc.	Nurse captures current image; matched with anchor image via FaceNet for identity verification
Phase 3 – Sign In	Pre-surgery Area (All Users)	Final check before anesthesia; all forms to be filled; patient consent reconfirmed	Checklist includes facial ID verification button; FaceNet compares stored and live images to confirm identity
Phase 4 – Timeout	Operation Theater (All Users)	Final readiness check before skin incision; equipment and patient condition reviewed	Surgeon performs final ID check; alerts triggered if any checklist is incomplete
Phase 5 – Sign Out	Post-surgery (All Users)	Last confirmations before patient exits the operating room; review of surgery details and equipment status	No facial recognition; critical wrap-up tasks performed by all users

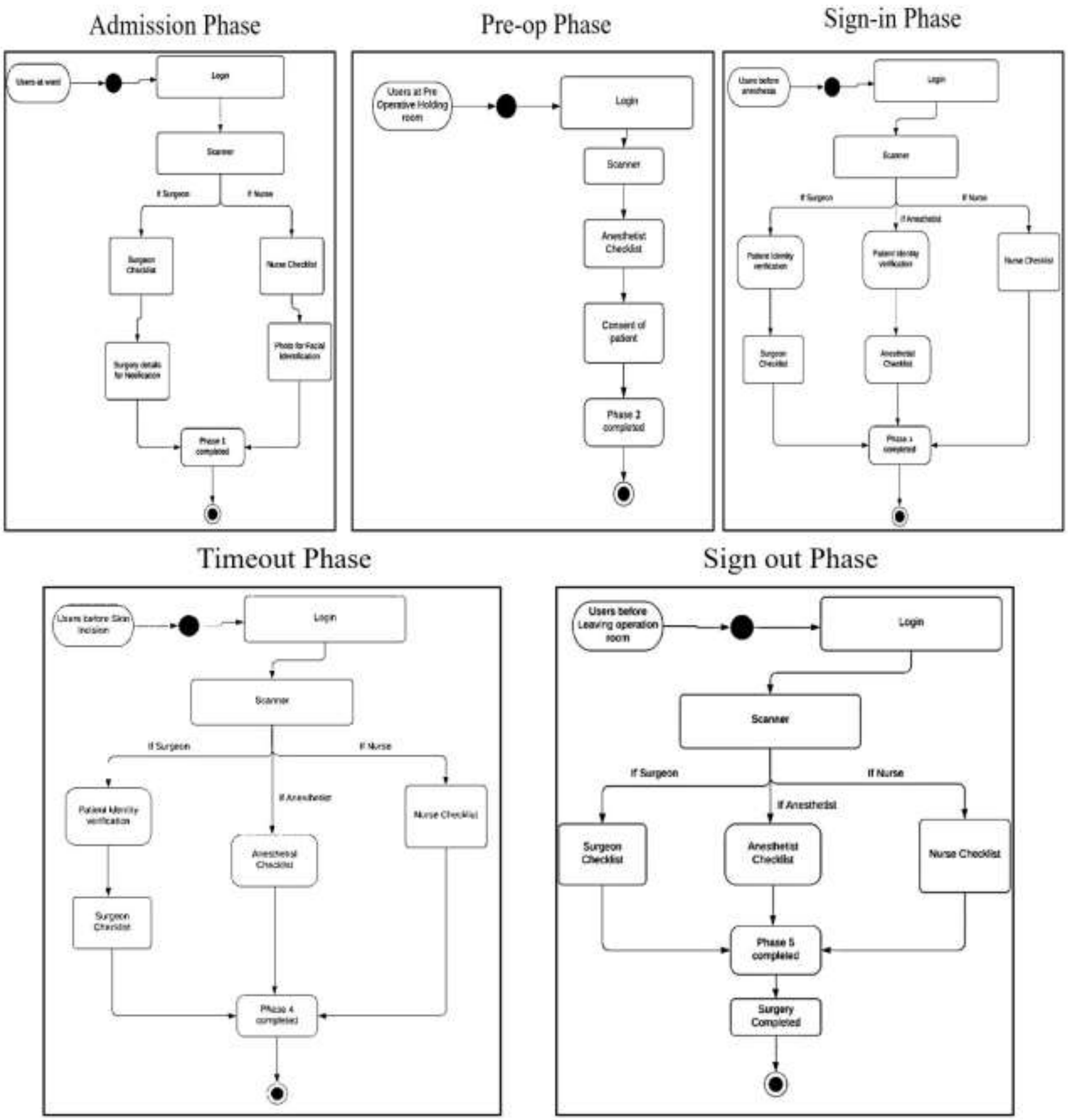

Figure 3. Different phases of the proposed system

To prevent Wrong-Site Surgery (WSS), a robust system is essential for verifying patient details and securing informed consent. The proposed application addresses this need by accurately collecting and displaying patient information and ensuring consent is obtained across multiple phases. To eliminate ambiguity in marking the surgical site, we introduce a reference terminology based on the anatomical position of unpaired organs, referring to the left and right sides of the body as "heart-side" and "liver-side," respectively. In accordance with established guidelines, the incision or insertion site must be clearly identified, and non-operative areas must not be marked. Marks should be made using an indelible pen to prevent smudging or transfer and must remain visible after the patient is prepped and draped. The marking should be performed by the surgeon or practitioner who obtained the consent, ideally while the patient is awake and aware. Wherever possible, involving a relative during this process is also encouraged for added accuracy and assurance. Figures 3 describes each phase of the proposed system.

Experimental Evaluation

To ensure reproducibility, the proposed system was developed and trained on an Ubuntu Linux platform using Python and the TensorFlow framework. For mobile deployment, the trained model was converted to TensorFlow Lite and integrated using Android Studio. The model was trained using Stochastic Gradient Descent with AdaGrad optimization, employing an initial learning rate of 0.05, a batch size of 32, and training over 50 epochs. A triplet loss function with a margin of 0.2 was used to learn 128-dimensional embeddings, with ReLU activation and L2 regularization ($\lambda = 0.0005$) applied to improve generalization. The proposed system underwent thorough evaluation using unit, integration, and validation testing, with all modules performing successfully. Integration testing particularly verified smooth interaction between the surgical checklist and facial recognition modules. The facial recognition component achieved a 100% detection rate and 98.33% recognition accuracy, resulting in an overall system accuracy of 100%. Table 3 and Figure 4 present the accuracy across various sample sizes. High performance was consistently observed under varying conditions, including changes in lighting, facial expressions, and pre/post-accident images, demonstrating the model's robustness. Efficiency was further improved by storing facial encodings instead of raw images, reducing storage and processing time.

Table 3. Detection and Recognition Accuracy for different sample size.

No of faces detected	**No of faces Recognized**	**No of faces failed to Recognize**
50	50	0
100	100	0
150	150	0
200	200	0
250	240	10
300	290	10
350	343	7
400	397	3

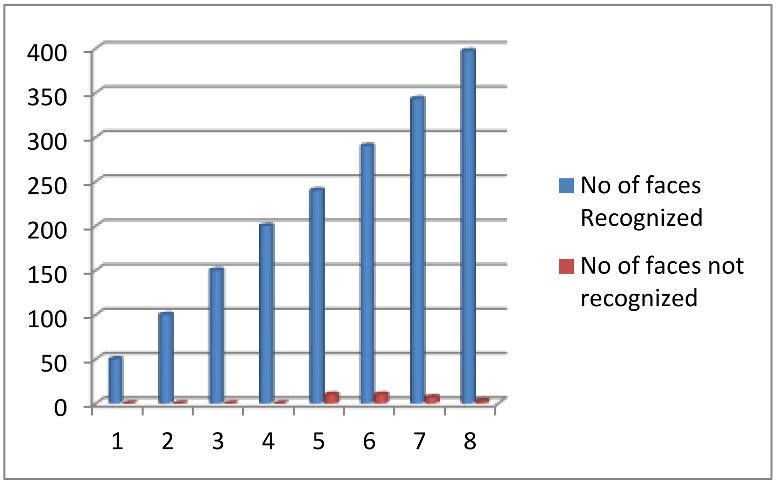

Figure 4. Visual representation of facial detection accuracy for different sample sizes

A 95% confidence interval for the recognition accuracy was calculated using a binomial proportion model, yielding an interval of 97.74% to 98.92%, indicating high reliability and consistency of the model across large sample sizes. The system achieved a 100% face detection rate and recognition accuracy remained at 100% up to 200 samples and showed a marginal decline for larger datasets. Overall recognition accuracy across 1,800 detected faces was calculated as 98.33%, with an error rate of 1.67%. All misclassifications corresponded to genuine users being rejected, resulting in a false rejection rate (FRR) of 1.67%.

Conclusion

The proposed AI-based mobile application reflects a pragmatic way of addressing the Wrong-Site, Wrong-Patient adverse events in high-volume surgical settings. The system can be used with automated patient identification through facial recognition and role-based surgical checklist to minimize errors caused by misidentification and non-adherence to the procedure and misidentification can be prevented through facial recognition which can fix almost 70% of the wrong-patient cases. The research in the future will be aimed at connecting the system with the current Hospital Information Systems (HIS) to facilitate a smooth flow of data and adoption of the workflow. Critical barriers to deployment such as clinician acceptance, infrastructure, and interoperability will be mitigated by means of usability optimization and gradual implementation. Moreover, the medical data privacy policies and clinical safety standards will also be adhered to aid in real-life implementation. In general, scalability of the proposed approach will reinforce WHO compliance with surgical safety and enhance patient outcomes, especially in resource-constrained healthcare facilities.

Acknowledgements

There is no grant or funding body to be acknowledged for this research work and for preparing this paper.

References

Anggo, M., & La Arapu, L. (2018). Face recognition using Fisherface method. *Journal of Physics: Conference Series, 1028*(1), 012119. https://doi.org/10.1088/1742-6596/1028/1/012119

Azam, M. A. R. N. H. N. H. W. W. S. A. S. (2013). *Face recognition using local binary patterns (LBP)*. ResearchGate. https://www.researchgate.net/publication/331645500_Face_Recognition_using_Local_Binary_Patterns_LBP

Chen, S., Liu, Y., Gao, X., & Han, Z. (2018). MobileFaceNets: Efficient CNNs for accurate real-time face verification on mobile devices. In *Lecture notes in computer science* (Vol. 10996, pp. 428–438). Springer. https://doi.org/10.1007/978-3-319-97909-0_46

Jothi Shri, S., Jothilakshmi, S., & Jawaherlalnehru, G. (2019). Real-time face recognition in group images using LBPH. *International Journal of Recent Technology and Engineering, 8*(2), 1362–1367. https://doi.org/10.35940/IJRTE.B2015.078219

Schroff, F., Kalenichenko, D., & Philbin, J. (2015). FaceNet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 815–823). https://doi.org/10.1109/CVPR.2015.7298682

Turk, M., & Pentland, A. (1991). Eigenfaces for recognition. *Journal of Cognitive Neuroscience, 3*(1), 71–86. https://doi.org/10.1162/jocn.1991.3.1.71

Wang, H., Wang, Y., Zhou, Z., Ji, X., Gong, D., Zhou, J., Li, Z., & Liu, W. (2018). CosFace: Large margin cosine loss for deep face recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5265–5274). https://doi.org/10.1109/CVPR.2018.00552

World Health Organization. (2009). *WHO surgical safety checklist*. https://www.who.int/docs/default-source/patient-safety/9789241598590-eng-checklist.pdf