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Risk Prediction Models for Prevention of Complications in Medical and Surgical Nursing: A Narrative Review of Pressure Injury, Venous Thromboembolism, Falls and Postoperative Delirium

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Abstract: Hospital-acquired complications remain major threats to patient safety and quality of nursing care. Pressure injury, venous thromboembolism, inpatient falls, and postoperative delirium are common among medical and surgical patients, particularly older adults, critically ill patients, postoperative patients, immobile patients, and those with multimorbidity. Traditional nursing risk assessment relies largely on clinical judgment and standardized scales, which are useful but may be insufficient for dynamic and individualized risk prediction. Recent studies have increasingly explored electronic health record-based models, artificial intelligence, machine learning, clinical decision support systems, and specialty-specific prediction tools to identify high-risk patients earlier and guide targeted nursing interventions. This review summarizes current progress in nursing-relevant risk prediction models for common medical and surgical complications, discusses their clinical application in pressure injury, venous thromboembolism, falls, and delirium prevention, and highlights methodological and implementation challenges. It further emphasizes that prediction models should not be treated as isolated statistical tools, but as part of a practical nursing safety system that connects risk identification with bedside decision-making, patient education, intervention delivery, outcome monitoring, and continuous quality improvement. Future nursing research should move from model development alone toward closed-loop systems that integrate prediction, alerting, stratified intervention, outcome evaluation, and workflow optimization.

1. Introduction

Patient safety is a core dimension of nursing quality. Medical and surgical inpatients are vulnerable to preventable or partly preventable complications because of acute illness, invasive treatment, immobility, surgery, anesthesia, polypharmacy, cognitive impairment, malnutrition, and comorbid disease. Pressure injury, venous thromboembolism, falls, and postoperative delirium are particularly important because they increase pain, disability, length of stay, cost, caregiver burden, and mortality risk [1]. These complications also reflect the complexity of modern inpatient care, where patients are often older, have multiple chronic conditions, and require continuous coordination among nurses, physicians, rehabilitation therapists, pharmacists, dietitians, and family caregivers.

Historically, nursing risk assessment has relied on standardized tools and bedside clinical judgment. For example, the Braden Scale and Waterlow Scale are widely used to assess pressure injury risk [2]. Caprini-based tools are commonly used to evaluate venous thromboembolism risk [3]. Fall-risk tools and delirium screening instruments are also widely implemented in hospitals. These tools are practical and familiar, but they often provide static assessments and may not fully capture rapidly changing clinical conditions. In real clinical practice, patient risk may change within hours because of surgery, sedation, infection, pain, new medications, hemodynamic instability, sleep disturbance, or changes in mobility. Therefore, a single admission assessment may be insufficient to guide prevention throughout hospitalization [4].

With the growth of electronic health records, large clinical datasets, and artificial intelligence, risk prediction in nursing is entering a new stage. Prediction models can integrate demographic characteristics, vital signs, laboratory tests, medication exposure, nursing documentation, functional status, and procedural factors to estimate individual risk [5]. These models may help nurses identify high-risk patients earlier, allocate prevention resources more efficiently, and deliver interventions before complications occur. For nursing practice, the goal is not only to predict complications but also to trigger timely, feasible, and targeted preventive care.

However, risk prediction should be understood carefully. A model with high statistical performance does not automatically improve patient outcomes. If a prediction score is not understandable, not trusted by nurses, not linked to clear interventions, or not embedded in daily workflow, it may create additional workload without reducing harm [6]. Therefore, nursing-relevant prediction models must be evaluated not only by accuracy, but also by interpretability, usability, clinical usefulness, fairness, and impact on patient safety. This review focuses on four common complications in medical and surgical nursing: pressure injury, venous thromboembolism, inpatient falls, and postoperative delirium. These conditions were selected because they are common, clinically significant, closely related to nursing care, and increasingly studied through electronic health record-based or machine learning prediction models [7].

2. Pressure Injury Risk Prediction and Prevention

2.1. Traditional Risk Assessment

Pressure injury is one of the most recognized nursing-sensitive adverse events. It is common among immobile, critically ill, older, malnourished, postoperative, orthopedic, and neurologically impaired patients. Pressure injury can cause pain, infection, delayed rehabilitation, longer hospitalization, increased cost, and reduced quality of life. It also places additional physical and emotional burden on patients and families. Because pressure injury is often preventable or reducible through early nursing intervention, accurate risk assessment is a central component of nursing safety management [8].

Traditional assessment tools such as the Braden Scale evaluate sensory perception, moisture, activity, mobility, nutrition, friction, and shear. The Waterlow Scale includes additional factors such as body mass index, skin type, sex, age, continence, mobility, appetite, medication, and special risks. These tools provide a structured method for identifying patients who may need preventive care. They are easy to apply, familiar to nurses, and useful for routine screening. They also support communication among nursing staff because risk status can be documented and transferred during handover.

These tools are useful for routine screening, but their predictive performance varies across populations and settings [9]. For example, an ICU patient’s risk may change rapidly because of vasopressors, ventilation, edema, sedation, hemodynamic instability, and device use [10]. A surgical patient's risk may be influenced by operation duration, anesthesia, blood loss, positioning, and postoperative mobility. An orthopedic patient may be unable to reposition because of pain, traction, casts, or surgical restrictions [11]. A patient with high body mass index may face increased interface pressure, skin fold moisture, and greater difficulty with repositioning [12]. Therefore, static scale-based assessment may fail to capture dynamic and specialty-specific risks.

Another limitation is that traditional scales may classify many patients as high risk, especially in intensive care or surgical wards. When too many patients receive the same risk level, nurses may find it difficult to prioritize preventive resources. In addition, scale scores may depend on subjective judgment, and scoring consistency can vary among nurses. These limitations do not mean that traditional scales should be abandoned. Instead, they suggest that pressure injury risk assessment should combine standardized scales, clinical judgment, specialty-specific risk factors, and data-driven prediction models.

2.2. Electronic Health Record and Machine Learning Models

Recent reviews show increasing interest in pressure injury prediction models based on electronic health records and artificial intelligence. These models may incorporate variables such as age, diagnosis, length of stay, mobility, nutritional status, albumin, hemoglobin, Braden score, vital signs, surgical duration, ICU admission, vasopressor use, and nursing documentation [13]. In surgical critical care, electronic health record-based models have been used to predict hospital-acquired pressure injury and support earlier preventive action. Compared with traditional scales, electronic models may update risk more frequently and identify complex interactions among clinical variables.

Artificial intelligence and decision support systems may improve prediction by processing complex interactions among multiple variables. For example, a patient with moderate immobility may not appear extremely high risk by a single scale score, but the combination of low albumin, anemia, fever, hypotension, vasopressor use, device pressure, and prolonged surgery may indicate increased risk. Machine learning methods can potentially detect such combined patterns. Electronic models can also reduce repeated manual scoring if they automatically extract data from existing records.

However, model performance alone is not enough. A model must be interpretable, externally validated, integrated into nursing workflow, and linked to prevention protocols. Otherwise, alerts may increase workload and alarm fatigue without improving outcomes. Nurses need to know why a patient is considered high risk and what action should follow. A risk score without explanation may be ignored, especially if it conflicts with bedside observation. Therefore, pressure injury prediction models should provide clinically meaningful risk factors, such as immobility, low nutrition, hemodynamic instability, device use, or moisture exposure, so that nurses can select appropriate interventions [14].

Another important issue is data quality. Electronic health record data are only useful if documentation is complete, timely, and accurate. Nursing notes may contain important information about skin condition, turning tolerance, moisture, device pressure, pain, and mobility, but these data may be recorded inconsistently or in free-text format. Predictive models should therefore be developed with attention to real nursing documentation practices. Nurse involvement in model design is essential because nurses understand which variables are clinically meaningful, which alerts are actionable, and which workflow steps may create unnecessary burden.

2.3. Nursing Prevention Strategies

Pressure injury prevention remains intervention-dependent. Key measures include regular risk assessment, skin inspection, repositioning, pressure redistribution surfaces, moisture management, nutritional support, device-related pressure injury prevention, and staff education [15]. For orthopedic patients, prevention should consider postoperative immobility, traction, casts, pain, and limited repositioning. For patients with high body mass index, prevention requires attention to skin folds, repositioning difficulty, equipment fit, and higher interface pressure.

Risk prediction models can support pressure injury prevention by identifying patients who need intensified turning schedules, specialized mattresses, nutritional consultation, skin-protection products, or more frequent monitoring. For example, a low-risk patient may need routine skin assessment and mobility encouragement, whereas a high-risk ICU patient may require a pressure redistribution surface, strict repositioning plan, moisture control, device padding, nutritional support, and daily multidisciplinary review. A patient with device-related risk may require targeted inspection under oxygen tubing, masks, catheters, braces, or compression devices.

The future direction is a closed-loop system in which risk scores automatically trigger nursing interventions and outcomes are continuously evaluated [16]. In such a system, risk prediction would not stop at alert generation. Instead, the electronic health record could recommend a prevention bundle, remind nurses of skin inspection, prompt documentation of turning, and track whether pressure injuries occur. Unit-level data could then be used for quality improvement. This approach may help transform prediction from a passive score into an active nursing safety process.

3. Venous Thromboembolism Risk Prediction and Nursing Management

3.1. Clinical Importance

Venous thromboembolism, including deep vein thrombosis and pulmonary embolism, is a serious complication among surgical, trauma, cancer, neurological, and immobilized patients [17]. VTE can be clinically silent until severe events occur. Therefore, early risk assessment and prevention are essential nursing responsibilities. Nurses support VTE prevention through risk screening, patient education, early mobilization, mechanical prophylaxis, anticoagulant monitoring, bleeding surveillance, and coordination with physicians. Because VTE prevention often involves both pharmacological and nonpharmacological measures, nursing care plays an important role in translating risk assessment into daily prevention.

Hospitalized patients may develop VTE because of venous stasis, endothelial injury, hypercoagulability, immobility, inflammation, cancer, trauma, surgery, central venous catheterization, or neurological impairment. Surgical patients are at increased risk because tissue injury, anesthesia, postoperative immobility, and inflammatory responses can promote thrombosis. Cancer patients may have additional thrombotic risk related to malignancy itself, chemotherapy, surgery, and central venous access [18]. Neurocritical patients may have impaired consciousness, paralysis, mechanical ventilation, and prolonged immobility, making risk assessment particularly important [19].

From a nursing perspective, VTE prevention requires continuous observation and patient participation. Nurses encourage early mobilization, ensure correct use of compression devices, monitor adherence to prophylaxis, observe for bleeding complications, and educate patients about warning symptoms. Patients should understand why they are encouraged to move early, why compression devices should not be removed without instruction, and why symptoms such as calf swelling, calf pain, dyspnea, chest pain, or unexplained tachycardia should be reported promptly.

3.2. Prediction Models and Machine Learning

Traditional VTE risk assessment often uses structured models such as the Caprini score. Recent studies have attempted to improve VTE prediction by incorporating laboratory markers, specialty-specific factors, and machine learning methods. For neurocritical patients, prediction models may include immobility, consciousness level, neurological deficits, mechanical ventilation, central venous catheterization, and coagulation indicators. For colorectal cancer surgery, machine learning-based models and web calculators have been developed to estimate postoperative lower limb DVT risk [20]. The integration of D-dimer thresholds into revised Caprini assessment has also been explored to improve prediction of deep vein thrombosis.

Systematic reviews of machine learning models for VTE prediction suggest that artificial intelligence may support individualized risk stratification, but methodological limitations remain [21]. Many models require external validation, calibration assessment, transparent reporting, and evaluation of clinical usefulness. A model that performs well statistically may still fail clinically if it does not change prevention behavior or reduce VTE events. For example, if a model identifies high-risk patients but does not guide prophylaxis decisions or nursing monitoring, its practical value will be limited.

VTE prediction models should also consider the balance between thrombosis risk and bleeding risk. High-risk patients may benefit from pharmacological prophylaxis, but anticoagulation may be unsafe for some patients after surgery, trauma, hemorrhage, or invasive procedures. Nurses need clear protocols for monitoring bleeding, such as bruising, wound bleeding, hematuria, gastrointestinal bleeding, abnormal laboratory findings, or sudden hemodynamic changes. Therefore, prediction models should support rather than replace multidisciplinary judgment.

3.3. Nursing Application

The nursing value of VTE prediction lies in risk-stratified prevention. Low-risk patients may require education and routine mobility encouragement. Moderate-risk patients may require structured early ambulation and mechanical prophylaxis. High-risk patients may require close monitoring, pharmacologic prophylaxis management, bleeding assessment, and escalation when symptoms occur [22]. Risk stratification can help nurses prioritize care, especially in busy wards where many patients need assistance with mobility and preventive devices.

Early mobilization is a key nonpharmacological strategy for DVT prevention [23]. Nurses should assess pain, dizziness, blood pressure, surgical restrictions, and lines before mobilization. They should also evaluate whether patients understand the mobilization plan and whether family members can assist safely when appropriate. For patients unable to walk, nurses can encourage leg exercises, position changes, and gradual sitting or standing as clinically allowed. Mechanical prophylaxis requires correct size, correct placement, regular skin checks, and patient cooperation. If compression devices are uncomfortable or removed frequently, nurses should identify the reason and provide education or adjustment.

Nurses should also educate patients to report calf pain, swelling, dyspnea, chest pain, or unexplained tachycardia. For cancer-associated VTE, evidence-based anticoagulant management and patient education are particularly important. Nurses’ knowledge and practice regarding VTE prevention directly influence implementation quality. Therefore, risk prediction models should be paired with nurse training, prevention checklists, and clear escalation pathways. The best use of prediction is not simply labeling a patient as high risk, but ensuring that high-risk status leads to visible and consistent prevention actions.

4. Inpatient Fall Risk Prediction and Prevention

4.1. Multifactorial Nature of Falls

Inpatient falls are common adverse events associated with injury, fear, prolonged hospitalization, and litigation [24]. Falls may cause fractures, head injuries, soft tissue injury, pain, reduced mobility, loss of independence, and psychological fear of future falls. Even when no physical injury occurs, a fall can reduce patient confidence and increase family concern. For hospitals, falls are important quality indicators because many fall events are related to environmental safety, medication effects, mobility assistance, communication, and observation.

Fall risk is multifactorial and may involve age, previous falls, impaired mobility, muscle weakness, cognitive impairment, delirium, urinary urgency, sedatives, antihypertensives, hypoglycemia, environmental hazards, poor footwear, and lack of assistance. Medical patients may fall because of weakness, infection, dizziness, or medication changes. Surgical patients may fall because of pain, anesthesia effects, drains, unfamiliar mobility restrictions, or attempts to walk without help. Older adults with cognitive impairment or delirium may not remember instructions and may attempt to get out of bed unexpectedly.

Traditional fall-risk scales can provide structured assessment, but they may not fully capture changing risk during hospitalization. For example, a patient may become high risk after receiving sedatives, developing infection, experiencing orthostatic hypotension, or becoming confused at night. A patient who appears stable during the day may be at high risk during nighttime toileting. Therefore, fall prevention requires dynamic reassessment rather than one-time screening. Nurses should combine formal risk tools with observation of gait, balance, cognition, toileting patterns, medication effects, and patient behavior.

4.2. Artificial Intelligence and Prediction Models

Machine learning-based fall prediction models have received increasing attention. These models can analyze electronic health record data, medication exposure, nursing notes, mobility status, diagnosis, laboratory values, and prior events to identify high-risk patients. Artificial intelligence may improve sensitivity by detecting complex nonlinear patterns that are difficult to capture with traditional scales [25]. For example, a combination of nighttime confusion, new sedative exposure, urinary urgency, prior fall history, and low blood pressure may indicate higher fall risk than any single factor alone.

However, fall prediction models face several challenges. Falls are relatively infrequent events, which may cause class imbalance in model development. Risk factors vary across units, such as medical wards, surgical wards, rehabilitation units, and ICUs. Moreover, prediction must be timely; a risk score generated too late may not prevent harm. Therefore, models should be updated dynamically and integrated with actionable nursing measures. A fall prediction score should ideally change when new medications are prescribed, when delirium develops, when mobility declines, or when vital signs suggest instability.

Interpretability is particularly important for fall prediction. If a model only reports a high-risk label, nurses may not know whether the main cause is medication, mobility, cognition, toileting, or environment. Different causes require different interventions. A patient at risk because of urinary urgency may need scheduled toileting, while a patient at risk because of sedatives may need medication review and closer observation. Therefore, fall prediction models should identify modifiable risk factors and connect them with tailored prevention bundles [26].

4.3. Nursing Prevention Strategies

Fall prevention should be individualized by risk level and cause. General measures include environmental safety, call-bell accessibility, adequate lighting, nonslip footwear, bed-height adjustment, mobility assistance, patient and family education, and toileting plans. High-risk patients may require closer observation, medication review, bed or chair alarms, assisted ambulation, and delirium prevention. Nurses should also ensure that commonly used items are within reach and that patients understand when and how to call for help.

Prediction models can help allocate nursing attention more efficiently. However, they should not replace bedside assessment. Nurses must interpret risk scores in context, especially when patients have sudden changes in consciousness, mobility, medication, or hemodynamic status. The most useful models will be those that identify modifiable risk factors and suggest prevention bundles. For example, a model that indicates risk related to hypotension could prompt blood pressure monitoring before ambulation, while a model indicating risk related to delirium could trigger orientation, sleep support, and family involvement.

Fall prevention also requires communication. During handover, nurses should report not only that a patient is high risk, but why the patient is high risk and what has been done. For example, “high fall risk due to nighttime confusion and urinary urgency; scheduled toileting and assisted ambulation are required” is more useful than a general risk label. Family education is also important because families may encourage patients to move without understanding restrictions. A prediction-informed approach should therefore support shared awareness among nurses, patients, caregivers, and other team members.

5. Postoperative Delirium Risk Prediction and Nursing Intervention

5.1. Clinical Significance

Postoperative delirium is an acute neurocognitive disorder characterized by fluctuating attention, consciousness, and cognition [27]. It is common among older surgical patients, ICU patients, cardiac surgery patients, and patients undergoing major operations. Delirium is associated with longer hospitalization, higher complication rates, functional decline, long-term cognitive impairment, and increased mortality. It may present as agitation, restlessness, hallucinations, disorientation, or unsafe behavior, but it can also present as quiet withdrawal, sleepiness, reduced attention, and decreased communication. Hypoactive delirium may be easily missed if nurses do not actively assess attention and cognition.

Nurses are often the first professionals to observe early delirium signs, such as sleep-wake disturbance, inattention, disorientation, agitation, withdrawal, or fluctuating consciousness. Therefore, delirium prediction and prevention are highly relevant to nursing practice. Early recognition is important because delirium may indicate underlying problems such as infection, hypoxia, pain, medication effects, dehydration, electrolyte imbalance, urinary retention, constipation, or sleep deprivation. Nursing observation can help identify these contributing factors before delirium worsens.

Postoperative delirium is not only a neurological problem. It is also connected with pain control, sleep quality, mobility, hydration, sensory impairment, environmental stimulation, family presence, and medication safety. Therefore, prevention requires coordinated nursing care. Risk prediction models can help nurses identify patients who need more intensive delirium prevention before symptoms appear.

5.2. Prediction Models

Systematic reviews have summarized risk prediction models for ICU delirium and postoperative delirium. Common predictors include age, baseline cognitive impairment, disease severity, comorbidities, emergency surgery, anesthesia duration, infection, pain, sedative use, mechanical ventilation, electrolyte imbalance, sleep disturbance, and functional dependence. Machine learning models have also been explored for postoperative delirium prediction. [28] These models may support earlier identification of vulnerable patients, especially in high-risk areas such as ICUs, cardiac surgery units, and major surgical wards.

Despite progress, delirium prediction models face limitations. Some models are derived from specific surgical populations and may not generalize to other settings. Others lack external validation or are not integrated into clinical workflows. Predictive accuracy should be evaluated together with clinical usefulness, because a model is valuable only if it leads to prevention or earlier management. In addition, delirium outcome definitions may vary among studies, and underdiagnosis can affect model development. If delirium is not consistently screened and documented, the model may learn from incomplete or biased outcome data.

Delirium prediction models should also be designed to support nursing action. A useful model should tell nurses not only that a patient is high risk, but also which factors contribute to that risk. For example, if risk is driven by sleep disturbance, sedative exposure, sensory impairment, and immobility, nurses can apply targeted interventions. If risk is driven by infection, hypoxia, or electrolyte imbalance, nurses should communicate promptly with physicians for medical evaluation. In this way, prediction can become a bridge between early warning and multidisciplinary prevention.

5.3. Nursing Prevention and Management

Delirium prevention requires multicomponent nursing strategies. These include orientation, sleep promotion, pain control, early mobilization, hydration, sensory aids, family engagement [29], avoidance of unnecessary restraints, reduction of nighttime disturbance, and careful observation of sedative effects [30]. In ICUs, minimizing excessive sedation, promoting day-night rhythm, and early mobilization are particularly important. Nurses should also help patients use glasses and hearing aids when needed, because sensory deprivation can worsen confusion and disorientation.

Risk models may allow nurses to identify high-risk patients before delirium occurs. For example, an older cardiac surgery patient with baseline cognitive impairment, long anesthesia exposure, sleep disruption, and postoperative infection would require enhanced monitoring and nonpharmacological prevention [31]. Nurses should also educate families to recognize changes in attention and behavior. Family members may notice subtle differences in personality, memory, or responsiveness that are not obvious during brief clinical assessments [32].

Once delirium occurs, nursing management should focus on safety, comfort, identification of contributing factors, and prevention of complications. Patients with delirium may remove tubes, fall, refuse treatment, or become frightened. Nurses should avoid unnecessary restraints when possible and instead use reassurance, reorientation, family presence, environmental adjustment, and close observation. Pain, urinary retention, constipation, hypoxia, fever, dehydration, and medication effects should be assessed [30]. Prediction models cannot replace clinical care, but they can help nurses anticipate risk and begin prevention earlier.

6. From Prediction to Closed-Loop Nursing Safety Management

Risk prediction should be viewed as the first step in a closed-loop safety system. A complete model-based nursing pathway includes risk assessment, risk alert, intervention selection, intervention implementation, outcome monitoring, and feedback improvement. Without this loop, prediction remains a statistical exercise rather than a patient safety intervention. In nursing practice, the value of a model depends on whether it changes care at the right time, in the right patient, and in a way that is feasible for nurses to perform [33].

Closed-loop nursing systems should specify which risk thresholds trigger which interventions. For pressure injury, high risk may trigger a turning plan, pressure-relieving surface, nutritional assessment, and daily skin inspection. For VTE, high risk may trigger mechanical prophylaxis, early mobilization, anticoagulant surveillance, and symptom education [34]. For falls, high risk may trigger environmental modification, toileting assistance, medication review, and closer observation. For delirium, high risk may trigger sleep protocol, orientation, sensory support, and early mobilization.

A closed-loop system should also include documentation and evaluation. Nurses need to know whether recommended interventions were completed, whether barriers existed, and whether the patient's risk changed. For example, if a high-risk pressure injury patient cannot tolerate repositioning because of pain, the care plan should be modified rather than simply marked incomplete. If a high-risk fall patient repeatedly attempts to get out of bed at night, the prevention plan should be adjusted with toileting, observation, and environmental changes. Feedback from outcomes can help improve both the prediction model and nursing workflow.

In addition, closed-loop management requires teamwork. Nurses cannot prevent all complications alone. Physicians, pharmacists, dietitians, rehabilitation therapists, wound care specialists, information technology staff, and hospital managers all contribute to prevention. For example, VTE prevention may require physician orders for prophylaxis, pharmacist review of anticoagulants, nurse monitoring, and patient cooperation. Delirium prevention may require medication review, sleep support, early mobilization, and family engagement. Therefore, risk prediction systems should support multidisciplinary communication rather than placing responsibility solely on nurses [35].

7. Methodological and Implementation Challenges

Several methodological issues limit current prediction-model research. First, many studies are single-center and lack external validation. A model developed in one hospital may not perform well in another hospital because of differences in patient population, documentation style, prevention protocols, staffing, equipment, and outcome definitions [36]. External validation is necessary before broad implementation. Second, outcome definitions vary, making comparison difficult. For example, pressure injury staging, fall injury classification, VTE screening practices, and delirium detection methods may differ across studies and institutions[37].

Third, missing data and inconsistent nursing documentation may reduce model reliability. Nursing-relevant variables such as mobility, skin condition, pain, sleep, nutrition, and cognition are essential for prediction, but they may not be recorded in structured fields [38]. Fourth, some machine learning models lack interpretability, making it difficult for nurses to understand why a patient is classified as high risk. This is a major barrier because nurses need clinically meaningful reasons to trust and act on model outputs [39]. Fifth, few studies evaluate whether prediction models actually reduce complications after implementation. Many studies report model performance measures, but fewer test whether model-guided interventions improve patient outcomes [40].

Implementation challenges are equally important. Risk alerts may contribute to alarm fatigue if too frequent or poorly targeted. Nurses may distrust models if predictions conflict with bedside judgment. Models may also worsen inequity if they are trained on biased datasets or fail in underrepresented populations. Therefore, nursing involvement in model design, validation, and implementation is essential. Nurses can help determine which alerts are useful, which thresholds are reasonable, which interventions are feasible, and how prediction should appear in workflow.

Another challenge is balancing automation with professional judgment. Data-driven models may identify patterns that are not obvious to clinicians, but they may also miss contextual information that nurses observe at the bedside. For example, a patient may appear low risk in electronic data but become unsafe because of new confusion, emotional distress, family absence, or refusal to follow instructions. Conversely, a patient may be labeled high risk but have strong support and good functional ability [41]. Therefore, prediction models should support nursing judgment rather than replace it.

8. Future Directions

Future research should prioritize clinically useful and nurse-centered prediction models. First, models should be developed and validated across multiple hospitals and patient populations. Multicenter validation can improve generalizability and identify whether model performance differs by age, sex, diagnosis, surgical type, unit, or comorbidity. Second, predictive variables should include nursing-relevant data such as mobility, skin condition, nutrition, cognition, pain, sleep, device use, and self-care ability. These variables are important because they are closely connected with both risk and nursing intervention.

Third, models should be interpretable and able to identify modifiable risk factors. A risk score is more useful when nurses can see whether risk is related to immobility, nutrition, medication, cognitive change, device pressure, or hemodynamic instability. Fourth, electronic health record integration should minimize manual data entry and avoid increasing nursing workload. Prediction systems should fit into existing nursing workflows, handovers, care plans, and quality improvement systems.

Most importantly, future studies should move beyond predictive accuracy and test patient outcomes. Randomized or pragmatic implementation studies are needed to determine whether model-guided nursing interventions reduce pressure injury, VTE, falls, delirium, length of stay, cost, and patient harm. Patient and family engagement should also be incorporated because many prevention strategies require cooperation, especially mobilization, skin care, hydration, and symptom reporting. A model that helps nurses communicate risk to patients and families may improve adherence and shared responsibility.

Future work should also explore how prediction models can support precision nursing. Instead of giving the same prevention bundle to all high-risk patients, models may help classify patients according to risk mechanism. For example, a fall-risk model may distinguish medication-related risk from mobility-related risk or delirium-related risk. A pressure injury model may distinguish immobility-related risk from nutrition-related risk or device-related risk. This kind of risk phenotyping can help nurses select more targeted interventions and avoid unnecessary workload.

Finally, ethical and governance issues should be considered. Hospitals should monitor whether prediction models perform equally across different patient groups and whether alerts lead to appropriate care. Patients should benefit from data-driven prediction without losing human-centered care. Nurses should be trained to understand model outputs, question them when needed, and use them as part of professional judgment. In this way, prediction models can become practical tools for safer and more individualized medical and surgical nursing.

9. Conclusion

Risk prediction models offer a promising pathway for improving medical and surgical nursing safety. Evidence is growing for pressure injury, venous thromboembolism, fall, and postoperative delirium prediction using traditional scales, electronic health records, and machine learning methods. These models may help nurses identify high-risk patients earlier, prioritize prevention resources, and support more individualized care. However, prediction alone cannot improve patient outcomes unless it is connected to timely and feasible nursing interventions.

Future nursing safety systems should integrate data-driven risk prediction with bedside judgment, stratified prevention bundles, workflow-friendly alerts, and continuous outcome evaluation. The most valuable models will be those that are accurate, interpretable, externally validated, easy to use, and directly connected with nursing action. Pressure injury, VTE, falls, and postoperative delirium prevention all require more than risk labeling; they require ongoing assessment, patient participation, multidisciplinary coordination, and feedback-driven improvement. By moving from isolated prediction models toward closed-loop nursing safety management, medical and surgical nursing can better prevent complications, reduce patient harm, and improve the quality of inpatient care.

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