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Artificial Intelligence-Driven and Technology-Interventions for the Prediction and Mitigation of Emergency Department Nurse Burnout

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Abstract. Background: Emergency department nurses face a high risk of burnout due to high-intensity workloads, long working hours and workplace violence, which is associated with the quality of care and increases nurse turnover. Traditional interventions often lack dynamic adjustment capabilities. Methods: This narrative review integrates research on burnout monitoring and prediction, system-level interventions, and individual-level interventions. Results: Machine learning models trained on questionnaire data can tell whether it is a risk when burning out. Wearable devices enable real-time monitoring to prevent burnout at the early stage of detection. But the problem also needs to be resolved with attention to compliance and measurement sensitivity. The problem also needs to be addressed in terms of compliance and recognition of sensitivity. AI-assist scheduling and prediction make system less unequal and lessen work burden. In terms of individuals, modules and digital psychological interventions through the just in time adaptive intervention framework with algorithm matching and the hybrid model of self-selection is to improve the user's interaction. Conclusions: AI-driven interventions for burnout among emergency department nurses provide evidence for the feasibility of proactive, closed-loop intervention programs. It is better to pay more attention to predicting the results of prediction. Translating this into concrete actions and sustaining it over the long term can effectively reduce burnout and maintain a good nursing turnover rate.

Keywords: emergency department nurses, burnout, artificial intelligence, machine learning

1. Introduction

Owing to high-intensity workloads, long working hours and workplace violence, emergency department nurses are at risk of burnout. According to the World Health organization's ICD-11, burnout is a syndrome conceived as resulting from chronic workplace stress that has not been successfully managed. Research shows that ED nurse burnout is strongly associated with care quality and patient safety. It also increases ED nurses' willingness to leave their position and exacerbates the shortage of emergency room staff. In New York, Illinois, and other places, a total of 58 percent of ED Nurses get burned out in a year and intended to leave the job [1].

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Prior approaches have been mainly focusing on the changes of personnel, leadership support and stress management courses. These approaches aim to reduce stress and enhance coping abilities in a non-sudden manner for all nurses. As the development of Artificial Intelligence, there has been a lot more personalized and dynamic solutions being proposed by the research that is focusing on AI based scheduling system for person according to what they choose, and there will be an AI assisted tailor system for stress management. But most of them focus only on one thing, or some factors that causes nursing staff to burn out [2,3]. Although AI has increased in terms of people's abilities like continuous observation, organizational adjustment and individual support, they aren't practical in workflow but there's no study carried out on these.

The research has analyzed the three aspects of the study, which is monitoring and prediction, the systematic intervention and individual intervention, to obtain some references for subsequent studies on the closed-loop interventions for burnout.

2. Monitoring and prediction of burnout

Research into the causes of burnout often combines questionnaires (e.g., the Maslach Burnout Inventory) with statistical analysis to identify related factors. However, these statistical analyses are conducted after burnout has occurred and have the disadvantage of not being suitable for early warning [4]. ED nurses often need to respond to patients requiring rapid treatment, and the increased burden of record-keeping affects patient safety and quality of care, relying on nurses' breaks to conduct surveys can lead to recall bias. Therefore, a key requirement for closed-loop interventions is the ability to continuously and accurately monitor nursing tasks without disrupting them.

One method for it is using the survey data to make a prediction of risks related to burnout [4]. proposes training a machine learning model that can predict burnout risk using statistical analysis of survey-derived data and machine learning. This study found that emotional exhaustion is the most central and most frequently reported dimension and is often associated with adverse health outcomes. The model is used to monitor the performance of hospital nurses by collecting data from 143 hospitals in South Africa during April and June 2021-2022. Because the data were not from emergency departments, it needs to be examined whether the results are applicable to emergency nurses. But also, the progress of research has gone a bit farther. When burnout outcomes are categorized into two binary variables, one is to have just single item measure of MBI-Q5 number of times my body feels tired, and secondly also has it on MBI as well. Based on the results of this study, work-related factors such as job experience, fatigue and trust in management and staffing capacity are more likely to cause burnout than demographic characteristics like age and duration of employment. Conclusion shows that emphasis mainly on works place to cause more risk of burning out. This study discovered that machine learning model could predict high risk and give proper methodological evidence and insights about key predictors. In terms of the perspective of closed-loop intervention, this work didn't have any subsequent conclusion as to how these predictions can be turned into action for it to make a real difference [4].

In addition, the survey-based machine Learning Prediction Research present above, another research of Liu et al., using wearable as well as machine learning Technology to predict work related fatigue for Nursing Tasks. This is to note, that the study was only about a short period of time for people to feel tired and it wasn't burn out. But according to Van Zyl-Cillié and others work on the subject of fatigue also is an important factor that cause burnout and works on the topic can become work related burnout. As a result, the data of emergency room in some persons was found to be really recorded quite well. With the model of catboost predict that there would be some work-related fatigue and the practical AUC result is 0.84. This approach allows for a high degree of operational

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flexibility within the workflow. However, there are some problems, too. There is a lack of compliance in practice, so people have also become more likely to be in those. In addition, when the class imbalance happens (class imbalance), it also tends to exclude low-risk cases, which can be a big disadvantage. But it is not able to identify truly high-risk cases. Therefore, according to above mentioned, it is more effective than the direct intervention method [5].

Both studies mentioned above are related to fatigue, which Van Zyl et al. identified as a good predictor of burnout. Liu and others who have used physiological data collected by wearables, proved systematic, continuous measures is feasible [5]. Table 1 provides an overall comparison of the two studies. In order to do it, it is as well about why a future design has been made. And in terms of the research focus, it has also changed to one that the main purpose for the research will be turned into getting what the results are when they come out.

Table 1. Overview of the focus areas and complementary relationship of the two studies

Dimension	AI-Assisted Tailored Intervention for Nurse Burnout [4]	Applying a Smartwatch to Predict Work-related Fatigue for Emergency Healthcare Professionals [5]	Synthesis
Primary outcome	Burnout risk factors	Work-related fatigue(short-term)	Fatigue can function as an upstream, earlier signal, while burnout is the downstreamclinical/occupational endpoint
Core question	Which factors predict burnout?	Can fatigue be predictedcontinuously in realtime?	/
Data modality	Survey-based	Wearable physiologicaldata	Combining subjectivequestionnaire data with objective physiological measurements
Key limitations	Self-report dependence, lesscontinuous	Willingness to wearwearable devices; highspecificity but lowsensitivity for high-riskcases	/
Best use-case	Strategic identification of burnout-related risk factors and targets	Screening and riskstratification for fatigue(not direct interventiondecision)	A feasible workflow concept:screening via wearable devices, triage incorporating contextual factors, and determination of intervention measures.
Next-step implication	Focus on translating predictedburnout risk into interventions	Move beyond predictionaccuracy to whetherpredictions triggeractionable interventions	Research focus should shift toactionability and interventioneffectiveness, using fatigue as a primary, monitorable target

3. System-level interventions

The system level intervention is a situation or problem caused by difference in the workload among people and lack of hours for people's breaks, unreasonable schedule for people to go home when having workday. These issues increase fatigue, undermine procedural fairness, and ultimately lead to burnout. The aim of system level intervention is to enhance the design of hospital decision-making system and reduce ED nurse's burnout through improving the system.

Maximizing its benefit, such as short inter-shift intervals, unreasonable shift rotations, excessive overtime hours, and workload imbalances across weekends and holidays. In a prospective and repeated measure, they used wearable accelerometers to measure sleep patterns, particularly those working with less than 11 hours off between consecutive shifts, showed a relationship between sleep duration and reduced sleep time. Furthermore, reduced sleep may exacerbate fatigue and impair work motivation. To make some changes in hospitals to avoid these problems, the problems would be caused by a lack of time. Then the things that are going wrong will not occur unless someone does what's right for their self, which could increase their motivation and support [6].

In this area, traditional participation scheduling and self-scheduling and so on, these can increase a sense of control. Not only gives nurses greater freedom of operation, but as well make their

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predictability, compatibility and negotiability, thus making it easier for the nurse to return to a shift. The fields questioned were done in the public sector of Finland to try if digital participation work time planning schedule can affect planning, less sleeping time and improving working efficiency by giving people more choices for their times. But no such changes in their mental discomfort have been observed. In accordance with this, these kinds of interventions are more likely than to lower the effects on changes to the sleeping and work performance etc. But not long-term [7]. Changes have some part that it is not has many variables and explanation for this happens such as having very good capability on understanding of that, full of energy. That is, after clarifying non-negotiable constraints (e.g., qualifications, regulations, minimum coverage) and optimization objectives (e.g., fairness, preferences, continuity, training opportunities), candidate schedules are generated using techniques like mixed-integer programming (MIP),constraint programming (CP), and real-time updated as needed. A qualitative study in Switzerland identified nurses and administrators' top concerns: fairness and participation, flexibility and autonomy, and the trade-offs between AI efficiency, reliability, and human oversight. These concerns were mapped to various algorithmic paradigms (e.g., mixed integer programming for fair allocation, constraint programming for complex rules, and genetic algorithms). Reinforcement learning has been used for absenteeism and dynamic reorganization, and a collaborative hybrid human-machine decision-making approach is proposed to be more likely to take both reliability and ease of use into account [7].

Predictive staffing is an equally important work system strategy. ED patient inflow and congestion fluctuate greatly. If staffing is mostly at average level, and experience as an element of a process then this will have a feedback loop whenever long understaffing occurs, that is if longer understating happens the better can be done, with a process being achieved through getting some of those options for base and peak working hours. The conclusion needs to be like in the above forms for it will give the results and reduce labor cost can keep that amount of time which they spend on these people won't have any effect, but a reduction would affect what they work at [8].

The aim of digital decision support is not to replace clinical judgement, but rather to translate key nodes of a complicated and highly variable workflow in emergency departments into more consistent, interpretable and actionable recommendations, reducing the burden on the system due to incomplete information and task switching. D'Costa and co found that there is a process in which people get to read about it so they can know if something was good or bad, or maybe not very good. Nevertheless, there are still some problems which need to be solved to guarantee the quality of the data. The problem of quality of data, mostly because there are problems such as data quality Problem dataset shift algorithm biases unfairness. As for these factors, personnel are important also. To improve the ability of quickness in providing assistances during the urgent phase, the triage AI should be integrated into EHR and the triage operation system with the real instruments (workflow integrate into within the EHR) and training medicine professional, clinical staff and HFE have to reduce its effect. And external testing is need as well. Monitoring short term Outcomes such as Discontinuation rate and Alarm ration for nurses [9].

In the field of emergency triage, a system review found that machine learning and natural language processing are commonly used to enhance the consistency and risk stratification of triage. However, the real-world application of these technologies is limited by a lack of workflow integration, interpretability, limited multi-center external validation, and the wide variety of reporting methods for clinical and operational outcomes, which precludes cross-comparable summary analysis of results [10].

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4. Individual interventions

At the individual level, psychological support and resilience training reduce stress exposure among ED nurses by improving personal resources and coping abilities (psychological flexibility/mindfulness). These benefits include low barriers to implementation, scalability, and fragmented use. However, their effectiveness is often reflected in short-term outcomes (stress, mental exhaustion, and emotional symptoms) rather than evidence of long-term causal effects on burnout. A systematic review found that digital approaches are likely to have a positive impact on nurse resilience interventions within shorter follow-up periods, while long-term sustainability relies on ongoing support and design tailored to individual needs. Meanwhile, personalized psychological interventions have generally shown signs of improving nurse burnout, but long-term follow-up data are scarce and studies are heterogeneous [11]. The key to ensuring that digital psychological support is usable and sustainably effective in real-world emergency care settings is not simply to expand functionality and pursue large-scale, comprehensive application, but to build interventions as modular, matchable systems and organize and evaluate them within a closed-loop framework. The monitoring phase continuously captures nurses' current status and needs (e.g., burnout level, recent stress/sleep, shift workload, utilization behavior, etc.). The prediction phase converts these signals into need types or risk stratification (e.g., whether current needs include emotional regulation, improved psychological flexibility, or support for interpersonal/patient-related fatigue). The support phase selects the most appropriate content and dosage from a module library and provides them accordingly.

Take Cho et al.'s Nurse Healing Space as an example, its module library covers mindfulness, acceptance and commitment therapy, reflective writing, storytelling, and laughter therapy, enabling on-demand access at the intervention content level. More importantly, the feedback link incorporates changes in outcome and burden signals (e.g., whether the intervention is disruptive, adds perceived task burden, or induces intervention fatigue) into system updates to adapt the matching strategy, accordingly, allowing the intervention to form an interpretable trade-off between effectiveness and burden. The advantage of placing tailoring within a closed-loop framework is that matching is no longer an abstract "personalization" rhetoric, but an auditable decision-making mechanism used to simultaneously address two of the most common real-world bottlenecks of digital interventions: lack of content relevance and lack of persistence [12].

Baek G.'s three randomized controlled trials compared AI-assisted matching groups with self-selection and control groups and found that the matching group showed greater benefits in several aspects of burnout, while the self-selection group showed more pronounced improvements in stress responses. At the same time, it can be said that this is the reason for it to have benefit of matching, there are changes in mechanism as well and self-organizing arrangements provided itself. So, if future studies use AI for preference, and combine it with the limit of self-selection will be better to achieve those. In accordance with the logic of closed-loop prediction / stratification. If a system can identify people with the types of needs they have, individual interventions are more likely to achieve a balance between efficiency and equity in emergency department [3].

Further strengthen the core part of the next round of interventions, to make it more prominent and be an important feature in this future. JITAI core is to incorporate support into daily and shift rhythms, select optimal intervention choices at different decision points according to current situation (e.g. lack of sleep, fatigue after consecutive shifts, emotional fluctuations in the middle of a shift, increased congestion in the shift).It makes the "appropriate support at the right moment", and its expectation is that it will cut down on the number of interventions or intervention during many years [13]. Closing circle, JITAI take in all the things and Short term evaluation, Start Time, end

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time Abandon point. The prediction is represented in the form of a rule hierarchy or an online learning model, and it can be determined by identifying high-risk windows. The prediction supports short-term, low impact interstitial modules exercise. Feedback use net effect as the optimization goal to track outcome changes and stress signal. Related to the research, Micro- randomized trials(MRT) that repeatedly performs the decision points of a certain kind in order for us determine whether it is helpful for our initial pushes to make the closeness outcomes better or not, learn more efficient methods such as when to push what to push and how many times to push with factors like intervention fatigue. According to these, the individual level AI changes is more of an adjustment mechanism in a closed loop. The main research problem changes from whether it works, which is who, when, how and where to do something is to get more benefit, It is an issue at this stage as well, which also goes along with some changes on these systems so they can be used like a long chain going back to start by getting more benefit.

5. Conclusion

The review reveals the feasibility of a closed-loop intervention system for occupational burnout in emergency rooms. It includes monitoring, prediction, systematic intervention and individualized intervention. The traditional burden reduction measures such as staffing adjustments and stress management training are mainly concentrated on the coping ability of ED nurses. However, the traditional solution lacks the ability to adjust dynamically and cannot make accurate predictions. In the recent years, Artificial Intelligence has been developed to make closed loop intervention possible. Regarding the monitoring and prediction, machine learning model based on questionnaire results will be able to identify main factors and offer feasible risk prediction. Wearable devices offer real-time fatigue tracking and use as indicators of burnout. However, recent research has highlighted challenges such as compliance and measurement sensitivity. Shifting from post-mortem analysis to proactive prediction is the feature of closed-loop intervention programs. System-level interventions include AI-based scheduling optimization, which gives ED nurses more freedom in scheduling choices, improves fairness and ultimately reduces ED nurse fatigue. AI-assisted triage based on machine learning and natural language processing can improve work-life balance and mitigate staffing shortages. Drawbacks contain data quality and workflow integration issues, requiring prospective validity verification, ethical oversight. Individual-level interventions provide personalized psychological support by using a modular digital platform. Hybrid pathways integrate AI recommendations with nurses' own preferences have shown the potential for lasting effects.

This review illuminates the potential of artificial intelligence in interventions for ED nurse burnout and looks back the feasibility of closed-loop interventions throughout the process. Future research should focus on how to convert monitoring information to actionable interventions and how to conduct closed-loop intervention validation experiments under ethical governance. Experimental results should also take place greater emphasis on long-term outcomes for ED nurses, for example, burnout and turnover.

References

[1] Muir, K.J., Sloane, D.M., Aiken, L.H., Hovsepian, V. and McHugh, M.D. (2023) The association of the emergency department work environment on patient care and nurse job outcomes. Journal of the American College of Emergency Physicians Open, 4(5), e13040.

[2] Boltin, N., Valdes, D., Culley, J.M. and Valafar, H. (2018) Mobile Decision Support Tool for Emergency Departments and Mass Casualty Incidents (EDIT): Initial Study. JMIR Mentally Health and Ubiquitous Health, 6(6), e10727.

DOI: 10.54254/2753-7048/2026.ZJU31975

[3] Baek, G., and Cha, C. (2025) AI-Assisted Tailored Intervention for Nurse Burnout: A Three-Group Randomized Controlled Trial. Worldviews on Evidence-Based Nursing, 22(1), e70003.

[4] Van Zyl-Cillié, M.M., Bührmann, J.H., Blignaut, A.J., Demirtas, D. and Coetzee, S.K. (2024) A machine learning model to predict the risk factors causing feelings of burnout and emotional exhaustion amongst nursing staff in South Africa. BMC Health Services Research, 24(1), 1665.

[5] Liu, S.-S., Ma, C.-J., Chou, F.-Y., Cheng, M.-Y., Wang, C.-H., Tsai, C.-L., Duh, W.-J., Huang, C.-H., Lai, F. and Lu, T.-C. (2023) Applying a Smartwatch to Predict Work-related Fatigue for Emergency Healthcare Professionals: Machine Learning Method. Western Journal of Emergency Medicine, 24(4), 693-702.

[6] Hatukay, A.L., Shochat, T., Zion, N., Baruch, H., Cohen, R., Azriel, Y. and Srulovici, E. (2024) The relationship between quick return shift schedules and burnout among nurses: A prospective repeated measures multi-source study. International Journal of Nursing Studies, 151, 104677.

[7] Shiri, R., Karhula, K., Turunen, J., Koskinen, A., Ropponen, A., Ervasti, J., Kivimäki, M. and Härmä, M. (2021) The Effect of Using Participatory Working Time Scheduling Software on Employee Well-Being and Workability: A Cohort Study Analysed as a Pseudo-Experiment. Healthcare, 9(10), 1385.

[8] Hu, Y., Chan, C.W., Dong, J., Kazekjian, A., Ophaswongse, C., Sugalski, G., Underwood, J.P. and Perotte, R. (2025) Implementing a prediction driven framework for emergency department nurse staffing to optimize real time decisions. npj Health Systems Science, 2, 16.

[9] Da'Costa, A., Teke, J., Origbo, J.E., Osonuga, A., Egbon, E. and Olawade, D.B. (2025) AI-driven triage in emergency departments: A review of benefits, challenges, and future directions. International Journal of Medical Informatics, 197, 105838.

[10] Abdalhalim, A.Z.A., Ahmed, S.N.N., Ezzelarab, A.M.D., Mustafa, M., Albasheer, M.G.A., Ahmed, R.E.A. and Elsayed, M.B.G.E. (2025) Clinical Impact of Artificial Intelligence-Based Triage Systems in Emergency Departments: A Systematic Review. Cureus, 17(6), e85667.

[11] Yu, F., Chu, G., Yeh, T. and Fernandez, R. (2024) Effects of interventions to promote resilience in nurses: A systematic review. International Journal of Nursing Studies, 157, 104825.

[12] Cho, A., Cha, C. and Baek, G. (2024) Development of an Artificial Intelligence-Based Tailored Mobile Intervention for Nurse Burnout: Single-Arm Trial. Journal of Medical Internet Research, 26, e54029.

[13] Nahum-Shani, I., Smith, S.N., Spring, B.J., Collins, L.M., Witkiewitz, K., Tewari, A. and Murphy, S.A. (2018) Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. Annals of Behavioral Medicine, 52(6), 446-462.