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DOI
10.4233/uuid:f878c309-acb4-4a2c-b2f1-caf59b9b7672

Publication date
2025

Document Version
Final published version

Citation (APA)
Bostan, I. (2025). *A Cognitive Approach to Improving Patient Monitoring Systems*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:f878c309-acb4-4a2c-b2f1-caf59b9b7672

A cognitive approach to improving patient monitoring systems

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A COGNITIVE APPROACH TO IMPROVING PATIENT MONITORING SYSTEMS

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology,
by the authority of the Rector Magnificus, Prof.dr.ir. T.H.J.J. van der Hagen
chair of the Board for Doctorates,
to be defended publicly on
Thursday 15 May 2025 at 12:30

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This thesis, part of the Vital Alarms Study of the Philips Vital Soundscapes Project, was supported by TKI-HTSM grant no 20.0385 via the PPS allowance scheme for public-private partnerships with funding contributions by Philips and Holland High Tech awarded to Elif Özcan at the Critical Alarms Lab, TU Delft.

Keywords: Cognitive Ergonomics, Human-Computer interaction, Human-Centered Design, Intensive Care Unit, Nursing Practice, Sound-driven Design

Printing: Ridderprint, ridderprint.nl
Layout and design: Erwin Timmerman, persoonlijkproefschrift.nl

ISBN: 978-94-6522-167-0
An electronic copy of this dissertation is available at: https://repository.tudelft.nl/

Hayat kısa, kuşlar uçuyor

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SUMMARY

The expansion of human lifespan has increased the demands for healthcare services. Meeting these demands requires healthcare to evolve and be more efficient. Rapidly advancing technology plays a crucial role in this evolution by automating tasks and supporting healthcare providers in their workflow. This requires a symbiotic collaboration between humans and digital systems. On the human side, healthcare providers understand the clinical context and are highly specialized in integrating information from several sources. Yet, they face limits in attention span and workload capacity. On the digital side, patient monitoring systems operate tirelessly and with precision, yet they lack the ability to interpret the clinical context of information. Consequently, effective patient care relies on each side playing their specific roles.

The relationship between the healthcare providers and medical systems is strained in the setting of intensive care units (ICUs). Rapidly advancing technology has resulted in numerous new sensors and highly sensitive measurement instruments capable of detecting minor effects. ICU nurses rely on patient monitoring systems to track patient vitals and receive timely information. These systems alert nurses through audible alarms. However, most of the alarms are non-actionable and do not convey clinical significance. Frequent non-actionable alarms lead to *alarm fatigue* in nurses, a condition in which nurses become desensitized to alarms, leading to stress and reduced responsiveness. Alarm fatigue threatens patient safety and disrupts clinical workflows, making it a critical issue to address.

Mitigating alarm fatigue is more complex than simply reducing the number of alarms. The systems are typically designed with liability as top priority. Medical device regulations impose a “better safe than sorry” principle, triggering alarms for even minor events without considering the clinical context. However, this design overlooks human cognitive limitations. Constant alarms burden the cognitive load by clouding perception with cacophony of noises, diverting attention and inducing negative feelings such as stress and annoyance. To address this, patient monitoring systems need to balance providing essential information to nurses without overwhelming them.

My research tackles this challenge through cognitive ergonomics, focusing on designing systems that align with human cognitive strengths and limitations. By studying how nurses process information, manage interruptions, and make decisions, I identify system improvements to reduce cognitive strain and enhance usability. Our research emphasizes optimizing monitoring systems to work *with* the way nurses think and operate, rather than against them.

I approached alarm fatigue from three main angles, investigating the ICU context, the system technology, and user characteristics. We used a diverse set of methodologies including data analysis, surveys, lab studies, and workshop to triangulate the issue. First, I analyzed the ICU environments to understand the root causes of high alarm rates across different unit types. This analysis revealed significant differences in alarm loads and highlighted which factors contributed the most to alarm fatigue. Identifying the factors contributing to alarm load offered a foundation for targeted improvements.

Second, I investigated the technology behind patient monitoring systems. My research showed that most alarms are of low to medium priority and often unnecessary, leading to delayed responses and diminished trust. I explored solutions such as customizable alarm thresholds and intelligent algorithms to prioritize critical alerts. One promising approach involved delaying low-priority alarms, which could significantly reduce alarm frequency while maintaining safety. This strategy highlights the importance of user-centered design in creating a calmer ICU environment and improving both nurse performance and patient outcomes.

Third, I studied ICU nurses themselves, recognizing the diversity in their approaches to alarm management. Through surveys and questionnaires, I examined how individual traits like personality type and musicality influence interactions with monitoring systems. Our findings align with the recent trends in healthcare towards personalized care and suggest that this approach should extend to healthcare providers as well as the patients. Monitoring systems designed to address distinct user needs through customizable features could help nurses manage alarms more effectively without increasing their workload.

Beyond the ICU, I conducted a controlled lab study to delve deeper into human cognition. In a simulated healthcare setting, participants were interrupted by alarms while performing tasks. Using electroencephalogram (EEG) technology, I measured their brain activity to assess the impact of these interruptions on annoyance, performance, and cognitive states. The results highlighted how frequent technology-induced interruptions can erode focus and elevate stress, reinforcing the need for systems that minimize unnecessary disruptions. Implications go beyond the ICU and extend to other high-stakes environments, such as aviation, in which clear and timely decision-making is vital.

To synthesize these findings into actionable solutions, I organized a multidisciplinary workshop. This brought together researchers, ICU nurses, intensivists, and industry experts in healthcare technology, including engineers, designers, and usability specialists. We aimed to give a voice to all those involved in this complex challenge. Together, we developed practical strategies for mitigating alarm fatigue while addressing the complex needs of ICU environments.

This research highlights the urgent need for smarter, user-centered monitoring systems. We offer a holistic approach to tackling alarm fatigue. Our work emphasizes the importance of multidisciplinary co-creation, bringing together diverse expertise to develop solutions that are both practical and impactful. This collaborative effort ensures that the systems we design not only improve patient safety but also enhance the well-being of healthcare professionals, contributing to effective healthcare workflows.

ÖZET

İnsan ömrünün uzaması, sağlık hizmetlerine olan talebi artırmıştır. Bu talepleri karşılayabilmek için sağlık sisteminin daha verimli hale evrilmesi gerekmektedir. Hızla ilerleyen teknoloji, görevleri otomatize ederek ve sağlık çalışanlarını iş akışlarında destekleyerek bu dönüşümde önemli bir rol oynar. Bu süreç, insanlar ile dijital sistemler arasında simbiyotik bir iş birliğini gerektirir. İnsan tarafında, sağlık çalışanları klinik bağlamı anlar ve çeşitli kaynaklardan gelen bilgileri entegre etme konusunda uzmanlaşmıştır. Ancak dikkat süreleri ve iş yükü kapasiteleri sınırlıdır. Dijital tarafta ise hasta başı monitörleri yorulmadan ve hassasiyetle çalışır, ancak bilgilerin klinik bağlamını yorumlama yeteneğinden yoksundur. Sonuç olarak, etkili hasta bakımı ancak her iki tarafın da kendi rolünü doğru bir şekilde oynamasıyla sağlanabilir.

Sağlık çalışanları ile tıbbi sistemler arasındaki ilişki, yoğun bakım ünitelerinde (YBÜ) zorluk altındadır. Hızla gelişen teknoloji beraberinde birçok yeni sensör ve en ufak etkileri bile tespit edebilecek hassasiyette ölçüm aletleri getirmiştir. YBÜ hemşireleri, hastaların yaşamsal değerlerini izlemek ve zamanlı bilgi almak için hasta başı monitörleri güvenirler. Bu sistemler hemşireleri sesli alarmlar aracılığıyla uyarır. Ancak, alarmların çoğu eylem gerektirmeyen ve klinik olarak anlamlı olmayan bildirimlerden oluşur. Sık yoğunluktaki eylem gerektirmeyen alarmlar, hemşirelerde stres ve alarm tepkisinde azalma gibi sonuçlarla kendini gösteren *alarm yorgunluğuna* yol açar. Alarm yorgunluğu, hasta güvenliğini tehdit eder ve klinik iş akışlarını aksatır; bu nedenle ele alınması gereken kritik bir sorundur.

Alarm yorgunluğunu hafifletmek, sadece alarm sayısını azaltmaktan daha karmaşık çözümler gerektirir. Sistemler genellikle en öncelikli hedefleri olarak hukuki sorumluluklar gözeterek tasarlanmıştır. Tıbbi cihaz düzenlemeleri, "her ihtimale karşı" yaklaşımı benimseyerek en küçük olaylar için bile klinik bağlamı dikkate almadan alarm tetiklenmesini dikte eder. Ancak bu tasarım, insanın bilişsel sınırlamalarını göz ardı eder. Sürekli alarmlar, dikkat dağınıklığı ve stres gibi olumsuz duyguları tetikleyerek bilişsel yükü artırır. Bu sorunu çözmek için hasta başı monitörlerinin, hemşirelere gerekli bilgileri sağlarken onları bunaltmamak arasında hassas bir denge kurması gerekir.

Araştırmam, bu probleme bilişsel ergonomi açısından yaklaşıyor ve sistemlerin insan bilişsel yeteneklerine ve sınırlamalarına uyum sağlaması gerektiğini vurguluyor. Hemşirelerin bilgiyi nasıl işlediğini, iş kesintilerini nasıl yönettiğini ve kararları nasıl aldığını inceleyerek, bilişsel yükü azaltmayı ve kullanılabilirliği artırmayı hedefleyen sistem iyileştirmeleri belirledim. Araştırmamız, monitör sistemlerinin hemşirelerin

düşünme ve çalışma şekline karşı gelecek değil, uyacak şekilde optimize edilmesi gerektiğini vurguluyor.

Alarm yorgunluğu sorununu üç temel açıdan ele aldım: YBÜ ortamı, monitör teknolojisi ve kullanıcı karakteristikleri. Sorunu derinlemesine incelemek için veri analizi, anketler, laboratuvar çalışmaları ve atölye çalışması gibi çeşitli yöntemler kullandık. İlk olarak, farklı YBÜ türlerinde yüksek alarm oranlarının kök nedenlerini anlamak için YBÜ ortamlarını analiz ettim. Bu analiz, alarm yüklerindeki önemli farkları ortaya çıkardı ve alarm yorgunluğuna en çok katkıda bulunan faktörleri vurguladı. Alarm yüküne katkıda bulunan faktörlerin belirlenmesi, hedefe yönelik iyileştirmeler için bir temel sağladı.

İkinci olarak, monitör sistemlerinin teknolojisini inceledim. Araştırmam, alarm yükünün büyük kısmını düşük ve orta öncelikli alarm bildirimlerinin oluşturduğunu ve bu bildirimlerin genellikle gereksiz olduğunu gösterdi. Bu durum, hemşirelerin sisteme olan güvenlerini azaltarak alarmlara duyarlılığını düşürüyor. Kritik alarmları önceliklendiren özelleştirilebilir alarm eşikleri ve akıllı algoritmalar gibi çözümleri araştırdım. Bu stratejilerden biri olan düşük öncelikli alarmların geciktirilmesi, güvenliği korurken alarm sıklığını önemli ölçüde azaltabilir. Kullanıcı odaklı tasarımın önemini vurgulayan bu yaklaşımlar, daha sakin bir YBÜ ortamı oluşturarak hemşire performansını ve hasta sonuçlarını iyileştirebilir.

Üçüncü olarak, YBÜ hemşirelerinin alarm yönetimi yaklaşımlarındaki çeşitliliği inceledim. Anketler ve formlar aracılığıyla, kişilik tipi ve müzik bilgisi gibi bireysel özelliklerin monitör sistemleriyle olan etkileşimleri nasıl etkilediğini analiz ettim. Bulgularımız gösteriyor ki sağlık sektörünün izlediği kişiselleştirilmiş bakım akımı yalnızca hastalara değil, sağlık çalışanlarına da uzanmalı. Özelleştirilebilir özelliklerle tasarlanmış monitör sistemleri, hemşirelerin alarmları daha etkili bir şekilde yönetmelerine yardımcı olabilir.

YBÜ'nün ötesinde, insan bilişini daha derinlemesine incelemek için kontrollü bir laboratuvar deneyi gerçekleştirdim. Simüle edilmiş bir sağlık ortamında, katılımcılar bir görev tamamlarken alarmlarla kesintiye uğratıldı. Elektroansefalogram (EEG) teknolojisi kullanarak, bu kesintilerin rahatsızlık, performans ve bilişsel süreçler üzerindeki etkilerini ölçtüm. Sonuçlar, sık teknoloji kaynaklı kesintilerin odağı zamanla nasıl zayıflattığını ve stresi nasıl artırdığını ortaya koydu. Bu bulgular, gereksiz kesintileri en aza indiren sistemlerin önemini bir kez daha vurguluyor. Alarmların insan bilişi üzerindeki olumsuz etkileri sadece YBÜ ile sınırlı olmayıp havacılık ve kontrol odaları gibi, net ve zamanlı karar almanın hayati olduğu diğer riskli ortamlara da uzanır.

Bu bulguları uygulanabilir çözümlere dönüştürmek için çok disiplinli bir atölye çalışması düzenledim. Araştırmacılar, YBÜ hemşireleri, yoğun bakım uzmanları ve sağlık teknolojisi sektöründeki mühendisler, tasarımcılar ve kullanılabilirlik uzmanlarını bir araya getirdik. Amacımız, bu karmaşık sorunla ilgili tüm paydaşların sesini duyurabilmekti. Birlikte, alarm yorgunluğunu azaltmak ve YBÜ ihtiyaçlarına yanıt verebilecek stratejiler geliştirdik.

Bu araştırma, daha akıllı ve kullanıcı odaklı izleme sistemlerine olan acil ihtiyacı ortaya koymaktadır. Bilişsel ergonomi ve çok disiplinli ortak çalışmayı bir araya getirerek alarm yorgunluğunu ele almak için kapsamlı bir yaklaşım sunuyoruz. Geliştirdiğimiz çözümler, hasta güvenliğini artırırken, sağlık profesyonellerinin çalışma koşullarını da iyileştirmeyi amaçlıyor. Böylece sağlık hizmetlerinin genel etkinliğine ve verimliliğine katkıda bulunuyor.

SAMENVATTING

De toename van de menselijke levensduur heeft geleid tot een grotere vraag naar gezondheidszorg. Om aan deze vraag te kunnen voldoen, moet de gezondheidszorg efficiënter worden. Snel voortschrijdende technologische ontwikkeling speelt een cruciale rol in deze evolutie door taken te automatiseren en zorgverleners te ondersteunen in hun werkprocessen. Dit vereist een symbiotische samenwerking tussen mensen en digitale systemen. Aan de menselijke kant begrijpen zorgverleners de klinische context en zijn zij gespecialiseerd in het integreren van informatie uit meerdere bronnen. Toch hebben zij te maken met beperkingen in aandachtsspanne en werkdruk. Aan de digitale kant werken patiëntmonitorsystemen onvermoeibaar en met precisie, maar zij missen het vermogen om de klinische context van informatie te interpreteren. Effectieve patiëntenzorg is dus afhankelijk van een goede rolverdeling tussen beide partijen.

De relatie tussen zorgverleners en medische systemen staat op gespannen voet in intensive care units (ICU's). ICU-verpleegkundigen vertrouwen op patiëntmonitorsystemen om vitale functies van patiënten te volgen en tijdig informatie te ontvangen. Deze systemen waarschuwen verpleegkundigen via hoorbare alarmen. Echter, de meeste alarmen vereisen geen actie en hebben geen klinische betekenis. De frequente van niet-actiegerichte alarmen leidt tot *alarmmoeheid* bij verpleegkundigen, een toestand waarin zij ongevoelig worden voor alarmen, wat leidt tot stress en verminderde reacties. Alarmmoeheid vormt een bedreiging voor de patiëntveiligheid en verstoort de klinische werkprocessen. Dit maakt het tot een kritiek probleem dat moet worden opgelost.

Het voorkomen van alarmmoeheid is complexer dan simpelweg het aantal alarmen te verminderen. De systemen zijn doorgaans ontworpen met wettelijke aansprakelijkheid als hoogste prioriteit. Regelgeving voor medische apparaten hanteert het principe "better safe than sorry", waardoor alarmen worden geactiveerd voor zelfs kleine gebeurtenissen zonder rekening te houden met de klinische context. Deze benadering negeert echter de cognitieve capaciteit van mensen. Constant geactiveerde alarmen verhogen de cognitieve belasting door perceptie te vertroebelen met een kakofonie van geluiden, aandacht af te leiden en negatieve gevoelens zoals stress en ergernis op te roepen. Om dit aan te pakken, moet de ontwerper van patiëntmonitorsystemen een balans vinden tussen het verstrekken van essentiële informatie en het niet overbelasten van zorgverleners.

Mijn onderzoek richt zich op deze uitdaging via cognitief ergonomische aanpak, waarbij systemen worden ontworpen die aansluiten bij de sterke en zwakke punten van de menselijke cognitie. Door te onderzoeken hoe verpleegkundigen informatie verwwerken, onderbrekingen beheren en beslissingen nemen, identificeer ik systeemverbeteringen om de cognitieve belasting te verminderen en de bruikbaarheid te verbeteren. Ons onderzoek benadrukt het optimaliseren van patiëntmonitorsystemen zodat ze meer passend zijn bij het verpleegkundig werk- en denkvermogen.

Ik ben alarmmoeheid vanuit drie hoofdinvalshoeken benaderd: het onderzoeken van de ICU-context, de systeemtechnologie en de gebruikerskenmerken. We hebben een diverse set methodologieën gebruikt, waaronder data-analyse, enquêtes, laboratoriumstudies en workshops, om het probleem vanuit meerdere perspectieven te belichten. Ten eerste heb ik de ICU-omgevingen geanalyseerd om de oorzaken van hoge alarmfrequenties in verschillende typen ICU's te begrijpen. Deze analyse onthulde significante verschillen in alarmbelastingen en benadrukte welke factoren het meest bijdroegen aan alarmmoeheid. Het identificeren van de factoren die bijdragen aan de alarmbelasting bood een basis voor gerichte verbeteringen.

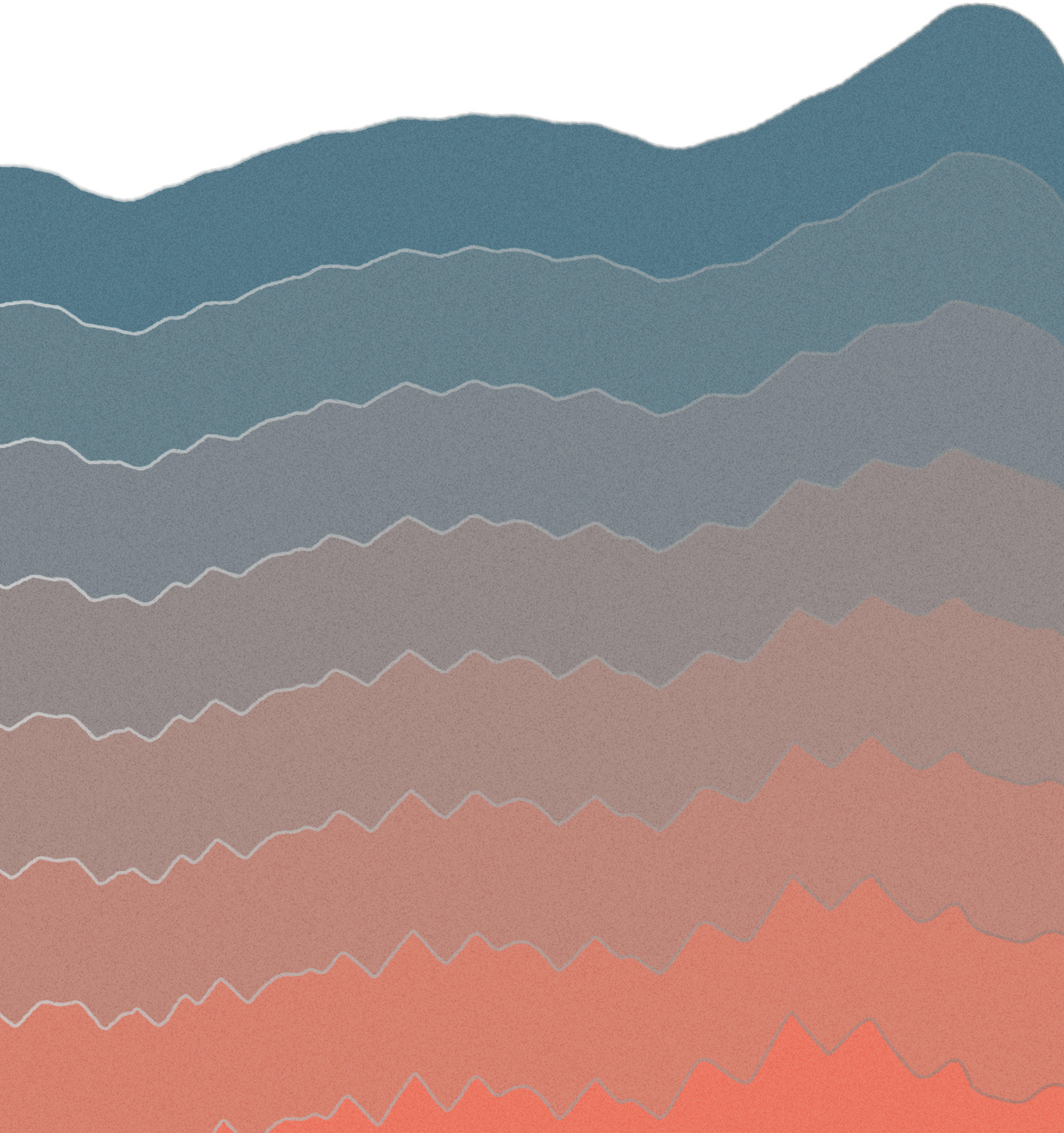
Ten tweede heb ik de technologie achter patiëntmonitorsystemen onderzocht. Uit mijn onderzoek bleek dat de meeste alarmen een lage tot middelmatige prioriteit hebben en vaak overbodig zijn, wat leidt tot vertraagde reacties en verminderde vertrouwen. Ik heb oplossingen verkend, zoals aanpasbare alarmdrempels en intelligente algoritmen om kritieke alarmen te prioriteren. Een veelbelovende aanpak was het uitstellen van alarmen met lage prioriteit, wat de frequentie van alarmen aanzienlijk kan verminderen zonder de veiligheid in gevaar te brengen. Deze strategie benadrukt het belang van gebruikersgerichte ontwerpen om een rustiger ICU-omgeving te creëren en zowel de prestaties van verpleegkundigen als de resultaten voor patiënten te verbeteren.

Ten derde heb ik ICU-verpleegkundigen zelf bestudeerd en erkend dat hun aanpak van alarmbeheer divers is. Via enquêtes en vragenlijsten heb ik onderzocht hoe individuele kenmerken, zoals persoonlijkheidstype en muzikaliteit, de interactie met monitorsystemen beïnvloeden. Onze bevindingen sluiten aan bij recente trends in de gezondheidszorg richting gepersonaliseerde zorg en suggereren dat deze benadering niet alleen op patiënten moet worden toegepast, maar ook op zorgverleners. Monitorsystemen die zijn ontworpen om aan de verschillende behoeften van gebruikers te voldoen via aanpasbare functies, kunnen verpleegkundigen helpen alarmen effectiever te beheren zonder hun werkdruk te verhogen.

Buiten de ICU heb ik een gecontroleerde laboratoriumstudie uitgevoerd om dieper in te gaan op menselijke cognitie. In een gesimuleerde zorgomgeving werden deelnemers onderbroken door alarmen terwijl ze taken uitvoerden. Met behulp van elektro-encefalogram (EEG)-technologie heb ik hun hersenactiviteit gemeten om de impact van deze onderbrekingen op ergernis, prestaties en cognitieve toestanden te beoordelen. De resultaten toonden aan hoe frequente, technologie-geïnduceerde onderbrekingen de focus kunnen ondermijnen en stress kunnen verhogen. Dit benadrukt opnieuw de noodzaak van systemen die onnodige verstoringen minimaliseren. De implicaties reiken verder dan de ICU en omvatten andere risicovolle omgevingen, zoals de luchtvaart, waar duidelijke en tijdige besluitvorming van vitaal belang is.

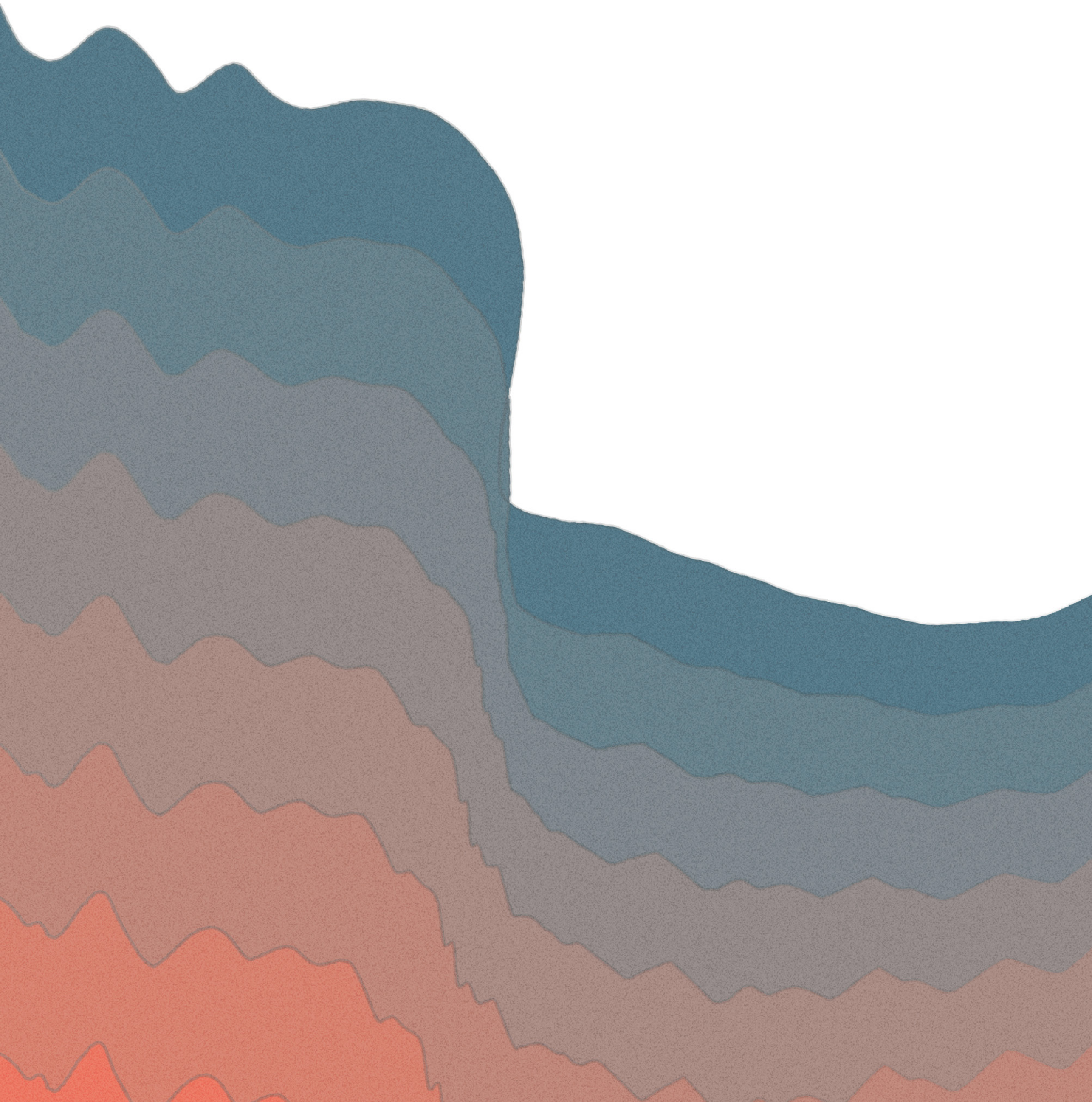
Om deze bevindingen om te zetten in bruikbare oplossingen, heb ik een multidisciplinaire workshop georganiseerd. Dit bracht onderzoekers, ICU-verpleegkundigen, intensivisten en experts uit de gezondheidszorgtechnologie-industrie samen, waaronder ingenieurs, ontwerpers en bruikbaarheidsspecialisten. Ons doel was om alle betrokkenen in deze complexe uitdaging een stem te geven. Samen hebben we praktische strategieën ontwikkeld om alarmmoeheid te verminderen en tegelijkertijd tegemoet te komen aan de complexe behoeften van ICU-omgevingen.

Dit onderzoek benadrukt de dringende behoefte aan intelligente, gebruiksvriendelijke monitorsystemen. We bieden een holistische aanpak om alarmmoeheid aan te pakken. Ons werk onderstreept het belang van multidisciplinaire samenwerking, waarbij diverse expertise wordt samengebracht om oplossingen te ontwikkelen die zowel praktisch als impactvol zijn. Deze gezamenlijke inspanning zorgt ervoor dat de systemen die we ontwerpen niet alleen de patiëntveiligheid verbeteren, maar ook het welzijn van zorgverleners vergroten en bijdragen aan effectieve werkprocessen in de gezondheidszorg.



1

Introduction



Advances in healthcare, medicine, and technology have significantly extended our lifespan, leading to longer, healthier lives. However, this success brings with it the challenge of aging populations. In developed countries, an older demographic poses two key issues: increasing demand for healthcare services and a shrinking workforce to meet it (*How the Aging Population Is Affecting the Nursing Shortage,* 2020; van der Geest, 2023). With current nurse shortages already impacting care, the need for healthcare professionals will only grow more pressing. Healthcare processes must evolve to address these challenges. Technology can play a crucial role in this evolution by automating tasks and facilitating stronger collaboration between healthcare workers and medical systems. Reducing the already pressing burden on nurses is a necessary step in making healthcare more efficient.

Healthcare in intensive care units (ICUs) relies on the seamless collaboration between healthcare staff and digital systems. On the human side, healthcare providers understand the clinical context and are highly specialized in integrating information from several sources to make timely decisions and medical interventions. Yet, they face limits in attention span and workload capacity. To maintain constant oversight of patient vitals, ICU nurses rely on patient monitoring systems. On the digital side, patient monitoring systems operate tirelessly and with precision, yet they lack the ability to interpret the clinical context of the information they gather. Consequently, effective patient care relies on the collaboration between healthcare providers and monitoring systems, each playing their specific roles. However, this collaboration has long been strained due to excessive number of alarms generated by patient monitoring systems.

Patient monitoring systems alert ICU nurses about medical and technical issues by generating audiovisual alarms. Alarms notify nurses of events such as vital parameters crossing set limits, irregularities in detected patterns, or sensor detachments. Alarms are designed to prompt actions from the nurses to address these events. However, the systems are typically designed with safety and liability as top priorities, not necessarily with human usability in mind. Medical device regulations impose operating on a “better safe than sorry” principle, triggering alarms for even minor fluctuations without considering the clinical context. Additionally, the rapid advancements in technology have brought about a wide range of new sensors for monitoring patient vitals, along with highly sensitive detectors capable of identifying even the slightest changes. Each new monitored parameter leads to even more alarms. Furthermore, current systems respond only to real-time data and lack integration of patient history or trend analysis. In summary, current patient monitoring systems do not accommodate for the humans using them, often working against their cognitive capabilities. This approach causes numerous non-actionable alarms, overwhelming nurses with alerts that don't always reflect critical changes in patient status.

Alarm fatigue

Up to 80-99% alarms in the ICU have been found to be non-actionable, meaning that they do not require actions from nurses (Cvach, 2012). Frequent alarms are distracting and interfere with clinical tasks. Excessive number of alarms in the ICU contribute to a disruptive sound environment, creating a cacophony that can hinder the healing atmosphere essential for patient recovery. This sound and information pollution leads to desensitization to alarms, in which responsiveness to alarms is reduced and clinically significant alarms may be missed. The reduced responsiveness is commonly referred to as *alarm fatigue* (Albanowski et al., 2023; Lewandowska et al., 2020; Sendelbach & Funk, 2013). Organizations such as The Joint Commission, ECRI Institute, the Association for the Advancement of Medical Instrumentation (AAMI), and the Healthcare Technology Foundation (HTF), have identified clinical alarm safety as a national patient safety concern for over a decade. Alarm safety has been on the ECRI list of top 10 healthcare technology hazards between 2007-2023 (Phillips et al., 2020; ECRI 2023). The issue of high rates of non-actionable alarms poses a serious threat to patient safety (Ruskin & Hüske-Kraus, 2015).

In addition to the risks to patient safety, high alarm rates are also detrimental to nurse well-being. Nurses need to listen to the alarm sounds to deliver timely care. However, nurses often express dissatisfaction with the overwhelming number of alarms in the ICU. They report feelings of annoyance and frustration, using striking words such as 'noxious' and 'unnerving' to describe them (Honan et al., 2015). In fact, 91-96% nurses believe that nuisance alarms disrupt patient care by interrupting workflow (Casey et al., 2018; Petersen & Costanzo, 2017). 93-100% of nurses acknowledge that frequent false alarms lead to dangerous behaviors such as ignoring alarms or inappropriately silencing them, which can result in delayed responses to real medical emergencies (Christensen et al., 2014; Lewandowska et al., 2020; Petersen & Costanzo, 2017; Sowan et al., 2015). Nurses feel irritated by alarms and experience cognitive stress as they are constantly interrupted in their workflow, reducing efficiency (Lewandowska et al., 2020; Wilken et al., 2017). Over time, this cumulative stress can lower job satisfaction and retention rates, further compounding staffing challenges in critical care environments (de Matos et al., 2020). The risks posed by alarms call urgently for interventions designed to support nurse well-being in the clinical workflow.

Participatory and sound-driven design approach

The ICU is a highly complex socio-technical environment, integrating numerous medical devices and diverse stakeholders. Tackling the challenges within this setting requires a comprehensive approach that deeply understands the capabilities and perspectives of all involved stakeholders (Özcan et al., 2018). It demands bridging disciplines to consider the diverse needs of healthcare workers and patients. In settings where sound plays a central role in modulating interactions between stakeholders, sound-driven design emerges as a critical approach.

Sound-driven design entails the research and design activities addressing issues in which the problem space is defined by sounds. It requires an in-depth understanding of the listeners' context and perspective in designing systems, products, and services. This approach views sounds as ecologically embedded within a context to enhance interaction and functionality. Sound-driven design offers a holistic and multidisciplinary approach, incorporating the varied approaches stakeholders take towards sound (Monache et al., 2022; Özcan & Gommers, 2020).

In the case of patient monitoring systems, the excessive number of alarms define the initial problem. While medical device regulations impose system architectures that prioritize sensitivity over specificity, fields of human factors and cognitive ergonomics show that nurses are not capable in responding to all these sound events (Sanz-Segura et al., 2022). Similarly, alarm sounds that may be routine for ICU nurses can seem unfamiliar and threatening to patients and visiting families, often causing unnecessary stress or anxiety. Involving diverse stakeholders in the solution process is thus crucial in effectively addressing the challenges.

Inclusive design for diversity in the ICU

Patient monitoring systems have largely been developed from a regulatory and engineering perspective, with minimal emphasis on user-centered design. However, the reality of ICU settings is a diverse landscape encompassing nurses with varied skill sets, distinct unit cultures, differences in institutional protocols, and unique patient populations. These variations call for more flexible system designs that can adapt to the specific needs of different users. Such an approach ensures that monitoring systems are inclusive and responsive to the diversity within healthcare environments.

A significant source of diversity within the ICU lies in the nurses themselves. Each nurse brings a unique set of experiences, skills, and responses to stress, all of which can influence how they interact with patient monitoring systems. Recent studies suggest that how nurses interact with alarms is influenced by individual differences among them. Nurses interact with alarms by customizing alarm settings, such as enabling/disabling certain vital parameters and customizing alarm limits. How nurses manage these settings often depends on their level of experience (Özcan & Gommers, 2020; Ruppel et al., 2018; Schokkin, 2019; Wung & Schatz, 2018). Nurses with extensive prior experience report that they can anticipate future clinical events more accurately, allowing for more confidence and freedom in customizing their alarms (Gazarian et al., 2015). Another factor that influences how nurses interact with alarms is their personality (Ruppel et al., 2019). Research shows that nurses' perceptions of workload and their emotional responses to alarms—such as boredom, apathy and distrust—are shaped by individual personality traits (Claudio et al., 2021; Deb & Claudio, 2015). Another interesting factor that influences nurses' relations to alarms is prior music training, which has been found to positively influence nurses' response times and accuracy in identifying alarms, making alarm management subjectively easier (Lacherez et al., 2007; Wee & Sanderson, 2008). Altogether, evidence suggests that interventions should be tailored to the individual nurse's needs, skills, and personality. As healthcare technologies become increasingly complex, addressing these personal differences will be crucial for designing effective systems that support both nurse well-being and patient care.

Previous efforts to mitigate alarm fatigue

After discovering the detrimental effects of excessive alarms on patient safety and nurse well-being, academia and the healthcare technologies industry joined forces to address these risks. Several approaches emerged ranging from improvements on alarm sounds, to system architecture design, and to interventions directly made to ICU nurses.

Improving alarm sounds

One of the initial attempts focused on improving the alarm sounds. Researchers and engineers worked on creating more distinct, less intrusive sounds. By adjusting the tones and frequencies, they aimed to reduce auditory fatigue and improve alarm recognition, ensuring that critical alarms were more noticeable without overwhelming the staff (Reynolds et al., 2019). The informative value of alarm sounds was studied by manipulating acoustic features of alarms through urgency mapping (Edworthy & Hellier, 2005; Hellier & Edworthy, 1999). Use of auditory icons was suggested, in which sounds directly represent the semantic meaning of the alarm, such as the heart rate related alarms sounding like heart beats. Auditory icons were repeatedly shown to outperform current alarms in speed and accuracy in identifiability, localizability, and detectability (Bennett et al., 2019; Edworthy et al., 2017; McNeer et al., 2018). Insights from music theory were used to reduce the unpleasantness of alarm sounds (Foley et al., 2020; Pereira et al., 2021).

Despite the immense efforts towards improving the sounds, they only addressed one facet of the larger issue. While the precise contribution of different factors (e.g., sound design, alarm localizability , clinical context and workflow, staff capabilities) to alarm fatigue remains uncertain, previous studies consistently show that the sheer number of alarms in ICUs is overwhelming. Clinicians are exposed to a near-constant stream of sound events which they must process. Best-designed sounds only offer limited relief as the overwhelming number of non-actionable alarms flood the ICU. Sound design can improve the perceptual qualities of alarms and reduce the burden on perceptual processing. However, the high rates of sound events that need to be processed still place a significant burden on the cognitive system. Without also tackling the excessive alarm load, even well-designed alarms risk contributing to fatigue simply due to their frequency. Therefore, reducing alarm quantity must be a priority alongside improving alarm quality.

Improving alarming algorithms

Reducing the number of alarms can be achieved through interventions to the patient monitoring system and the alarming algorithms. A substantial line of research worked on incorporating more intelligence into alarm systems through systems engineering and design perspectives (Sanz-Segura et al., 2022). Manufacturers distinguish between *alarming conditions*, the underlying medical or technical event that triggers the alarm, and *alarming signals*, the audiovisual signal generated by the system. Algorithms designed to suppress, aggregate, and prioritize alarming conditions to generate fewer but more meaningful alarm signals have been developed (Ansari et al., 2016; Blum & Tremper, 2010; Manna et al., 2019; Schoenberg et al., 1999). Newly developing technologies such as machine learning and artificial intelligence have been explored to support the efforts (Chromik et al., 2022; Fernandes et al., 2019; Piri et al., 2022). Implementing delays between the onset of alarming condition and the alarm signal has been proposed to reduce the number of non-actionable alarms (Welch, 2011). Currently, a consortium of industrial partners and hospitals are developing smart algorithms for suppressing alarms at the patient side while providing the most relevant info for nurses (IHI, 2023). Lastly, shifting from single-device alarms to networked-system paradigm has been proposed to integrate data from multiple devices and vital parameters, generating fewer but more informative alarms (Koomen et al., 2021; Paul et al., 2016). Such strategies aim to shift some decision-making responsibility from nurses to the monitoring system, thereby reducing the cognitive load on healthcare providers.

Human factors

Another line of research involved restructuring the information in the medical system and how it is presented to the user through human factors engineering. The underlying premise in this approach was displaying the medical information more intuitively and allowing it to be readily comprehended, thereby reducing cognitive load. Strategies include effective techniques of visualizing information and integrating relevant sets of information to present them in comprehensive and intuitive ways (Koomen et al., 2021; Özcan et al., 2018). For example, integrating information from several sources such as laboratory values and monitor data can be synthesized into a summary of the status of an organ. Then, this information can be presented in explicit visual representations of organs in humaniform representation to increase recollection rate (Garot et al., 2020). In this approach, improving the system design to increase the user-friendliness is highlighted (Paul et al., 2016; Phansalkar et al., 2010). Guiding nurse attention more efficiently using multimodal alarms, such as both auditory and vibrotactile, or wearable attention aids were explored (Cobus & Heuten, 2019; McFarlane et al., 2018). This line of research aims to reduce the cognitive load by presenting holistic inventory of a patient instead of fragmented and scattered data over time and across devices.

Behavior change and training

The last line of research focused on ICU nurses, investigating their individual characteristics (Claudio et al., 2021; Deb & Claudio, 2015; Ruppel et al., 2019), attitudes towards alarms (Honan et al., 2015; Wung & Schatz, 2018), and perceptions about alarm fatigue (Petersen & Costanzo, 2017; Salameh et al., 2024; Torabizadeh et al., 2017). Training programs were designed to enhance alarm management practices, such as education on customizations of settings and improved use of sensor electrodes (Aysha & Ahmed, 2019; Bi et al., 2020; Cvach et al., 2015; Dewan et al., 2019; Nyarko et al., 2023; Paine et al., 2016; Sowan et al., 2016). Research underlined the importance of not only incorporating better alarm management practices on the individual level, but also improving the alarm management culture and awareness collectively within the unit (Graham & Cvach, 2010). Although these interventions yielded limited reduction in number of alarms, they have not yet resulted in sustained, widespread improvements (Albanowski et al., 2023; Sowan et al., 2016; Yue et al., 2017).

Nurses as users of patient monitoring systems

User-centered design approach emphasizes the consideration of the user needs and context demands while designing the system architecture. In this case, ICU nurses are the users of patient monitoring systems, and understanding their needs is essential for targeted improvements of system elements. Similarly, investigating the demands imposed by the ICU environment is crucial to design ecologically relevant systems which support clinical workflow. Figure 1 illustrates the triadic relationship between the context, the user, and the system. Within this framework, alarms act as the interface between the user and the system: Patient monitoring systems relay information to nurses via alarms, and nurses in turn interact with the system through responding to alarms (e.g., silencing, enabling, customizing limits). By studying the alarms, we are in fact studying the interaction between the user and the system grounded within the context. To improve this interaction, the first step is unraveling the friction points in the triadic relationship and identifying targeted solution opportunities.

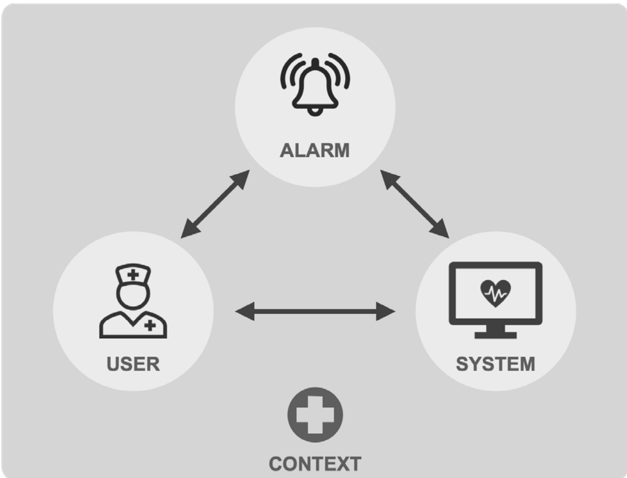


Figure 1. ICU nurses are users of patient monitoring system. Alarms are the interface in which nurses interact with the system. This relationship is grounded in the sociotechnical complexity of ICUs.

Reshaping the flow of information communication in the ICU

Current patient monitoring systems do not account for variations in patient populations, nurse capabilities, or contextual factors. These systems often generate alarms for every minor event to prioritize safety. This can often lead to the opposite effect in which nurses become desensitized to too many alarms, diminishing their responsiveness. To ensure effective collaboration between nurses and monitoring systems, it is essential to restructure how information flows in the ICU. Rather than overwhelming nurses with endless alerts, patient monitoring systems should be designed to adapt to user input, reducing unnecessary alarms while still addressing critical issues. Integrating insights from cognitive ergonomics would enhance nurse engagement and improve patient care by making alarms more relevant and manageable.

Adapting system behavior to users can only be possible by understanding what nurses need from the patient monitoring systems. What are the nurse capabilities and preferences? What do the patient monitoring systems need to know to alter their behavior?

Which features are relevant to factor in when designing the information architecture of patient monitoring systems? Which contextual factors should be considered?

Design directions for better patient monitoring systems
Despite being the primary users, nurses often find patient monitoring systems challenging to navigate and not user-friendly (Ruppel et al., 2019). This strained relationship could evolve into one of symbiotic collaboration if systems were designed to deliver contextually relevant information while accounting for nurse cognitive load. Human factors and cognitive ergonomics play a crucial role in this process, emphasizing the need to design systems that align with human cognitive strengths and limitations. By considering how nurses process information, handle interruptions, and make decisions, these disciplines can guide the development of systems that reduce cognitive strain and enhance usability. To make this shift, new design directions are needed to improve patient monitoring systems that prioritize usability.

Thesis objectives and structure

Decades of research into improving alarm sounds have shown that the sounds themselves are merely a symptom of a larger problem rooted in system design. The real challenge lies in how these systems are structured and how they interact with their human users. The aim of this thesis is to provide insights into how patient monitoring systems can be designed to better meet the cognitive needs of nurses. First objective of the thesis is to determine the system elements that create friction points within ICU workflows, contributing to stress and annoyance in nurses. Second objective is to use these insights to explore strategies to redesign these systems in ways that alleviate cognitive burden and reduce alarm fatigue, improving both nurse performance and patient safety in high-stakes clinical environments.

In this thesis, this is done by examining the ICU context, the underlying technology of patient monitoring systems, and nurses as their primary users (Figure 1). Insights from this investigation are then used to develop nurse-centered design directions that support clinical workflow and reduce cognitive strain.

Following the three key themes of the context, system, and the user, this thesis is divided into three sections as illustrated in Figure 2. First, the ICU context that the interaction takes place in is explored. Secondly, the technology of patient monitoring systems and their underlying algorithms is investigated. Lastly, ICU nurses are examined as users and their needs are investigated. Design directions are presented to address the challenges identified through these sections.

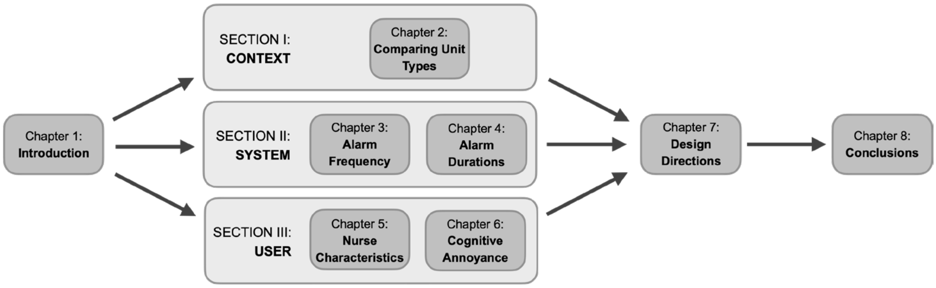


Figure 2. Structure of the thesis

Section I: Context

Chapter 2 In this chapter, the alarm load in three types of ICUs in one hospital has been investigated. In an observational study, the alarm data is analyzed to document and compare the number and nature of patient monitoring alarms in adult, pediatric, and neonatal ICUs. The operational dynamics in the ICU are investigated to gain a deeper understanding of the patient populations and daily and weekly routines. A diagnostic approach is followed to unravel the main friction points leading to an excessive number of alarms. By doing so, opportunities for design and engineering interventions to reduce the number of non-actionable alarms are revealed.

Section II: System

Chapter 3 In this chapter, the frequency of alarms in a neonatal ICU was investigated through an observational study using alarm data (Bostan et al., 2022). Metrics such as the frequency of occurrence of alarms per patient, the proportion of medical/technical alarming conditions, levels of priority, and alarming parameters were calculated. This analysis reveals the high alarm frequency within the patient monitoring system in this unit, exposing how often nurses are exposed to alarm events. Understanding the algorithms behind these alarms is crucial for identifying factors contributing to excessive alarm rates. This study set the stage for exploring adjustments to these parameters, aiming to reduce unnecessary alarms while still ensuring patient safety.

Chapter 4 This chapter is built on the previous chapter by examining alarm durations in an adult ICU (Bostan et al., 2024b). As alarms can last anywhere between one second to several minutes, the characteristics of continuous sound events, rather than single occurrences, were studied. The acoustic environment was explored from the perspective of nurses, and the length of their exposure to alarm signals was investigated. Results indicated that most alarms last shorter than 10 seconds. This allows the opportunity to delay the onset of alarm signals and reduce the number of non-actionable alarms. Design implications and behavior change campaigns for implementing alarm delays are discussed. These insights pave the way for context-sensitive alarm systems that better align with clinical workflows and nurse needs.

Section III: User

Chapter 5 This chapter is focused on the individual characteristics of ICU nurses (Bostan et al., 2024a). Previous research has indicated diversity among nurses in terms of personality traits, but knowledge gaps existed regarding how these traits interact and influence alarm interactions. Surveys were employed to gauge individual nurse characteristics that may impact interactions with patient monitoring systems. Individual factors were measured through personality type, vulnerability to stress, sensory sensitivity, musicality, and risk tolerance. Nurses were then clustered based on similarities across these dimensions. The analysis revealed four distinct nurse profiles. Design implications were discussed to address the specific needs of different user types, highlighting the value of supporting nurse needs through targeted system design elements.

Chapter 6 This chapter addressed task interruptions. Although alarms are often annoying due to their acoustic characteristics, their most disruptive impact on nurses arises from workflow interruptions. This study specifically examined the cognitive annoyance caused by task interruptions. In a controlled lab experiment, the effects of task interruptions were measured based on subjective feelings of annoyance, performance metrics, and cognitive states as recorded by electroencephalogram (EEG). Results showed that increase in interruptions leads to slight increase in annoyance levels, decrease in performance outcomes, and elevated stress levels as indicated by EEG. The level of stress remains elevated between interruptions, revealing the lasting effects of these disruptions. The sustained stress observed suggests that even anticipating alarms can increase cognitive load, potentially compromising decision-making and attention. This underscores the importance of designing alerting systems that minimize unnecessary interruptions and lessen cognitive strain on healthcare providers and other professionals.

Design Directions

Chapter 7 In this chapter, findings from the previous chapters were synthesized to develop design directions aimed at addressing the risks posed by alarms and supporting ICU nurse needs. A multi-disciplinary workshop was conducted, involving ICU nurses, doctors, industry experts, designers, and researchers. The resulting design directions focused on enhancing patient monitoring system design, introducing supportive technologies, and building awareness and expertise across multiple levels. Outcomes from this workshop provide actionable solution bundles that consolidate previous insights and introduce novel approaches, offering a holistic, collaborative perspective on mitigating alarm fatigue.

Conclusions
Lastly, **Chapter 8** summarizes the findings of these studies and draws conclusions from the research. Reflecting on the outcomes and chosen methods, this chapter presents the contributions to design research. Additionally, implications for improved patient monitoring practices are listed as actionable solutions. Finally, research limitations are addressed, and directions for future studies are proposed.

The work in this thesis utilized mixed-method research to investigate the context, technology, and use of patient monitoring systems. Initial familiarization to the ICU context began by informal observations, interviews, and shadowing ICU nurses and physicians. These allowed getting a general sense of the workflow and the operational dynamics of the ICU. Afterwards, questionnaires and surveys were employed to investigate the individual characteristics of nurses. To measure the impact of cognitive strain caused by alarms, controlled lab studies were conducted in which subjective ratings, objective performance metrics, and measures of brain oscillations were used to triangulate the measured effects. Investigating the alarm load in the units was done by extensive data analysis using descriptive and inferential statistics. Clustering algorithms and linear modeling were employed to interpret the data. Finally, a co-creation workshop was conducted to bring stakeholders together to explore ways of reducing the number of alarms. Following such a mixed methods approach allowed gathering a holistic understanding of the issue at hand. Quantitative methods provided accurate and precise measures, while qualitative methods illuminated the ‘why’ and the ‘how’ of the findings, contextualizing them in the human experience. The results of the mixed-method research allowed for a triangulation of the contextual, technology-driven and nurse-centered insights for offering bases for sound-driven design directions.

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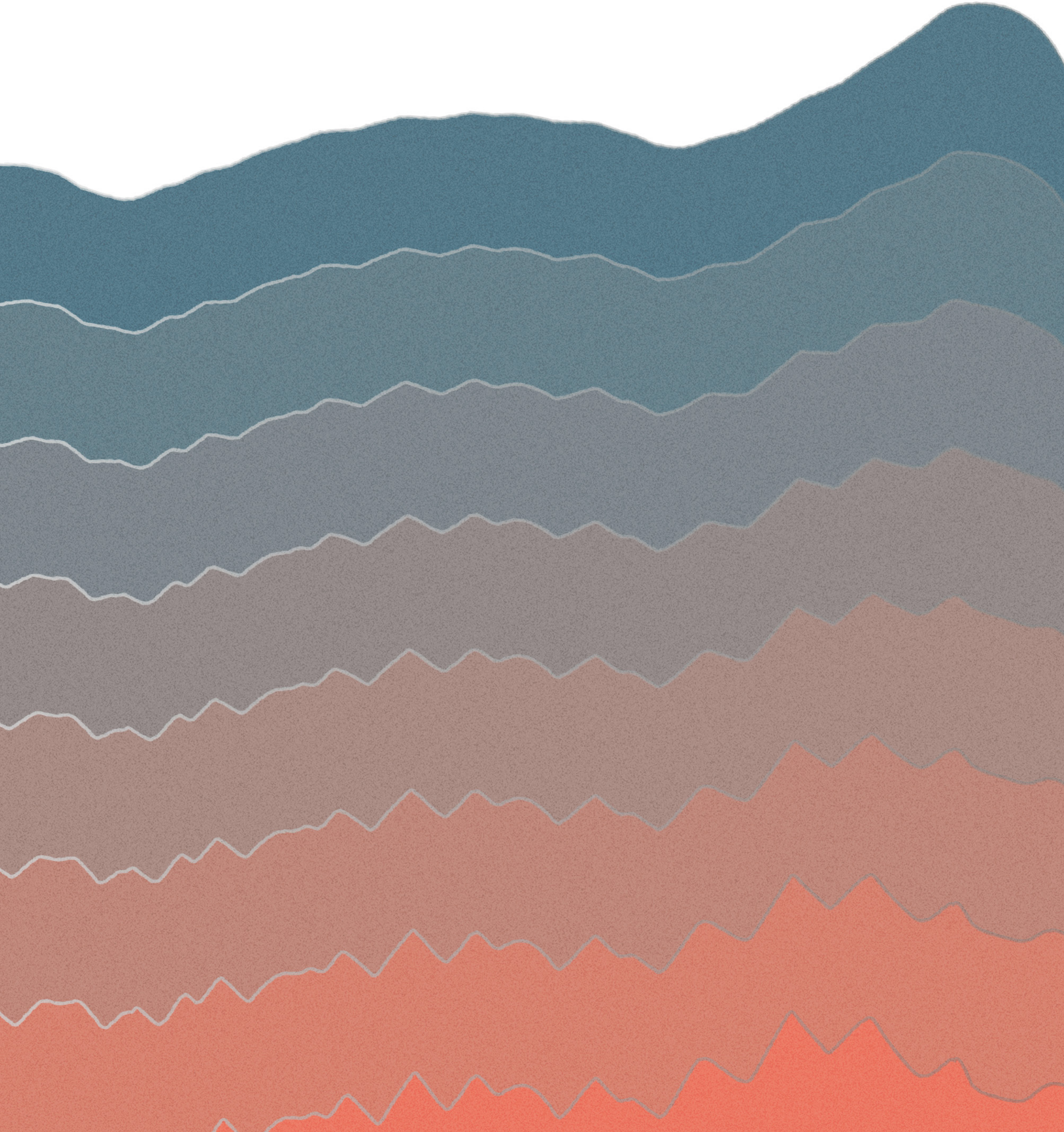

2

A Tale of Three ICUs: Documenting Alarm Loads in Adult, Pediatric, and Neonatal Intensive Care Units to Reveal Implications for Design and Practice

This chapter has been submitted as the following research article:
Bostan, I., Goos, T., van Egmond, R., Gommers, D., Özcan, E. (*submitted*). A Tale of Three ICUs: Documenting Alarm Loads in Adult, Pediatric, and Neonatal Intensive Care Units to Reveal Implications for Design and Practice

Abstract

Excessive number of alarms pose threats to patient safety and impair the well-being of the healthcare staff in the ICUs. Reducing the number of irrelevant alarms requires design and engineering solutions, as well as behavioral changes and workflow improvements. For these changes to be effective, they must be informed by the specific medical context and tailored to the unique needs of each setting. In this study, our aim is to document the number of alarms in three types of ICUs to unravel the friction points that lead to excessive number of non-actionable alarms in various ICU settings. Through an observational study, we analyze the alarm data from adult, pediatric, and neonatal intensive care units to illustrate the current alarm load and compare the number and nature of alarms. We follow a diagnostic approach to understand and interpret the root causes of alarm load with contextual insights related to the patient populations, unit cultures, clinical practices, and technological limitations. Our results revealed that the main drivers of alarm load were the variations in patient physiology, differences in unit cultures, common clinical practices across all units, technological limitations, and unit layouts. Key factors that lead to the high number of alarms were sensitive physiology of young patients, lack of alarm limit customization, daily care routines, and open-bay layout. Such predictable patterns offer opportunities for design and engineering solutions to reduce the number of alarms. Context-aware solutions which account for the listed factors can significantly reduce the number of alarms. Solution strategies include empowering nurses to customize alarm limits, accounting for daily unit routines through systems engineering, accounting for standard medical procedures, improvements on faulty sensors, and implementing improved alarming algorithms. Achieving the sensitive balance between patient safety regulations and nurse well-being requires tailored solutions addressing unique needs of diverse contexts.

2.1 Introduction

Alarms in intensive care units (ICUs) are crucial for alerting nurses to potential medical issues. Nurses rely on patient monitoring systems to track vital parameters and provide timely medical intervention. However, the overwhelming number of alarms, with nearly 90% being non-actionable, creates significant challenges (Cvach, 2012; Drew et al., 2014). Nurses face cognitive overload, frustration, stress, and diminished responsiveness, which jeopardizes patient safety and nurse well-being (Deb & Claudio, 2015; Dehghan et al., 2023; Honan et al., 2015; Lewandowska et al., 2020; Ruskin & Hüske-Kraus, 2015; Salameh et al., 2024). Decades of research and industry attention have not yet resulted in large-scale, sustainable solutions (Dehghan et al., 2023). Addressing the challenges posed by excessive number of alarms in various settings requires a grounded understanding of the clinical context of use of the patient monitoring systems. Contextualizing alarms within specific environments helps us identify the friction points leading to excessive number of alarms. These points can then be used to generate targeted solutions that cater to the distinct demands of each unit (Bostan et al., 2022; Bostan et al., 2024). In this study, we investigate the alarm load in three types of ICUs within the same hospital to reveal opportunities for design and engineering solutions.

Improving the alarm management in ICU requires insights into the alarm load and its handling in a unit (Cosper et al., 2017; Hüske-kraus et al., 2018). Identifying the factors that contribute to non-actionable alarms will be the first step to eliminating them. In order to quantify the alarm load and the quality of alarm management practices, Hüske-Kraus proposed a list of calculations based on alarm data. These include alarm durations, ratio of acknowledged alarms to all alarms, average number of alarms per (patient) bed per day and several others. This model has been used effectively by previous studies to identify issues with the alarm load in the context of surgical IC units (Poncette et al., 2021). In their study, they have demonstrated that simple data analysis steps can help generate valuable insights for designing alarm management interventions. In this study, we utilize this framework and follow a diagnostic approach to understand the root causes of observed trends and patterns, thereby providing a look into the operational dynamics of ICUs.

Existing research aimed at reducing the number of alarms often focuses on specific types of ICUs in isolation. However, ICU environments are not uniform, and they cater to distinct patient populations with varying clinical needs and physiological baselines. This variability is likely to influence both the frequency and nature of alarming conditions, yet few studies have systematically compared alarm loads across these different types of ICU settings. In this current study, we address the gap by directly comparing the alarm load in adult, pediatric, and neonatal ICUs within the same hospital, documenting key alarm parameters and trends over time. Such a comparison provides valuable insights into how alarm management practices can be refined to meet the specific needs of diverse ICU environments (American Association of Critical-Care Nurses, 2018). By conducting the study among different units within the same medical center, we control for cultural and regional policy differences that can lead to varying practices and protocols, thus increasing the internal validity of the results. Comparing alarm loads across different ICUs helps engineers and designers gain a better understanding of how patient demographics and health conditions influence alarm frequency and types. Our aim is to describe the context of use for patient monitoring alarms, identify the friction points leading to excessive number of alarms, and to inform future interventions aimed at reducing the number of alarms to increase staff well-being and patient safety.

2.1.1. Unit Layout

ICUs either have single-patient rooms or multi-patient open layout. Single-patient rooms are quieter and calmer in terms of sound pressure levels, both in the patient rooms and at the nurse stations (Özcan et al., 2024), and are often preferred by patients and visiting families (de Matos et al., 2020). While this layout has its benefits, it translates into longer walking distances and total travel time for ICU nurses (Obeidat et al., 2022; Zadeh et al., 2012). ICU staff were found to experience higher levels of stress in this layout compared to multi-patient units. While the exact reasons were not clear, it is hypothesized that single-bed rooms contribute to stress due to increased travel distances caused by long corridors, limited visibility of both patients and other staff, and challenges in communicating with other caregivers. Additionally, the increased travel distance has a potential to influence alarm settings (Joshi et al., 2018). Nurses in multi-patient rooms may keep their alarm settings conservative and use the number of alarms as an implicit metric of patient stability, as responding to alarms requires relatively less effort in this unit layout. On the other hand, the increased effort to walk long corridors to respond to alarms may discourage nurses in single-patient units from generating many alarms, incentivizing looser alarm settings.

2.2 Methods

2.2.1. Setting and Design

The data was collected in the Erasmus MC; in a general ICU for adults (Adult ICU), a pediatric ICU (PICU), and a neonatal ICU (NICU). The Adult ICU consisted of eight beds in separate patient rooms (Figure 1). Nurse to patient ratio was often 1:1. Each room was equipped with its own patient monitoring system: the Dräger Infinity Acute Care System composed of C700 and M540 modules. A Masimo RD SET Pulse Oximetry module was attached to the system for the measurement of oxygen saturation. Electrocardiogram (ECG) and oxygen saturation modules were connected to the Dräger system and displayed information through the patient monitor. Infusion pumps (B.Braun Space, Melsungen, Germany) were present for medication delivery. Patient rooms were further equipped by other medical devices such as mechanical ventilators and dialysis machines depending on the patient needs. Myco 2 pagers (Ascom, Baar, Switzerland) connected to the central alarm system, were carried by the nurses, conveying the alarms of the Dräger monitoring system with contexed, consisting of the priority level and the type of alarm. Other equipment was connected through the MOS part of the Ascom system and conveyed without additional contexed besides location and device type. Nurses in the adult ICU were free and required to customize alarm limits on the patient monitor as they saw fit for their patients.

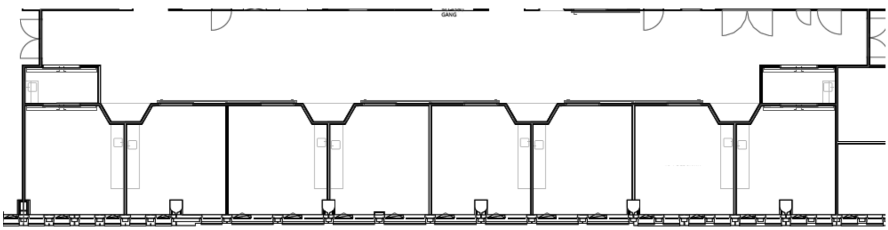

Figure 1. Floor plan of Adult ICU in Erasmus MC. Individual patient rooms lined along the corridor, with a nurse desk placed in pockets between each two rooms. Desks face the patient beds and nurses can instantly see inside the room through windows placed on the wall.

The PICU and NICU were open bay units, consisting of six beds in the PICU, and eight beds in the NICU (Figure 2) with an additional single patient room per unit. Nurse to patient ratio was 1:1 in the PICU, and 1:3 in the NICU. In both units, patient beds were placed in a U-shape, with a central nurse desk facing the beds. Each bed was equipped with the same patient monitoring system as used on the Adult ICU: the Dräger Infinity Acute Care System composed of C700 and M540 modules with Masimo RD SET Pulse Oximetry module for measuring oxygen saturation, and B.Braun infusion pumps. Other medical devices such as mechanical ventilators and dialysis machines could be used depending on the patient needs. Pagers were not used in these units due to the open layout. Instead, alarms generated by patient monitoring systems were signalled on the bedside monitor and the Dräger central station on the desk. And alarms from the other medical equipment was only visible and audible on the equipment itself. PICU nurses were free and required to customize alarm limits as they see fit for their patients. However, in the NICU, alarm limits were controlled by protocols and nurses were not allowed to customize limits for their patients.

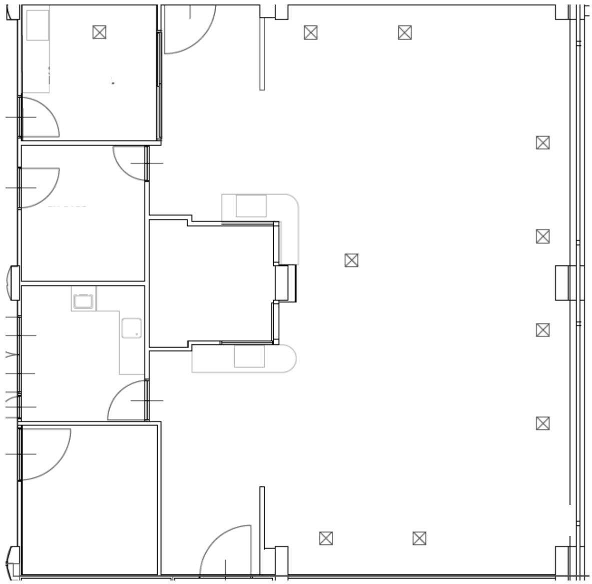

Figure 2. Floor plans of PICU and NICU at Erasmus MC. Patient beds were placed in a U-shape, facing the central nurse desk. Both units had the same layout, with six beds in the PICU and eight beds in the NICU.

The data collected is based on alarm data logs from the patient monitoring systems which were retroactively extracted from the patient monitoring system for one month in 2023. The anonymized alarm data log consisted of the date and time stamp for each alarm, the room (or bed) number, the alarm type, the alarm-generating parameter, the parameter value at the time of the alarm, the alarm limits at the time of the alarm, the alarm priority level, the alarm duration in seconds, and the associated alarm message. The patient-identifying information was removed by the medical institute prior to the data analysis to ensure anonymity.

2.2.2. Patient Populations

The adult ICU, PICU and NICU at Erasmus Medical Centre (Rotterdam, the Netherlands) show great variation in terms of the central concerns for their patient populations and standard practices in addressing these. Adult ICUs typically admit patients with acute or chronic medical conditions such as traumatic brain injuries, sepsis, or post-surgery recovery. The most prominent medical concerns relate to respiratory support, septic shock, and multi organ failure. This unit does not admit cardiac patients as a separate Cardiac-ICU department exists in Erasmus MC. PICU patients encompass a wide age range, from infants to adolescents. As pediatric patients vary greatly in size, physiology, and developmental stages, they require highly individualized care. Some central medical concerns relate to fluid balance, respiratory illnesses, and traumatic brain injuries. Finally, NICUs host premature infants and term newborns with birth asphyxia. Typical medical concerns relate to immature organs, thermoregulation, respiratory issues, nutritional support and sepsis. Overall, while adult ICUs handle larger, complex, multi-system issues with more invasive monitoring; PICU and NICUs require more tailored, developmentally appropriate care as the vital parameters of these patients change faster. Thus, one-design-fits-all approach may not be suitable when catering for the specific needs of differ critical care environments.

2.2.3. Inclusion and Exclusion Criteria

All patients admitted to these units during the study period were included in the analysis. The study only included alarms generated by the patient monitoring system and excluded any other medical equipment. Some patient beds were rarely used, only for training or testing purposes. These outlier beds (and their associated alarms) were excluded from the analysis. The vital parameters which generated fewer than 200 alarms in total throughout the entire month were excluded from the analysis to ensure the generalizability of results and readability of the tables and plots. In some calculations, different exclusion criteria were used to ensure readability, and these are reported in the relevant result sections and are listed in (Table 1).

2.2.4. Data Metrics and Calculations

Our analysis investigated alarm load from various angles and compared across the units. We calculated the sums, averages, and percentages where appropriate. All the calculations made per unit are listed in (Table 1).

Table 1. The alarm metrics used in the study, explanation of the calculations, and further exclusion criteria where applicable.

Alarm Metrics	Metric Calculation	Exclusion
1. Number of alarms per month	Sum	-
2. Average number of alarms per patient bed per day	Mean	-
3. Number of alarms per hours of the day	Sum	-
4. Average number of alarms per days of the week	Mean	-
5. Number of alarms per vital parameters	Sum	-
6. Percentage of each parameter within the unit	Percentage = n(parameter)/N(all)	-
7. Alarm durations, most frequent parameters	Smoothed histogram	n<500
8. Percentage of alarm ending messages	Percentage = n(message)/N(all)	-
9. Percentage of ending messages per parameters	Percentage = n(message)/n(parameter)	n<5%
10. Bandwidths, most frequent parameters	Upper limit – lower limit	n<5%

The Dräger Infinity Acute Care System used abbreviations to represent the vital parameters. The definitions and medical explanations of the parameters included in this analysis are listed in (Table 2).

Table 2. List of parameter abbreviations used by the patient monitoring system, along with their meaning and medical explanations.

Parameter name	Parameter meaning	Medical explanation
ARR	Arrythmia	Irregular or abnormal heart rhythm
ART M	Art median	Mean arterial blood pressure
ART S	Art systolic	Systolic arterial blood pressure
CPP	Cerebral perfusion pressure	Pressure of blood flow to the brain
HR	Heart rate	Number of heart beats per minute
ICP	Intracranial pressure	Fluid pressure on brain tissue
SpO_2	Oxygen saturation	Percentage of blood oxygenation
PLS	Pulse rate	Number of heart beats per minute
RESP	Respiration	Number of breaths per minute
Ta	Temperature	Body temperature

Note that heart rate (HR) and pulse rate (PLS) both represent the action of the heart, although HR measures the electrical activity and is monitored through the electrocardiogram (ECG) while PLS measures the pulsation of the blood and is monitored by the pulse oximeter. The common practice was to use the ECG for the heart rate monitoring, and PLS alarms were deactivated at the oxygen saturation module to avoid double alarms. However, patients could be taken off the ECG when their medical condition was improving. Furthermore, ECG electrodes were not used on extreme preterm neonates in fear of damaging their skin. In these cases, heart rate was monitored through pulse oximetry and alarms were based on the PLS.

Similarly, respiration rate could be monitored by the ventilator device and the ECG. When patients were connected to a ventilator, their respiration was monitored more accurately through this device, and the RESP alarms were disabled on the patient monitoring system. When patients came off the ventilator, their respiration was monitored by the ECG, and RESP alarms were enabled on the system.

2.2.4. Data processing and Analysis

The dataset was cleaned, analyzed, and visualized in R programming software, using the packages *tidyverse, psyc, cowplot* and *viridis* (Garnier et al., 2024; Revelle, 2019; Wickham et al., 2019; Wilke, 2024). In the dataset, each alarm was represented by two rows: one for the beginning and one for the ending of the alarm. The beginning-rows did not include the alarm duration variable as this was not yet defined. Frequent artefacts induced by system errors or sensor errors were also registered in the data set as beginning-rows, introducing anomalies to the dataset. The alarm duration was only present at the alarm ending-rows. Therefore, we ran the analyses on the ending-rows and excluded the beginning-rows from the analysis.

2.2.5. Contextualizing the Data

Three clinical experts (two nurses and one clinical technologist) representing three respective units acted as judges to interpret the results. Independently held discussions provided context to the findings and explored the underlying causes behind the observed alarm patterns. We cross-checked the insights across units to ensure consistency and ecological relevancy, aiming to ground the quantitative data in actual ICU experiences. This process helped us delve into the "why" behind the data, offering a nuanced understanding of unit-specific practices through a diagnostic approach.

2.3 Results

2.3.1. Number of Alarms

The total number of alarms observed in one month was 20340 in the Adult IC, 30550 in the PICU, and 88162 in the NICU, as illustrated in (Figure 3A). The median number of alarms per bed per day per unit were calculated as suggested by previous literature (Hüske-Kraus et al., 2018; Poncette et al., 2021), accounting to 86.0 alarms in the Adult ICU, 152.5 in the PICU, and 508.5 in the NICU, as illustrated in (Figure 3B).

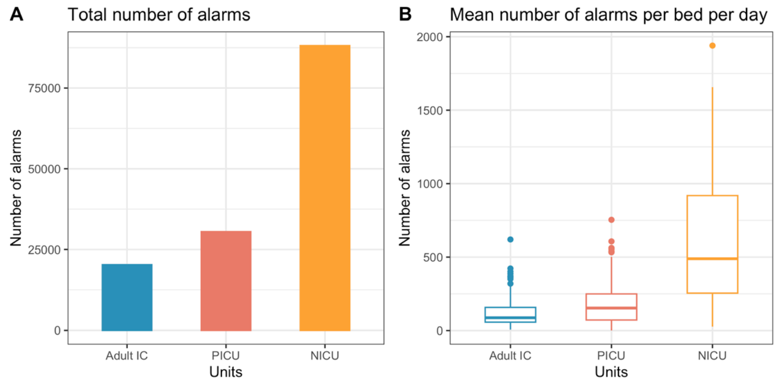

Figure 3. A) Total number of alarms generated in the unit in one month. Adult IC had the lowest number of alarms, and NICU had significantly more alarms than the other units. B) Mean number of alarms per patient bed per day. Once more, NICU had a higher number of alarms compared to the other units, and also showed a larger variation.

2.3.2. Hours of the Day

The number of alarms fluctuated throughout the day. For each unit, the total number of alarms per hour The number of alarms fluctuated throughout the day. For each unit, the total number of alarms per hour over hours of the day is illustrated in (Figure 4). In all units, the peak number of alarms in the day occurred around 9:00, during the morning rounds and daily clean-up of the patients. For Adult IC and NICU, the second peak was at 20:00, while for PICU it was at 15:00.

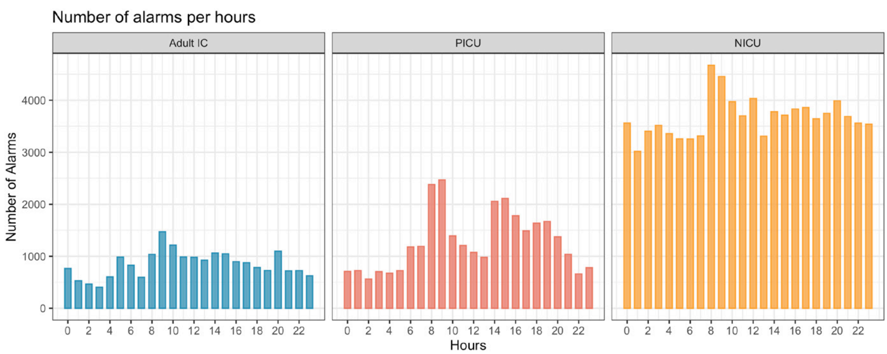

Figure 4. Number of alarms per hours of the day for each unit. x-axis represents the midnight-to-midnight hours in one day. In all units, the peak number of alarms were generated around 9:00.

2.3.3. Days of the Week

The mean number of alarms per days of the week were calculated. Note that this calculation is not the total number of alarms, but averaged per days, since some days occurred for five times in that month while others occurred for four times. In Adult ICU, Fridays were associated with the highest number of alarms as seen in (Figure 5). In the PICU, the first three days of the week had the highest number of alarms. In the NICU, Wednesdays and Fridays had the highest number of alarms. In all units, more alarms occurred on the weekdays than the weekends.

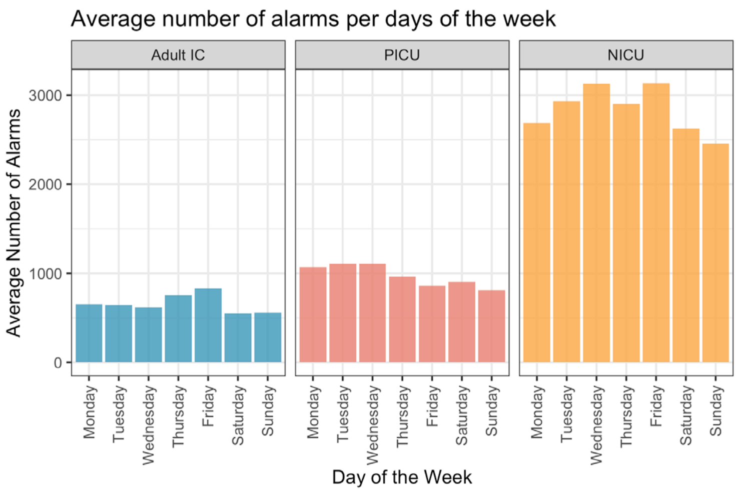

Figure 5. Mean number of alarms per days of the week. In Adult IC and NICU, Fridays had the highest number of alarms. In PICU, Monday to Wednesday had the highest number of alarms. In all units, the least number of alarms were generated on the weekends.

2.3.4. Vital Parameters

Vital parameters generated various numbers of alarms per unit. The total number of alarms per parameter are illustrated in the (Figure 6). In the Adult IC, blood pressure (ART M) generated the highest number of alarms, followed by oxygen saturation (SpO_2) and heart rate (HR). In the PICU, oxygen saturation generated the highest number of alarms, followed by heart rate and pulse rate (PLS). In the NICU, oxygen saturation generated the highest number of alarms, followed by heart rate and respiratory rate (RESP). The percentage of each parameter compared to all parameters per unit are listed in (Table 3).

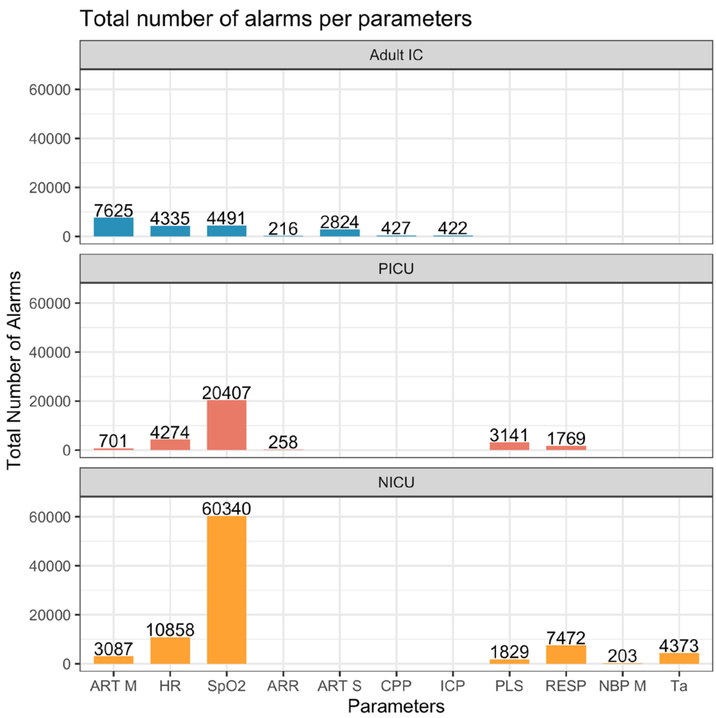

Figure 6. Number of alarms generated by each parameter in each unit. Parameters that are not marked by a number did not appear as alarms in that unit. For example, PLS was measured in PICU and NICU but not in the Adult IC.

Table 3. Percentages of parameters to all alarms in the unit. The blank cells indicate zero alarms were generated by that parameter in the unit. Note that only the parameters measured in all units are included to allow for comparison between unit types.

	ART M	HR	SpO_2	ARR	PLS	RESP
Adult	37.68%	21.21%	22.20%	1.05%	-	-
PICU	2.29%	13.99%	66.80%	0.84%	10.28%	5.79%
NICU	3.44%	12.18%	68.21%	-	2.04%	8.90%

2.3.5. Alarm Durations

Alarm duration was measured as the seconds an alarm lasted for. An alarm could end due to four reasons. The first three is due to nurse intervention: nurse acknowledging (silencing) the alarm, medical intervention to the patient, or changing the alarm limits. The fourth reason is the underlying condition disappearing (vital parameter returning to within the alarm limits). Therefore, this metric relates to nurse reaction time but cannot be seen as a direct measure of it. Alarm durations varied per parameters.

(Figure 7) illustrates the number of alarms per duration in seconds. Parameters that generated fewer than 500 alarms per month were excluded from this plot for better visibility of the distributions. Note that the x-axis includes alarms up to 30 seconds, as the great majority of alarms lasted shorter than 30 seconds and this representation provides a better visibility of the distributions.

In the Adult ICU, most of the oxygen saturation alarms lasted less than five seconds (31.7%) and constituted the parameter that had the shortest alarm duration. In the PICU, pulse rate and oxygen saturation alarms had the shortest alarm durations. In the NICU, pulse rate, oxygen saturation, and temperature alarms had the shortest durations.

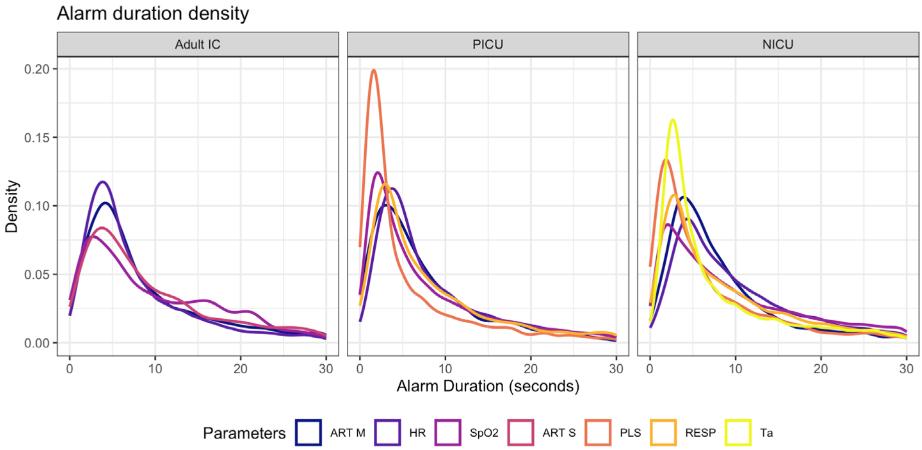

Figure 7. Density plot illustrating the frequency of alarms of certain durations. Can be observed as a smoothed version of a histogram. In all units, SpO_2 alarms ended quickly.

2.3.6. Alarm Messages

Each alarm ended with an alarm message displayed on the patient monitor. There were four types of alarm messages. When the underlying alarming condition disappeared, this was recorded by the system as *Solved* (e.g., "Solved: SpO_2 < 89"). When the alarm was acknowledged by a nurse by hitting the Silence button, this was recorded as *Silenced* (e.g., "Silenced: SpO_2 < 89"). Finally, some alarms ended while the vital parameter was still out of the alarm limits (e.g., "ART M < 65") or due to a technical issue or an artefact (e.g., "ART M static pressure", "N/A"), and these were collected into the category *Other* in this study. The percentage of alarm messages per unit are illustrated in (Figure 8). In all units, most alarms ended due to the alarming condition disappearing (Solved), followed by nurses acknowledging the alarms (Silenced). The proportion of Silenced alarms was higher in the PICU compared to the other units.

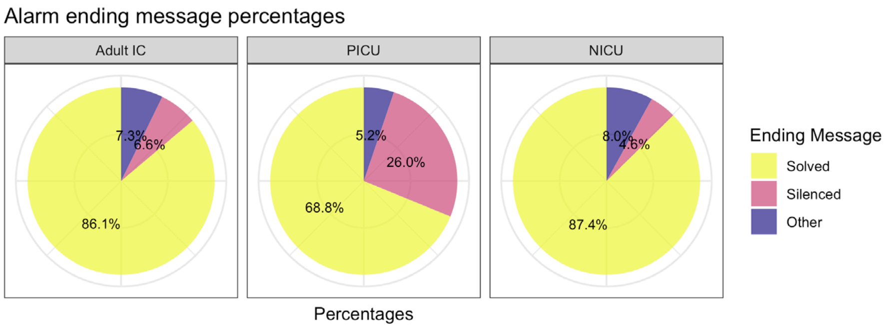

Figure 8. Percentages of alarm messages in each unit. In all units, majority of the alarms ended as 'Solved', due to the alarming condition disappearing.

Proportions of alarm messages varied across the vital parameters. (Table 4) lists the percentage of alarm messages for each parameter aggregated for all units. Note that only the parameters which generated more than 5% of all the alarms were included in this table for clarity. Heart rate alarms were associated with the highest proportion of technical artefacts recorded in the system. On the other hand, the most often silenced vital parameter was oxygen saturation.

Table 4. Alarm ending percentages per vital parameters.

Units		ART M	HR	SpO_2	RESP
Adult	**Solved**	86.65%	87.82%	82.16%	-
	Silenced	7.21%	3.17%	6.36%	-
	Other	5.85%	9.02%	11.48%	-
PICU	**Solved**	70.19%	65.61%	67.20%	78.52%
	Silenced	27.25%	22.13%	28.99%	17.58%
	Other	2.57%	12.26%	3.81%	3.90%
NICU	**Solved**	87.63%	77.85%	88.90%	89.95%
	Silenced	3.98%	5.26%	4.44%	1.39%
	Other	8.39%	16.89%	6.66%	8.66%

2.3.7. Bandwidths

To assess the variability in alarm parameter ranges, we calculated the percentage variation in bandwidth relative to the median bandwidth for each parameter. The median bandwidth, representing the typical range between the upper and lower alarm limits, was used as a baseline. The percentage variation was computed by comparing the absolute bandwidth value to the median value, allowing to quantify how much tolerance exists in alarm thresholds across different unit types. This analysis highlights the degree of variability in alarm settings, with higher percentages indicating more variable or 'looser' ranges; while lower percentages implying tighter or more consistent alarm ranges.

Results are illustrated in (Figure 9). Note that parameters that constituted less than 5% of all alarms were excluded from this plot for increased visibility. These results indicate that alarm thresholds were typically more flexible in the Adult ICU, while PICU and NICU tended to have stricter controls. For example, the median variation from the typical blood pressure baseline was around 64.87% in the Adult ICU, 50% in the PICU, and 41.56% in the NICU. The same respective pattern was observed for heart rate (77.78%, 70.37%, 66.67%) and oxygen saturation alarms (8.33%, 8.33%, 6.52%).

Figure 9. Relative bandwidths per parameters for each unit. Bandwidth = Upper alarm limit - Lower alarm limit. Typically, alarm ranges were looser in the adult ICU and the tightest in the NICU.

2.4 Discussion

The results of this study illustrated the alarm load in three types of intensive care units in one hospital: Adult ICU, PICU, and NICU. We extracted the alarm data from the patient monitoring systems of three units and followed a diagnostic approach to interpret the data and understand the root causes of the observed patterns. In this section, the findings are contextualized to identify the factors contributing to high number of alarms. Furthermore, design and engineering solutions targeted at reducing the number of alarms are discussed.

2.4.1. Limit Customization and Unit Layout Impact the Number of Alarms

Results suggest that number of alarms depend largely on the ICU type, with NICU scoring almost four times more alarms than Adult ICU and three times more than the PICU. One reason for this related to the differences among the unit cultures. While the nurses in Adult and Pediatric units were allowed and required to set the alarm limits for their patients, NICU nurses could not customize their alarm limits. This may have contributed to significantly more alarms in NICU compared to the other units. Furthermore, the Adult IC consisted of individual patient rooms with sound isolation, while PICU and NICU were open bays. Open bay units often generate higher number of alarms compared to single-patient room units (Joshi et al., 2018), possibly due to the relative convenience of responding to alarms. The effort needed to respond to alarms in single-patient rooms is greater, motivating wider alarm limits to prevent non-actionable alarms. The large difference in the number of alarms in NICU compared to the other units highlights the importance of allowing nurses to customize alarm limits to reduce the number of alarms.

Another reason for the large difference in the number of alarms between the units related to the patients' physiology. Younger patients fluctuate rapidly in their vital parameters, triggering many alarms which often self-resolve quickly. Furthermore, the physiology of the patients and the fear of hyperoxia in preterm infants will play a significant role in the tight alarm limits that are used on the NICU. Technical limitations also contributed to higher number of alarms in PICU and NICU. Attaching oxygen saturation sensors to younger patients is challenging due to their thin and fragile skin (Cosper et al., 2017). Sensors often got detached and led to faulty readings, generating many non-actionable alarms.

2.4.2. Daily Routines Determine Hourly Alarm Rates

In all units, patterns in the alarm load reflected the daily clinical practices. Night hours were associated with the least number of alarms as patients were often sleeping. Morning rounds and daily clean-up of the patients around 9:00 generated the peak number of alarms. The increased bed movement and mobility of patients during this time frequently led to sensor detachment or increased pressure on the sensors, causing abnormal readings and triggering false alarms. Additionally, the movement and surrounding activity often caused patients to wake or become alert, leading to elevated heart rates, which in turn generated more alarms. In the Adult ICU and NICU, a second alarm peak was observed around 20:00, due to a similar care routine and procedures at this time.

Differences observed between the units related to the unit cultures. In the PICU, early afternoon was resting and napping time for the patients. Curtains around the patient beds were closed and the light was dimmed. Decrease in overall movement in the unit led to fewer alarms during this period. Care activities began again around 14:00, with more people in the unit and procedures such as x-rays and ultrasounds being conducted. These activities led to the second peak of the day. Lastly, the timing of the night care activities such as cleaning were not as fixed in this unit as in the Adult IC. This was due to the diversity in patient ages and developmental stages leading to varying daily cycles. While the teenagers had a more stable daily routine, babies could be less predictable, and the nurses followed the patients' natural routines. For example, a nurse would not wake up a baby to brush their teeth; they would rather do it when the patient naturally wakes up. Therefore, the pattern of night-care alarms was not as distinctive in this unit as it was for the Adult ICU.

The predictable daily routines present valuable opportunities for targeted design and engineering solutions to reduce the number of alarms. A technical limitation in the current system design is that nurses are aware certain routine procedures will trigger alarms, yet these non-actionable alarms are still generated despite being expected and unnecessary. A potential solution to this issue is extended alarm silencing durations during known procedures (currently standard procedure is at two minutes). Allowing longer silencing durations for these highly predictable times (e.g., morning and evening rounds) would prevent the cacophony caused by a cascade of non-actionable alarms. By acknowledging the alarm, nurses could extend the mute period, reducing the burden of repeated alarms that are not clinically significant and would not be requiring medical attention.

Another solution could be the implementation of 'Nursing mode' on the patient monitoring systems, where nurses inform the system that they are conducting a routine procedure. During this period, the monitoring system would be 'aware' of the nursing activities, and all non-critical alarms (such as those related to sensor disconnection or mild fluctuations in vital signs) would be automatically suppressed. High-priority alarms should still remain active to ensure patient safety, but this would prevent unnecessary alarms from overwhelming staff during routine care procedures.

2.4.3. Weekly Alarm Rates Depend on Resource Management

In both the Adult ICU and NICU, the highest number of alarms during the week occurred on weekdays and especially on Fridays. This was not the case in PICU, where a more uniform distribution was observed. This pattern was largely shaped by hospital resource management strategies, which directly influenced the common clinical practices and unit cultures. With fewer staff working over the weekend, certain procedures were restricted to weekdays. Nurses reported a tendency to avoid leaving key decisions or procedures for the weekend, leading to a sense of urgency on Fridays. Procedures such as bronchoscopy, physiotherapy, and certain scans, which are known to generate high number of alarms, were often finalized before the weekend.

This finding highlights an opportunity to reconsider how resources are allocated throughout the week to ensure a more balanced distribution of planned procedures and acute events. By optimizing resource allocation across the week, hospitals can reduce the bottleneck of procedures performed before weekends, which can reduce alarm loads and enhance patient safety.

2.4.4. Diverse Patient Populations, Different Vital Parameters

Results showed that blood pressure (ART M) measurements generated the greatest number of alarms in the Adult ICU followed by heart rate (HR) and oxygen saturation (SpO_2), following the order of concern for most adult ICU patients. In the PICU and NICU, oxygen saturation was the primary cause of alarms. The prevalence of oxygen saturation alarms in younger patients is a well-established phenomenon. This can be attributed to three main factors related to patient physiology. First, in adults, only low oxygen saturation presents a significant risk, and alarms are typically set for the lower threshold. However, in neonates, both low and high oxygen saturation levels pose risks, requiring alarms for both the lower and upper limits. Second, neonates and pediatric patients are more prone to rapid fluctuations in oxygen levels leading to a higher incidence of alarms. Lastly, oxygen saturation sensors often have difficulty being attached to younger patients, especially neonates, since their skin is thin and fragile. The overall higher mobility of children often causes detachment of the sensors, leading to abnormal readings and false alarms. Optimizing skin attachment of the SpO_2 sensors, through new material design or other wearable devices to hold it in place, holds the potential to reduce a high volume of alarms in this context.

2.4.5. Alarm Durations Present Opportunities for Improving Alarming Conditions

Oxygen saturation alarms had an early peak as most of these alarms lasted only a few seconds. This was due to two factors related to patient physiology. First was that irregularities in oxygen saturation pose a more time-sensitive challenge for the human body, whereas adults can tolerate low heart rate or blood pressure for relatively longer. Due to the medical urgency, nurses tend to respond faster to oxygen saturation alarms. The second reason was that this parameter fluctuates rapidly, and the vital value can often be out of limits but return to the limits within a few seconds, thereby ending the alarm.

Differences in unit cultures may also have influenced the alarm durations. As PICU and NICU were open-bay units, responding to alarms is relatively quicker and easier in these units. On the other hand, responding to alarms in the single-patient room adult unit usually requires changing location and added efforts. However, alarm duration is influenced by both nurse intervention and resolving of underlying condition. Therefore, this metric cannot be seen as a direct measure of nurse responsivity.

Preventing short alarms may be possible with implementing alarm delays as brief as five to ten seconds (Bostan et al., 2024; Welch, 2011). This would filter out momentary dips in oxygen saturation that self-correct quickly and don't require immediate intervention. Many monitoring systems already allow for adjustable delay settings, and this could be optimized based on unit-specific patterns. Another approach is to incorporate smarter algorithms to predict patient instability or the severity of upcoming event, and use this information to generate alarms. Such systems hold the potential to automatize deterioration and even medical interventions (e.g., increasing oxygen flow in case of unstable oxygen saturation levels). Currently, a consortium of industrial partners and hospitals are developing smart algorithms for suppressing alarms at the patient side while providing the most relevant info for nurses (IHI, 2023).

2.4.6. Patient Physiology and Unit Culture Shape Alarm Management Approaches

The proportion of alarm messages was largely influenced by patient physiology. In the NICU, most alarms self-resolve due to the neonates' rapidly changing physiology, leading to a higher proportion of Solved alarms. Alarm silencing was more common in the PICU compared to Adult and Neonatal ICUs. In the PICU, the high rate of Silenced alarms was due to the unit culture, where nurses often silenced each other's alarms from the central desk. Nurses were highly sensitive to noise and prioritized maintaining silence in the unit. When a nurse was already engaged with patient care at the bedside and was aware of the medical condition causing the alarm, colleagues at the central desk would suggest silencing the alarm. They would silence the alarm from the desk after receiving confirmation, and prevent redundant noise to the best of their ability.

2.4.7. Alarm Limit Bandwidth is Influenced by Patients and Unit Layout

Overall, alarm limit ranges were looser for adults and got tighter for younger patients in PICU and NICU. This pattern was likely due to the differences in patient physiology in which smaller ranges are observed in younger patient populations. Neonates and young children often experience less physiological variability compared to adults. Alarm systems are typically adjusted to avoid unnecessary disruptions while ensuring timely responses to critical changes in vital signs. Other reasons for the observed pattern may relate to unit cultures and layouts. Adult ICU has a single-patient layout, which is often associated with looser alarm limits. In line with this expectation, the open layout in PICU and NICU may have contributed to tighter alarm limits.

Reducing the number of alarms in various ICU contexts is possible through implementing context-dependent solutions tailored to the unique characteristics and vital parameters of each patient group. Given that neonates and children have higher baseline heart rates and more volatile oxygen saturation, alarm thresholds should be tighter but also flexible. Introducing dynamic or adaptive alarm thresholds could account for normal fluctuations during certain activities (e.g., feeding or routine care) without triggering alarms unnecessarily. Multimodal monitoring (which integrates multiple vital parameters) can reduce the reliance on single-parameter alarms. For example, instead of triggering an alarm solely based on oxygen saturation, the system could consider other factors like heart rate and respiratory rate to assess whether the event is critical. This would prevent unnecessary alarms for brief or non-harmful fluctuations.

Another solution involves context-aware alarm delays. Since oxygen saturation levels tend to fluctuate rapidly in younger populations, applying a short delay before an alarm is triggered (e.g., 5-10 seconds) may reduce the number of alarms. Whereas in adults where blood pressure can safely vary within a broader range, a longer delay (e.g., 30 seconds) could be applied before triggering alarms for non-critical changes. This would allow more time to see if the blood pressure normalizes without intervention.

Finally, the unit policy of not allowing the nurses to change alarm limits lead to a great number of alarms in the NICU compared to the other units. Allowing nurses to customize alarm limits could potentially reduce the overall number of alarms, yet it also introduces risks by possibly overlooking critical signs of patient deterioration or instability. This challenge lies in balancing the frequency of alarms with tolerable levels of patient fluctuations to maintain safety. Achieving this balance requires thoughtful calibration of alarm thresholds, considering both the need to prevent alarm fatigue and maintaining patient safety. In addressing this challenge, trend alarms that monitor the number of events within a time window could be useful in recognizing deterioration patterns.

2.4.8. Key Findings and Patterns Influencing ICU Alarm Rates

We provide a summary list of the most evident and recurring friction points leading to excessive number of alarms based on our findings. These points can be addressed to mitigate the high non-actionable alarm rates by incorporating context-aware solutions:

- **Customizing the alarm limits reduces the number of alarms**: Lower number of alarms was observed in unit cultures where nurses are allowed to customize alarm limits (i.e., Adult and Pediatric ICU). Allowing wider alarm settings could reduce the number of alarms in the NICU, but they may also increase patient risks, particularly since younger patients tolerate fewer fluctuations. Further investigations are needed to explore how customization in neonatal settings can be implemented without compromising patient safety.
- **Units work in daily routines**: In all units, clinical practices during morning and nighttime care activities routinely generate non-actionable alarms. This is due to technical limitations that fail to consider the clinical context. Predictable non-actionable alarms can be silenced or suppressed with improved system features that account for routine clinical workflows. For example, incorporating nursing mode could prevent known non-actionable alarms.
- **Planned procedures generate many non-actionable alarms**: Patients differ in their criticality and physiology, often requiring planned activities such as drawing blood, physiotherapy or ultrasound. Excessive number of alarms occur due to technical limitations that cannot account for such clinical activities. These non-actionable alarms could be preventable if the system design allows for situational suppressing of alarming events.
- **SpO_2 sensors generate non-actionable alarms**: Sensors often get detached from younger patients in Pediatric and Neonatal ICUs due to increased mobility or skin fixation issues. This issue is due to technical limitations which fail to account for patient physiology. Improved sensors with better attachment methods that accommodate for infant movements and skin structure would reduce significant number of non-actionable alarms.
- **Most of the alarms are very short**: In all units, most alarms last less than 10 seconds. Many of these are self-resolving, often not requiring medical intervention. Due to technical limitations, current systems cannot determine clinical significance. Such non-actionable alarms can be prevented by incorporating alarm delays, multi-parameter alarms or trend alarms.

2.5 Conclusion

This study illustrates the variation of alarm loads across three types of ICUs within a single medical center, controlling for factors such as regional medical policies and cultural differences that may vary across different hospitals and countries. Analyzing the alarm load in three distinct unit types with a diagnostic approach unraveled factors pertaining to patient physiology, unit cultures, clinical practices, technical limitations, and unit layouts that contribute to the number of alarms. This comparative approach revealed best practices in each unit and issues that are common to all units.

Many of the identified friction points were due to technical limitations and can be addressed with improved system design and customization strategies tailored to specific needs of ICU types and patient physiologies. Current medical device regulations impose operating on "better safe than sorry" principle, triggering alarms for even minor deviations without considering the clinical context. The manufacturer incentive is capturing every event, not necessarily increasing nurse responsivity. However, excessive alarm rates desensitize nurses to alarms, thereby reducing nurse responsiveness and once again increasing patient risk. Therefore, the challenge lies in achieving a sensitive balance between these two considerations. Findings in this study highlight once again that one-size-fits-all solutions cannot tackle the complexity of the challenge. Instead, context-dependent solutions customized to hospitals, departments, unit cultures, patient populations, and even nurses are needed to meet the demands. This may require more flexible system design offering customization features to the users based on local needs. This study takes a step in identifying the nuances between three unit types and revealing opportunities for tailored interventions. Insights from the alarm data highlights the benefits of multi-disciplinary collaboration between data scientists, engineers, designers, and healthcare professionals to co-create solutions.

2.5.1. Limitations

This study documented the alarm load generated by the patient monitoring system in three types of ICUs with different layouts. However, alarms generated by other medical equipment around the patients, such as mechanical ventilator and infusion pumps, were not included in this data analysis. Furthermore, cleaning the dataset involved several steps in which unclear observations had to be filtered out to ensure the validity of the analysis. It is possible that some of the excluded observations were alarms reflecting technical errors and artefacts. Therefore, the alarm metrics reported in this study underestimate the actual alarm load in the units. Future studies may include alarms generated by all the medical devices in their analysis to estimate the true impact of alarms and discover further intervention points.

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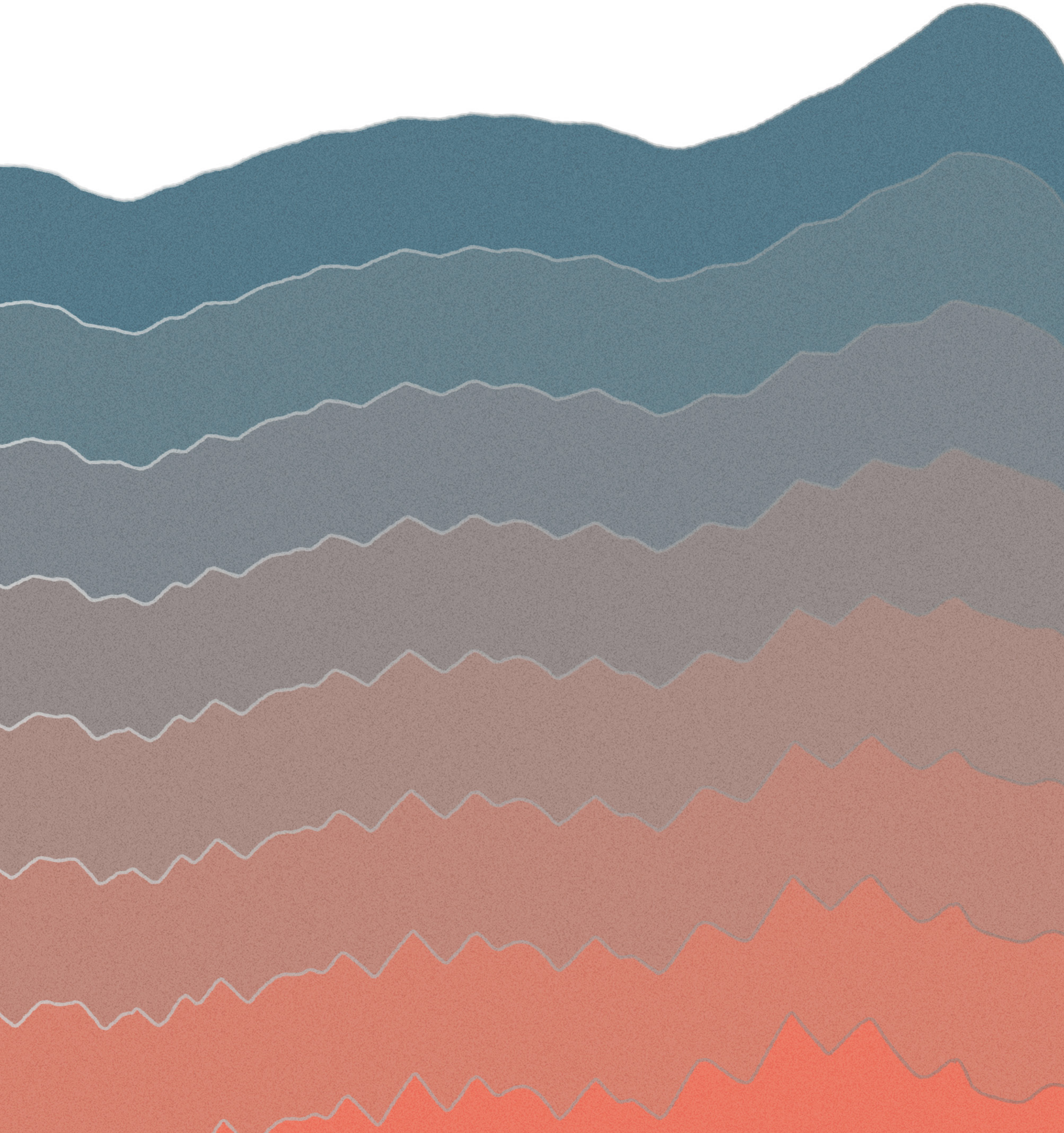

3

Annoyance by Alarms in the ICU: A Cognitive Approach to the Role of Interruptions by Patient Monitoring Alarms

This chapter have been published in the following research article:
Bostan, I., Özcan, E., Gommers, D., & van Egmond, R. (2022). Annoyance by Alarms in the ICU: A Cognitive Approach to the Role of Interruptions by Patient Monitoring Alarms. *Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2022 Annual Conference.*, 133–148.

Abstract

Nurses rely on patient monitoring systems for care delivery in ICUs. Monitoring systems communicate information to nurses and alert them through audiovisual alarms. However, excessive numbers of alarms often interrupt nurses in their tasks, and desensitize them to alarms. The affective consequence of this problem is that nurses are annoyed and feel frustration towards monitoring alarms. This situation leads to stress on nurses and threatens patient safety. Literature on sound annoyance distinguishes between annoyance induced by bottom-up (perceptual) and top-down (cognitive) processing. Extensive research on perceptual annoyance informs us on how to alleviate the problem by better sound design. However, addressing the cognitive aspect requires a broader understanding of annoyance as a construct. To this end, in this paper we distinguish between the annoyance induced by sensory unpleasantness of alarm sounds, and annoyance induced by frequent task interruptions. We present a conceptual framework in which we can interpret nurses' annoyance by monitoring alarms. We further present descriptive analysis of the occurrence frequency of patient monitoring alarms in a neonatal ICU to illustrate the current state with regards to alarms. We aim to support nurses' organizational well-being by providing an alternative hypothesis to explaining nurses' affective states caused by auditory alarms. Future research can benefit from this paper through understanding of the context and familiarizing with the cognitive processes relevant to processing of patient monitoring alarms.

3.1. Introduction

Intensive care unit (ICU) nurses deliver care to patients by observing and evaluating patients' condition, assisting doctors in their assessments, administering treatment, and supporting all-round recovery. Through their workflow nurses rely on patient monitoring systems to observe the vital parameters and changes in patients' status. Rapidly advancing technologies have allowed us to monitor an increasing number of parameters. Patient monitoring systems display vital parameters visually. Information about emerging medical and technical conditions, such as vital parameters exceeding thresholds or sensors getting detached, are communicated to nurses through audio-visual alarms. Consequently, with the increase of the number of measured parameters, the number of alarms in the ICU has also increased (e.g., monitoring blood oxygenation rate, ventilating patients, connecting patients to dialysis machines). Alarms are designed to attract attention and prompt action. However, up to 90% of alarms have been identified as false or non-actionable (Cvach, 2012; Deb & Claudio, 2015; Siebig et al., 2010). Consequently, they often interrupt the workflow without benefiting care delivery. This situation can result in desensitization; inducing stress in nurses and posing threats to patient safety (Lewandowska et al., 2020; Özcan & Gommers, 2020; Wilken et al., 2017). As a result, the affective outcomes are annoyance and frustration towards alarms (Cho et al., 2016; Sowan et al., 2015). Despite the research on solution strategies to mitigate problems related to alarms, there has not been a gratifying improvement until now (Sowan et al., 2016; Yue et al., 2017). In this paper, we present a conceptual framework of cognitive annoyance supported by a data collection from eight patient monitors in the Erasmus Medical Center ICU. With this framework, we aim to inform system design to support organizational well-being of nurses.

Research to support healthcare industry in challenges related to alarms has been ongoing for several decades. Studies mostly focus on improving (psycho)acoustic characteristics of alarms to make them less annoying (Foley et al., 2020; Sreetharan et al., 2021). Indeed, psychoacoustic characteristics such as sharpness, roughness, loudness, and tonalness have been shown to influence sensory (un)pleasantness of alarm sounds (Zwicker & Fastl, 1999). However, research indicates that acoustic characteristics only explain a small portion of variance in annoyance ratings. In fact, several psychological and contextual factors, such as noise sensitivity or time of day, have been shown to play larger roles in annoyance by sounds (Janssen et al., 2011; Paunović et al., 2009; Pierrette et al., 2012). Consequently, research indicates that there are two aspects to annoyance; perceptual and cognitive (Guski et al., 1999; Sreetharan et al., 2021). The perceptual aspect of annoyance relates to (psycho)acoustic characteristics of sounds, which induce annoyance in a bottom-up processing manner. On the other hand, influences by top-down processing are categorized as cognitive annoyance and relate to the disturbing effects, such as frequent repetitions or task interruptions (Zimmer et al., 2008). As stated, an inventory of knowledge on perceptual predictors of annoyance exists; however, mechanisms of cognitive annoyance remain unexplored. We believe the persistence of the alarm annoyance problem, despite all the efforts and extensive research, stems from the knowledge gap in understanding of nurses' cognitive needs during interaction with the monitoring system. Sounds may be well designed but poorly positioned within the workflow, therefore causing annoyance.

In this paper, we aim to identify the mechanism underlying nurses' annoyance of patient monitoring alarms. We argue that alarms are annoying to nurses on a cognitive level due to the conflict they pose in their information processing; rather than simply being unpleasant sounds. To support this hypothesis, we present data of an IC unit that captures the current situation of interruptions that nurses experience.

3.1.1. Cognitive Annoyance

In our approach, we frame cognitive annoyance as the negative feeling induced by a sound that is the result of the cognitive processing of the sound; rather than its perceptual qualities. In the following section, we present a series of cognitive processes that take place during nurses' interaction with patient monitoring alarms, and attempt to explain the potential reasons to nurses' annoyance of them. We consider the interruptions caused by alarms as a form of conflict in information processing, which is a well-established theory in the field of cognition (Botvinick et al., 2001).

Alarms in Human Information Processing

While tending to alarms is an essential part of nurses' workflow, the excessive number of alarms limits the time and attention for other clinical tasks. Furthermore, high rates of false alarms burden the cognitive load without requiring immediate action. In the field of cognitive science, the negative impact of task interruptions is well known. Interruptions are highly costly to performance and cognition: they increase reaction time, error rates, anxiety, annoyance, and perceived task difficulty (Bailey et al., 2000). This can be interpreted using the Human Information Processing model (HIP) (Figure 1, adapted from Wickens), which explains how the mind receives and processes physical stimuli (Wickens et al., 1992). The first stage of HIP is *perception* in which incoming physical stimuli are received by the senses, and formed into basic perceptual elements. In the case of patient monitoring alarms, this is when sound waves are received by the ears and turned into electrochemical signal for further processing. Within this stage, basic features of sounds (e.g., frequency, amplitude) are detected as perceptual elements that gives rise to psychoacoustical evaluation of alarms (e.g., sensory unpleasantness caused by loud or sharp tones). The second stage is *cognition*, in which meaning is attributed to perceptual elements. This stage involves evaluation of current information against prior knowledge, and decision making on the basis of meaning within the context. Attention is engaged to selectively direct resources to relevant stimuli and task related motor functions. For the processing of alarms, this stage involves an evaluation of the alarm to determine its source (e.g., oxygen saturation, or device such as mechanical ventilator), meaning (e.g., too much oxygenation), and actions it requires (e.g., reduce the oxygen intake by adjusting the dosage). Finally, the *response* stage is when a reaction to the physical phenomenon occurs. For alarms this can involve a physical action (such as tending to the patient or to the device for adjusting settings), or simply deciding the alarm is not relevant and therefore ignoring it.

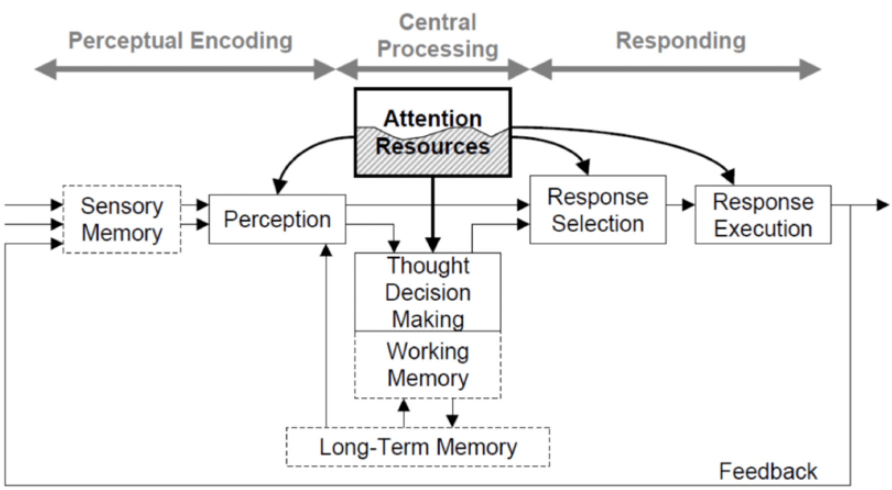

Figure 1. Human Information Processing Model demonstrating the processing of physical stimuli by the human mind. Consists of main stages: perception, cognition, and response. Note that attention is depicted as a limited resource.

Conflict in Human Information Processing

Attention is a limited resource, as also exemplified in the HIP model (Figure 1). When multiple stimuli are competing for the same resource, a conflict occurs. Resources must be shared between competing stimuli, limiting availability and therefore impairing performance. Different modalities engage different resources, so the degree of overlap between the competing stimuli influences the loss in performance (Wickens, 2008). Monitoring alarms initially engage visual and auditory resources for perception, then cognitive resources for processing, and finally motor resources for response. Within the workflow, nurses are often engaged in various clinical tasks, to which alarms add competition with ongoing tasks. It might often be the case that several alarms are generated within one unit at the same time, inducing further conflict to information processing.

Conflict in information processing is most commonly demonstrated by Stroop task (Stroop, 1935). In this paradigm, participants are asked to name the color of the ink a word is written in aloud, disregarding the word itself. In congruent trials, ink color matches the semantic meaning ("blue" written in blue); while incongruent trials demonstrate a mismatch ("blue" written in red). Incongruent trials involve higher error rates and increased reaction times. This is due to the competition between the response of reading the word and the response of verbalizing the ink color. Both responses demand resources, resulting in a conflict.

Conflicts signals are well established to be instrumental for cognitive functioning. The mind monitors the degree of conflict in the environment, modulating level of cognitive control to match the demands (Botvinick et al., 2001). Remarkably, research indicates that conflicts are further registered as aversive signals (Dignath et al., 2020; Dreisbach & Fischer, 2012). Meaning that even in neutral and arbitrary conflicts such as the Stroop task, where the conflict holds no personal or emotional significance, people perceive it as negative affect. Therefore, the mind can be thought to keep count of conflicts in information processing and registering them as negative signals on a micro scale.

Conflict Resolution

Tasks competing for the same resources create bottlenecks in information processing (Broadbent, 1958). In order to complete both tasks, one must either multi-task or switch task. Mechanism underlying multitasking is modelled by the Threaded Cognition Theory, which draws the analogy of a thread for each 'train of thought', or task-related processing (Salvucci & Taatgen, 2008). The theory posits that multi-tasking, even when seemingly concurrent such as talking and writing at the same time, is actually a serial process in which processing related to both tasks are sequentially alternated on a range of milliseconds. According to this view, threads are executed by favoring the least recently processed thread to balance performance outcomes. However, more recent research indicates that people have personal preferences in task prioritization (Jansen et al., 2016). When multiple arbitrary tasks are competing for resources, individual preferences influence which task is prioritized for serial processing. By rapidly alternating between multiple tasks, bottlenecks in information processing are resolved with minimal loss in performance.

Despite the efforts to attenuate the loss in performance, switching between tasks is still costly. Task switching is well known to increase error rates and reaction times (Monsell, 2003), and multi-tasking increases stress levels (Appelbaum et al., 2008). Remarkably, performance costs are less during voluntary task switching compared to involuntary task switching (Douglas et al., 2017; Vandierendonck et al., 2010). This phenomenon is thought to be due to anticipation of approaching conflict in the case of voluntary switching, in which elevated cognitive control alleviates the loss. This means frequent task-switches and periods of multi-tasking threaten the efficiency of workflow while burdening the cognition.

Annoyance by patient monitoring alarms

In light of the series of cognitive functions presented above, in this section we will attempt to describe how nurses might get annoyed by patient monitoring alarms. In the ICU, each new alarm imposes a new task for the nurse. Even a false alarm still requires re-allocation of perceptual and cognitive resources to identify them as false alarms, and potentially motor resources to silence the alarm. Each alarm induces a new thread to the multi-tasking processor. Therefore, alarms interfere with ongoing tasks and require frequent task switching. Discrepancy between available resources and demands induced by multitude of tasks induces conflict in information processing, and triggers aversive signals. Since task-switches are not voluntary but imposed by alarms, they are more detrimental to cognition and performance. Consequently, we hypothesize that nurses' annoyance of monitoring alarms is an accumulation of aversive conflict signals in information processing. A schematic explanation is portrayed in Figure 2.

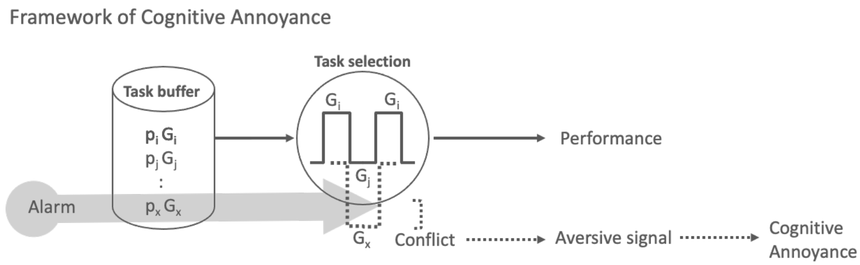

Figure 2. Schematic representing alarms inducing new tasks into the central processor. Each alarm adds a new, involuntary task (G_x), and over burdens cognitive resources. (p) is the prioritization coefficient of each task. While people have personal pr preferences on task prioritization, alarms, by design, override other tasks. Alarms have varying priority weights based on whether they are high, medium, or low level of priority. More task demands than available resources create conflict. Conflicts are registered as aversive signals. Accumulation of conflict signals is experienced as annoyance. Adapted from (Jansen et al., 2016) with permission.

3.2. Data Collection

In order to quantify the frequency of alarms in the ICU and establish a description and understanding of the context, a data collection was conducted in Erasmus Medical Center, Rotterdam in the Netherlands between March and April 2022. All output from the patient monitoring system was recorded in a neonatal intensive care unit (NICU). Monitoring system automatically logs all events, so we accessed the logs to draw the data set. This study focused on alarms generated solely by the patient monitoring system. All other devices that generate audiovisual alarms, such as infusion pump or ventilation device, were not included in the analysis.

The neonatal unit contains eight patient beds in an open layout; where all beds are located close to each other and facing towards a central nurse station. This means all the alarms generated within the unit are audible to all the health care providers and patients in the unit. Nurses work in three shifts: morning, afternoon, and midnight.

3.3. Results

In a span on one month, 25 different patients were registered to the unit over different periods of time. Distribution of number of alarms per patient through the month is indicated in Figure 3. During this period, 83.023 alarms were recorded in total. Mean number of alarms per day in the unit was 2594.69, *SD* = 866.15. Minimum daily alarm count was 1296, and maximum was 4451. Median number of alarms generated by one patient was 1460, with a minimum of 100 and maximum of 13405.

Number of generated alarms fluctuated throughout the day. An hourly distribution of number of alarms summer over the month is presented in Figure 4a. On average, there were 111.45 alarms an hour, *SD* = 49.24. Minimum number of alarms per hour was 2, while maximum was 332. A frequency distribution of alarm counts per hour is presented in Figure 4b. While approximately 100 alarms per hour was the most commonly observed case, it was possible to observe over 300 alarms per hour.

Number of alarms peaked between 8:00-9:00. This period is known to be patient handover and the start of the morning routine. Patients are cleaned and daily check-ups are performed, in which sensors may get detached and trigger alarms. This is further exemplified by examining the condition that generates the alarm. Alarms were categorized into medical (those triggered by vital parameter measurements, e.g., blood oxygenation threshold exceeded, asystole), and technical alarms (those related to the monitoring system and devices, e.g., sensor detached). Overall, 82.62% (68593) of alarms were of medical events, and 17.38% (14430) were technical events. Zooming into the time window of 8:00-9:00; 77.08% were of medical events (3377) while 22.92% (1004) were technical. This indicates more device related technical alarms were generated during the morning rounds compared to the daily averages.

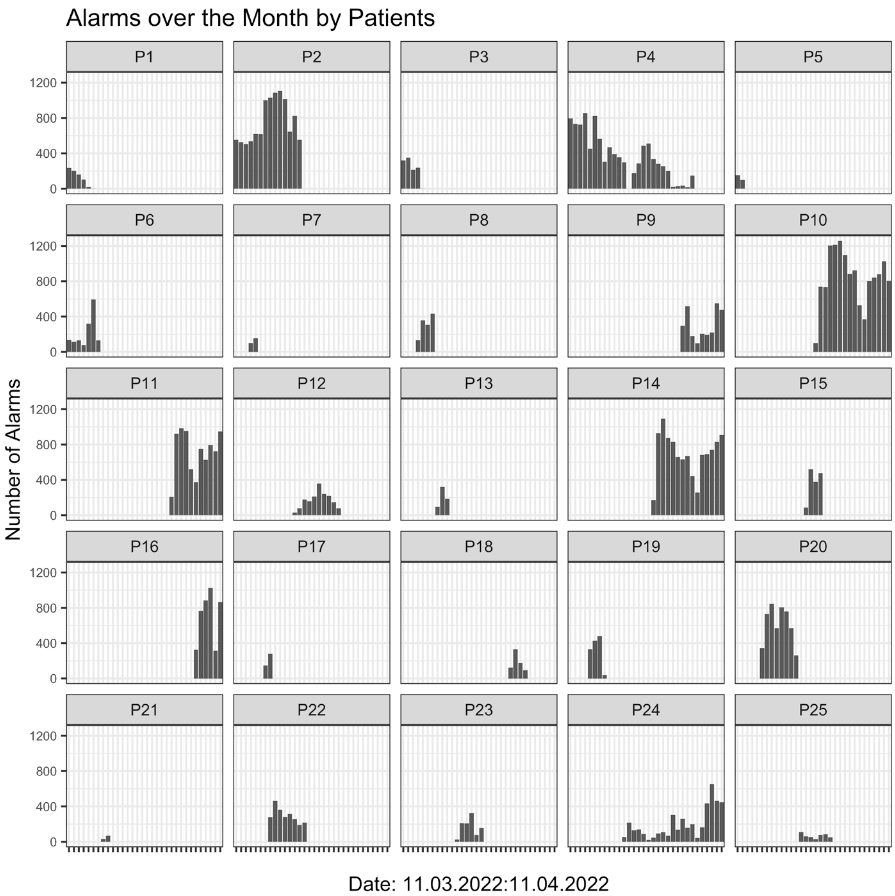

Figure 3. Number of alarms generated by each patient over the month. While some patients stay for longer periods of time; some are discharged quicker, as can be observed from the number of bars representing one day per patient.

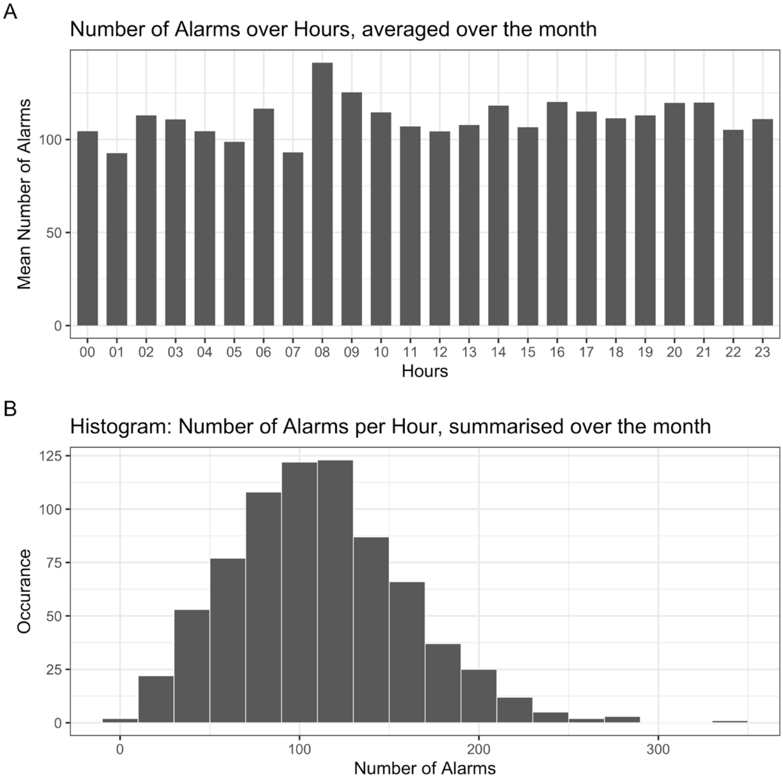

Figure 4. (A) Hourly distribution of mean alarm counts over the day. Number of alarms generated peaks around 8:00-9:00. (B) Frequency distribution of count of alarms per hour. While approximately 100 alarms per hour is commonly observed, it was possible to observe over 300 alarms per hour.

We investigated the differences between morning, afternoon, and midnight shifts. Summarized over the patients, a daily average of 1151.84 (35.81%) alarms were generated during morning shifts, 1135.16 (32.67%) during afternoon shifts, and 1033.92 (31.52%) during midnight shifts. The number of alarms per shifts was converted into proportions for each shift and patient. These proportions were analyzed by a within-subjects General Linear Model with shifts as the within-subjects factor of 3 levels. Wilk's Lambda was used a multivariate test, $F(2, 23) = 2.71$, $p = .087$. However, contrasts between levels showed a significant difference, in which there were more alarms in the morning shift (.36) compared to the midnight shift (0.32), $F(1, 24) = 5.65$, $p = .026$.

By medical standards, alarms are categorized into high, medium, and low levels of priority. Exploring the output from the patient monitor, majority of the alarms were medium priority (76.91%), while 12.97% were low priority, and only 10.05% were high priority alarms. High and medium priority alarms were often originated by medical conditions, while low priority alarms were often due to technical conditions (Table 1).

Table 1. Number of alarms per level of priority and alarming condition. Numbers are presented along with the percentage of the condition within one level of priority.

	Alarming Condition	
Level Of Priority	**Medical**	**Technical**
Low	224 (2.08%)	10547 (97.92%)
Medium	60215 (94.22%)	3697 (5.78%)
High	8154 (97.77%)	186 (2.23%)

We investigated the variation among individual patients. Proportions of alarm priority levels and causes of alarms varied by patients. Distribution of priority levels for each patient is displayed in Figure 5a, and distribution of alarming condition is displayed in Figure 5b.

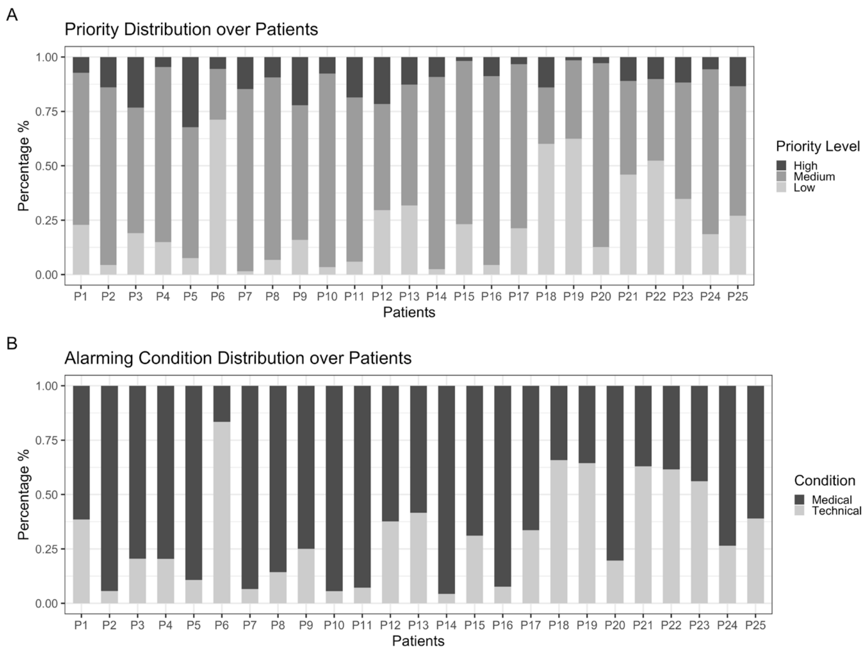

Figure 5. (A) Stacked chart of alarm priority level distribution per patient. (B) Stacked chart of alarming condition distribution per patient.

Figure 5a demonstrates that the majority of alarms were medium priority for most of the patients. However, more low priority alarms were generated by certain patients (e.g., P6, P18, P19). Figure 5b illustrates that these patients also generate relatively high proportion of technical alarms. This indicates that these patients are relatively more mobile than others, resulting in more sensors getting detached and therefore generating more technical alarms.

Vital parameters that generate the alarms were analyzed to investigate which medical and technical conditions were most relevant for this IC unit. The patient vital parameter that generated most of the alarms was oxygen saturation level (SpO_2, 56.81%), followed by electrocardiogram (ECG, 10.43%) technical alarms. A breakdown of number of alarms by alarming vital parameter is presented in Table 2.

Table 2. Breakdown of vital parameters triggering the alarms. Threshold refers to the alarm being triggered by vital parameter exceeding the set threshold; while technical refers to technical alerts such as artifacts, or sensor being detached. Parameters that occur less than 1% of the time are aggregated as 'other'. SpO_2: oxygen saturation, ECG: electrocardiogram, HR: heart rate, RRi: impedance respiratory rate.

	Percent	Count
SpO_2 threshold	56.81%	47162
ECG technical	10.43%	8658
SpO_2 desaturation	9.19%	7631
HR threshold	5.41%	4491
SpO_2 technical	5.35%	4444
Hf threshold	5.21%	4327
RRi threshold	3.21%	2665
Temperature threshold	2.05%	1699
RRi technical	1.43%	1186
Other	1%	760

While the number of alarms presented so far represent the alarming instances, alarms are often audible for longer periods of time. Therefore, the auditory stimuli present in the IC unit is in fact more prevalent than the number of alarms indicate. To capture this, we analyzed the duration of alarms. Excluding the outliers where alarm duration was greater than 180 seconds, median alarm duration was 10 seconds, mean was 22.81, and *SD* = 30.85. A histogram of alarm durations is presented in Figure 6a. Alarm durations differed for levels of priority. High priority alarms had a mean duration of 14.15 seconds, medium alarms had mean of 25.54, and low priority alarms had a mean of

13.77 seconds (Figure 6b). Alarm durations also varied by the vital parameter that generates the alarm. Mean duration in seconds per parameter is presented in Figure 6c.

Cumulative number of alarms in the unit represent the total auditory stimuli in the environment. While the alarms are audible within the whole unit, each nurse is responsible for tending to the alarms generated by the patient assigned to them. To capture the demand of responsibility, we analyzed the number of alarms generated by each patient during one shift. Averaged over the month and patients, mean number of alarms generated by one patient during one shift was 123.90, *SD* = 78.71.

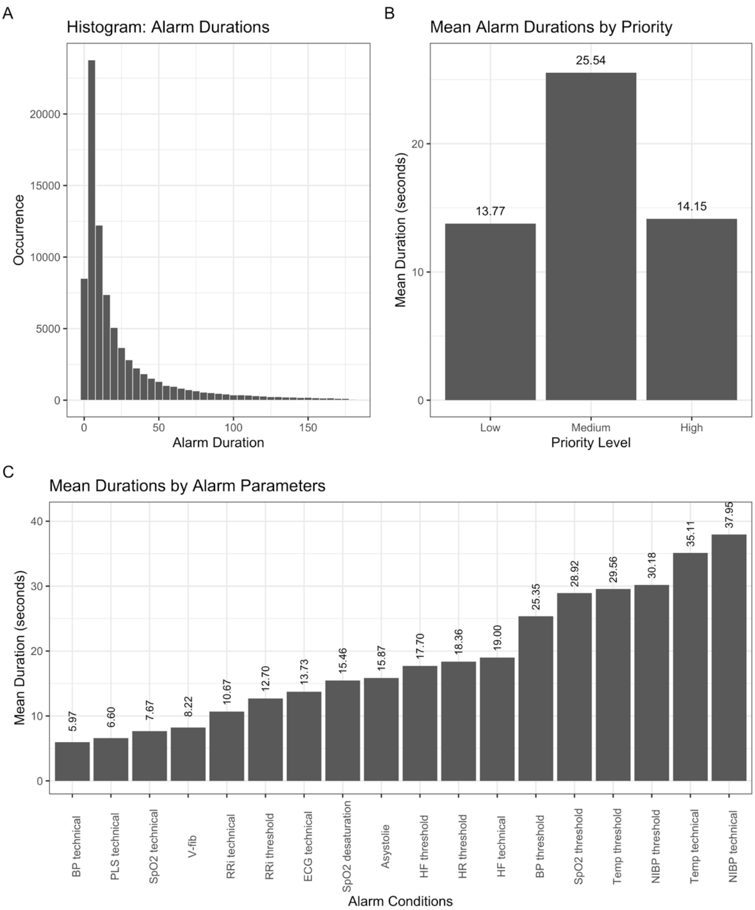

Figure 6. Alarm durations in seconds, outliers greater than 180 excluded. (A) Histogram of alarm durations. (B) Mean alarm durations by alarm priority levels. (C) Mean alarm durations in seconds by vital parameters.

3.4. Discussion

Our results of the output from patient monitors demonstrate the prevalence of alarms in the ICU. Realizing the excessive number of alarms helps us understand the experiences of ICU nurses within their workflow. Our results show that almost two alarms per minute were generated in the unit, and one patient generated an alarm every 3.22 minutes. Average duration of alarms was over 20 seconds, indicating that alarms are almost constantly audible in the IC unit. These results paint a clear picture of the auditory stimuli present in the unit as experienced by nurses and patients. The majority of studies aiming to improve patient monitoring alarms has focused on the acoustic characteristics of alarm sounds (Edworthy et al., 2018; Foley et al., 2020; Schlesinger et al., 2018; Sreetharan et al., 2021). While efforts to improve the sound design of alarms will benefit the sensory experience, our results make it clear that the main cause of the problem is the excessive number of alarms. This number indicates the frequency by which nurses are interrupted in ongoing tasks. Consequently, we argue that the understanding of the cognitive mechanisms of the processing of alarm sounds is more important to explain the experienced annoyance. In our framework, each interruption burdens the cognitive resources by creating conflict in information processing. As conflicts are experienced as aversive signals by the mind, each interruption adds to the feeling of annoyance towards patient monitoring alarms in nurses. Therefore, we argue that efforts to improve nurses' organizational well-being requires an approach beyond enhancing the alarm sounds. Consideration of nurses' cognitive needs, capabilities, and preferences is needed to improve the information communication between patient monitoring systems and nurses.

More specifically, our analysis of the generated alarms reveals potential points to improve system design. Results demonstrate that high priority alarms are the least occurring alarms, which is the only type of alarm that requires immediate action. Low and medium priority alarms constitute the majority of alarms. These can be reduced in number by human interventions (such as customizing alarm limits), or by improvements in the system design (such as smart algorithms to prioritize and eliminate alarms). Most commonly observed cause for alarms was related to blood oxygen saturation level, which is typical for neonatal patients. Interventions that target the optimization of blood oxygen saturation monitoring can yield considerable improvement in the number of generated alarms.

We found that there is a large variation in the number and type of alarms generated by each patient. Currently, the settings of the monitoring system remain similar for each patient. However, the distribution of vital parameters that generate the alarms varies over patients. This can be explained either by the patients' medical status (relatively stable or critical), or by the frequency of movements. Patients who move around frequently cause sensors to become detached more often, leading to more technical alarms. The same effect is also visible in the reduced number of alarms during night shifts. Patients are more likely to be sleeping during the night; and there is a reduced number of lights, sounds, and general activity during night time; leading to fewer alarms generated. Such differences in patient characteristics, and conditions surrounding the patient could be an input for the monitoring system to suppress non-actionable alarms based on current needs.

For essential events that do need to be notified to the nurse, literature has suggested methods to minimize the negative consequences of task interruptions. These involve methods to design smart algorithms to prioritize alarms. This can be achieved by context aware computing that suppress notifications based on location signals or certain periods of time, and user aware computing that generates notifications based on attentional cues from the user (Ansari et al., 2016; Bailey & Konstan, 2006; Welch, 2011). These methods aim at notifying the user to system conditions on particular moments where the interruption is thought to yield the minimum negative effect on performance and cognition. By understanding the cognitive mechanisms that make patient monitoring alarms annoying to nurses, we can employ design strategies in a targeted manner to minimize these effects.

In this paper, we suggested a framework in which accumulation of aversive conflict signals caused by interruptions are experienced as annoyance towards monitoring alarms (Figure 2). Our theoretical framework opens up new directions for future research. One of these is to measure annoyance when task interruption is induced by another modality, since different modalities require different resources. Another intriguing direction would be to build up on the research suggesting increased costs for involuntary task switches compared to voluntary switches. This difference is thought to be caused by anticipation of conflict (Vandierendonck et al., 2010). Endsley (1995) indicates that anticipation is an important factor in Situation Awareness. This aspect is often overlooked in the interaction between nurses and patient monitoring systems. Investigating the role of anticipation on annoyance ratings can present insights into how nurses handle (un)expected information presented through alarms. This knowledge would then inform design of the interaction between the system and the nurse as a user. These aspects will form the basis of our future research activities on cognitive annoyance in ICUs.

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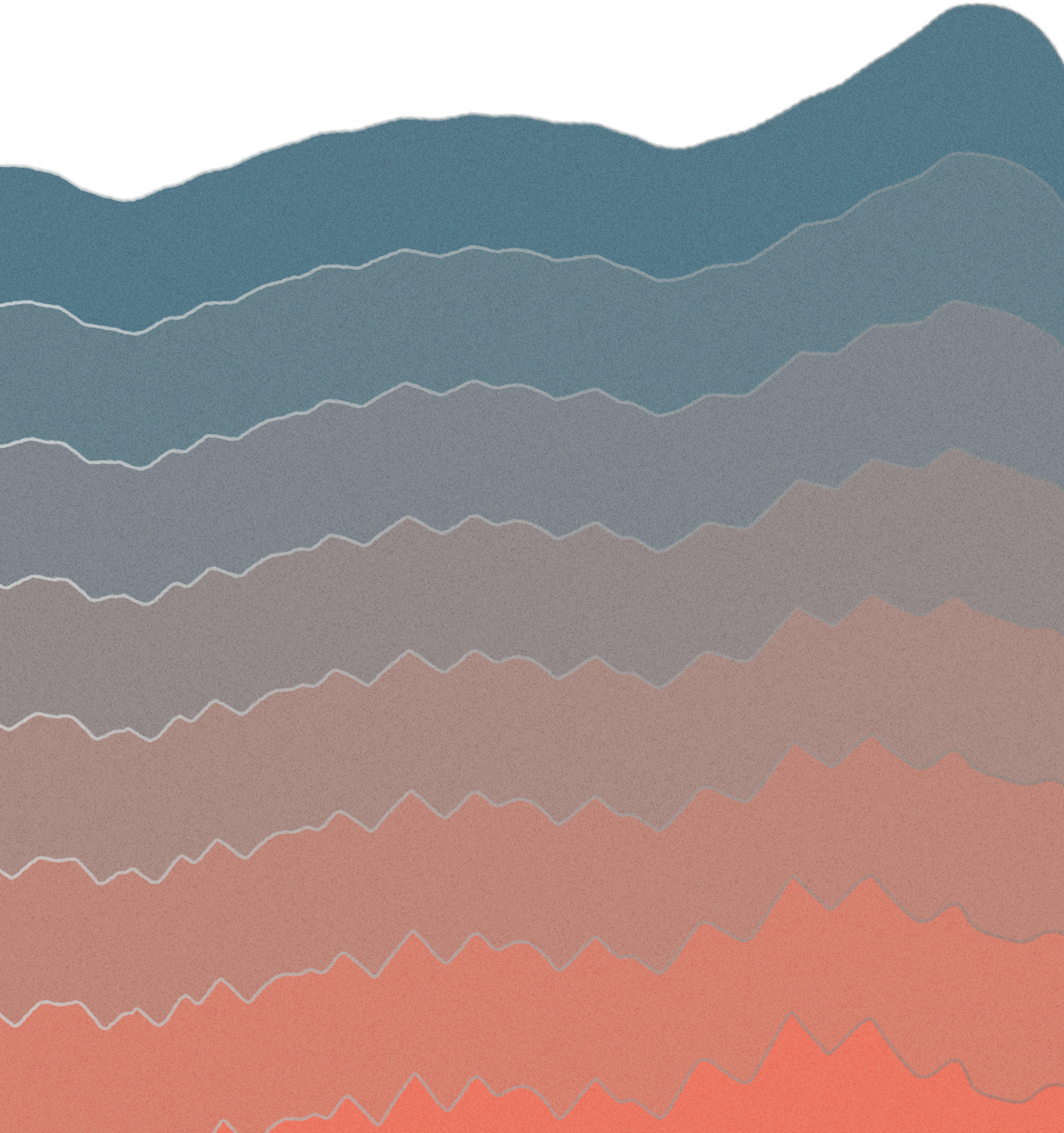

4 ICU Alarm Management Reimagined: Sound-driven Design and the Role of Acoustic Biotope

This chapter have been published in the following research article:
Bostan, I., van Egmond, R., Gommers, D., & Özcan, E. (2024, June 23). ICU alarm management reimagined: Sound-driven design and the role of acoustic biotope. *Design Research Society*. https://doi.org/10.21606/drs.2024.553

Abstract

Staff well-being and patient safety are undermined by false alarms in the ICU. This study focuses on enhancing the effectiveness of sound-induced actions in the ICU by assessing the distinctness and informativeness of alarm sound events as perceived by nursing staff. We investigated the alarm load in an adult ICU, with an emphasis on alarm durations and their impact on actionability. As a strategy to mitigate false alarms, we simulated the introduction of alarm delays and examined how this affected alarm characteristics across various vital parameters. Results demonstrate that the introduction of alarm delays reduce the number of alarms remarkably, with a 10-second delay eliminating more than half of the alarms. Our results indicate that delays should be tailored to each specific vital parameter and medical context. We further address key considerations for implementing alarm delays in alarm management practice.

4.1. Introduction

Intensive Care Unit (ICU) nurses play a pivotal role in patient care. They rely on patient monitoring systems to continuously assess the vital parameters of their patients (e.g., heart rate, blood pressure). Patient monitoring systems alert nurses through audiovisual alarms. However, the proliferation of false alarms has led to a cascade of challenges, including desensitization, frustration, annoyance, and fatigue among healthcare providers, and ultimately threats on patient safety (Cvach, 2012; Deb & Claudio, 2015; Honan et al., 2015; Lewandowska et al., 2020; Ruskin & Hüske-Kraus, 2015). Consequently, the interaction between the system and the user is undermined by a failure in communication of information through alarm sounds. Decades of efforts on improving the sound of alarms have not brought the so much needed solution. Therefore, there is a pressing need for a holistic approach to redesigning the collaborative relationship between these systems and ICU nurses (Özcan et al., 2018). In this study, our aim is to identify opportunities for system design through revealing the informative value of alarms. To do so, we investigate patient monitoring alarms as sound events within the ICU. We scrutinize patient monitoring alarms in an adult ICU to reveal the characteristics of vital parameters, their durations, and the possibilities for filtering certain alarms. Our goal is to streamline the alarm experience by making an inventory of the alarm events and alarm load as experienced by users, ensuring healthcare providers receive relevant and actionable information, ultimately improving patient care and safety.

4.1.1. Sound Induced Actions in ICU

Sound-induced actions are part of the workflow in several socio-technological environments such as mission control rooms and airplane cockpits (Özcan et al., 2022). The intensive care is another example, where nurses operate on the basis of incoming alerts in the form of alarm sounds. Sounds emitted by products can be consequential, as generated by the operating product itself, or intentional, as added intentionally to a product (Langeveld et al., 2013; van Egmond, 2008). Alarms are intentional product sounds; specifically designed and added to patient monitoring systems with the intention of inducing action. Özcan and colleagues have introduced the notion of *acoustic biotopes*, in which different operators within an environment listen to sounds with intentions aligned to their individual goals and engage in relevant sound-induced actions (Özcan et al., 2022). In the acoustic biotope of the ICU, nurses listen to patient monitoring alarms to be informed about upcoming medical actions. However, accounting to a staggering 80% to 99% of all alarms, false alarms do not require medical intervention (Lewandowska et al., 2020; Petersen & Costanzo, 2017; Sowan et al., 2015). They pollute the acoustic biotope with irrelevant, non-actionable information. Özcan and colleagues clarify that possibilities for sound-induced actions can be enhanced only when the listeners can meaningfully interpret the sound events within the environment (Özcan et al., 2022). In other words, a clear acoustic biotope is needed to increase the saliency of distinct sound events and prompt correct action.

The interpretation of sound events involves a perception-action trajectory starting with the perception of the sound, meaning attribution through cognition, response selection through decision making, and ultimately action. Frequent false alarms undermine this trajectory on several stages and even function as stressors. Perception is challenged by *masking* caused by cacophony, and *compromised localizability* due to noisy environment (J. Edworthy et al., 2017; Sowan et al., 2015). The cognition stage, in which semantic meaning is attributed to perceptual elements, is challenged due to *depleted attention resources* and *burden on memory* (Koch et al., 2012). Nurses experience desensitization, resulting in diminished ability to register the alarms (Özcan & Gommers, 2020; Sreetharan et al., 2021). Nurses may lack knowledge of or recall the meaning of many alarms (Cropp et al., 1994; J. Edworthy et al., 2013; J. R. Edworthy et al., 2018). Nurses also experience *negative emotions*, as evident in their accounts of stress, annoyance, and frustration towards alarms (Deb & Claudio, 2015; Honan et al., 2015). Lastly, the action stage is severely undermined by false alarms. Frequent false alarms lead to *habituation*, the cognitive effect in which repetitive or prolonged exposure to monotonous stimuli no longer prompts the required action. Through a cry-wolf effect, false alarms reduce trust in the system and fail to prompt appropriate and timely action. Nurses' response to monitoring alarms may be delayed or reduced because of false alarms (Graham & Cvach, 2010; Lewandowska et al., 2020; Phansalkar et al., 2010; Schmid et al., 2013; Sendelbach & Funk, 2013). In conclusion, false alarms hinder the sound-induced perception-action trajectory as prescribed by patient monitoring alarms at several stages.

In order to increase the rate of appropriate sound-induced actions, a correct interpretation of sound events needs to be facilitated. This requires alleviating the obstacles along the perception-action trajectory. Currently the boundaries of sound events are blurred due to excessive number of false alarms. Within this polluted acoustic biotope, numerous sound events are unwanted and harmful. Mitigation of unwanted sounds is imperative in increasing the distinctiveness of relevant sound events and ensuring each sound event is correctly interpreted by the listener (Özcan et al., 2022).

4.1.2. Increasing Distinctiveness of Sound Events

An increase in the distinctiveness of sound events is possible by generating fewer, but more informative sounds and reducing the pollution in the acoustic biotope. Our previous work demonstrates the prevalence of alarms in the ICU, illustrating the pollution in acoustic biotope (Bostan et al., 2022). An important factor that determines the number of alarms is the algorithm governing the patient monitoring systems. To date, numerous strategies to reduce the number of alarms have been put forward. One of the most effective methods has been to implement alarm delays. The introduction of alarm delays can reduce the number of alarms by 25-80% (M. M. Cvach et al., 2014; de Waele et al., 2014; Gul et al., 2023; Schmid et al., 2017; Varisco et al., 2021; Welch, 2011; Winters et al., 2018).

An alarm delay refers to the postponement of the onset of the alarm signal with a certain time interval after the emergence of the alarming condition (the underlying medical/technical condition). Currently, alarm signals are triggered as soon as the alarming conditions emerge. However, the majority of alarming conditions spontaneously recovers without nurse intervention within seconds. As such, they are clinically irrelevant. Ideally, alarms should only be generated when the action of a nurse is required. The introduction of alarm delays will prevent erroneous alerting of nurses when their action is not required. As illustrated in Figure 1, a delay interval is initiated when the alarming condition emerges. Alarm signals are suspended during the delay interval. In Figure 1A, the alarming condition spontaneously recovers in a period shorter than the delay interval. In this case, no alarm signal is generated. In Figure 1B, the alarming condition persists longer than the delay interval, in which case alarm signal is generated at the end of the delay interval.

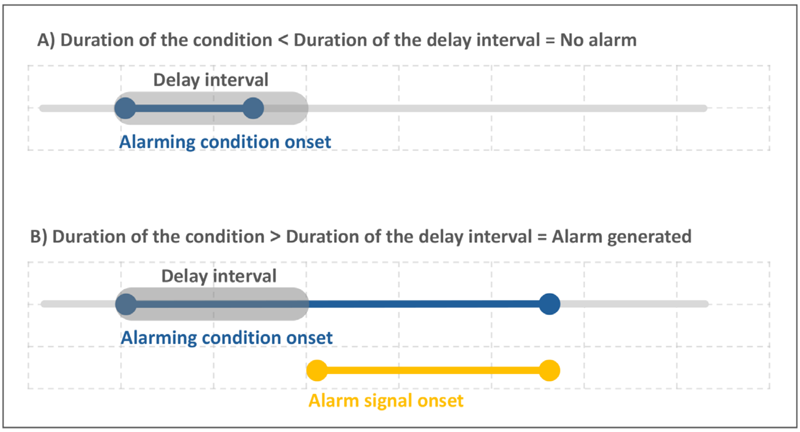

Figure 1. In 1A, the alarming condition (blue) ceases to exist during the delay interval (gray), thus no alarm signal is generated. In 1B, the alarming condition persists longer than the delay interval, thus an alarm signal (orange) is generated at the end of the delay interval.

4

The alarm delay may be implemented directly at the source monitor, or indirectly as a delay in the notification of the alarms through the nurse pagers. Recent studies have further explored the notion of progressive or adaptive alarm delays, where the duration of delay is inversely proportional to the severity of the alarming condition (Pater et al., 2020; Schmid et al., 2017). Recently, manufacturers have been including the option of alarm delays into the patient monitoring systems. Although alarm delays are implemented in some hospitals, the extent to which delays are used vary greatly depending on factors such as the hospital protocols, the patient population, and the specific patient monitoring systems in use. Despite being proposed for several decades as a mitigation strategy for false alarms, the widespread adaptation of delays in patient monitoring systems is yet to be realized.

4.1.3. Duration of Sound Events

The acoustic biotope of the ICU encompasses not only the number of sound events but also their duration. An alarm can last anywhere from one second to several minutes. Negative affective responses, such as noise annoyance, correlate with duration of exposure to unwanted sounds (Zimmer et al., 2008). Therefore, the duration of sound events is another factor of interest in considering the clarity of the acoustic biotope.

Previous research suggests that nurses do not respond to alarms by immediately acting on them, but rather reconsidering the sequencing of their clinical tasks as indicated by the alarm (Bitan et al., 2004). An inner 'alarm duration clock' is implied by several studies, by which nurses wait for a buffer time before they act on the alarms (Bitan et al., 2004; Görges et al., 2009). This means nurses intuitively expect the false alarms that are highly likely to auto-terminate without requiring clinical intervention. In fact, the duration of alarms has been identified as one of the major factors determining nurse responsivity, along with prior knowledge on patient criticality and type of alarm (Despins, 2017; Joshi et al., 2017). The likelihood of a nurse responding to an alarm increases with increasing alarm duration. Keeping such an inner clock adds to the workload of nurses and burdens cognitive capabilities. A framework for analyzing alarm durations as 'alarm responsiveness' was put forward by Hüske-Kraus and colleagues (Hüske-Kraus et al., 2018). More recently, it was demonstrated that following this framework generates valuable insights in describing the context with regards to alarm durations and reveals opportunities for alarm management interventions (Poncette et al., 2021).

Increasing the rate of appropriate sound-induced actions hinges on clearing the acoustic biotope through mitigating irrelevant sound events. To discern which sound events are unwanted or harmful in the ICU, this study scrutinizes the alarm load in an adult ICU throughout one month. We focus on alarm durations and investigate possibilities for alarm delays. In doing so, we identify strategic opportunities for design interventions aimed at reducing the number of false alarms generated by patient monitoring systems.

4.2. Methods

4.2.1. Data Acquisition

The data for this study was recorded in a general ICU for adults in the Erasmus Medical Center, Rotterdam, the Netherlands. The unit consisted of 9 beds in separate patient rooms. Two rooms were rarely used, only for training or testing purposes, and were removed from the analysis. Each room was equipped with its own patient monitoring system: the Dräger C700 Infinity Acute Care System. A Masimo SET Pulse Oximetry module was attached to the system for the measurement of oxygen saturation. Infusion pumps were present for medication delivery. The rooms could be further equipped by other medical devices such as mechanical ventilators and dialysis machines depending on the patient needs. Ascom pagers, connected to the central alarm system, were carried by the nurses, which were connected to the Dräger monitoring system to convey alarm information on the mobile, consisting of the priority level and the type of alarm.

Alarm data logs from the patient monitoring systems were retroactively collected for a month in 2023. Thirty-one patients were admitted to the unit in this period. The alarm data log consisted of the date, the time stamp for each alarm, the room number, the alarm type, the alarm-generating parameter, the parameter value at the time of the alarm, the alarm limits at the time of the alarm, the alarm priority level, the alarm duration in seconds, and the associated alarm message. The patient-identifying information was removed by the medical institute.

4.2.2. Setting

The patient rooms were lined on the two sides of a long corridor. The door to each patient room was sound-proofed. Nurse stations were placed between each two rooms, facing the rooms with an opportunity to directly observe inside through the windows. Each nurse station included two desktop computers, along with monitors mirroring the patient monitoring information inside the room. Alarms were audible on these monitors along the corridor. Nurses could mute the alarms from the nurse stations. The unit was staffed with one nurse per patient per shift. Nurses worked on a 3-shift basis. Daily medications were administered around 5:00. Morning rounds were conducted around 9:00, where patients were washed, cleaned, and received other daily care. Family visitation ended at 20:00, and nightly care routine took place, such as brushing teeth.

Erasmus MC has been part of the Silent ICU Project together with Critical Alarms Lab, Delft University of Technology for the past seven years, resulting in certain know-how and awareness of alarm management practices (Schokkin, 2019). This had impact on the unit culture and influenced the number and type of alarms. During the study period, patients were often mildly sedated compared to other units. Nurses exhibited a culture of enabling fewer vital parameters on the patient monitoring system, leading to fewer alarms generated.

4.2.3. Data Analysis

The dataset was cleaned, analyzed, and visualized on R programming software, using the packages *Tidyverse* and *psyc* (Revelle, 2019; Wickham et al., 2019). Cleaning involved three main steps. First step was the choice of observations to include. In the original data set collected from the system, each alarm was represented by two rows: one marking the beginning of the alarm and one marking the end of the alarm. In total there were 29691 rows. Some information, such as alarm priority level, was only present on the beginning-rows, whereas some information, such as alarm duration, was only present on the ending-rows. Frequent artefacts induced by system errors or sensor errors were also registered in the data set as beginning-rows, introducing anomalies to the dataset. To calculate the total number of alarms, we focused exclusively on the ending-rows, as they provided a comprehensive and accurate count of distinct alarm events and contained the alarm duration information. By considering only the ending-rows, we obtained a reliable measure of alarm frequency for our study. This resulted in 15499 observations.

Second step of data cleaning related to vital parameters. To ensure the generalizability of results and readability of tables and plots, parameters which generated fewer than 100 alarms in total throughout the entire month were excluded from the analysis.

Third step of cleaning related to alarm durations. Some alarm durations were unrealistically high, encompassing several days. The technical expert for patient monitoring alarms in the unit suggested this was highly likely due to system artefact. In similar conditions, (Poncette et al., 2021) discarded alarms longer than 8 hours, corresponding approximately to one nurse shift, and (Görges et al., 2009) discarded alarms longer than 180 seconds. In deciding the cut-off point, we conducted an outlier analysis of the alarm durations. Due to highly skewed distribution of the data, interquartile outlier analysis was performed based on the log transformations of alarm durations. This calculation revealed the cut-off point to be at 180 seconds. As this outcome matched previous literature, we discarded alarms longer than 180 seconds. This may result in some margin of error where remarkably longer alarms are missed out; but ensures reliability of the data analysis.

4.3. Results

There were 12192 patient monitoring alarms during the observed period of one month. Four main parameters triggered most of the alarms. The most observed alarm was mean arterial blood pressure (ART M) with 7152 observations (58.66% of alarms), followed by oxygen saturation (SpO_2) with 2425 observations (19.89%). Heart rate (HR) alarms were observed 1868 times (15.32% of alarms), and systolic arterial blood pressure (ART S) alarms were observed 747 times (6.13%).

The number of alarms observed throughout the day showed variation based on time of day. Figure 2 illustrates the distribution of all observed alarms through hours of the day. The largest peak of the day was around 9:00, followed by high numbers of alarms around 12:00 and 20:00. Overall, 38.04% of the alarms occurred during morning shift, 33.76% occurred during afternoon shift, and 28.2% occurred during night shift.

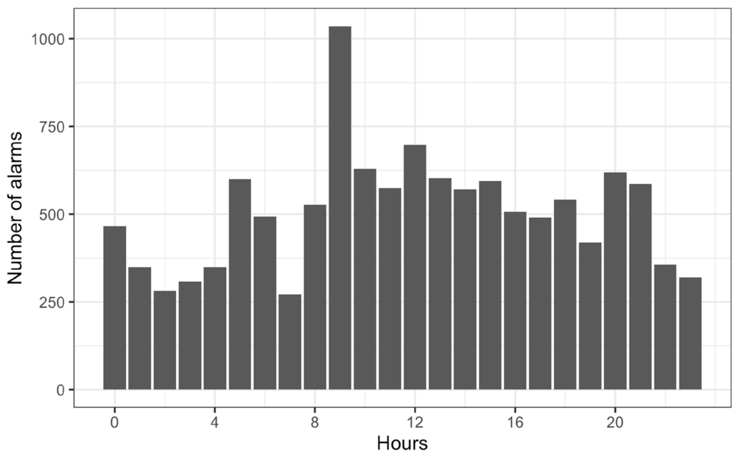

Figure 2. Frequency of all alarms per hours of the day. X-axis is hours 0:00 to 23:00.

4.3.1. Alarm Durations

After the exclusion of alarms longer than 180 seconds, the analyzed alarms had a minimum duration of 1 second, maximum of 179 seconds, mean of 17.0 seconds, median of 8 seconds, mode of 4 seconds, with SD = 24.6. The large difference between the mean and median values was due to skewed distribution of alarm durations, with a skewness value of 3.23. Figure 3A illustrates the histogram of all alarm durations. Observing the figure showcasing the full data range is challenging due to highly skewed distribution of alarm durations. To increase visibility of the distribution, Figure 3B is cut off at 30 seconds.

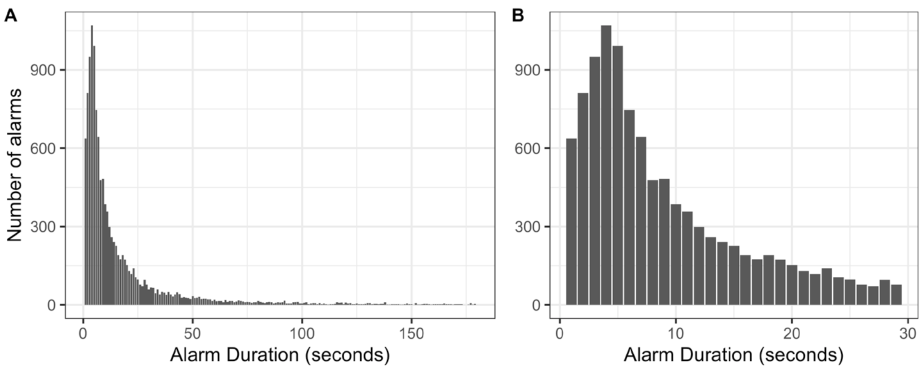

Figure 3. Histogram of alarm durations. X-axis is alarm duration in seconds; y-axis is the corresponding number of alarms. Although both figures illustrate the same data, B is cut-off at 30 seconds for better visibility of the distribution of short alarms. Majority of the alarms ended within half a minute.

The duration of alarms differed per parameter. Mean, median, and mode values in seconds for the duration per each parameter, along with associated standard deviation (SD) are presented in Table 1. Durations per parameter are illustrated in Figure 4A and 4C. Kruskal-Wallis H test indicated that the differences in parameter durations were statistically significant than each other, $\chi 2(3, 12192) = 139.26$, $p < .001$. The distributions of alarm durations were also different per parameter. To increase visibility of the skewed distribution, Figure 3B is cut off at 30 seconds.

Table 1. Summary statistics of alarm durations per parameter.

Parameter	Mean	Median	Mode	SD
ART M	16.16	7	4	24.15
ART S	19.06	8	5	26.65
HR	13.91	7	5	20.75
SpO_2	21.22	11	2	27.16

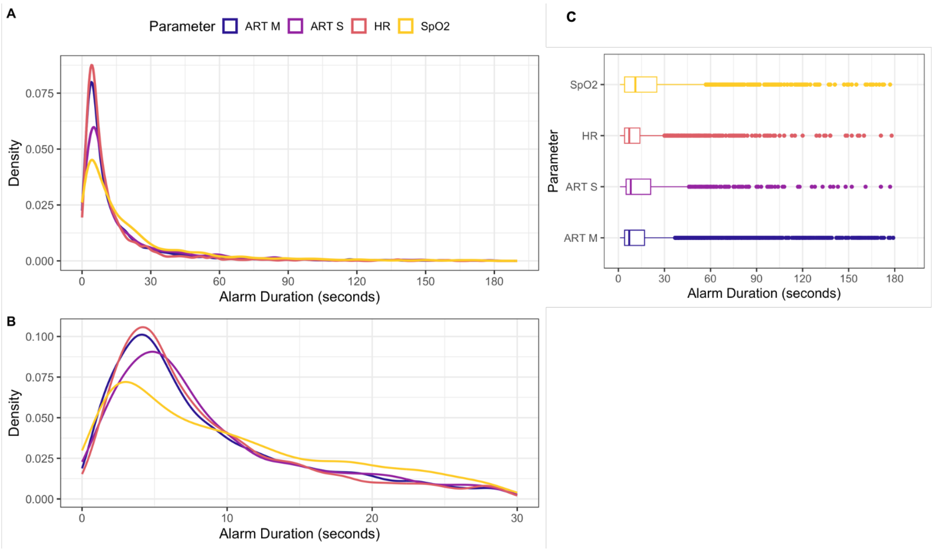

Figure 4. A and B are density plots, illustrating the probability of observing an alarm of a certain duration per each parameter. B is cut off at 30 seconds for better visibility of short alarms. Each parameter varied in the distribution of alarm durations. For all plots, x-axis is alarm duration in seconds and colors represent different parameters. C illustrates boxplots of durations, showcasing the median value along with outlier observations.

We investigated the alarm durations between different shifts. For morning shift, the mean alarm duration was 16.73 seconds, median 8, and *SD* = 24.79. For afternoon shift, mean was 17.75, median 8, and *SD* = 25.22. For night shift, mean was 16.46, median 8, and *SD* = 23.46. Kruskal Wallis test revealed that differences in alarm duration between different shifts were not statistically significant, $p > .05$.

4.3.2. Alarm Delays

We investigated opportunities for delaying alarms by certain time intervals. We simulated the conditions in which alarms under 5, 10, 15, 30, 60, or 120 seconds were delayed. Each delay level excluded alarms shorter than the delay interval (*removed*) and allowed alarms persisting longer than the interval (*remaining*). The delay intervals were chosen based on the author's clinical expertise and previous literature. Table 2 shows the number of alarms *remaining* after each delay level and summary statistics of alarm durations per delay level. Percentage of the alarms *remaining* and *removed* are presented in Figure 5. The following table and plot present the summary statistics for all parameters together.

Table 2. Cumulative for all parameters, the number of alarms and summary statistics of durations (in seconds) for remaining alarms after the introduction of delays. The original number of alarms was 12192. The number of remaining alarms decreased with increasing delay period since fewer alarms can pass the threshold.

Delay Level	No of alarms	Min	Mean	SD	Median	Mode	Skew
5 Sec	7731	6	24.95	27.9	14	6	2.68
10 Sec	4997	11	34.41	30.83	22	11	2.22
15 Sec	3615	16	42.68	32.65	30	18	1.92
30 Sec	1755	31	65.10	34.69	52	31	1.36
60 Sec	698	61	99.10	31.54	91	65	0.83
120 Sec	169	121	146.37	17.37	144	138	0.28

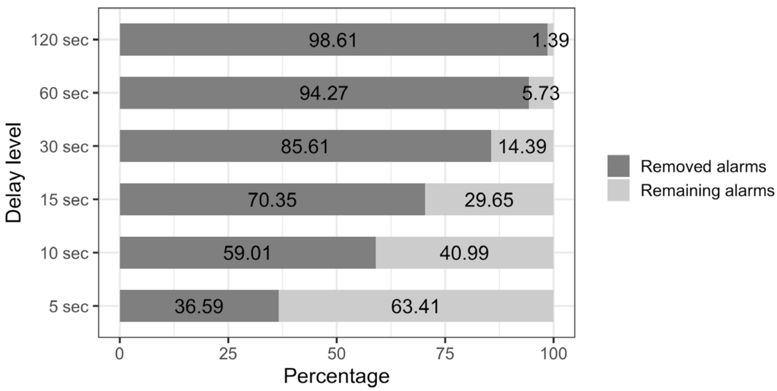

Figure 5. Percentage of alarms removed (dark gray) and alarms remaining (light gray) per each delay level. For example, introducing a 10-second delay would eliminate 59.01% of all alarms. Percentage of eliminated alarms increased with longer delays. This plot is cumulative for all parameters.

Table 3 presents the remaining percentage of the alarms per each parameter, compared to the number of alarms per parameter in the original dataset. Results are presented per delay level. For example, in 10-second delay condition, 2763 of the ART M alarms remained from the original 7152, corresponding to 38.63% of the original set.

Table 3. Percentages of the alarms remaining per parameter for each delay level. The number of alarms per parameter is compared against the number of alarms per parameter in the original dataset. Increasing delay period eliminated higher percentage of alarms for each parameter. However, the rate of reduction varied by parameter. For example, 10-second delay reduced HR alarms to 34.85% while 52.33% of the SpO2 alarms persisted.

Delay Level	ART M	ART S	HR	SpO_2
5 Sec	61.69%	67.07%	59.37%	70.47%
10 Sec	38.63%	42.04%	34.85%	52.33%
15 Sec	27.50%	32.26%	22.70%	40.54%
30 Sec	13.21%	18.07%	9.74%	20.33%
60 Sec	5.33%	7.50%	3.53%	8.04%
120 Sec	1.38%	1.61%	0.96%	1.65%

Composition of the proportion of parameters changed by delay levels. The proportions of the number of alarms for parameters is presented in the Figure 6 per delay level. The proportions were calculated within each delay level: the proportion of a parameter corresponds to the number of alarms of that parameter divided by total number of alarms within that delay level. The proportion of remaining alarms changed as delay level increased. SpO2 alarms became more prevalent whereas ART M reduced in proportion. However, the highest level of delay of 120 seconds resembles the original, non-delayed parameter distribution.

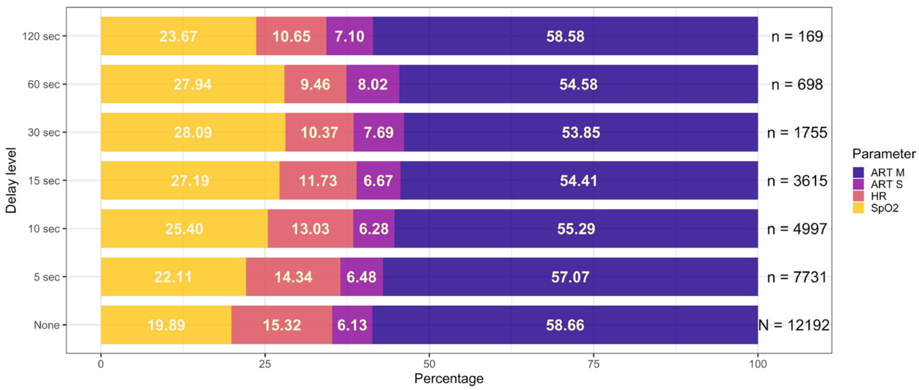

Figure 6. Proportions of remaining alarms per parameter for each delay level. In the non-delayed condition, 19.89% of alarms were triggered by SpO2 and 58.66% by ART M. Introducing a 30 second delay changed the composition: 28.09% of the alarms would be triggered by SpO2 and 53.85% by ARTM.

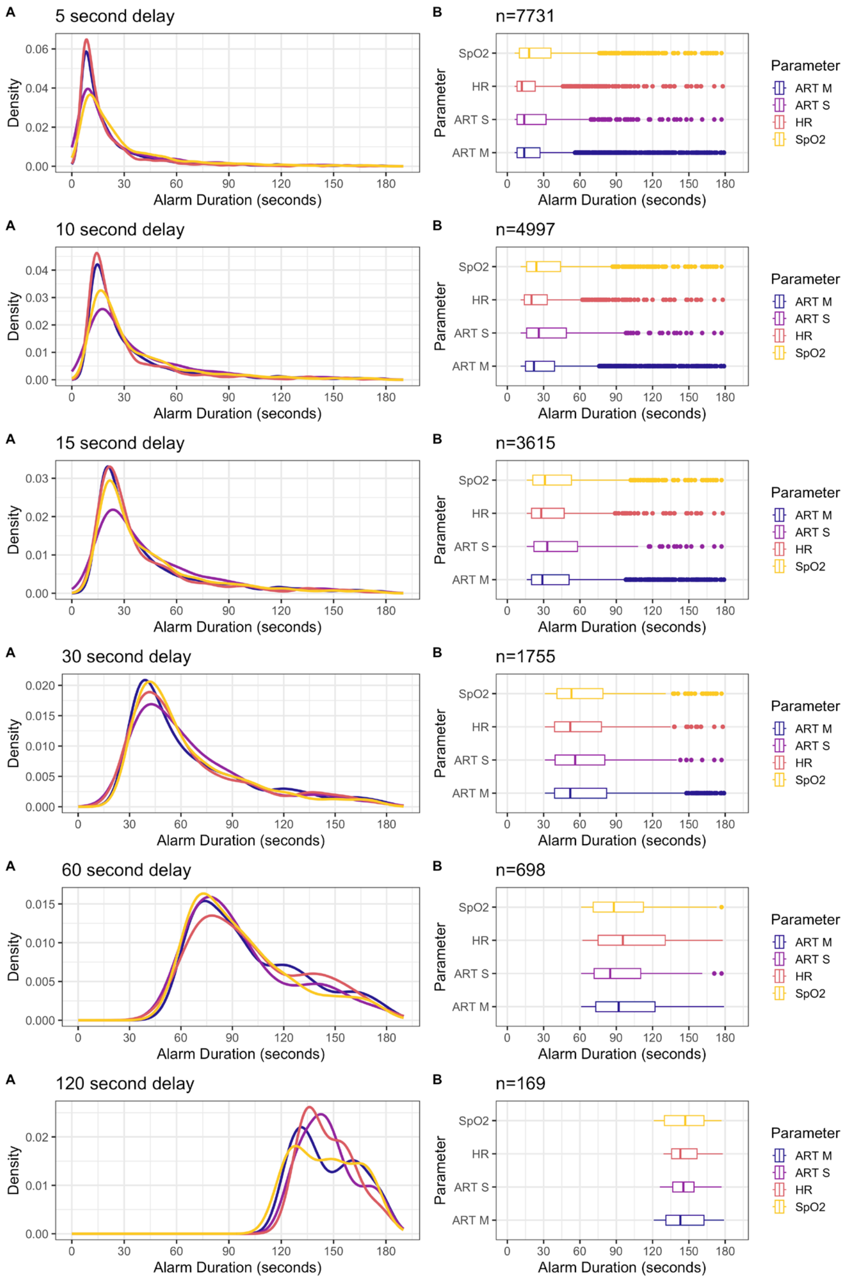

Figure 7. For each level of delay, A is the density plot and B is the boxplot. Different parameters are represented by colors. For shorter levels of delay, density plots are highly skewed due to the high number of outlier long alarms. For longer levels of delay, short and non- actionable alarms are excluded, therefore the number of outliers is low, and density plots resemble normal distribution.

Introducing delays affected the distributions of the remaining alarm durations. The distribution of durations per parameter is presented in Figure 7 for each delay level. Each row illustrates a level of delay, starting with 5 seconds and extending to 120 seconds. On the left side, each figure A demonstrates the density plot of alarm durations per parameter. This indicates the likelihood of observing an alarm of a certain duration per each parameter. On the right-hand side, each figure B exhibits the boxplots of alarm duration per parameter for each delay level, presenting the median and outliers. Reading the plots from top to bottom showcases the alarm duration distribution in the hypothetical situations that an alarm delay of increasing time interval was introduced. As delay level increases, median value increases and number of outliers decrease. Distributions resemble normal distributions as skewness decreases. Longer alarms become part of the normal distribution.

4.4. Discussion

The results show the number and characteristics of alarms generated by patient monitoring systems in an adult IC unit over the course of one month, with a focus on alarm durations and possibilities for introducing alarm delays of certain intervals.

We found that arterial blood pressure (ART M and ART S), heart rate (HR), and blood oxygenation (SpO2) cause the most alarms. In addition, the *number of alarms* fluctuate over the day with peaks at specific hours. The highest peak of the day occurs around 9:00 am during care activities. These activities increase the moving of the patients, which leads to sensors getting detached, arterial lines receiving pressure, and other similar movement-related causes, thus generating more alarms. Similar daily care also occurs around 8:00 pm, explaining the increase in the number of alarms at this point of the evening. The administration of daily medication around 5:00 am also generated more alarms.

4.4.1. Alarm Durations

The duration of alarms does not show major differences between the morning, afternoon, and night shifts. This is surprising because of the changing context and medical routine within each shift. For example, many of the alarms generated in the morning were due to the daily cleaning and care routines, whereas this routine does not exist for the afternoon shift. Characteristics of alarms generated during such care activities may be different than regular alarms. Similarly, characteristics of night shift alarms could be expected to differ, given the considerations for silence during night shifts to facilitate sleep for the patients. However, these considerations were not visible in the analysis.

We investigated the informative value of alarms by focusing on the alarm durations for several parameters. Alarm durations show a large variation with a negatively skewed distribution. This indicates that while most of the alarms were resolved within the first half a minute, there is still a noteworthy number of alarms lasting for several minutes. Durations varied per vital parameter. For example, SpO_2 alarms had the smallest mode of only 2 seconds, while they had the highest median of 11 seconds and a *SD* of 27.16. A mode of 2 seconds indicates that most of the SpO_2 alarms were auto terminated due to the alarming condition ceasing to exist within 2 seconds. On the other hand, compared to the other parameters, there was a larger proportion of alarms with a higher duration caused by SpO_2. The finding that a large proportion of SpO_2 alarming conditions disappear within a couple of seconds raises doubt on the informative value of these alarms within this time window. An implication of this finding is that vital parameters come with their unique properties and should be treated as such while building the system architecture.

While alarms are designed to induce action in nurses, the false alarm rates due to quickly resolving alarms pose threat to the actionability of alarms. The alarming condition disappearing before the nurse has a chance to act on the alarm raises questions on the informativeness of such alarms and reduces trust in the system (Lewandowska et al., 2020). Previous studies have suggested that nurses keep an 'inner clock' of the alarm duration, where the probability of nurse acting on the alarm increases with increasing alarm duration (Bitan et al., 2004; Görges et al., 2009). Since nurses are expecting the false alarms, they do not feel it necessary to act immediately. This indicates that while nurses listen for the alarms, they often implement *internal delays* on the alarms, given the fact that they recognize the action-inducing call of an alarm only after a certain time interval. Maintaining such an inner clock adds to the cognitive workload. Although a certain workload is necessary to achieve an optimal performance, a workload that is too high will only diminish performance (de Waard, 1996; Shanmugham et al., 2018). In the ICU, there are opportunities to off-load such cognitive workload to patient monitoring systems, allowing nurses to focus on clinically relevant tasks. By mitigating unwanted sound events, we can achieve increased actionability of patient monitoring alarm sounds within the acoustic biotope of the ICU.

4.4.2. Alarm Delays

Mitigation of unwanted sounds generated by the patient monitoring systems is possible by alarm delays. Previous literature has explored possibilities of introducing delays of certain time intervals, starting from 5 seconds (Welch, 2011) to 5 minutes (Pater et al., 2020). In our study, we extended the approach of delay simulations from previous literature by adding more parameters in the context of a single-bed adult ICU. Compellingly, our results aligned with previously established expectations. Like Welch, we found that a delay of 10 seconds would eliminate 59.01% of alarms, whereas a 30 second delay would eliminate 85.61% of the alarms. Previous studies have simulated delay possibilities in various types of ICUs, such as neonatal units, and focused on specific parameters, such as only the SpO2. Our study substantiates previous findings, reiterating the need and indicating a lack of improvement over the last decade.

The decision on which delay interval to implement needs to take the response times of nurses and the unique characteristics of vital parameters into account. In this study, we investigated the effect of delay for four vital parameters. Our results indicate that a specific delay yields a different number of remaining alarms for each vital parameter. For example, when a 10-second delay is implemented, 34.85% of the HR alarms remain while 52.33% of the SpO2 alarms persist. This difference can be understood if one considers distribution of alarm durations as shown in Figures 4 and 7. Figure 7 further demonstrates that the distribution of alarm durations resembles the normal distribution more and more in a phasic manner per each delay level. In other words, an increase in the duration of an alarm delay leads to alarms previously labeled as outliers to become part of the normally distributed and expected alarms.

4.5. Design Implications

The transition into a system including alarm delays will necessitate an adjustment period. Nurses, accustomed to frequent auto-terminating alarms, may initially demonstrate slower response times due to this ingrained habit of an internal clock that keeps track of alarms. This means that during the transition phase, there is a potential risk of delayed response by nurses when an alarm is generated after a delay. However, the risk associated with a delayed response of a few seconds is minimal. Nurses are often not directly near a patient when the alarm is triggered, therefore the response time is often longer than a minute. Hospital protocols typically allow for medium-priority alarms to be addressed within a couple of minutes, rather than seconds. In fact, (Bitan et al., 2004) demonstrate that the probability of a neonatal ICU nurse acting on an alarm is approximately 5% within 15 seconds, and 10% within 60 seconds after alarm onset. Consequently, we are inclined to state that an alarm delay of several seconds does not pose a significant risk to patient safety. However, it is essential to recognize that high-priority red alarms require immediate attention. In such cases, alarm delays may be selectively implemented for medium and low priority alarms to mitigate any associated risks, while ensuring prompt response to high-priority alarms.

Alarm delays are imperative and should vary per parameter

This study highlights the potential in implementing alarm delays on reducing false alarm rates. Alarm delays and notification delays have been suggested by previous literature numerous times and have been implemented by some manufacturers. Despite the extensive research and discussion around this notion, its widespread adoption in alarm management practices has been limited. Our study illustrates the potential of delays in reducing alarm rates, even after certain alarm management practices have been put in place. Furthermore, the characteristics of alarm durations differ per vital parameter, therefore the proportion of alarms removed by each delay level will be different. Due to these unique characteristics of vital parameters, sampling rates and alarm delay levels need to be considered on the basis of each parameter. However, this method would also require clinical evaluation and a consequent risk analysis by the manufacturers. In fact, the EU funded Smart and Silent ICU (SASICU) project (Innovative Health Initiative (IHI) grant agreement No 101132808) in which Critical Alarm Lab takes place gathers the manufacturers of a patient monitoring system, mechanical ventilator, and infusion pumps in addition to the central alarm distribution system in an attempt to filter out alarms intelligently and test the solution clinically. Our findings have already been instrumental in the simulation phase of data filtering.

Training to learn the new interaction

Nurses habitually act on alarms after an inner delay, but the introduction of alarm delays will change this dynamic. Off-loading this process from ICU nurses to the monitoring systems will require nurses to change their way of interaction. Nurses will need to un-learn the inner alarm delays and learn the novel dynamic in which an alarm means the underlying condition has been persistent for some time. Change in such a fundamental task may induce confusion and resistance in the beginning. Understanding the appropriate use of alarm delays may require a training and an adjustment period. Therefore, institutions implementing the alarm delays need to consider training of healthcare providers to support the transition.

Sounds need to reflect the novel dynamic

The transition to novel patient monitoring interactions can be facilitated by employing new alarm sounds. Currently, patient monitoring systems employ beeps to communicate the alarm message. Most of these alarm sounds have been designed decades ago, lack sufficient acoustic complexity to communicate information readily, and are perceived to be annoying (Kristensen et al., 2016; Sreetharan et al., 2021). Over the last decades, extensive research has demonstrated the necessity of using improved alarm sounds to mitigate these issues (J. R. Edworthy et al., 2018). Information can be communicated faster, easier, and more conveniently by improved sound design. The transition to delay-implemented monitoring systems can be facilitated by introducing new alarm sounds that communicate the novelty of the interaction style. The difference in sounds will highlight the change and support adaptation to the new system more readily.

Institute-wide strategies

Medical implications and related liability issues on alarm delays need to be discussed in multi-stakeholder settings with a participatory approach and implemented considering the specific needs of each unit. For example, heart rate alarms may be more crucial to cardiac ICUs whereas blood oxygenation is more relevant for neonatal or pediatric ICUs. Therefore, different delay strategies may be required for various types of ICUs. Delay settings need to align with clinical protocols and should be based on evidence-based practices. Collaboration with clinicians is crucial in this regard. Regular audits and reviews of alarm data to assess the effectiveness of the alarm delay settings are necessary. Adjustments may be needed based on the data and feedback from healthcare providers. Such considerations require multidisciplinary collaborations including healthcare providers, biomedical engineers, system designers, policy makers, expert users, and device manufacturers.

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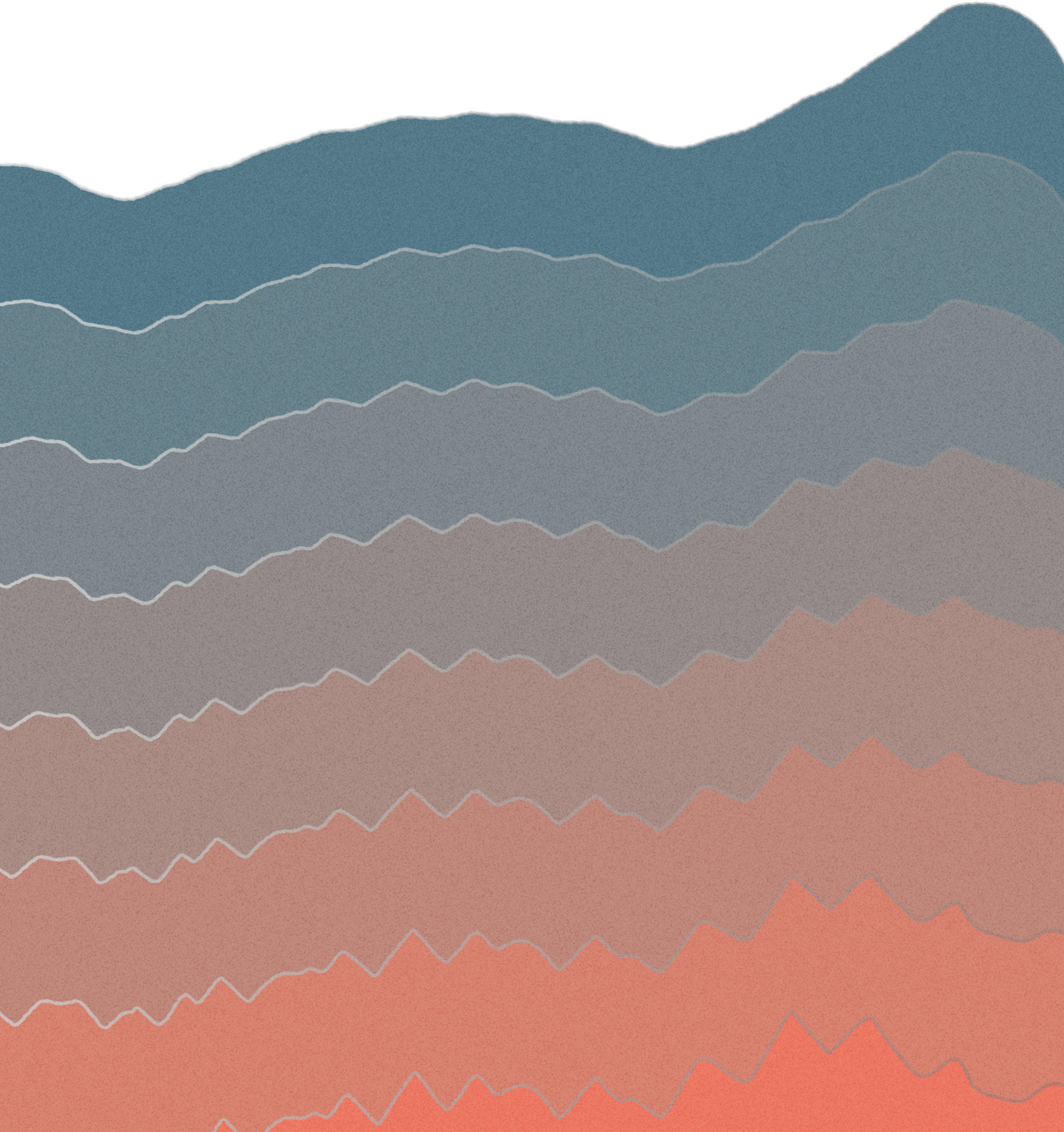

5

Customizing ICU Patient Monitoring: A User-Centred Approach Informed by Nurse Profiles

This chapter have been published in the following research article:
Bostan, I., van Egmond, R., Gommers, D., & Özcan, E. (2024). Customizing ICU patient monitoring: a user-centered approach informed by nurse profiles. *Cognition, Technology and Work*. https://doi.org/10.1007/s10111-024-00763-9

Abstract

Intensive Care Unit (ICU) nurses are burdened by excessive number of false and irrelevant alarms generated by patient monitoring systems. Nurses rely on these patient monitoring systems for timely and relevant medical information concerning patients. However, the systems currently in place are not sensitive to the perceptual and cognitive abilities of nurses and thus fail to communicate information efficiently. An efficient communication and an effective collaboration between patient monitoring systems and ICU nurses is only possible by designing systems sensitive to the abilities and preferences of nurses. In order to design these sensitive systems, we need to gain in-depth understanding of the user group through revealing their latent individual characteristics. To this end, we conducted a survey on individual characteristics involving nurses from two IC units. Our results shed light on the personality and other characteristics of ICU nurses. Subsequently, we performed hierarchical cluster analysis to develop data-driven nurse profiles. We suggest design recommendations tailored to four distinct user profiles to address their unique needs. By optimizing the system interactions to match the natural tendencies of nurses, we aspire to alleviate the cognitive burden induced by system use to ensure that healthcare providers receive relevant information, ultimately improving patient safety.

5.1. Introduction

Alarms in intensive care units (ICUs) are crucial for alerting nurses to potential medical issues. Nurses rely on patient monitoring systems to track vital parameters and provide timely medical intervention. However, the overwhelming number of alarms, with nearly 90% being non-actionable, creates significant challenges (Cvach, 2012; Drew et al., 2014). Nurses face cognitive overload, frustration, stress, and diminished responsiveness, which jeopardizes patient safety and nurse well-being (Deb & Claudio, 2015; Dehghan et al., 2023; Honan et al., 2015; Lewandowska et al., 2020; Ruskin & Hüske-Kraus, 2015; Salameh et al., 2024). Decades of research and industry attention have not yet resulted in large-scale, sustainable solutions (Dehghan et al., 2023). Addressing the challenges posed by excessive number of alarms in various settings requires a grounded understanding of the clinical context of use of the patient monitoring systems. Contextualizing alarms within specific environments helps us identify the friction points leading to excessive number of alarms. These points can then be used to generate targeted solutions that cater to the distinct demands of each unit. In this study, we investigate the alarm load in three types of ICUs within the same hospital to reveal opportunities for design and engineering solutions.

Intensive Care Unit (ICU) nurses are under constant influx of information generated by patient monitoring systems in the form of audio-visual alarms. Alarms are designed to attract attention and induce action in nurses. However, patient monitoring systems generate alarms regardless of the nurses' capacity to receive and act on them. Excessive number and continuous inflow of alarms overwhelm the sensory and cognitive capacities of nurses, leading to 'alarm fatigue' (Cvach, 2012; Lewandowska et al., 2020; Sendelbach & Funk, 2013). Nurses become desensitized to alarms, resulting in inappropriate or lack of response to alarms, increased stress in nurses and threats on patient safety (Kristensen et al., 2015; Ruskin & Hüske-Kraus, 2015). The problem has been on the radar of the healthcare industry and academic community for several decades; yet no sustained improvements have been achieved so far (Özcan et al., 2018). The mismatch between the functionalities of patient monitoring systems and the perceptual and cognitive abilities of nurses results in burdened workload, stress, and fatigue. Such negative outcomes can be mitigated by system design improvements (Nuamah & Mehta, 2020). Aligning system functionalities to nurse abilities requires an in-depth understanding of ICU nurses as system users. In this study, our aim is to gain a deeper understanding of ICU nurses through investigating their latent individual characteristics. We employ surveys to scrutinizing individual characteristics. Based on survey outcomes we develop data-driven user profiles to reveal four distinct types of ICU nurses. Our work can inform future design and human factor studies aimed at enhancing patient monitoring interactions, ultimately contributing to advancements in healthcare (Grootjen et al., 2010).

Innovation and design efforts for healthcare is rapidly introducing novel products and systems at nurses' disposal. It is critical that these novel approaches are well-adjusted to nurses' needs so that their acceptability is increased, and adoption process is shortened. End-user involvement in the design process has been put forward as one of the five major requirements for information technology adoption in healthcare (Bernstein et al., 2007). Consideration of the well-being of healthcare providers is one of the elements for optimizing ICU care delivery (Bueno & La Calle, 2020). By considering the needs and preferences of nurses through a user-centered design approach, we take a step towards humanizing intensive care.

In the field of human factors, recent efforts to mitigate the alarm problem have brought the focus onto nurses. Strategies involve optimizing the way medical information is presented to nurses so that the burden on cognitive load is minimized (Garot et al., 2020; Koomen et al., 2021). However, system features that make work easier vary for different types of users. Efforts so far have often targeted a generic ICU nurse. While substantial body of work demonstrates numerous ways to ameliorate nurse-system interactions, we propose the interaction can be further tailored to address the needs of distinct types of users. People appraise events and respond differently based on their individual backgrounds, memories, associations, and characteristics (Scherer et al., 1999). Recent studies point to this variation among nurses and suggest nursing styles differ based on personal differences (Ruppel et al., 2019). Capturing this variation among nurses is valuable as it allows designing for distinct user groups in a more tailored manner. Patient monitoring systems currently in use offer the same interaction possibilities to all users without room for customization. However, nurses may have different natural tendencies in system use based on individual differences. For example, needs of an expert ICU nurse will differ from those of a nurse who recently started work. Addressing these unique needs through improved design has the potential to reduce the additional workload and stress induced by use of patient monitoring systems.

In this paper, our aim is to understand latent nurse characteristics that may impact how nurses interact with patient monitoring systems. We believe this will offer new tools for designers who aim to facilitate nurses' willingness to interact with novel products and systems. We describe the processes involved in the cognitive processing of patient monitoring alarms and explore how individual differences (e.g., personality, vulnerability to stress, sensory sensitivity, musicality, and risk tolerance) play roles throughout the perception-action trajectory.

5.1.1. Cognitive Processing of Alarms

Alarms are audio-visual signals intended to communicate information to nurses. Audio-visual information requires cognitive processing to decode its meaning and induce action. An understanding of information processing via the widely accepted Human Information Processing Model helps illuminate the significance of individual differences (Wickens, 2002). Within this framework, information processing involves three main stages: perception, cognition, and response (Figure 1). Perception involves the bottom-up reception of the sensory signal and transformation into neural signal for further processing. Perceptual processing of alarms has been thoroughly investigated by previous studies, and generated extensive inventory of knowledge in making alarm sounds more readily informative and pleasant in the acoustic complexity of the ICU (Bennett et al., 2019; J. Edworthy & Hellier, 2005; J. R. Edworthy et al., 2017; Foley et al., 2020; Pereira et al., 2021; Sreetharan et al., 2021).Nevertheless, previous work indicates that simply improving sensory quality of alarms is not sufficient (Andrade-Méndez et al., 2020; Sanz-Segura et al., 2022). Nurses are cognitively overwhelmed by the sheer number of alarms (Bostan et al., 2022; Cvach, 2012).

The stage of cognition involves attributing meaning to perceptual elements through processes such as attention and decision-making. This process is modulated by long- and short-term memory (Figure 1). We focus on the individual differences in this modulator as indicated by the darker box in the figure. Individual differences in one's memory, associations, and habits influence what meanings are attributed to perceptual elements. In the field of noise annoyance, personal differences in noise-sensitivity and attitudes towards sound source are predictors of level of annoyance by sounds (Crichton et al., 2015; Haac et al., 2019; Janssen et al., 2011; Paunović et al., 2009). This applies to ICU nurses, where it was shown that nurses with musical training identify and respond to audible alarms faster (Yue et al., 2017). This demonstrates individual differences in cognitive processing influence nurse responses to patient monitoring alarms.

Final stage of the HIP model involves response and lastly a feedback loop. Response is the stage where user acts on the stimulus. Alarm fatigue is often associated with inappropriate, or lack of, response, such as seeming to ignore an alarm (Sendelbach & Funk, 2013). On the one hand, studies indicate that the probabilities of nurses responding to alarms depend on the causes of the alarm, its duration, and the characteristics of the patient (Bitan et al., 2004). On the other hand, alarm responsivity has been shown to be influenced by individual differences among nurses, such as personality type (Claudio et al., 2021; Deb & Claudio, 2015). Feedback loop can also be influenced by such individual differences. A nurse annoyed by the loud environment can customize system settings to generate fewer alarms or can turn up the volume to increase chances of hearing. The action upon the patient monitoring system is therefore based on this personal appraisal of the environment.

We argue certain individual factors affect how nurses process alarms, resulting in differences in how they interact with the patient monitoring systems. In the following section, we explore which factors we consider to be relevant.

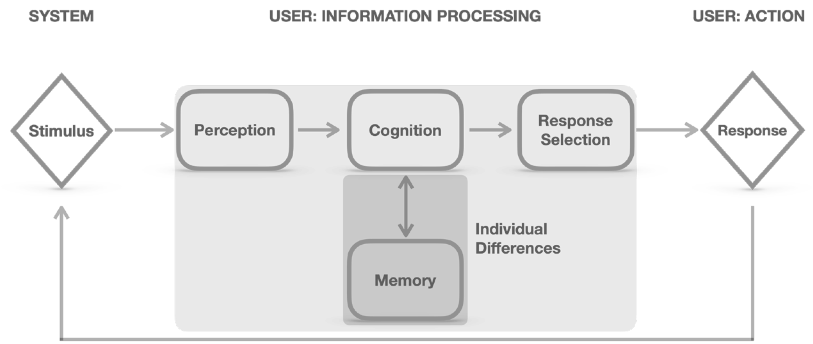

Figure 1. HIP model simplified and adapted from Wickens, illustrating the cognitive processing of information during human-system interaction. Audio-visual stimulus is generated by the system and processed by the user. Processing involves the stages of perception, cognition, and response selection. Individual differences in memory modulate information processing. Finally, the user responds to the stimulus by taking action.

5.1.2. Factors that Influence Cognitive Processing of Alarms

In efforts to improve the alarm responsivity of nurses, one seldom asks the question of who the ICU nurse actually is. Studies in human factors and training/intervention programs often target a generic nurse. Moreover, studies in this field often target the observable interaction, yielding measures such as reaction times or usability scales. However, growing evidence indicates a diverse range of nursing styles with regards to how they manage alarms (Ruppel et al., 2019). Recent studies suggest that what is 'user friendly' may depend on individual needs of nurses (Sanz-Segura et al., 2022). We argue that latent individual properties underlie and modulate the cognitive processes related to interacting with the system. To explain this further, we refer to Figure 2. In the figure, observable behavior and attitudes constitute the tip of the interaction iceberg. This is the portion of the interaction that has been brought to the surface and made visible by human factors research up to date. Revealing more of the iceberg requires bringing the latent portion closer to the visible surface. Shifting our focus from observable, explicit interaction behavior to latent individual properties can offer new insights into addressing the needs of nurses. A focus on latent individual differences, such as those in cognition or personality, have long been suggested as an important factor in the design of adaptive systems and interfaces (Benyon, 1993; Pocius, 1991). However, these considerations have not been addressed in the design of patient monitoring systems. By understanding what drives the actions of the user, we can determine the most effective cognitive cues to optimize the interaction with the system.

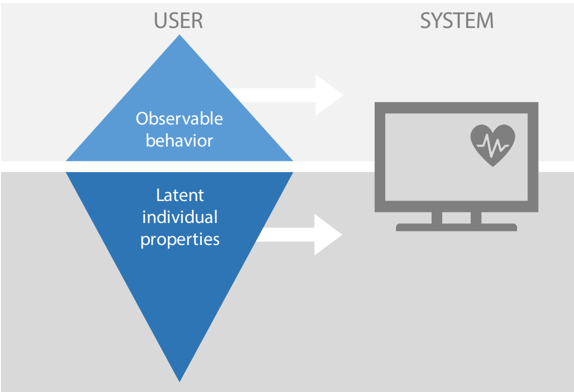

Figure 2. Observable system interaction behaviors are driven by latent individual properties.

Numerous factors influence the response of ICU nurses to patient monitoring alarms. While some of these are external factors, such as alarm duration, patient census, patient severity, and staffing (Bitan et al., 2004), some of them are internal to nurses. In this paper, we focus on these internal individual factors and argue that these modulate the way alarms are cognitively processed, appraised and responded to. An example of this is the subjective experience of annoyance by noises. Level of noise annoyance hinges upon several individual factors such as noise sensitivity and attitudes towards the sound source (Crichton et al., 2015; Haac et al., 2019; Janssen et al., 2011; Paunović et al., 2009). In the ICU, nurses who feel more annoyed by alarms may be more inclined to decrease the number of alarms generated by the patient monitoring system by customizing alarm settings. Nurses vary in how they customize alarm settings (Özcan & Gommers, 2020; Ruppel et al., 2018). To capture this variation and scrutinize its effects on the use of patient monitoring systems, we list several factors that we consider influential in how nurses process alarms.

Nursing Experience

The first relevant factor that influences nurse-system interactions is the level of nursing experience. Several studies have suggested experience level to be a main factor in determining how nurses set their alarms (Özcan & Gommers, 2020; Ruppel et al., 2018; Wung & Schatz, 2018). Nurses report their response to alarms is influenced by their prior experience since experience and expertise enables them to anticipate future events more accurately (Gazarian et al., 2015). This allows more confidence and freedom in customizing alarm settings. Customizing the alarm limits of a vital parameter to be wider yields fewer alarms, while narrow bounds generate more alarms. Nurses with more experience tend to feel more confident in their judgement and set the bandwidth of limits wider (Ruppel et al., 2019; Wung & Schatz, 2018). Inexperienced nurses use alarms as a form of distant monitoring of patient status and tend to set narrower bandwidths, increasing the number of audible alarms. Consequently, the number of alarms is partially determined by the user's actions, even before the alarm-generating medical condition occurs.

Personality

A second relevant factor is *nurse personality*. Deb and Claudio have shown 'nurse individuality' measured as personality type is one of the predictors of alarm fatigue (Deb & Claudio, 2015b). Nurses with different personality traits attach different meanings to alarms, have different affective responses to them, and are influenced by the negative effects of alarm fatigue differently. Similarly, Ruppel et al. have shown that nurse 'expertise, education, knowledge, and style' are factors in nurses' clinical reasoning about alarm customization (Ruppel et al., 2019). Even though the term 'style' remains relatively vague, their discussion suggests that this attribute is related to personal values and personality. Previous investigations from our research group indicate that nurse personality plays a role in how and why they set their alarm limits (Özcan et al., 2018; Schokkin, 2019). Taken together, these studies suggest clear differences in nurse-system interactions based on personality; yet efforts to mitigate alarm fatigue fail to capture this variation.

Operationalizing personality is challenging since factors such as context and culture are highly influential. A widely accepted approach has been the Big Five Personality Inventory (BFI) (John & Srivastava, 1999). In this approach, personality varies among five distinct dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. People lie within the range between two extremes for these five dimensions. Extraversion is related to sociability and emotional expressiveness. Higher scores are associated with outgoing, lively character while lower scores indicate more introspective and reflective character. Agreeableness relates to interest in others and prosocial behavior. Higher agreeableness is marked by considerate, nurturing, warm demeanor whereas lower scores suggest assertive, independent, direct disposition. Conscientiousness encompasses level of organization and goal-directed behavior. Greater scores relate to disciplined, methodological, and responsible character while lower scores indicate more spontaneous and easy-going personality. Neuroticism relates to emotional stability. Higher scores are associated with more emotional and temperamental nature whereas lower scores reflect a calmer, resilient and stable demeanor. Finally, openness is related to creativity and novelty. Higher scores indicate a curious, imaginative, and inventive mindset whereas lower levels are distinguished by a preference for practicality, conventionality, and a realistic approach. In the context of ICU, the importance of certain personality traits is highlighted. For example, an ICU nurse would be expected to be a highly conscientious person so that they are diligent about the details of their work and are able to perform clinical actions in an organized manner. A rather spontaneous nurse might pay less attention to how the patient monitor alarms are set, while an organized nurse might have higher regard for such details. In the case of neuroticism, a nurse who is often carried away by their emotions can have stronger negative reactions to alarm fatigue (Claudio et al., 2021b). Considering such influences, we posit personality as operationalized by the BFI is important to investigate in understanding nurse-system interactions. In this study, we used the validated translation of the BFI in Dutch language (Denissen et al., 2008).

Other traits that influence alarm processing

There are several other factors that we suggest play roles in nurse-system interactions. One of these is one's *inherent vulnerability to stress*. Noise in ICUs in general (Morrison et al., 2003), and monitoring alarms in particular cause stress in nurses (Ruskin & Hüske-Kraus, 2015; Wung & Schatz, 2018). People differ in how well they are equipped with coping mechanisms against stress. These mechanisms may be in the form of lifestyle choices, in the form of psychological resilience, and in the form of neurobiological resilience (Connor et al., 2007; Pfau & Russo, 2015). Although nurses are trained and well-equipped for dealing with high stress, ultimately, they are not invulnerable. We argue their level of vulnerability to stress can influence how they process and respond to alarms as a stressor. In this study, we operationalize stress via the Vulnerability to Stress Scale (SVS) (Miller & Smith, 1985). This validated questionnaire measures vulnerability to and ability in dealing with stressful events of daily life. Items are related to lifestyle choices and personal attitudes, such that healthier choices in diet, exercise, and social life leads to higher resilience to stress, whereas engaging in bad habits such as smoking leads to higher vulnerability to stress. Higher scores in SVS indicate higher vulnerability to stress.

Another factor we consider to be influential is *sensitivity to physical stimuli*. People vary in their subjective ratings of how annoying they find the same sound based solely on differences in individual noise sensitivity (Haac et al., 2019; Paunović et al., 2009). Noise sensitivity has been shown to be a predictor of noise-related stress (Topf, 1989) and is associated with higher levels of annoyance in nurses (Aletta et al., 2018). Consequently, we argue sensitivity to stimuli will determine how nurses evaluate alarms and modulate their responses. As in the example above, nurses who are more sensitive to noise in the environment may be more likely to reduce the noise. To measure sensitivity, we use an adjusted version of the Highly Sensitive Person Scale (HSPS). This validated scale measures sensitivity to physical, emotional, and social stimuli (Aron & Aron, 1997). Only the physical sensitivity dimension is relevant for our research. We used this subset of items to measure sensitivity to sensory stimulation. This gives an indication with regards to an individual's sensitivity to strong stimuli such as loud noises and bright lights. Higher scores indicate higher sensitivity.

An additional factor that might play a role is *musicality*. A systematic review reveals that nurses who have a musical background (e.g., music theory, singing, playing an instrument) differ in how they respond to alarms (Yue et al., 2017). Musically trained nurses have faster response times to alarms (Lacherez et al., 2007). Such nurses identify alarms more accurately and find the task to be subjectively easier (Wee & Sanderson, 2008). Experience with music influences how sensitive one's ear is to musical tones. Consequently, we believe nurses' ability to process alarm sounds may be influenced by their musical background. To gauge musical background, we used the validated Goldsmiths Musical Sophistication Index (MSI). MSI measures musical involvement, ability, and knowledge of non-musicians on several dimensions (Müllensiefen et al., 2014). We used a subset of MSI to include the relevant items along the dimension of 'perceptual ability'. This dimension evaluates of one's abilities in perceiving musical and sound related attributes. Higher scores indicate higher perceptual ability for music.

A final factor we believe to be influential is *risk tolerance*. Risk assessment is one of the key roles of nurses (Henneman et al., 2012). Nurses need to make risk-assessment calculations frequently in deciding the course of action (Despins, 2017). For example, ignoring or silencing an alarm without tending to the patient requires taking a well-calculated risk (Schokkin, 2019). People vary in how risk-tolerant they are (Dohmen et al., 2011). Therefore, we argue that the level of risk tolerance could play a role in how nurses process and act on alarms. Recent literature on risk tolerance suggests simply asking people to rate their risk-taking attitudes prompts them to consider several relevant domains of life and yields valid and reliable results (Mata et al., 2018). Consequently, we included a single item to inquire how risk-taking participants perceived themselves to be. Higher scores indicate higher risk-taking tendency.

Unit Differences
A final set of differences that can lead to variations in alarm processing is differences in alarm culture within the unit. Nurses report their customization of alarm settings are influenced by factors such as how alarms are managed within the unit, whether the unit is already noisy or relatively quiet, and some broader factors such as leadership styles and staffing (Ruppel et al., 2019). Another observation study supports this notion, suggesting that 'sound cultures' within units compel nurses to adopt particular alarm customization habits (Schokkin, 2019).

Physical attributes of the unit may further influence how alarms are processed. Some units are open layout with all patients in one large room; meanwhile some units consist of individual chambers for each patient. Physical layout of the unit directly influences where the patient monitoring systems are located and how sound is dispersed within the environment. This creates differences in the soundscape and influences how nurses hear the alarms. Furthermore, nurses often carry wearable devices that relay alarm information while they are mobile. Such wearable devices vary on which information they can provide (e.g., only a notification that signals that an alarm has been generated or a more detailed description of the alarm such as the level of priority and the parameter that triggered it). Different types of technology offer various possibilities of interaction. For example, while it may not be possible to acknowledge or silence an alarm through a wearable device, this may be possible through the central nurse desk. Physical location of the nurse desk or the possibilities afforded by wearable devices thus directly influence how nurses respond to alarms.

Another difference lies in the protocols regarding family visits. While some units only allow for visitation during particular hours, some units allow family to be around more often. The number of people around the patient and concerned questions from the family following each alarm can force the nurses to be more considerate of their alarm settings. Finally, characteristics of the patients also differ between units. Some units accommodate adults, while others accommodate children or even neonates. Some units involve patients around planned surgeries, while other units have patients following unplanned acute trauma (e.g., after car accident). The type of patient influences the type of alarms generated. Therefore, we argue unit related differences also play role in how nurses interact with patient monitoring systems.

To explore the relevance of above-mentioned individual characteristics, we conducted a survey study as the first step of the investigation of our hypothesis. This step involved acquiring information on the relevant individual characteristics listed above. Our future studies will investigate how individual characteristics influence nurse-system interactions in the form of alarm settings.

5.2. Methods

5.2.1. Design

This survey study consisted of questionnaires administered to ICU nurses from two different IC units at Erasmus Medical Center, Rotterdam between March 2022 – September 2022. A compilation of five validated questionnaires were used. Ethical permissions were granted by de Medisch Ethische Toetsings Commissie in Erasmus Medical Center Rotterdam.

5.2.2. Participants

Nurses from *Pediatric* ICU (PICU) and *Adult* ICU (ICU) took part in the study. Inclusion criteria consisted of certified and registered nurses, who actively work as critical care nurses. Participants were sampled by convenience sampling method, based on availability and willingness to participate. Participants could withdraw from the study with any reason at any time. Exclusion criteria consisted of participants who dropped out for various reasons, and participants who did not complete the surveys in a suitable manner (>30% questionnaire items neglected). The online survey was sent to approximately and 80 *Pediatric* ICU nurses and 200 *Adult* ICU nurses, yielding in a total response rate of 18.93%.

Fifty-three ICU nurses took part in the survey. Forty-two were females, eleven were males. Mean age was 37.80 years, SD = 14.92. Twenty-eight of participants were *Pediatric* nurses, while 25 were from the *Adult* ICU. The average experience as an IC-nurse was 13.71 years, $SD = 11.64$; ranging from 0 years (several months) to 42 years. As expected, age was highly correlated with experience, $r(14) = 0.97$, $p < 0.001$. Mean years of experience for females was 12.7, while for males it was 17.7. Mean years of ICU nursing experience for *Pediatric* was 15.9 years, and for *Adult* was 10.9 years. Difference in the years of experience between the units was not statistically significant, $p > .05$.

5.2.3. Setting

This study was conducted in two ICUs within the same medical center. First unit was the Adult Intensive Care Unit. This department consisted of four units in four long corridors. In each unit, there were nine single-patient rooms along the corridor. Nurse desks were stationed on the corridor, facing the patient rooms, and had direct visual contact to the patient bed via windows. Each room opened to the corridor via sliding doors, thus alarm sounds generated from patient monitoring systems were mostly contained within one room. In addition to the monitors, there were several other medical equipment in the room that generate alarms such as ventilator device, infusion pumps, and dialysis machine. Patient monitoring alarms were carried over to the corridor via the computers on nurse desks, which were connected to the patient monitoring system inside the room. In this unit, families could visit patients during limited visiting hours.

The second unit that took part in this study was a Pediatric Intensive Care Unit (PICU) consisting of four units in the shape of big rooms in open layout. In each unit, eight patient beds were placed in a U-shaped manner. The nurse desk was in the center of the room, with visual access to all patient beds. Patient beds were separated from each other by means of curtains around the beds. This means alarms from one patient monitor were audible all around the room. Monitors were also connected to computers on the nurse desk. Since patients in this unit were young, they were often accompanied by family. Due to these differences, there were more people and general movement around this unit compared to the adult unit.

5.2.4. Procedure

This was a hybrid study in which online and offline data acquisition methods were combined in order to facilitate more participation, as the ICU nurses were under stress due to the long-lasting effects of the pandemic. Online questionnaires were administered via the data collection platform Qualtrics (www.qualtrics.com). The link to the survey was communicated to the nurses through weekly newsletters circulated by the unit nurse managers, accompanied by a paragraph explaining the purpose of the study. First page of the questionnaire included an extensive explanation of the study goals, associated risks, contact information of involved researchers, and informed consent form. Participants could only continue to the questionnaire items if they gave their consent.

Offline questionnaires were administered by one of the authors, visiting the units and approaching nurses during their break time. Layout and the structure of the questionnaires were similar to the online version, with the first page consisting of relevant information and informed consent forms. The researcher explained the study purposes and asked if the nurse was interested in participating. After informed consent, nurses continued onto responding to the items.

5.2.5. Measurement Instruments

This study consisted of five sub-questionnaires measuring individual characteristics of nurses in nine dimensions. Each sub-questionnaire represents the operationalization of the relevant characteristics, as listed above. Questionnaires used to measure each trait are listed in Table 1.

Table 1. List of questionnaires used, their respective ranges, and number of items.

	Questionnaire	Range	Number of items
Personality	BFI	1-5	44
Stress	SVS	20-100	20
Sensitivity	HSPS (subset)	1-7	7
Musicality	MSI (subset)	1-7	11
Risk-taking	-	1-7	1

5.2.5. Data Analysis

All data was processed and analyzed on R for MacOS, version 2022.07.2. Packages "Tidyverse" and "psych" were used (Revelle, 2019; Wickham et al., 2019). Summary scores were calculated for each questionnaire. For BFI, the mean score of each dimension was calculated by averaging the relevant 8 to 10 items. Scores of negatively phrased items were reversed to positive. Final scores range between 1-5, with 1 being the lowest extreme of the continuum. Thus, for each participant there were 5 summary scores representing each dimension. For SVS, all twenty items were summed, as this is the suggested method by literature. Final scores range between 20-100, with 20 indicating the least vulnerability to stress. HSPS scores were calculated by taking the mean of 7 items. Final scores range between 1-7, with 1 indicating the least sensitivity. Similarly, MSI scores were based on the means of 11 items. Scores of the negatively phrased items were reversed. Final scores range between 1-7, with 1 indicating the least musical association. Finally, risk was measured by a single item. Scores range between 1-7, with 1 indicating the least risk-taking tendency. Thus, summary score for each 9 trait was calculated by first averaging (in the case of Stress, summing) the relevant items on the questionnaire, and then taking the mean of relevant nurse groups. All tests were conducted at an alpha level .05.

5.3. Results

For each participant, there were summary scores for nine traits: Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness, Stress, Sensitivity, Musicality, and Risk-taking tendency. Table 2 demonstrates the mean scores and standard deviations (*SD*) for all 53 nurses, and separately per unit (*pediatric* and *adult*). Finally, Cronbach's alphas are listed for each trait, representing the internal consistency of each trait.

Figure 3 illustrates the mean scores of BFI traits for *Pediatric* and *Adult* ICUs to allow for a visual comparison between units. Error bars represent the standard error of the mean (SEM) for each trait. Figure 3 indicates that units differ from each other on personality traits. Mean scores of *Pediatric* nurses were higher for Extraversion, Agreeableness, and Conscientiousness. Mean scores of *Pediatric* nurses were lower than *Adult* nurses in Neuroticism and Openness. Independent samples t-test was performed to investigate whether differences were statistically significant. Results indicated that *Pediatric* nurses scored significantly higher on Extraversion, $t(51) = 2.65$, $p = .011$, Cohen's $d = 0.73$. Pediatric nurses scored significantly higher on Agreeableness, $t(51) = 2.04$, $p = .047$, Cohen's $d = 0.56$. For all other traits, no statistically significant difference was observed between the units, $p > .05$.

For both units, one sample t-test were performed to test whether mean BFI scores deviate from a hypothetical mean of 3, as represented in Figure 3 by the dashed line. For *Pediatric*, mean scores of nurses were statistically significantly different than the mean for all traits. Mean scores of nurses for Extraversion, $t(27) = 8.66$, $p<.01$, Cohen's $d = 1.64$; Agreeableness, $t(27) = 11.53$, $p<.01$, Cohen's $d = 2.18$; Conscientiousness, $t(27) = 8.92$, $p<.01$, Cohen's $d = 1.69$; and Openness, $t(27) = 4.82$, $p<.01$, Cohen's $d = 0.91$ were higher than the hypothetical mean of 3. Mean scores of Neuroticism were lower than the hypothetical mean of 3, $t(27) = -7.15$, $p<.01$, Cohen's $d = -1.35$.

Similarly, for *Adult*, mean scores were statistically significantly different than 3 for all traits. Mean scores of nurses for Extraversion, $t(24) = 4.71$, $p<.01$, Cohen's $d = 0.94$; Agreeableness, $t(24) = 8.51$, $p<.01$, Cohen's $d = 1.70$; Conscientiousness, $t(24) = 14.81$, $p<.01$, Cohen's $d = 2.96$; and Openness, $t(24) = 5.93$, $p<.01$, Cohen's $d = 1.19$ were higher than the hypothetical mean of 3. Mean scores of Neuroticism were lower than the hypothetical mean of 3, $t(24) = -5.24$, $p<.01$, Cohen's $d = -1.05$.

Table 2. Mean and standard deviations (in parenthesis) for nine traits. Last line is Cronbach's alpha indicating internal consistency. Range for the first five personality traits is 1 to 5, for Stress 20 to 100, for the last three characteristics is 1 to 7.

	Extraversion	Agreeableness	Conscientious.	Neuroticism	Openness	Stress	Sensitivity	Musicality	Risk
Pedi.[a]	4.05 (0.64)	4.17 (0.54)	4.10 (0.65)	2.16 (0.62)	3.47 (0.51)	43.14 (8.50)	3.98 (1.13)	4.56 (1.09)	4.39 (1.40)
Adult [a]	3.59 (0.63)	3.88 (0.51)	3.92 (0.31)	2.40 (0.58)	3.48 (0.40)	44.52 (10.10)	4.05 (1.18)	4.40 (1.00)	4.76 (1.16)
Overall [b]	3.83 (0.67)	4.03 (0.54)	4.01 (0.52)	2.27 (0.61)	3.47 (0.46)	43.80 (9.22)	4.02 (1.14)	4.49 (1.03)	4.57 (1.29)
α [c]	.88	.82	.81	.78	.69	.76	.83	.88	-

[a] Mean and *SD* values for pediatric and adult units.

[b] Mean and *SD* for all nurses.

[c] Cronbach's alpha scores for each trait, ranging between 0 and 1.

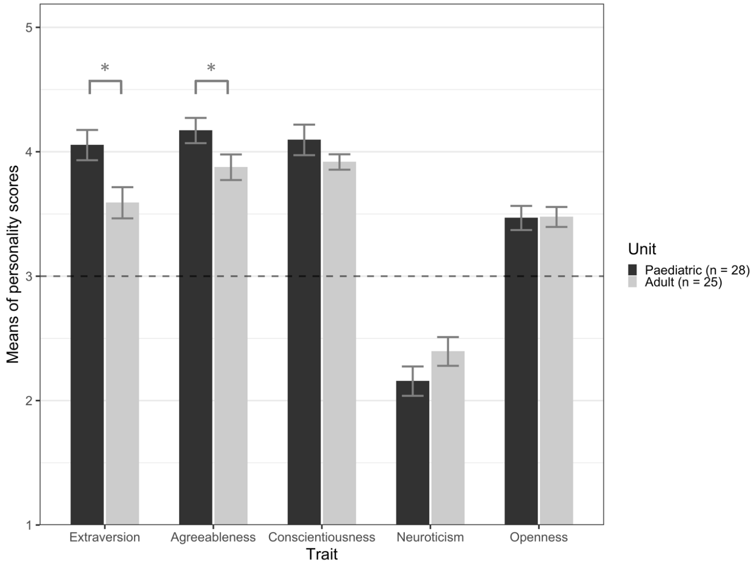

Figure 3. Differences in personality scores between the units and from the mean of 3. Error bars are SEM. Only the difference in Extraversion and Agreeableness scores were statistically significant between the units. All trait scores were significantly different than the mean of 3.

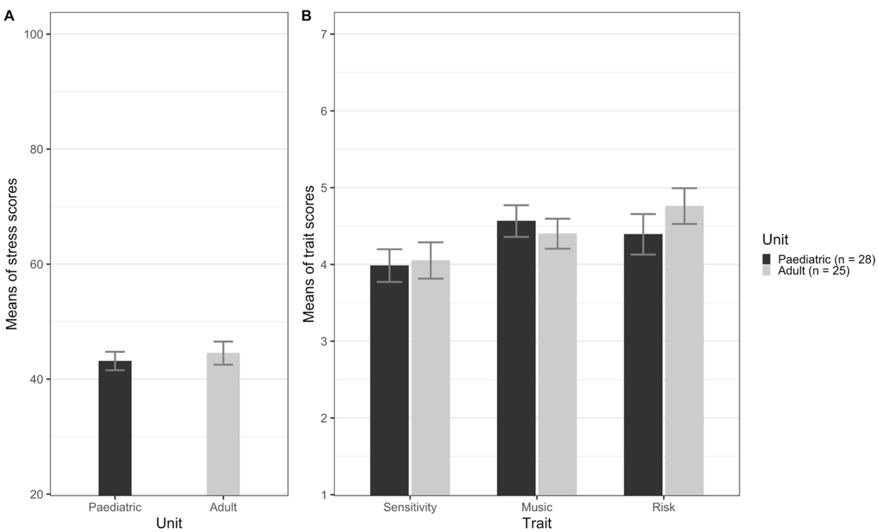

Figure 4. Differences in trait scores between the units. Error bars are SEM. Differences between the units were not statistically significant.

Figure 4A illustrates the difference in mean Stress scores for *Pediatric* and *Adult* units; while 4B illustrates differences in the mean Sensitivity, Music, and Risk traits. 4A shows that ICU nurses scored relatively low on Stress Vulnerability regardless of the units. Figure 4B shows that nurses were relatively medium on trait of Sensitivity, Musicality, and Risk. The differences between the units were not statistically significant as indicated by independent samples t-tests, $p > 0.05$.

Regression analysis was performed to test the association of Experience with the other traits. Results indicated Experience was not a statistically significant predictor of any traits, $p > .05$.

Regression analysis was performed to test whether Stress Vulnerability was associated with any of the traits. There was a statistically significant negative association between Stress Vulnerability and Extraversion ($R^2 = .071$, $F(1, 51) = 4.97$, $p = .030$). In other words, Extraversion predicted Stress Vulnerability ($\beta = -4.10$). This is illustrated in Figure 5A. Black dots represent individual nurse scores and area around the regression line represents 95% confidence interval. Similarly, as seen in Figure 5B, there was a statistically significant negative association between Stress Vulnerability and Risk, ($R^2 = .067$, $F(1, 51) = 4.74$, $p = .034$), ($\beta = -2.08$). The other traits did not show statistically significant relations to Stress, $p > .05$.

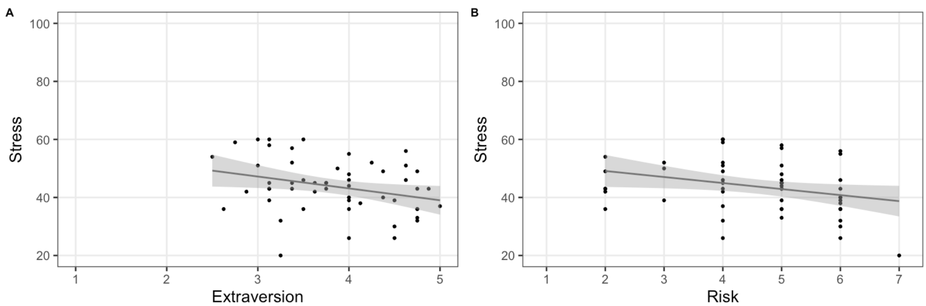

Figure 5. Regression analysis indicated Extraversion and Risk were negatively associated to Stress Vulnerability.

Hierarchical Cluster Analysis

The obtained scores of the nine traits and years of Experience were analyzed by a Hierarchical Clustering Analysis (HCA) with Ward's method. Since regression analysis indicated that Experience was not associated with any traits, we were able to use it as a new factor without the risk of confounding. HCA has been previously used in user centered design research to derive data-driven user profiles ((Holden et al., 2017; Zhang et al., 2016). R software packages of "stats", "dendextend", and "factoextra" were used to perform and visualize the analysis (R Core Team, 2013; Galili, 2015; Kassambara & Mundt, 2020).

Hierarchical Cluster Analysis was performed on the scores of 49 nurses. Four participants were excluded from the analysis due to missing data on Experience scores. Analysis yielded four clusters. Resulting dendrogram is illustrated in Figure 6. The dendrogram indicates that the Cluster 1 consisted of 19 nurses and was the most closely related to Cluster 3 (n = 6). Following in similarity was Cluster 4 with n = 8. Cluster 2 consisted of 16 nurses and was the most distant to the other clusters. For each Cluster, group size, proportion of Adult/Pediatric nurses, and cluster means for all traits are presented in Table 3.

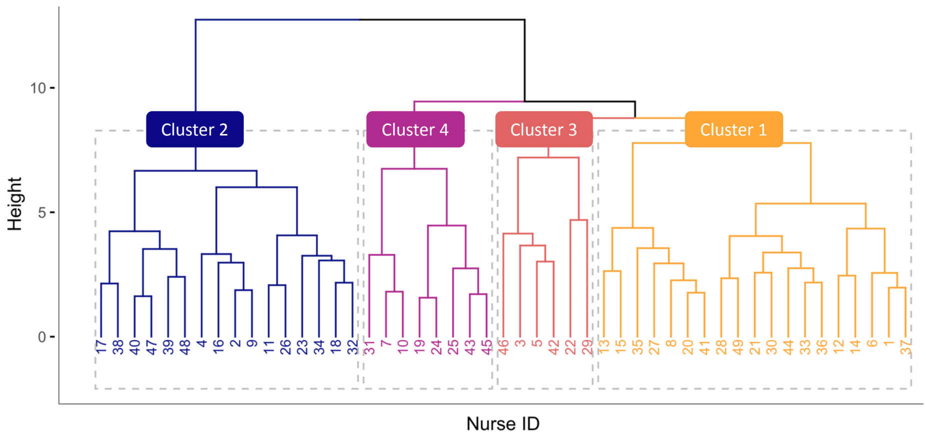

Figure 6. Dendrogram illustrating nurse clusters generated by Hierarchical Cluster Analysis. Each participant number is illustrated as a leaf. Branches closer together indicate similarity in characteristics. Clusters 1 and 3 were the most closely associated, while Cluster 2 was the most distant. Resulting clusters differed in their sizes.

To investigate the distinct characteristics of each user group, we compared the trait scores and experience levels between the clusters. All mean scores were transformed into z-scores to scale the varying ranges. For each cluster, mean z-scores of 10 variables are illustrated in Figure 7. It is important to note that these scores are relative within the sample of nurses measured in this study.

Table 3. Mean trait scores for all clusters and overall nurses. Notice N=49 due to exclusion. Range for the first five personality traits is 1 to 5, for Stress 20 to 100, for the last three characteristics is 1 to 7.

	Extraversion	Agreeableness	Conscientious.	Neuroticism	Openness	Stress	Sensitivity	Musicality	Risk	Experience	n Pediatric / n Adult
cluster 1 n = 19	3.85	3.96	3.77	2.01	3.19	47.89	4.10	4.06	4.42	9.58	11/8
cluster 2 n = 16	4.42	4.26	4.45	1.95	3.79	38.94	3.19	4.95	5.06	18.31	9/7
cluster 3 n = 6	2.98	3.48	3.54	3.08	3.40	47.50	3.81	4.06	4.17	28.00	3/3
cluster 4 n = 8	3.61	4.31	4.17	2.84	3.51	38.75	5.64	5.02	4.00	3.63	5/3
overall n = 49	3.89	4.06	4.03	2.26	3.47	43.4	4.02	4.41	4.53	13.7	28/21

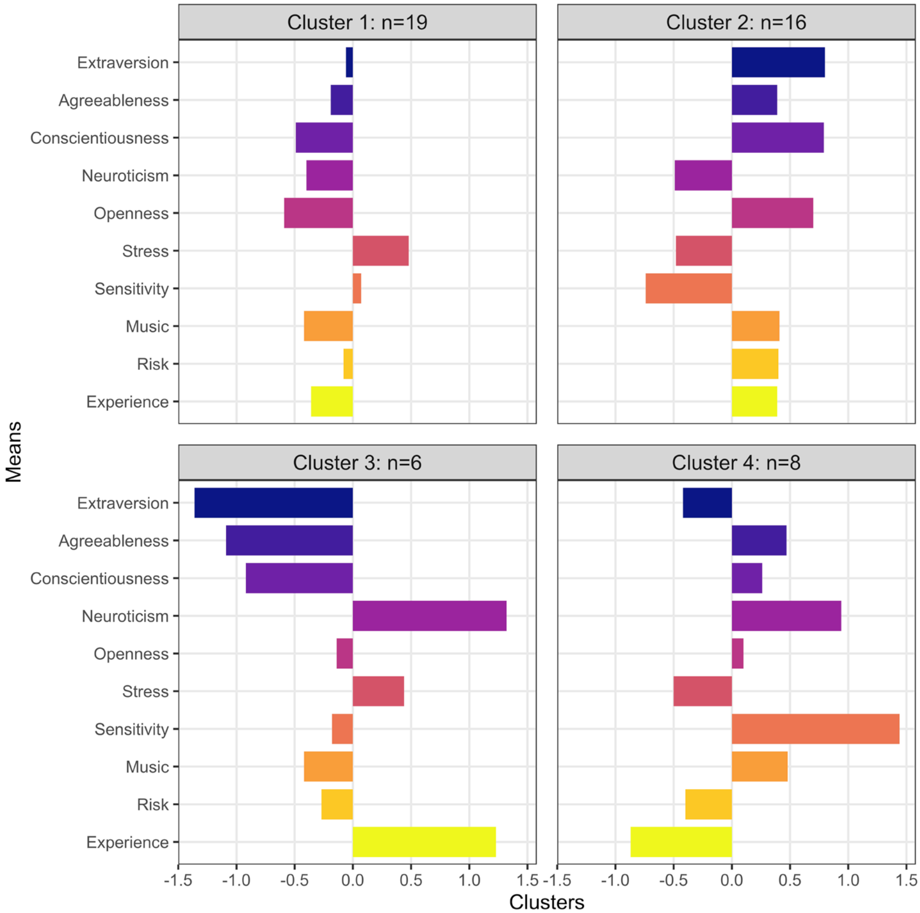

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Figure 7. Cluster mean scores illustrated in individual panel. Y-axis is the traits; x-axis is the corresponding z-scores of cluster trait means. Comparison demonstrates the differences among the clusters. For example, Cluster 3 had the highest level of experience while Cluster 4 had the lowest. Clusters 1 and 3 were the most closely associated to each other.

Cluster 1 represented the largest group of nurses with 9.58 years of experience. They scored moderately on most of the traits. This is seen in Figure 7 by the relatively low deviations from the mean. As indicated in Table 3, they were less open to new experiences (3.19) and less musical (4.06) compared to clusters 2 and 4. Relative to the other clusters, they were more vulnerable to stress with a score of 47.89.

Cluster 2 represented the second largest group of nurses (n = 16) and scored the highest in social traits such as Extraversion (4.42) and Agreeableness (4.26). They were relatively the most open to new experiences (3.79) and more musical (4.95).

They were less sensitive to physical stimulation (3.19) and the most emotionally stable group (1.95). They were relatively experienced in their profession with an average of 18.31 years of experience. This cluster was the least similar to the other clusters, as represented by the dendrogram in Figure 6.

Cluster 3 represented the smallest group of nurses (n = 6) with the highest level of experience (28.00). They scored relatively lower on Extraversion (2.98) and Agreeableness (3.48). They were also the most emotionally reactive group of nurses (3.08). This group may be more vulnerable to stressful situations with a stress vulnerability score of 47.50. This group was the most similar to Cluster 1 and shared the same score in musicality (Figure 6).

Cluster 4 represented the least experienced group of nurses with average 3.63 years of experience. They scored moderately on social traits as seen in Figure 7 by the relatively low deviations from the mean. On the other hand, they were relatively emotionally reactive with a score of 2.84. Compared to the other groups, they were more sensitive to physical stimulation (5.64).They were the most musically involved group with a score of 5.02.

5.4. Discussion

In the following paragraphs, we first focus on the general nurse traits, and then discuss more specific differences between the identified nurse profiles. In general, the relatively high Cronbach's alpha scores indicate high internal consistency of the measurement tools employed in this study.

Results indicate that ICU nurses in all five dimensions of personality significantly differed from the mean. In general, they were highly extraverted, agreeable, conscientious, emotionally stable (neuroticism), and open to new experiences. Taken together, these scores suggest someone that is social, caring, disciplined with high care for detail, and in control of their emotions. These personality traits are clearly adaptive for the requirements of ICU nursing job. Such disposition allows nurses to cope with the stressful environment while having the utmost care for detail and high regard for patient well-being. The same outcome was also seen on the stress vulnerability scores where nurses showed low vulnerability to stress. In general, they were well equipped to deal with stress due to their healthy lifestyle choices, such as eating and sleeping habits, social support, and personal care.

Nurses scored about average on the sensitivity to physical stimulation, musicality, and risk-taking. Considering nursing training and profession require significant time investment, it is pleasant to see many nurses had some involvement with music. This implies that in interacting with alarm sounds, a more than average listening ability with involvement in music can be safely assumed.

We investigated the differences in nurse traits between adult and pediatric ICUs. We expected differences in the dispositions of the nurses who work in these two contexts due to the differences in the physical layout, patient population, and workflow between the units. We observed small differences between the units for all the measured traits. The differences in extraversion, agreeableness, and conscientious were statistically significant, with *Pediatric* nurses scoring higher in general. This points to a slightly more caring and nurturing personality for pediatric nurses which is in line with the social demands of tending to young children and families. This difference in their personality can be adaptive for their work or they may choose pediatrics because they are more caring and nurturing by nature. It is important to note that both units still scored higher than the general population as both units scored higher than the mid-point scale. Sensitivity to physical stimulation, musicality, and risk-taking tendency appeared to be less defining characteristics between the units.

Nurse Profiles

The four data-driven clusters indicated that there were distinct groups of nurses in terms of their individual characteristics. Each cluster represents a unique user profile with their individual characteristics and preferences. The unique characteristics of profiles have the potential to provide new user insights for designing system features to match the natural tendencies, needs, and preferences of ICU nurses for ease of use and acceptability. By focusing on the latent individual properties and how these differ across the profiles, we can reflect on their possible needs for the design of future patient monitoring systems.

Although the nurse profiles show significant differences in their traits, these differences should only be interpreted within the limits of the sample in this study, and it should be noted that these scores are relative within the sample of nurses measured. For example, Cluster 3 scored the highest in Neuroticism. Indeed, they represent the group of nurses with the highest emotional reactivity within this study. Even so, their score was 3.08 in the range of 1 to 5, which demonstrates relative emotional stability compared to the general public. Therefore, it is important to note that the clusters represent a spectrum of users of the patient monitors; and the extremes of this spectrum should only be interpreted within the boundaries of this study. Although the profiles were driven by the current sample, it provides a method of identifying and describing users for future human factors research. Below we further elaborate on the similarities and differences of the user profiles and investigate the implications for interaction and system designers for healthcare.

5.5. Nurse Profiles as Inspiration for New System Interactions

Our analysis yielded four data-driven user profiles. We posit that optimizing the interaction between the patient monitoring system and its users is achievable through a user-centric approach tailored to the distinct needs of each user type. An adaptive system, capable of accommodating the changing needs of diverse user types, holds the potential to enhance efficiency and foster collaborative efforts. Prior research has also indicated the potential benefits of user-sensitive patient monitoring systems (Özcan et al., 2018). Thus, in this section we will have a first attempt to explore nurse profiles as inspirational input for devising new functions for patient monitoring systems. We acknowledge that our reflections are not based on a systematic study employing co-creation methods with the involvement of nurses and manufacturers. This type of work with the inclusion of expert users has been successfully implemented before to reveal design directions (Louwers et al., 2024; Monache et al., 2022). Our reflections in this study are the result of a first exercise to see whether there might be a fitting solution for each nurse type. Our future work will include a co-creation session based on the outcomes of this study.

The Moderate & Straightforward (Cluster 1)
This profile of nurses is based on Cluster 1, representing the largest group of nurses. They score moderately on most of the traits, although they are relatively less open to changes and not highly musical. They also have a higher vulnerability to stress. Taken together, these indicate they will prefer resilient, methodical and logical approach in their work. From system design perspective, these users could benefit from simple, straightforward interaction style. A system with a clear and logical organization may help them navigate through the system more efficiently.

The Sociable & Flexible (Cluster 2)
This group is based on Cluster 2. Even though they represent the second largest group, this profile is the least similar to the other groups. They are high in extraversion, agreeableness, emotional stability, openness to new experiences, musicality, and professional experience. These indicate that they will be open to changes and customization. Alterations in system elements and customization affordances may

be appreciated by this group. They may constitute the early adaptors of novel system elements. They may play around with system settings that offer flexibility to find their desired system state. This group holds the potential to be interested in providing constructive feedback in iterative process of user-centered design collaborations.

The Experienced & Short-tempered (Cluster 3)
This profile is based on Cluster 3. This is the smallest group of nurses. Although they are relatively similar to Cluster 1, this group of nurses is distinct by higher levels of experience and emotional reactivity. Their score on social traits is relatively lower, indicating preference for personal time and quiet. These may imply that they might be vulnerable to stressful situations. To minimize the potential for stress and anxiety, it would be helpful to streamline the interaction with the patient monitoring system.

The Young & Sensitive (Cluster 4)
This profile is based on Cluster 4, which consists of the young and novice nurses. They are relatively emotionally reactive and sensitive to physical stimulation. Taken together, these depict the picture of a novice nurse that is in the progress of adapting to the ICU culture. These nurses could get overwhelmed by noisy environments and excessive number of alarms. They might benefit from system design which alleviates the cognitive load and reduces the sensory stimulation (e.g., less audible alarms or visual alerts). Keeping the user interface simple and uncluttered, with clear and concise instructions would prevent nurses from getting lost in complexity.

Designing a system to address the unique needs of distinct profiles requires a system that is flexible and adaptive to the user's needs. User groups that prefer a simple and straightforward interaction style can benefit from features such as shortcuts to system functions or automation tools. A simple user interface with reduced number of steps required to complete tasks will help minimize the cognitive load induced by the use of the system. Novice users will benefit from a design which supports learning during system use. This can be achieved by a design which provides assistance in the form of directions and actionable insights, such as smart alarm limit calculators or alarm delay suggestions. Providing feedback to the user after successful task completion will help build confidence. On the other hand, expert users who are more comfortable with customization can be involved in the design and testing processes as their feedback will be valuable for system upgrades. Overall, designing the system to be simple and logically organized, with minimal distractions and clear guidance and support, may improve the user experience for this user group.

5.6. Conclusions

This study expands the multidisciplinary efforts to mitigate alarm fatigue through system design improvements. Substantial body of previous work establishes the factors that influence nurse responsivity to patient monitoring alarms. Numerous human factors studies have worked to improve the perception, cognition, and decision-making processes in the Human Information Processing model to minimize the cognitive load during the use of patient monitoring systems (Figure 1). This study builds on that foundation by highlighting the potential of considering the latent individual properties of ICU nurses in the design process. We argue that accounting for personal differences in this model will result in designing a better fit for the cognitive needs of the user group. By identifying and targeting the unique needs and preferences of distinct user groups, designers can create effectively tailored user-centered systems that minimize cognitive load during interaction with the system.

As healthcare moves toward more personalized care, such considerations could extend to healthcare providers. Furthermore, this study acknowledges that while alarm management styles and cultures exist within IC units, nurses are individuals with their own needs. Therefore, design decisions should not be imposed top-down. Design should be informed by the input and feedback from nurses themselves. Overall, a user-centered approach that is sensitive to changing needs of ICU nurses is essential to support an effective and healthy workflow for nurses, improving patient safety and the quality of care in intensive care units.

Further studies in different types of medical centers and geographical locations can be useful in validating the findings of this research. In the future, we intend to measure the interaction behavior and attitudes of the data-driven user groups. With observation studies, experiments, and in-depth interviews, we aim to see the user groups in action, test how they interact with the patient monitoring systems, and explore the motivation behind their actions. In addition, we are planning a co-creation session with nurses, device manufacturers, designers for healthcare and alarms designers in which we will explore the extent to which these nurse profiles can indeed inform system design decisions for improved interactions with medical alarms.

5.7. References

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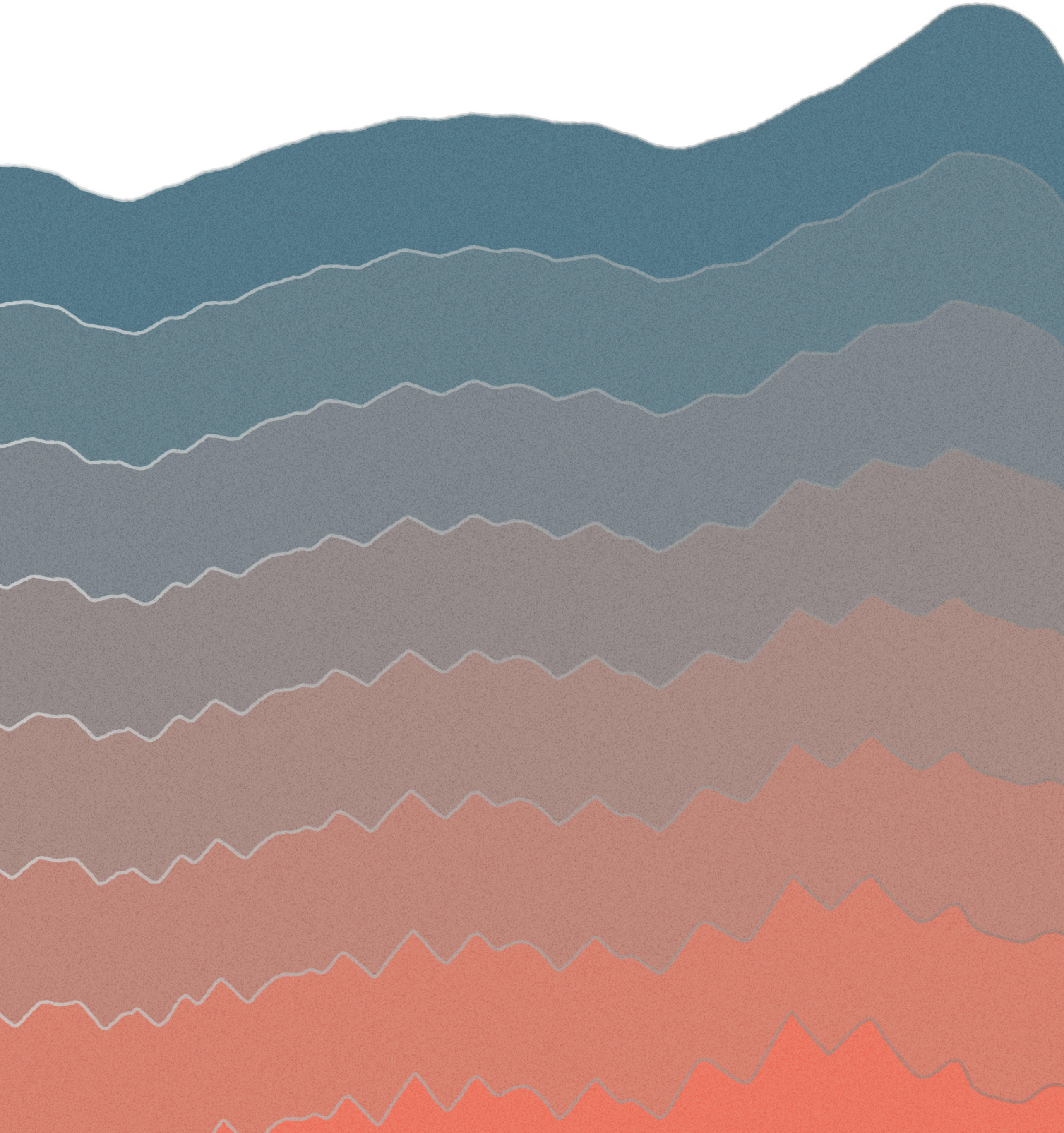

6 Annoyance by Task Interruptions in Healthcare Workflows: Underlying Cognitive Mechanisms

This chapter has been submitted as the following research article:
Bostan, I., Özcan, E., Gommers, D., van Egmond, R. (*submitted*). Annoyance by Task Interruptions in Healthcare Workflows: Underlying Cognitive Mechanisms

Abstract

Task interruptions are pervasive in dynamic environments, such as intensive care units where nurses are frequently interrupted by alarms. These interruptions can impair task performance and contribute to stress and annoyance. While alarms are inherently disruptive due to their acoustic properties, they further burden the cognitive load. The mechanism by which this cognitive load translates into subjective feelings of annoyance, however, remains unclear. In this study, we propose a cognitive framework suggesting that task interruptions lead to cognitive conflict, which is perceived negatively, and the accumulation of these adverse conflicts results in annoyance. To test this hypothesis, we manipulated levels of cognitive conflict and introduced interruptions during task completion in a lab environment. We then assessed the effects on task performance, subjective annoyance, and cognitive states of stress and attention, measured using a commercial electroencephalography system. Findings indicate that task interruptions are annoying and stressful, and the effect is likely to intensify as the frequency and complexity of interruptions increase. These findings highlight the risks of frequent interruptions and emphasize the need for improved system design to support sustained cognitive performance and effective workflow.

6.1. Introduction

In dynamic socio-technical environments such as cockpits and intensive care units (ICUs), alarms interrupt operators by prompting to switch from an ongoing task to a newly introduced task. In the ICU, nurses rely on alarms generated by patient monitoring systems to deliver timely patient care. However, the sheer number of alarms and high rate of false alarms strain this relationship. The alarm overload in the ICUs leads to desensitization, impaired response, stress, and negative emotional responses in nurses (Deb & Claudio, 2015; Dursun Ergezen & Kol, 2020). Repetitive instances of alarm overload negatively impact nurse well-being and threaten patient safety (Cvach, 2012; Lewandowska et al., 2020; Ruskin & Hüske-Kraus, 2015). Frequent false alarms unnecessarily interrupt nurses from their ongoing primary tasks, such as medicine administration and documentation. Interruptions are prevalent in the ICU and lead to errors (Drews et al., 2019; Santomauro et al., 2018). The negative impact of technology-induced interruptions on task performance and feelings of annoyance has been well-documented in the fields of human-computer interaction and cognitive psychology (Bailey et al., 2000; Kiesel et al., 2022). Addressing the challenges in clinical settings requires understanding the mechanisms of task interruptions and integrating insights from both cognitive psychology and healthcare (Douglas et al., 2017). Our current study investigates the cognitive mechanisms that underlie the annoyance caused by alarm-induced task interruptions with the aim of informing future clinical interventions.

6.1.1. Interruptions in Healthcare

Research on interruptions in healthcare context has focused on observational studies and impacts on patient safety (Douglas et al., 2017). Extensive literature has well established that interruptions in healthcare are frequent and impact patient safety negatively (Drews, 2007; Göras et al., 2019; Grundgeiger et al., 2010; Li et al., 2012; Santomauro et al., 2018; Westbrook et al., 2010, 2018). In the ICU, most of the interruptions originate from humans (i.e., other nurses, physicians, patient family), followed by interruption from alarms. Notably, tasks during alarm-interruptions are three times more likely to lead to safety hazards compared to non-interrupted tasks (Drews et al., 2019). Our previous studies have demonstrated the prevalence of alarms in a neonatal ICU, at a rate of one alarm every 3.22 minutes generated by one patient monitor (Bostan et al., 2022). Even after filtering certain non-actionable alarms, the frequency of interruptions is still high in the ICU and poses challenges to nurse workflow (Bostan et al., 2024). Nurses use numerous strategies to minimize the negative effects of interruptions, such as making their work more visible to colleagues (Klemets & Evjemo, 2014), ignoring the interruption until primary task is completed, and physical reminders and artefacts of the primary task while attending to the secondary task (e.g., holding a syringe, placing pencil on the medication to remember a procedure) (Grundgeiger et al., 2010; Walter et al., 2014). Such efforts further burden nurses' cognitive load. Studies converge on the need to establish feasible frameworks for managing task interruptions in healthcare that account for the sociotechnical complexity of the environment (Sanderson & Grundgeiger, 2015; Werner & Holden, 2015).

6.1.2. Task Interruptions

The field of cognitive science has investigated task interruptions from a mechanistic and experimental point of view. Task interruptions lead to reduced task performance, increased feelings of annoyance, and heightened anxiety (Bailey et al., 2000) . At its core, an interruption involves switching from a primary task (T1) to an interrupter task (T2) with the intention of eventually returning to the primary task. This process, well-established as *task switching*, incurs *switch costs*, which exhibit as longer reaction times and higher error rates (Monsell, 2003) . Trafton et al. further clarify the mechanism of switch costs by illustrating that interruptions place burden on memory, as one needs to remember and rehearse goals related to T2 and T1 upon return (Trafton et al., 2003) . Their "memory for goals" model, extensively tested and validated, remains one of the most widely accepted explanations of the increased cognitive load caused by task interruptions (Kalgotra et al., 2019; Puranik et al., 2020), even in the context of the ICU (Grundgeiger et al., 2010) . Supporting this model, neuroimaging studies using electroencephalogram (EEG) have shown that technology-induced interruptions heighten activation in memory-related brain regions, contributing to cognitive fatigue (Chen et al., 2021; Kalgotra et al., 2019). Moreover, research indicates that involuntary task switches are more costly than voluntary ones, as voluntary switches allow individuals time to mentally 'wrap up' T1 before moving on to T2 (Vandierendonck et al., 2010). Numerous other factors influence the effects of interruptions on performance, such as interruption duration, task complexity, task similarity, opportunity to delay the interruption, interruption frequency, and interruption position (Hirsch et al., 2022). The cognitively straining effects of task interruptions have thus been well documented through extensive literature on increased cognitive load. However, the mechanism underlying the subjective experience of annoyance as a result of task interruptions remains unknown.

6.1.3. Cognitive Mechanisms of Annoyance

ICU nurses experience annoyance and frustration as a result of alarms (Morrison et al., 2003; Sowan et al., 2015). Annoyance induced by sounds can be understood in two distinct ways. First of these is the perceptual annoyance, arising from the acoustic properties of the alarm sound itself such as its loudness and pitch (Guski et al., 1999;

Sreetharan et al., 2021). In contrast, cognitive annoyance relates to the interference with ongoing activities, thereby requiring a task switch and disrupting cognitive processes. This is the aspect of sound annoyance not explained by the acoustic characteristics. Level of annoyance is influenced by the degree of interference with the task at hand (Zimmer et al., 2008). This implicates task interruptions as a central factor in the experience of cognitive annoyance by sounds, linking it to the broader context of cognitive load and task performance. Andringa's review on the health impacts of sounds integrates cognitive science and soundscape perception to demonstrate that annoying sounds take away from attentional resources required for primary tasks, thereby increasing cognitive load (Andringa & Lanser, 2013).

6.1.4. Annoyance through Cognitive Conflict

Continued exposure to technology induced task-interruptions can lead to negative emotions, and its long-term effects have been identified as a critical issue for future research (Cheng et al., 2020; Kong et al., 2020; Puranik et al., 2020). In this study, we address the negative feeling of annoyance caused by task interruptions through a cognitive framework. Attending to multiple tasks demands substantial use of cognitive resources such as attention and memory. When multiple tasks compete for the same resources, *cognitive conflict* arises *(Botvinick et al., 2001; Puranik et al., 2020; Salvucci & Taatgen, 2008)*. Cognitive conflict is exemplified by the Stroop task, in which the task is to name the color of the ink of a printed color-word, (e.g., the correct response for BLUE written in red ink is red). When the ink color and the word's semantic color are mismatched, the goals of naming the color and reading the word compete for cognitive resources, resulting in conflict (Littman et al., 2019; Puranik et al., 2020). Typically, this produces increased error rates and reaction times. Notably, research has shown that conflicts are subjectively experienced as aversive signals *(Dignath et al., 2020; Dreisbach & Fischer, 2012)*. This suggests that even arbitrary, impersonal tasks like the Stroop task are appraised and experienced negatively. In this study, we propose that the annoyance induced by task interruptions arises from the accumulation of these aversive conflict signals.

6.1.5. Current Study

In the current study, we investigate the cognitive mechanisms of annoyance induced by task interruptions. In a lab setting, we induced cognitive conflict by interrupting participants through an audible alarm and requiring switching to an interrupting task. We manipulated the level of cognitive conflict, operationalized as the time window allowed for task completion. We examined the resulting effects on subjective annoyance, task performance, and cognitive states. Measures of cognitive states were obtained by the EEG device Emotiv EPOC, which has been used in similar studies and provides convenient estimates of cognitive processes during task completion (Paranthaman et al., 2021; Strmiska & Koudelkova, 2018; Taylor & Schmidt, 2012; Williams et al., 2020). We triangulated our findings by incorporating subjective measures of annoyance, objective assessments of cognitive states, and behavioral outcomes.

This study employed a lab-setting to increase the level of control over the variables. We took several steps to increase the ecological validity of the study and approximate the ICU context. First one of these related directly to the main task, in which the daily medical reports of hypothetical ICU patients were used. Secondly, we simulated the level of urgency experienced by ICU nurses by manipulating the time windows available for the tasks, in which short time windows imposed higher urgency. Third, we cued the task interruptions via audible alarms similar to the patient monitoring systems. Furthermore, the participants needed to change their physical location to respond to the alarm and the second task, as nurses often have to do in the ICU. This study constitutes a baseline measurement of annoyance under various interruption conditions. Ultimately, these findings must be validated in the real-world ICU environment in higher fidelity research to address the sociotechnical complexity of the setting (Sanderson & Grundgeiger, 2015).

6.2. Methods

6.2.1. Participants

Twenty-four participants took part in the study (fifteen females, 9 males), consisting of university staff and students. All had normal or corrected-to-normal vision and hearing. Age ranged between 25 and 78 years *(M = 34.58, SD* = 12.04). Participants were recruited on a voluntary basis through convenience sampling, using posters placed on campus and via university mailing lists. All participants provided informed consent and were compensated for their time.

6.2.2. Materials

The experiment utilized two MacBook Pro laptops running macOS Sonoma 14.5 with 13-inch screens. These laptops were placed on separate desks within the experiment room, spaced such that participants needed to get up and walk to another desk to complete Task 2. The software to simulate the tasks and interruptions in the experiment was programmed using PsychoPy v2022.1.4 (Peirce et al., 2019).

The experimental tasks involved responding to True/False statements based on daily logs of hypothetical ICU patients. Each trial consisted of information about a patient displayed on the left side of the screen, while a statement related to the patient's log appeared on the right. Participants evaluated the correctness of the statement and responded by pressing the <t> or <f> keys on the keyboard. An example of a hypothetical patient log and associated trial question are presented in Figure 1B, and example task statements are presented on Table 1. For each participant and each trial, correct rates and response times were recorded.

Subjective annoyance was measured using a 5-point Likert scale slider embedded in the experiment ("*Please rate how annoyed you feel right now*"), similar to previous studies (Cobus & Heuten, 2019; Pedersen & Persson Waye, 2004; Zimmer et al., 2008).

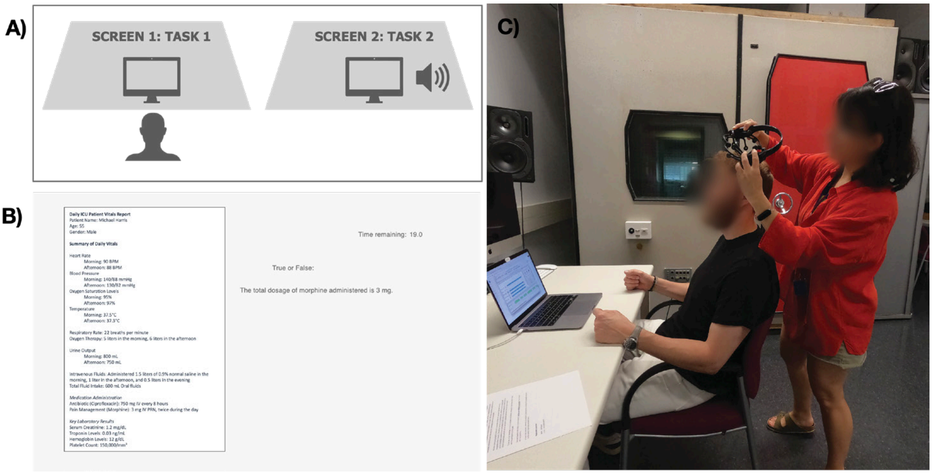

Figure 1. Experiment methodology. (A) A schematic of the experimental setting. Participants were seated in front of Screen 1 to complete Task 1 and switched to Screen 2 when alarm cued Task 2. (B) A screenshot from the experiment trials. On the left side was hypothetical patient logs, and on the right side was a true/false statement about the patient. Participants responded by key press. (C) Experimenter placing the Emotiv EPOC on a participant.

Table 1. Example trial statements based on the hypothetical patient logs and correct responses.

Experimental statements	Correct response
Michael's average heart rate for the day was 89 bpm.	T
Michael's oxygen saturation levels consistently increased throughout the day.	T
Michael is receiving 5 liters of oxygen per minute through therapy.	F
The total dosage of morphine administered is 3 mg.	F
Serum creatinine was measured at 12 g/dl.	F

6.2.3. Design

Objective levels of stress and attention were measured using EEG recordings. Brainwaves were acquired using the Emotiv EPOC device, integrated within the PsychoPy software to facilitate data collection and event time stamping. As participants completed tasks and responded, EEG data were recorded with precise time stamps directly within the experiment software. The system is wearable and ultra-light, it is equipped with 14 electrodes using saline solution, placed according to the International 10/20 Positioning System. Emotiv's software offers *Performance Metrics*, which are estimates of cognitive states based on the EEG data. These metrics are driven by machine-learning algorithms and provide measures of various cognitive states including Attention, Engagement, Excitement, Interest, Relaxation, and Stress. EPOC provides a measure of each cognitive state at a rate of twice per second. In this study, objective measures of cognitive states were based on the Stress and Attention metrics provided by EPOC. Stress/Frustration is defined as the (lack of) comfort with the current challenge, inability to complete a negative task and negative feelings associated with it. Attention/Focus is defined as the depth of fixed attention on task (*Performance Metrics*, 2023).

The experiment consisted of four blocks (2x2) and followed a within-subject design where each participant completed all the block types. The block types varied based on the level of cognitive conflict, operationalized by the time window allowed for responding to trials. Shorter time windows increased temporal demands on cognitive resources, thereby intensifying the degree of conflict. Both the main task (T1) and the interrupter task (T2) allowed Long or Short time windows for response. Therefore, participants needed to respond within *Long-Long, Long-Short, Short-Long,* and *Short-Short* trials. The time windows were set to 30 seconds for *Long* durations and 20 seconds for *Short* durations. A time counter displayed in the upper right corner of the screen indicated the remaining time, resetting for each trial, such that participants were aware of the temporal demands in each trial, Figure 1B.

The 2x2 block structure is presented in Figure 2A. Each block contained 20 T1 trials, accounting to total of 80 T1 trials in the whole experiment. Long blocks contained six, Short blocks contained four T2 trials. The order of blocks was counterbalanced across participants. In the LL block type, participants had 30 seconds to respond to all questions. In the LS block type, participants had 30 seconds for T1 and 20 seconds for T2. In the SL block, they had 20 seconds for T1 and 30 seconds for T2. In SS blocks, participants had 20 seconds for all tasks. This four-block structure allowed us to investigate the differences in varying degrees of conflict.

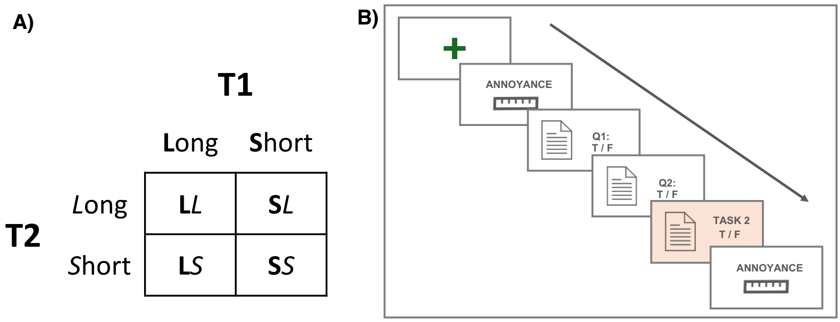

Figure 2. (A) 2x2 block design. For each block, the first letter represents the time window for T1 (bold), and the second letter represents the time window for T2 (in italics). There were four types of blocks in total. LL and LS were Long blocks, while SL and SS were Short blocks. (B) Experiment began with a baseline annoyance measurement. In T1 tasks participants responded true/false to statements about patient logs. Alarms tone cued the T2 (orange screen). After T2, they returned to T1 to complete the remaining statements. Annoyance measure was taken every 10 trials.

6

6.2.4. Procedure

Participants were seated in front of computer Screen 1 for the main task (T1), as seen in Figure 1A & 1C. The interrupting task (T2) was presented on computer Screen 2, requiring participants to change location and perform motor actions, mimicking the flow of events in an ICU where nurses often need to move between different locations.

The experiment consisted of four blocks, each consisting of 20 True/False trials and lasting approximately 9 minutes. Sessions began with the experimenter welcoming the participant, presenting the informed consent form, and explaining the instructions. This was followed by a 5-minute training session to familiarize the participant with the tasks, interface, and the procedure. After training, the EEG cap was fitted on the participant. Once a high-quality signal was confirmed, the experiment begun. Participants had one-minute breaks between each block to minimize carryover effects. The sessions lasted approximately one hour. Participants were debriefed after the experiment.

At the start of the experiment, a baseline measurement of annoyance was recorded. Participants then began the main task (T1) items. Every 90 seconds, an alarm tone signaled the interrupting task (T2). Upon hearing the alarm, participants moved to Screen 2 to respond to the T2, then returned to Screen 1 for T1. Often by their return, the time allowed for T1 would elapse, and the experiment would proceed to the next trial before participants had a chance to respond. This meant that the participants missed certain trials, or needed to prioritize their actions to avoid missing. This was done to simulate the time-constrained environment of an ICU where nurses must frequently prioritize between tasks. After every 10 trials, the annoyance measurement was taken, ensuring that the level of annoyance was assessed both during and at the end of each block. Including the baseline measurement, nine annoyance ratings were collected per participant. A simplified visual depiction of the experiment timeline is presented in Figure 2B. Due to the 90-second alarm intervals and differences in time window durations, Short blocks (SH and SS) by nature lasted shorter, and included only four interruptions per block. Long blocks (LL and LS) lasted longer and included six interruptions.

6.2.5. Data Analysis

The behavioral data was collected by the PsychoPy software as csv files. This data was then cleaned, preprocessed and analyzed in R programming software in *Tidyverse* (Wickham et al., 2019) and *rstatix* (Kassambra, 2023) in version 2022.12.0+353 (R Core Team, 2023). Data was analyzed across the four blocks and the baseline condition before the trials. Task performance data was measured by repeated measures ANOVA for parametric distributions; and by Friedman test and Kruskal-Wallis rank order when the distribution violated the normality assumptions. When significant effects were observed, post-hoc analysis with Bonferroni correction was conducted to detect the pairwise effects.

EEG data analysis leveraged the built-in analysis software offered by the Emotiv EPOC. Stress and Attention was measured at a rate of twice per second and was presented in a csv file. This was then transferred to R software for preprocessing and analysis. The measurements outside of block durations were excluded and only the measurements during the blocks were included in analysis. This was done to minimize movement-related artefacts in the beginning of the experiment and during break times. Cognitive states of *Stress* and *Attention* were plotted and inspected as time-series for each block type. Between-block comparisons and within-block interruption effects were fitted into generalized liner mixed models (GLMM) since the dataset was non-parametric and consisted of repeated measures. This was done with the *lme4* package (Bates et al., 2015). Post-hoc analyses and effect size calculations were made with the *multcomp* package (Hothorn et al., 2008).

6.2.6. Ethical Considerations

This study was approved by the University's review board HREC with application number 3848. Participants were informed about the study's purpose, procedures, and their right to withdraw at any time without penalty. All data were anonymized to protect participants' privacy.

6.3. Results

6.3.1. Annoyance Ratings

Mean subjective annoyance score was 2.12. Subjective annoyance ratings were averaged between participants for the Baseline condition (before the trials) and all block types. The means for all conditions were calculated as Baseline $M = 1.35$, ($SD = 0.57$); block LL $M = 2.1$, ($SD = 0.82$); block LS $M = 2.23$, ($SD = 0.91$); block SL $M = 2.42$, (SD = 0.95); and block SS $M = 2.46$, ($SD = 1.06$). Summary statistics are plotted in Figure 3, indicating the mean values.

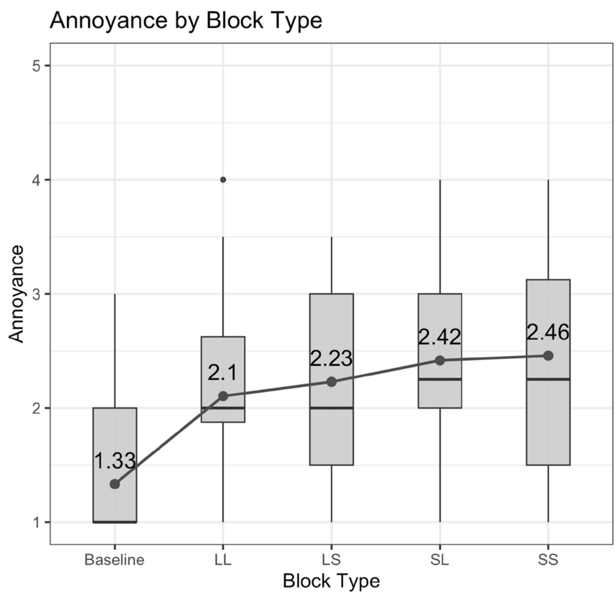

Figure 3. Boxplot representing the mean and median scores for level of annoyance and SD for each block type and the baseline level. The line indicates the change in mean score between block types. The lowest level of annoyance was measured at the baseline before the experiment, and had a trend of increasing as the allowed time windows grew shorter.

Results demonstrated an increase in annoyance in all blocks compared to the baseline, indicating that the experiment induced some level of annoyance. Furthermore, level of annoyance increased systematically as the time window available for T1 and

T2 became shorter. In other words, the mean values followed a systematic increase in which $M_{Baseline} < M_{LL} < M_{LS} < M_{SL} < M_{SS.}$

A Friedman test was conducted to evaluate differences in median annoyance across different block types. The Friedman test is a non-parametric test used for comparing more than two paired groups. The Friedman test revealed significant differences in median annoyance scores among the different block types ($\chi^2(4, N=80) = 38.6$, $p<.001$, Kendall's $W = .40$). This suggests that at least one of the measurement levels significantly differs from the others in terms of median annoyance.

Pairwise comparisons using Wilcoxon signed-rank tests with Bonferroni correction were performed to determine which specific pairs of block types differed significantly. The post-hoc tests indicated that median annoyance scores were significantly higher for the Baseline compared to LL, LS, SL, and SS block types after the corrections, with a moderate effect size. However, no significant differences were found among the other pairs of block types (LL vs. LS, LL vs. SL, LL vs. SS, LS vs. SL, LS vs. SS, SL vs. SS) after corrections for multiple comparisons.

6.3.2. Accuracy

Average number of correct responses, incorrect responses, and misses were calculated for each block type, and are presented in Figure 4.

To evaluate whether there were significant differences in the number of *correct* responses across different block types, a Kruskal-Wallis rank sum test was performed. This non-parametric test was appropriate given that the data did not meet the assumptions of normality and homogeneity of variances. The Kruskal-Wallis test indicated that there were statistically significant differences in the number of correct responses among the different block types ($\chi^2(3, N=80) = 9.46$, $p<.05$). However, the pairwise comparisons did not show statistically significant differences between individual block types after adjusting for multiple comparisons. This suggests that while there was an overall effect, the differences between specific pairs of block types were not significant.

A second Kruskal-Wallis rank sum test was conducted to assess the differences in the number of *misses* across block types. The test indicated that there were statistically significant differences in the number of misses among the different block types ($\chi^2(3, N=80) = 12.92$, $p<.01$). Pairwise comparisons showed significant differences between the block types LL vs. SS and LS vs. SS after adjusting for multiple comparisons. In summary, the SS block type had a distinct impact on the number of misses compared to the other block types.

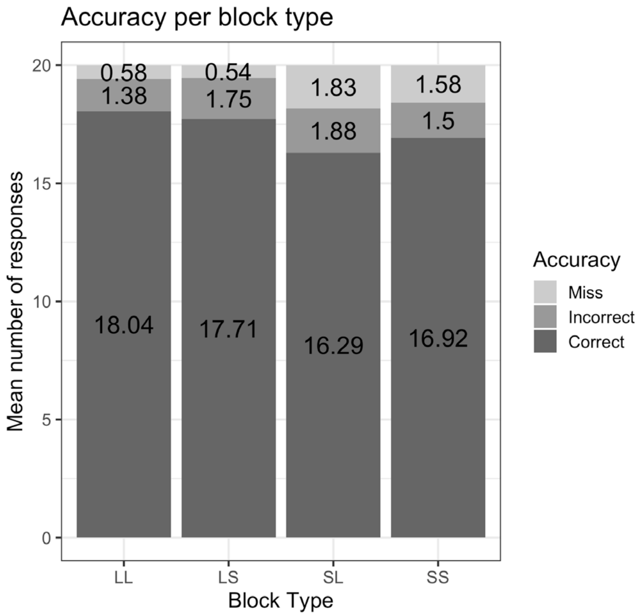

Figure 4. Average number of correct, incorrect, and miss responses per block type. Long blocks had higher correct rates, and lower miss rates than Short blocks.

6.3.3. Response Times

Average response times (RT) were measured as response time to T1 (seconds it takes for T/F key press) per block type and are illustrated in Figure 5. Block type LL had Mean = 13.01 (*SD* = 3.21), LS Mean = 13.14 (*SD* = 2.83), SL Mean = 10.41 (*SD* = 1.83), and SS Mean = 9.92 (*SD* = 1.75).

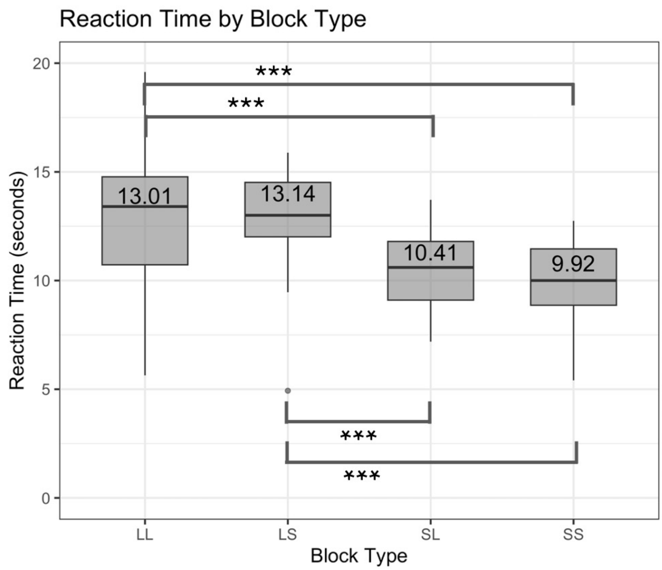

Figure 5. Boxplot of mean response times to complete the task in seconds across block types. LL and LS had significantly longer response time than SL and SS blocks.

RT scores did not violate the normality and Sphericity assumptions. Therefore, a repeated-measures ANOVA was conducted to evaluate the effect of block type on mean response time. The analysis revealed a significant effect of block type on mean response time, $F(3,69) = 20.34$, $p<.001$, indicating that response times differ significantly across the different block types. The effect size measured by Generalized Eta Squared was 0.267, suggesting a moderate effect.

Post hoc pairwise comparisons revealed significant differences between the block types LL vs. SL, LL vs. SS, LS vs. SL, LS vs. SS. No significant differences were found between LL vs. LS and SL vs. SS.

6.3.4. Cognitive States Between Blocks

Measures of cognitive states were obtained by the EEG Emotiv EPOC software for Stress and Attention. These were tested between block types to investigate the effect of block type on the cognitive state.

Stress/Frustration

The measure of Stress throughout the blocks is illustrated in Figure 6. The figure is split into Long and Short blocks for better visibility.

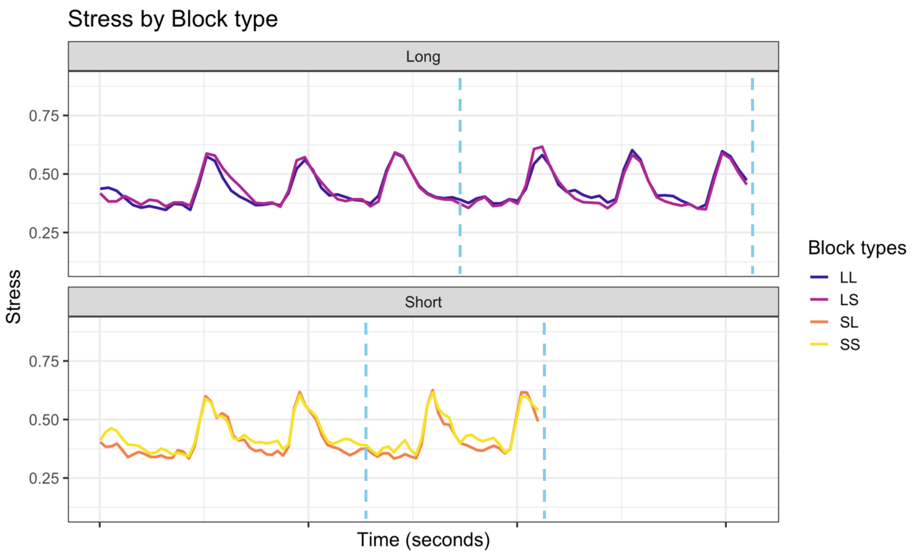

Figure 6. Emotiv Performance Metric: Stress as a measure of time. Colored lines represent the different block types. Dotted blue lines indicate the annoyance rating. Stress varied throughout the blocks, peaking during T2. The upper graph plots Stress over the Long blocks, and the lower graph plots Stress over Short blocks. As the LL and LS blocks were longer and included more interruptions, the blue and purple lines are longer and display more peaks. Overall, stress levels were not very high and displayed peaks during interruptions. Lines were smoothed using GAM with formula = y ~ s(x, bs = "cs"), with method = "REML", with k = 50.

A linear mixed-effects model was fitted to the distribution to examine the effect of block type on Stress, with participant as the random effect, showing a significant result, $F(3, 99429) = 98.76$, $p <.001$. The intercept was estimated at 0.45 ($SE = 0.006$, $t = 72.89$). In the analysis, the estimate of block type LL was zeroed, and the estimate of block type SL = -0.021, ($SE = 0.002$, $t = -14.36$, $p < .001$). The estimate of block type SS = 0.003, ($SE = 0.002$, $t = 1.94$, $p = .21$), and the effect of block type LS = -0.0004, ($SE = 0.001$, $t = -0.3$, $p = .99$).

Subsequently, post-hoc analysis using Tukey's HSD was conducted to perform pairwise comparisons between the block types. Significant differences were found between SL vs. LL ($p < .001$), SL vs. LS ($p < .001$), and SL vs. SS ($p < .001$). No significant differences were found between LS vs. LL, LS vs. SS, LL vs. SS. These results indicate that the Stress was significantly lower for block type SL compared to LL, LS, and SS.

Attention

Attention throughout the blocks is illustrated in Figure 7. The figure is split into Long and Short blocks for better visibility.

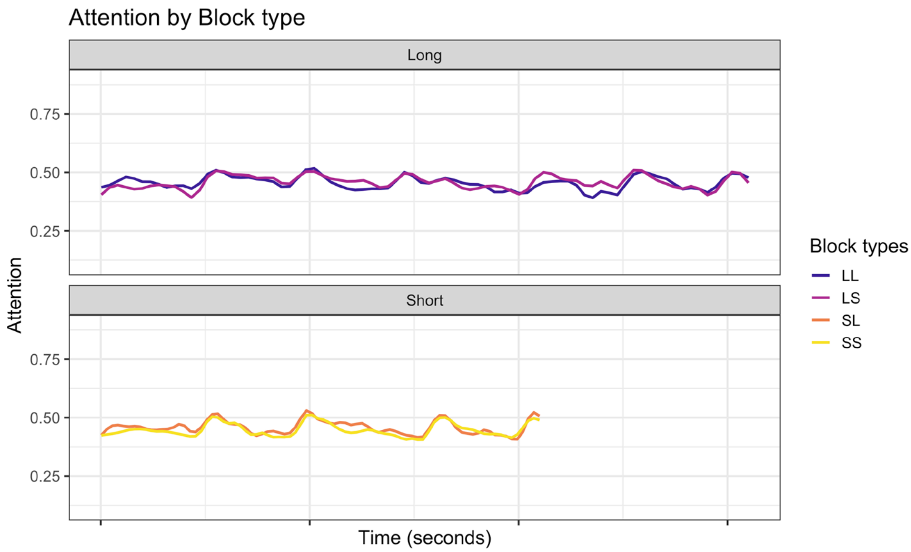

Figure 7. Emotiv Performance Metric: Attention/Focus as a measure of time. Colored lines represent the different block types. Attention varied throughout the blocks. The peaks in Attention correspond to alarm interruptions and switching to T2. The upper graph plots Attention over the Long blocks, and the lower graph plots Attention over the Short blocks. As the LL and LS blocks were longer and included more interruptions, the blue and purple lines are longer and display more peaks. Overall, attention levels were around a medium range and displayed peaks during interruptions. Lines were smoothed using GAM with formula = y ~ s(x, bs = "cs"), with method = "REML", with k = 50.

A linear mixed-effects model was fitted to the data to examine the effect of block type on Attention, with participant as the random intercept, $F(3, 97875) = 61.29$, $p < .001$. The intercept was estimated at 0.46 ($SE = 0.000$, $t = 52.40$). The estimate of block types LS = 0.004 ($SE = 0.0008$, $t = 4.57$, $p < .001$; block type SL = 0.0041 ($SE = 0.001$, $t = 4.59$, $p < .001$); and block type SS = -0.007 ($SE = 0.001$, $t = -8.06$, $p < .001$).

Post-hoc analysis using Tukey's HSD was conducted to perform pairwise comparisons between the block types. Significant differences were found between LS vs. LL ($p < .001$), SL vs. LL ($p < .001$), SS vs. LL ($z = -8.06$, $p < .001$), SS vs. LS ($z = -12.18$, $p < .001$), SS vs. SL ($z = -11.53$, $p < .001$). No significant differences were found between SL vs. LS. Finally, significant differences were found between the blocks SS vs. LS ($z = -12.18$, *p* <.001) and SS vs. SL (*z* = -11.53, *p* <.0001). In other words, the attention scores were higher in LS and SL compared to LL; and attention scores was lower in SS compared to LL. The comparison SL vs. LS indicated no substantial difference between SL and LS.

6.3.5. Cognitive States Within Blocks: Alarm Interruptions

Cognitive states of Stress and Attention peaked during T2 interruptions, Figures 8 & 9. The effect of time period within the blocks was analyzed through a mixed model. To measure the level of Attention and Stress as a factor of alarm interruptions, the time data was segmented into three *Periods*: before any alarms (T1 baseline), during interruption (T2), and T1 between alarms (T1). T2 period was defined as the time from the start to the end of the interruption time window. As LL and LS blocks differ in total time duration and number of interruptions per block, this analysis was conducted separately for Long (LL & LS) and Short (SL & SS) blocks.

Stress

The mean, SD, and median of the Stress levels per activity period is presented in Table 2. Stress across the block periods is illustrated in Figure 8.

Table 2. Mean, SD, and median values for Stress within blocks. Stress was the highest during the interruption (T2), was elevated between interruptions (T1), and was the lowest before any interruptions (Baseline T1).

Period	Mean	SD	Median
Baseline T1	0.39	0.13	0.36
T2	0.56	0.20	0.51
T1	0.41	0.13	0.38

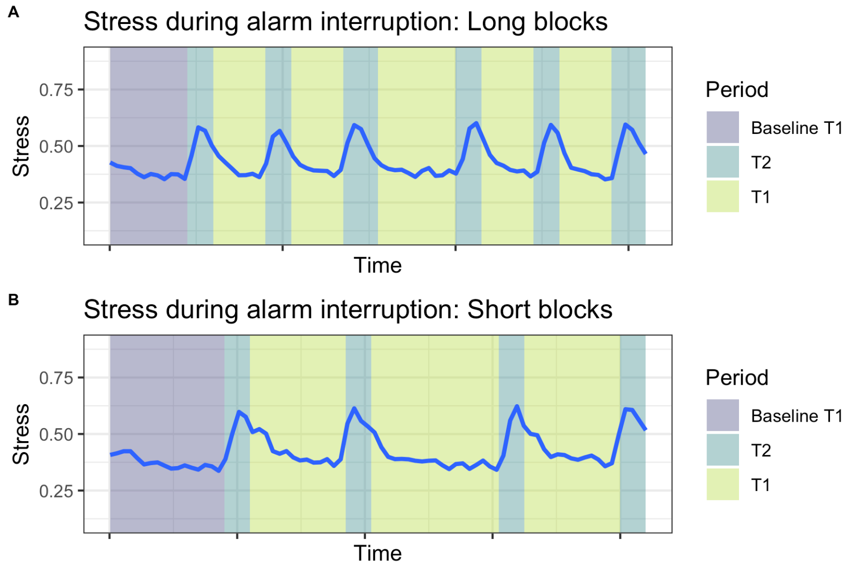

Figure 8. Cognitive state Stress during the blocks. (A) illustrates the time period in Long blocks (SS & SL); (B) illustrates the time period in Short blocks (LL & LS). In both figures, the background colors represent the time period within the block. Dark blue is Baseline T1 before any alarms, dark green is interruption periods (T2), and light green is T1 period between the alarms. Blue line is the average level of stress. Stress peaked during interruptions (T2).

A linear mixed-effects model was fitted to assess the impact of period on stress levels, with random intercepts for each participant. The intercept was estimated at 0.39 (SE = 0.006, t = 62.34), representing the baseline stress level. The T2 period was associated with a significant increase in stress by 0.19 (SE = 0.002, t = 108.05, p < .001), while the T1 period showed a smaller, yet significant increase in stress by 0.03 (SE = 0.002, t = 21.84, p < .001). In summary, the intervention periods (T2) showed a substantial and statistically significant increase in attention compared to the Baseline T1. Stress levels during periods between interventions (T1) also showed a significant increase compared to the baseline, though the effect was smaller than during the T2 periods. This indicates elevated levels of Stress during T1 compared to the Baseline.

Attention

The mean, SD, and median for the Attention level per activity period is presented in Table 3. Attention across the block periods is illustrated in Figure 9.

Table 3. Mean, SD, and median values for Attention within blocks. Attention was the highest during the interruption (T2), was elevated between interruptions (T1), and was the lowest before any interruptions (Baseline T1).

Period	Mean	SD	Median
Baseline T1	0.44	0.10	0.44
T2	0.47	0.11	0.47
T1	0.45	0.10	0.44

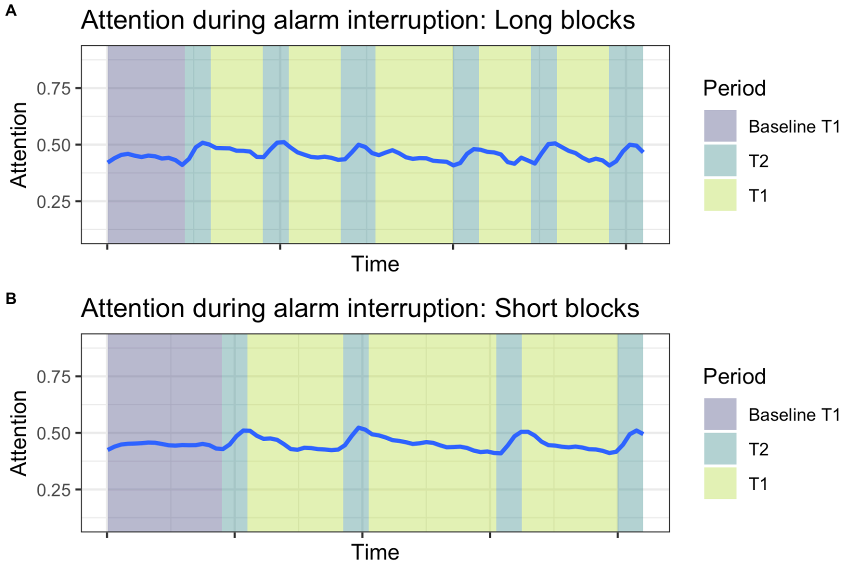

Figure 9. Cognitive state Attention during the blocks. (A) illustrates the time period in Long blocks (SS & SL); (B) illustrates the time period in Short blocks (LL & LS). In both figures, the background colors represent the time period within the block. Dark blue is Baseline T1 before any alarms, dark green is interruption periods (T2), and light green is T1 period between the alarms. Blue line is the average level of stress. Attention peaked during interruptions (T2).

A linear mixed-effects model was fitted to examine the effect of different periods on attention levels, with random intercepts for each participant. The intercept was estimated at 0.45 (SE = 0.009, t = 51.38), representing the baseline attention level. The T2 period was associated with a significant increase in attention by 0.04 (SE = 0.001, t = 36.29, p < .001), while the T1 period showed a smaller yet significant increase in attention by 0.02 (SE = 0.001, t = 16.75, p < .001). In summary, the model revealed significant increase in attention levels during the intervention periods (T2) and between interventions (T1) compared to the Baseline T1.

6

6.4. Discussion

In this experiment, we assessed the subjective level of annoyance, behavioral performance outcomes, and objective measures of cognitive states as people were interrupted by audible alarms during task completion. To assess these, we investigated the self-reported ratings of annoyance, accuracy rates, response times, and Stress and Attention metrics obtained through the Emotiv EPOC EEG system, under varying degrees of cognitive conflict caused by task interruptions. We assessed the differences across four types of blocks defined by time available to complete the tasks.

We hypothesized that block type (LL, LS, SL, SS) would influence perceived annoyance. In LL blocks, participants had the same time window available for responding to T1 and T2. In LS blocks, they had longer time for T1 than T2. In SL blocks, there was shorter time for T1 than T2. Finally in SS blocks, participants had the same, but short, time window available for responding to T1 and T2. We expected participants to feel the increase in temporal demand, especially in SL and SS blocks, leading to increased levels of subjective annoyance and objective stress.

6.4.1. Annoyance Ratings

We found the main effect of the experimental conditions compared to the baseline, indicating that the experiment was successful in inducing some level of annoyance. This is in line with previous literature demonstrating the annoying effects of interruption (Bailey et al., 2000; Cheng et al., 2020). Furthermore, the results indicated a trend of systematic increase in annoyance scores as temporal demands increased, as marked by shorter time windows for T1 and T2. The average annoyance was higher for Short blocks (SL & SS) than Long blocks (LL & LS) as expected, indicating that the conflict induced by temporal demand was experienced as annoying by the participants. Although the effect was not statistically significant, the trend was observed in the expected direction.

Upon reflection, one potential reason for the lack of statistical significance in the effects relates to the instructions provided before the experiment. We allowed participants to interpret annoyance freely based on their personal definition. During post-experiment debriefing, many participants expressed that they found the experiment enjoyable and gamified their responses between the two tasks. As they enjoyed the overall experience, they seldom rated annoyance on higher scores. For future studies of similar kind, it is crucial to instruct participants to rate annoyance *relatively* within the context of the experiment, rather than rating their global levels of annoyance with the experiment.

Another reason for the lack of significant differences may be the small difference between the Short (20 seconds) and Long blocks (30 seconds). Even though the Short blocks allowed for less time, it was still sufficient to complete the task successfully, and did not pose serious urgency. Greater time difference between the two tasks would create greater temporal demands and conflict, which would be expected to reflect on the perceived levels of annoyance (Hirsch et al., 2022).

6.4.2. Accuracy

Our findings indicated that the overall correct rates were high, indicating the task was not difficult for the participants. Between the blocks, the LL blocks yielded the highest number of correct responses, followed by LS, SS, and SL blocks. This finding aligns with expectations, as the LL blocks allowed participants more time to thoroughly read the patient logs, reducing temporal demand. Despite these observed trends however, the differences in correct responses across block types were not statistically significant. This indicates that the imposed urgency was not felt very drastically in the Short blocks. Future studies should implement greater difference between the experimental conditions.

6.4.3. Response Times

Response times (RT) were longer in the Long blocks compared to the Short blocks, with statistically significant differences. This, coupled with the accuracy results, suggests that when participants had more time, they utilized it to read the patient logs more thoroughly, resulting in more correct responses. Conversely, under increased time pressure in the Short blocks, participants responded more quickly, indicating that the experiment effectively induced a sense of urgency. RT increases with increasing task interruptions, illustrating the effect of switch costs in these blocks (Bailey et al., 2000; Monsell, 2003).

6.4.4. Cognitive States between Blocks

When investigating stress measurements across block types, objective stress levels were generally consistent, with the notable exception of the SL block, which exhibited reduced stress compared to all other blocks. The higher stress observed in SS compared to SL suggests that when participants had sufficient time to address interruptions, they did not experience the temporal pressure typically associated with T2. In contrast, when the time windows for T1 and T2 were equal, or when T2 demanded more urgency, participants experienced heightened stress.

This has implications for the design of notifications and alerts. When people know they have more time to address interruptions, they tend to 'relax' into their main task, 'wrapping it up' before attending to the interruption (Hirsch et al., 2022). However, if the main task is less time-sensitive but the interruption demands immediate attention, it may lead to increased stress. In designing alerts and notifications, providing users a grace period to disengage from T1 before reorienting to T2 may lower the stress associated with task interruptions.

Assessments of attention levels indicate that participants exhibited the highest focus during the LS and SL blocks, followed by LL, with SS blocks showing the lowest attention. This metric reflects the participants' ability to concentrate on task-relevant stimuli while suppressing distractions. The SS blocks where both tasks induce high conflict appear to strain participants' focus the most and reduce the attention levels. This aligns with previous research suggesting multitasking imposes switch costs, leading to reduced performance in both tasks (Hirsch et al., 2022). In this context given the high temporal pressure, participants might have struggled to suppress T2-related distractions, resulting in reduced focus.

6.4.5. Cognitive States within Blocks: Alarm Interruptions

In addition to comparing stress and attention across the blocks, we also investigated these metrics at three different time periods within each block. T1 baseline was defined as the first 90 seconds before any alarms, T2 was the interruption task period, and T1 was the 90-second periods between alarms. Both stress and attention were the highest during the interruption (T2), followed by T1 between alarms (T1), and the lowest before any alarms (T1 baseline).

Stress increased during T2 due to the increased time demands and cognitive conflict during this period. Participants know that they must respond to both T1 and T2, but tight time windows make it impossible to attend to both successfully. During T1 baseline, participants engaged in a single task associated with lower stress levels. After the T2 interruption, participants went back to the single-task paradigm for the next 90 seconds (T1), but their stress levels remained elevated. This is highlighted by P20's comment during debriefing: "The anticipation is already making me annoyed because I know the alarm is coming, so I'm never relaxed." This reflects the effect of *dread*, defined as the anticipation of an unwanted stimuli, increasing stress levels (Berns et al., 2006; Harris, 2012). In this context, simply knowing that the alarm will come resulted in elevated stress levels during T1 compared to Baseline T1. This concept is closely related to the widely used theory of Situational Awareness (SA), which describes the decision-making processes of operators in socio-technically complex environments, such as the ICU. According to SA, operators—in this case, nurses—must first perceive the elements in their environment, comprehend their significance within the context of the situation, and then anticipate the future status of these elements (Endsley, 1995). When the occurrence of unwanted stimuli is anticipated, it can elevate stress levels even before the stimuli are present.

Elevated attention levels during T1 are in line with previous literature on cognitive control (Botvinick et al., 2001). When the environment is challenging and high levels of conflicts are detected, the brain modulates the level of cognitive control to match the demands of the situation. We observe this effect here, where the baseline attention level is low (T1 baseline), increases greatly during the interruption (T2), and remains elevated between the interruptions (T1) even though the participants are engaged in a single task. The previous interruptions demonstrate to the brain that the environment is challenging, and the brain attempts to compensate by utilizing more attention resources, resulting in elevated levels of attention.

6.5. Conclusions

In this study, we investigated the cognitive mechanism of annoyance induced by task interruptions. We triangulated the effects by incorporating subjective measures of annoyance, objective assessments of cognitive states, and behavioral outcomes. We observed a small increase in the level of annoyance as temporal demands and number of interruptions increased. Furthermore, behavioral performance suffered as evident by increased response times and error rates. Finally, EEG results showed that participants experienced increased stress during task interruptions. The level of stress remained elevated between the interruptions demonstrating the lasting effects of interruptions. For ICU nurses and other operators interrupted by alarms and alerts, these findings suggest that frequent interruptions not only increase annoyance but also impair performance. The sustained stress observed between interruptions indicates that even the anticipation of alarms can heighten cognitive load, potentially compromising decision-making and attention. This underscores the importance of designing alerting systems that minimize unnecessary interruptions and reduce the cognitive burden on healthcare providers and other professionals.

6.5.1. Limitations and Future Research

In this study, T1 and T2 were similar tasks, both involving responding True/False to statements about hypothetical patients. Although the two tasks always related to different 'patients', the nature of the task was very similar at its core. The (dis)similarity between the main task and the interrupting task influences task performance and subjective levels of annoyance (Hirsch et al., 2022). Although our study serves as a baseline, future studies should alternate between various types of tasks (e.g., various modalities, language-based, mathematical, spatial, social) and measure levels of annoyance under these circumstances.

In this study we did not investigate the effects of task priority. We allowed the participants to try their best efforts to address all tasks in a timely manner. In real life contexts, main and interrupting tasks can impose strict degrees of priority. In the ICU context, the priority level is imposed directly by strict protocols through alarm priority levels (i.e., red, yellow, or technical alarms). A red alarm requires the ICU nurse to drop all other tasks and take immediate action. Future studies may investigate effects of task priority as imposed through the instructions. This can be expanded by mapping level of priority to different alarm sounds, such that the levels of annoyance and task performance can be measured when the alarm sounds more urgent.

This study took place in a lab setting under heavily controlled conditions. The alarms were generated by a single device at a regular interval of 90 seconds. In real life settings, people are exposed to a much greater extent of stimuli competing for attention (e.g., working in open layout office settings, driving). In the ICU context, alarms are not only generated by one patient monitor, but by numerous devices (e.g., ventilator, infusion pumps, dialysis machine) connected to several patients, on unpredictable time intervals. Especially in open layout units, all alarms can be heard by all the nurses on the unit, and one nurse may be responsible from several patients and their alarms. Future studies can build on the current experiment by testing with 'alarm trains' that quickly build on each other. Alarms can be generated through several devices that overlap at times. The frequency of alarm occurrence can be mapped onto real frequencies of alarms observed in ICU contexts, as documented by literature in studies on alarm loads (Bostan et al., 2024; Poncette et al., 2021). Furthermore, future work can manipulate the acoustic characteristics of the alarms to measure their effects, for example by testing regular beep sounds against the newly developed auditory icon alarms.

This study synthesizes knowledge from a broad range of disciplines, including cognitive science, human-computer interaction, and nursing. We strived to extensively review and integrate relevant literature to develop a conceptual framework for understanding cognitive annoyance caused by task interruptions. While this was a challenging task, bridging these disciplines and establishing dialogue is necessary to tackle the complexity of real-life issues, ultimately leading to more holistic and effective solutions.

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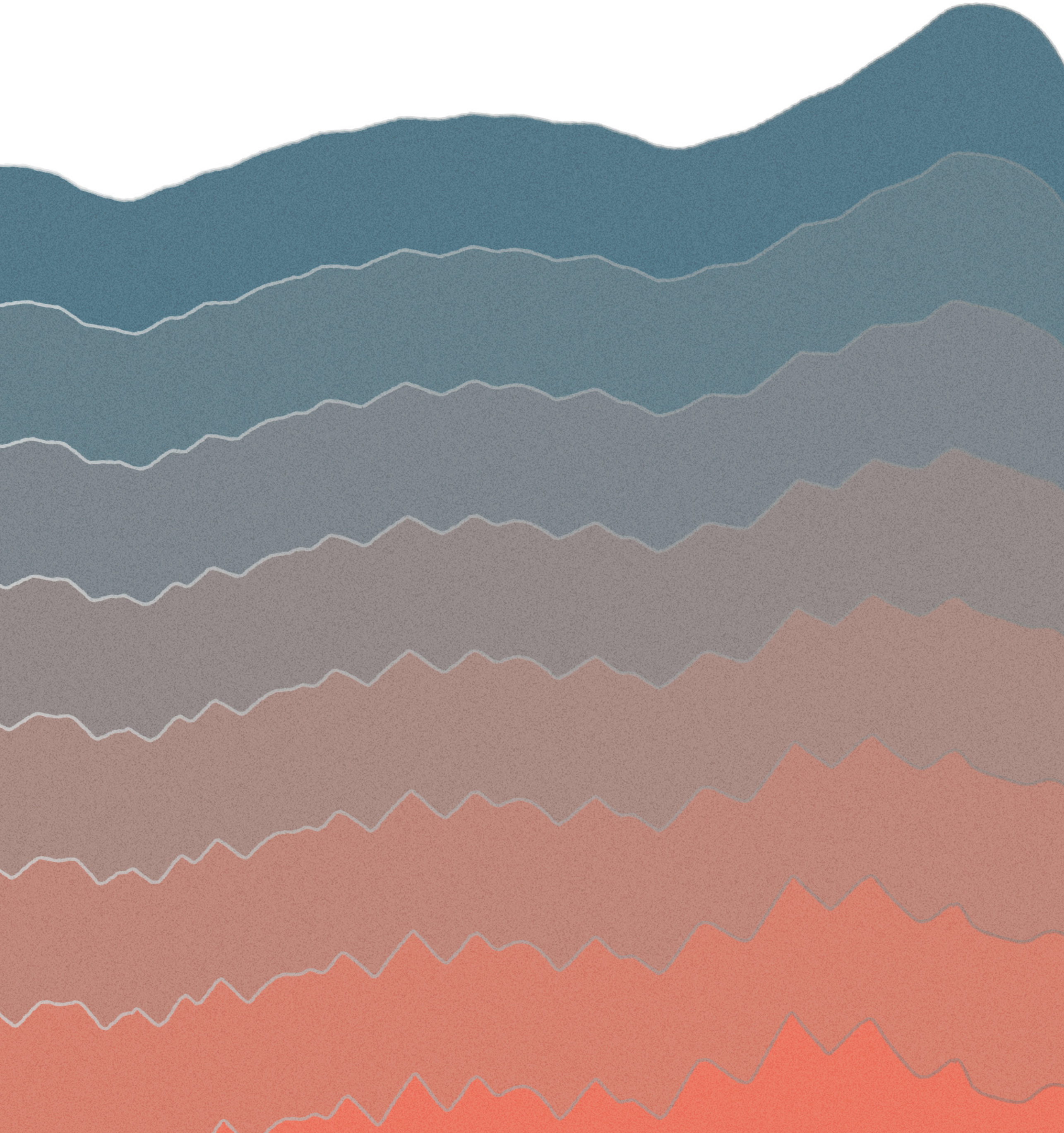

7

From Research to Practice: A Collaborative Approach to Tackling Alarm Fatigue in ICUs

This chapter has been published as the following research article:
Bostan, I., van Egmond, R., Gommers, D., Özcan, E. (2025). From Research to Practice: A Collaborative Approach to Tackling Alarm Fatigue in ICUs. *Proceedings of the Forum Acousticum Conference*.

Abstract

Alarm fatigue describes the desensitization and negative emotions experienced by ICU nurses due to the excessive number of alarms generated by patient monitoring systems. Although alarms are intended to prompt action, high numbers of non-actionable alarms undermine nurse responsiveness and pose risks to patient safety. This study builds on previous research of the authors exploring the characteristics of ICU nurses as users of the system, system features of patient monitors, and alarm prevalence across different ICU types. In this study, we synthesize previous findings into research insights. We conducted a multi-disciplinary workshop using a sound-driven design approach with diverse stakeholders, including ICU nurses, doctors, industry experts, designers, and researchers. Previous research insights were used to stimulate discussion and develop design directions aimed at mitigating alarm fatigue and supporting ICU nurse needs. The outcomes of this workshop produced actionable solution bundles that consolidate previous insights and introduce novel approaches, offering a holistic and collaborative perspective on mitigating alarm fatigue.

7.1. Introduction

Alarm fatigue is the condition in which intensive care unit (ICU) nurses can be desensitized to frequent alarms generated by patient monitoring devices, often leading to frustration, stress, annoyance, and reduced responsiveness to alarms (Deb & Claudio, 2015; Honan et al., 2015; Lewandowska et al., 2020; Salameh et al., 2024). Despite decades of attention from both academia and the industry, efforts to mitigate alarm fatigue have only led to improvements in isolated cases, with large-scale solutions still remaining out of reach (Albanowski et al., 2023; Dehghan et al., 2023). Past efforts to reduce alarm fatigue in ICUs have initially focused on improving alarm design and reducing non-actionable alarms. Enhancing alarm sounds to be more informative has shown potential to lessen nurses' cognitive load, but this approach alone is limited due to the sheer volume of alarms (Bennett et al., 2019; Cobus & Heuten, 2019; J. Edworthy et al., 2017; J. R. Edworthy et al., 2018; Foley et al., 2020; McNeer et al., 2018; Pereira et al., 2021; Reynolds et al., 2019; Sreetharan et al., 2021). Reducing alarm frequency through advanced algorithms and machine learning can help prioritize actionable alerts, while networked systems integrating data from multiple devices offer fewer, more relevant alarms (Ansari et al., 2016; Bostan et al., 2024b; Chromik et al., 2022; Fernandes et al., 2019; Koomen et al., 2021; Manna et al., 2019; Paul et al., 2016; Piri et al., 2022; Welch, 2011). Nurse-focused interventions, such as investigating nurse-centered design directions, training on alarm settings and improved equipment use, aim to improve alarm management practices (Bi et al., 2020; Bostan et al., 2024a; Claudio et al., 2021; Cvach et al., 2015; Deb & Claudio, 2015; Dewan et al., 2019; Honan et al., 2015; Nyarko et al., 2023; Paine et al., 2016; Petersen & Costanzo, 2017; Ruppel et al., 2019; Salameh et al., 2024; Sowan et al., 2016; Torabizadeh et al., 2017; Wung & Schatz, 2018). Emphasizing collective alarm culture and awareness has led to local improvements, though sustained changes remain challenging (Albanowski et al., 2023; Cvach et al., 2015; Sowan et al., 2016; Yue et al., 2017).

Eradicating alarm fatigue requires a deep understanding of the complexity of the problem, and the roles and needs of each stakeholder involved in the issue. To this end, our aim in this study is to generate consolidated design directions to mitigate alarm fatigue. We bring together experts from diverse backgrounds to collaborate on solution strategies in a multistakeholder setting. This approach prioritizes the needs of ICU nurses as users of patient monitoring devices, considering the limitations of the underlying system technology and context-specific constraints.

7

7.1.1. Bridging Perspectives for Collaborative Solutions

In the ICU, nurses listen to alarm sounds to initiate sound-induced actions (Özcan et al., 2022). However, a polluted sound environment obscures the critical alarm sounds, challenging the nurses' ability to perceive and comprehend the relevant sound events (Bostan et al., 2024b). In settings which sound plays a central role, sound-driven design emerges as a required critical approach, emphasizing the importance of 'designing with listening in mind' (Delle Monache et al., 2021; Monache et al., 2022). This framework suggests that agents interpret sounds aligned with their intentions (Tuuri & Eerola, 2012). For instance, nurses listen to alarms with the intent to act, while patients often listen to alarms anxiously, without any power to respond. The sound-driven design model highlights the varied approaches stakeholders take towards sound, emphasizing the value of including individuals from varied backgrounds in collaborative efforts which sound plays a central role (Monache et al., 2022). This shows that optimizing patient monitoring devices requires more than just *engineering* of systems, services or products; it calls for a multidisciplinary perspective for the designed outcome to survive its ecological relevance. Evidence-based design can help bridge this gap by providing scientific insights and evidence as input for a multidisciplinary, participatory, sound-driven design process (Morales Ornelas et al., 2023).

Our aim in this study is to generate consolidated design directions to mitigate alarm fatigue. To this end, we brought together experts from various disciplines to collaboratively tackle the challenge of alarm fatigue. We organized a multidisciplinary sound-driven design workshop to co-create actionable design directions and recommendations to address the identified challenges and support ICU nurse needs. The input for the workshop consisted of previous work of the authors investigating alarm fatigue. Main findings from previous work were summarized into research insights and were used as input to stimulate discussion in the workshop. We promoted interdisciplinary collaboration by bringing together ICU nurses, doctors, industry specialists in ICU technologies, designers, and researchers with the goal of generating user-centered solutions. Such collaborative workshops have been instrumental in generating innovative design directions (Louwers et al., 2024), and in bridging the gap between diverse stakeholders for a holistic approach (Monache et al., 2022; Özcan et al., 2018).

7.2. Methods

7.2.1. Participants

Fourteen participants (eight males) took part in the workshop. Participants consisted of three of the authors (IB and EÖ as design researchers, DG as intensivist from

Erasmus MC), four ICU nurses from Erasmus MC, and seven industry experts in health technology consisting of engineers, designers, and usability experts. The workshop was lead and facilitated by a senior design researcher from the industry experts. The participants formed three groups to work on the three distinct themes, with each group consisting of at least one ICU nurse, one design researcher, and one industry expert. Participants were informed about the study's purpose, procedures, and their right to withdraw at any time without penalty. Participants provided informed consent prior to the workshop.

7.2.2. Workshop Input

In the workshop, the issue of alarm fatigue and strategies to mitigate it were explored with a user-centered approach, scrutinizing the interaction between ICU nurses and patient monitoring systems within the ICU context. Following this triadic relationship, we developed three core themes: *user*, *system*, and *context*. Insights from the authors' prior research was used as workshop input, and figures generated in these studies were used as prop materials. Through three previous studies, we explored user-related factors focusing on ICU nurses (Bostan et al., 2024a), system attributes of patient monitoring systems (Bostan et al., 2024b), and the broader alarm loads within different ICU environments (Bostan et al. *submitted*), uncovering key characteristics in each area to understand the dynamics at play.

Each of the core themes was explored by one group of participants, totaling three groups of participants covering all the three themes. We presented the participants with previous research findings related to these three themes, presented the relevant figures and prompted ideation and brainstorming in multi-disciplinary sub-groups. Although the workshop took place within the context of health technologies industry, the exploration of solutions was not confined to technology-driven ideas. Instead, we encouraged a holistic approach to address the problem of excessive number of alarms comprehensively, respecting the wide range of expertise areas.

The theme *user*, assigned to Group 1, was based on previous work categorizing ICU nurses into user profiles according to their individual characteristics such as personality traits, musicality, and sensory sensitivity (Bostan et al., 2024a). This study revealed the diversity in nurses as users of patient monitoring systems. More specifically, four nurse profiles were identified with distinct needs, habits, and preferences towards the monitoring system. Group 1 worked on the insights from this study, scrutinizing the individual differences among nurses and their influence on system use. One relevant factor was years of experience, which was highlighted to significantly impact alarm management styles and use of the system. Insights drawn from this study were enriched with supporting quotes collected from nurses, demonstrating the variations among the nurse perspectives towards alarms. Main insights used by Group 1 are illustrated in Figure 1 (also in Chapter 5, Figure 7).

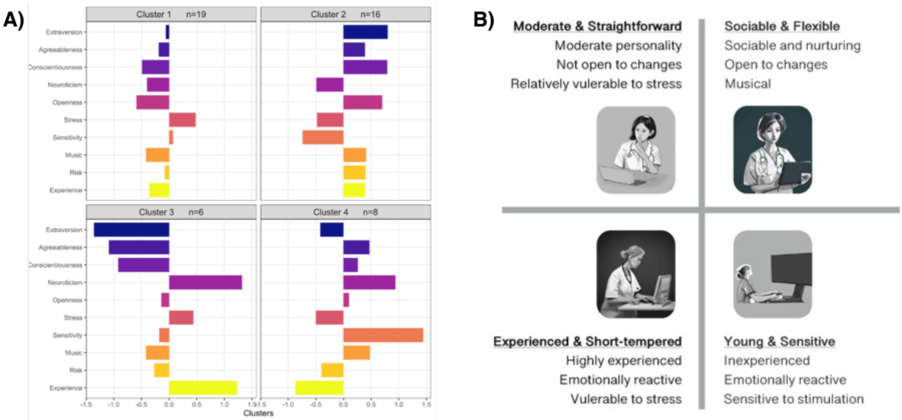

Figure 1. Theme **User** was based on previous work about nurse profiles (Bostan et al., 2024a). A) Nurses were clustered into four categories based on their individual characteristics such as personality. B) The four clusters were formed into four nurse profiles with distinct habits and needs.

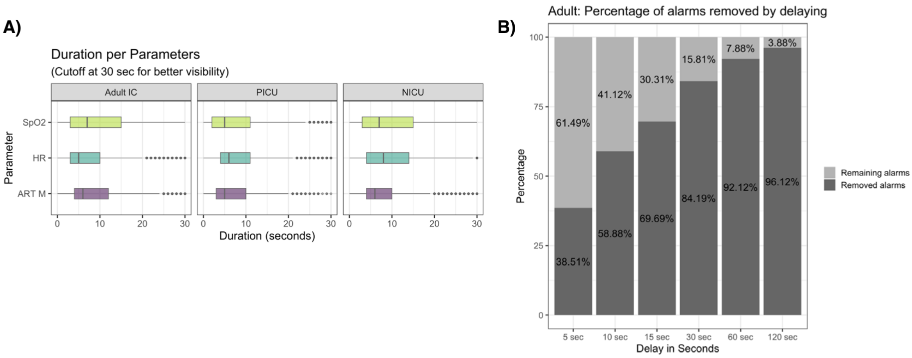

Figure 2. Theme **System** was based on previous work on alarm durations and delays (Bostan et al., 2024b). A) Median alarm durations were calculated for different ICU types and vital parameters. B) Alarm delays were implemented at increasing lengths, showcasing the percentage of eliminated alarms.

The theme *system*, assigned to Group 2, was based on previous work investigating the duration characteristics of alarms generated by the patient monitoring system (Bostan et al., 2024b). In this study, the durations of alarms (e.g., between different ICU types, vital parameters) were investigated and implementation of alarm delays was simulated. It was shown that delaying alarms by 10 seconds can eliminate more than half of the alarms. Several factors, related to alarm priority levels and vital parameters, were identified as points to be considered in determining length of delay. Group 2 worked on these insights related to the underlying technology of patient monitoring systems, exploring potential changes to the system architecture (Figure 2).

Finally, the theme *context*, assigned to Group 3, was based on a data analysis conducted on the alarm loads of three types of ICUs at Erasmus MC: Adult IC, Pediatric IC (PICU), and Neonatal IC (NICU) (Bostan et al., *submitted*). This study investigated the frequency of alarm occurrence in three types of units per several factors such as hours of the day, days of the week, and vital parameters. Results indicated that alarm load in distinct unit types are influenced by patient physiology, unit cultures, standard routine practices, unit layout, and technological limitations. These findings were presented to Group 3 to foster a comparative approach in identifying the context-specific needs for distinct ICU types as well as needs applicable to all unit types. Some examples of the insights used by this group are illustrated in Figure 3.

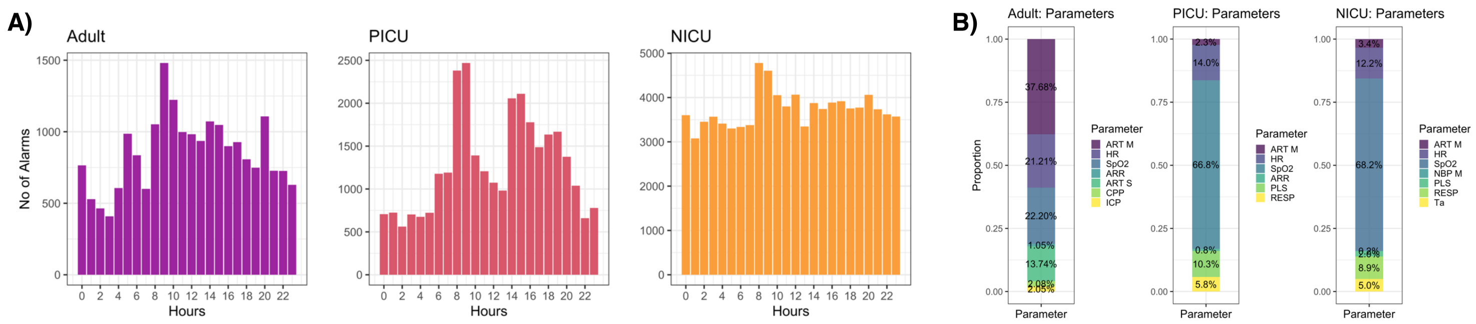

Figure 3. Alarm load in three types of ICUs was documented and compared with each other. A) Number of alarms per hours of the day was documented for each unit type, showcasing distinct patterns throughout the day. B) Percentage of alarms per vital parameters was calculated for unit types. The most common alarm was blood pressure in the Adult ICU, while it was blood oxygen saturation in the PICU and NICU.

The workshop lasted one workday and was hosted in a co-creation space at Philips Design on High-Tech Campus in Eindhoven. The workshop was divided into four phases based on the 'Co-Creation Process', a Philips Experience Design implementation of design thinking: **Discover**, **Frame**, **Ideate**, and **Build** (Philips, 2022; Philips, 2021). Each of the three groups underwent the same four-step procedure. The **Discover** phase was the scientific introduction to the topic for the evidence-based design practice. In this phase, one of the authors (IB) presented previous work to all participants and detailed the results in a lecture of 45 minutes. This way, participants were familiarized with the insights and all groups learned about all the themes.

For the phases of **Frame**, **Ideate**, and **Build**, pre-formatted posters were prepared to be populated during the workshop with ample white space. This allowed the participants to use materials such as markers, post-its, and stickers, and move them around freely in response to the instructions and questions presented on the posters. Populated posters were pictured per group at the end of each phase. After every phase, each group presented their outcomes to all participants for five minutes, and short discussions took place among all participants. Sound recordings were collected during these presentations.

The **Frame** phase lasted 50 minutes and consisted of 'From/To' statements, where each group answered the questions of "*How can we describe the current experience?*" and "*How can we describe the ideal experience?*" based on their distinct theme and insights. They defined the problems with the current situation and defined what would constitute an improved situation. In the **Ideate** phase, participants explored the solution space creatively and transformed insights into ideas within 60 minutes. In this phase, each group populated three posters. The first one asked prompting questions to stimulate ideation and brainstorming, the second one was an impact prioritization of the generated solution ideas, and the third one required a risk/benefit analysis on the solutions deemed the most impactful. The three posters filled in by Group 3 during the Ideate phase are illustrated in Figure 4 as an example. Finally, the **Build** phase consisted of further refining the ideas to make them more tangible and lasted 65 minutes. Each group picked several of the most impactful ideas and discussed the key enablers to build this idea and promote its use in healthcare. Enablers could be solutions, research methodologies, collaborations, capabilities, materials, and know-how.

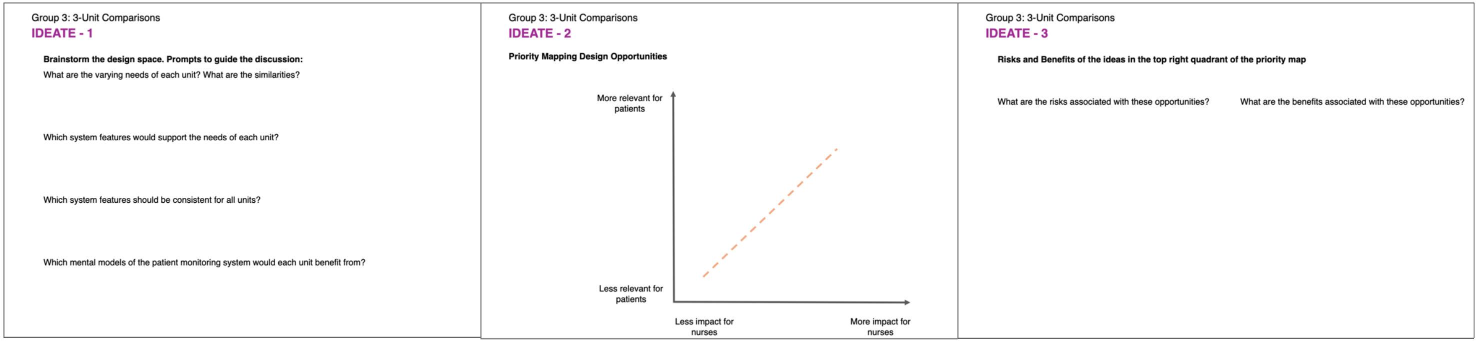

Figure 4 Ideate phase consisted of populating three posters. The first poster prompted ideation and brainstorming. The second poster was a prioritization of the generated design solutions. The third poster was a risk/benefit analysis of the most impactful solutions.

7.2.4. Data Analysis

A Miro board was created replicating the pictures taken after every phase for each group, such that further analysis and classification can be conducted digitally. Sound recordings collected during group presentations were transcribed into text. Further explanations, remarks, and comments made during the group presentations were added on top of the posters of each group for every phase. Data analysis was made on these enhanced digital posters. Outcomes of the analysis are presented per group as their final solution strategies against alarm fatigue. Afterwards, thematic analysis was conducted based on the workshop output of the phases Frame, Ideate, and Build (Braun & Clarke, 2021). The recurring patterns across the groups were identified and categorized them into clusters. This is presented as a final solution bundle across a broad solution space.

7.3. Results

Each group developed several design directions to mitigate alarm fatigue as illustrated in Figure 5. This section presents the outcomes of the three groups focusing on insights related to the user, to the system, and to the context in respective order. Subsections first outline the identified friction points within each theme, afterwards detail the solution space generated by each group. Finally, common themes across groups emerging from thematic analysis are presented as a comprehensive solution bundle.

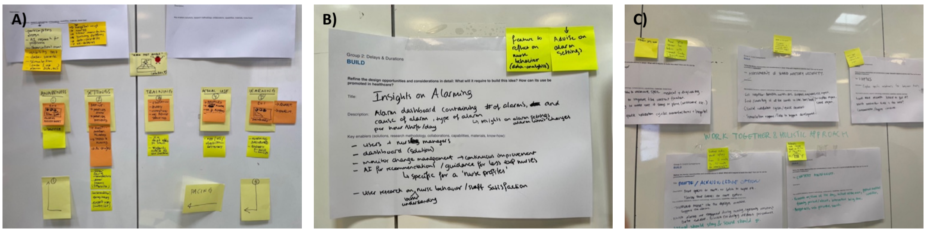

Figure 5. Solution strategies developed by groups. A) Group 1, B) Group 2, C) Group 3.

7.3.1. Challenges Faced by Users – Group 1

In considerations of ICU nurses as the users of patient monitoring systems, it was expressed that current systems do not accommodate for diversity among the users. Instead of offering the same system features and settings to each user, the patient monitoring systems should take user variability into account and offer customization opportunities to different types of users. It was concluded that a flexible system addressing the diversity in the users' capabilities, needs, and preferences is needed. In addition to user profiles, this flexibility should extend to address other varying factors such as nurse level of experience, various unit cultures, and patient populations.

An example offered was the nurses' level of experience. Young and novice nurses may need substantial guidance from the system in setting their alarm limits and enabling the monitoring parameters. These nurses may yet not be heavily affected by alarm fatigue as their exposure has been shorter, yet they may feel less confident in their decisions due to their lack of experience. On the other hand, older and more experienced nurses may be confident and firm in their decisions and use of the patient monitor, yet they may be heavily burdened by alarm fatigue as they have been long exposed to alarms. The system could offer different features to these two distinct types of nurses based on their unique needs.

A general outcome for all user profiles was that alarms act as eyes and ears for ICU nurses. Nurses ideally want to hear only the actionable alarms, as noted by P12: "As the nurses we only want the real alarms, right? We want to filter out all the fake alarms and only get triggered by the alarms that are necessary to take action." Therefore, the importance of providing a high degree of information while minimizing irrelevant noise was highlighted. Overall, patient monitoring systems designed with the user needs in mind were deemed essential.

Design solutions addressing user needs

The solution strategies proposed in this theme consisted of a solution bundle, designed to have a greater collective impact than any single part (Figure 5). A flexible system tailored to the needs of different user profiles was seen as essential for benefiting all users. The importance of a holistic, multidisciplinary approach was emphasized as crucial for addressing the problem. Participants also stressed the need for gradual, incremental change, recognizing that the fast-paced changes do not align well with the structured, protocol-driven environment of healthcare. A slow and steady implementation allows healthcare providers time to appreciate the value of new solutions, leading to higher acceptance rates. The steps of the proposed five-step bundle, named the "Circle of Alarms," are listed in Table 1, including changes in design, service, training, and behavior. The table details each step of the solution bundle and lists the required design elements needed for implementation.

First step of the bundle related to creating awareness. Even though nurses suffer from the number of alarms, they may not always be aware of their own role in the situation. Nurses can directly influence the number of alarms by altering alarm limits and disabling parameters, when the medical institution protocols allow it. Creating alarm dashboards that display descriptive statistics of the unit's alarm load and simulating how individual nurse behavior affects alarm frequency can help create awareness and accountability.

Second step related to the system settings and the alarming algorithm. Patient monitoring systems should be sensitive to user profiles and patient profiles, and adapt features conveniently (e.g., heart rate alarms may be crucial and prioritized for cardiac units, while not as relevant in other units). The algorithm should detect trends in patient vitals and converge information from several vital parameters to generate trend alarms and multi-parameter alarms. This prevents erroneous alarming based on single value alarms.

Third step related to the training and guidance on effective use of the system. Supportive peer models, such as buddy system in the unit or 'alarm champion' in the department, were suggested to support new nurses toward optimal use of the system. The system should also make suggestions and offer guidance on-device.

The fourth step of the bundle related to the actual use of the system. Once more, the significance of trend alarms and multi-parameter alarms were highlighted, along with a profile-based system to address various nurse needs.

Finally, the fifth step constituted of a feedback loop through learning. It was noted that the impact of implemented changes should be constantly monitored and analyzed, and further steps should be taken based on the outcomes.

Table 1. Circle of Alarms: 5-Step Bundle addressing ICU nurse needs

Solution Title	Solution Description	Design Elements
Awareness	Begin by creating awareness that there is a problem.	- Create dashboards to visualize and assess alarm load. - Provide service to end users to see how their behavior impacts the number of alarms.
Settings	Help users navigate alarm settings. Allow for flexibility in user profiles and patient-based profiles.	- Develop multi-parameter alarms. - Develop trend-based alarms. - Facilitate the use of AI to analyze alarm trends. - Collaborate with other device manufacturers and teams within the hospital. - Involve biomedical engineers and expert users (ICU nurses and doctors) in the development cycle.
Training	Train users to guide effective use. Education should be prioritized.	- Employ buddy system in the unit to train newcomer nurses or nurses with less experience - Create alarm 'Champions' at hospital or department level to guide alarm reduction best practices across the hospital. - Provide on-device training. The system should make suggestions and provide assistance as needed. - ICU department should take initiative in training. - Involve experts outside of the ICU.
Use	Improve system design and alarming algorithms to be more informative.	- Include user profiles in the system to accommodate various user types - Develop trend alarms - Develop multi-parameter alarms - Involve designers of apps, UI, and algorithm to optimize the system design
Learning	Constantly observe the impact of the changes implemented. Make adjustments as necessary.	- Make use of dashboards to observe the changes in alarm numbers. - Employ qualitative and quantitative methods to inquire. - Learning outcomes might affect all the previous stages. Watch the numbers for a year, crunch the numbers and implement changes.

7.3.2. Limitations of Current Systems – Group 2

Discussions on alarm durations and the potential for implementing alarm delays highlighted several key concepts. These included multi-parameter alarms, trend alarms that respond to repeated alarming conditions, and context-aware alarming systems that consider patient history. Improved blood oxygenation (SpO_2) sensors were also identified as a crucial area for development. Differences in alarm duration between various units were linked primarily to patient populations and unit protocols. For example, the SpO_2 parameter typically triggers alarms only for low oxygen levels in adults, but in pediatric and neonatal units, additional alarms are necessary for high oxygen levels due to its toxic effects on young people. These differences emphasize the need for system designs that account for context-specific characteristics, ensuring that alarm delays are implemented effectively.

Design solutions addressing system capabilities

Three main solution packages emerged from these discussions as outlined in Table 2. The first focused on developing alarm dashboards that display alarm loads alongside descriptive statistics for various factors. Such a logging and monitoring tool was deemed essential for identifying problem areas and brainstorming solutions. These dashboards could reveal how changes in behavior (e.g., different way of customizing alarm limits) might impact the number of alarms, helping to raise awareness. Collaboration between nurses and nurse managers would be crucial in identifying areas for improvement, directly supporting training and guidance for less experienced nurses.

The second solution direction centered on implementing alarm delays. It was considered critical that delay times be tailored based on individual patient measurements and history. Key factors included patient age (adult vs. pediatric), the magnitude of vital parameter deviations, and repetitive patterns. These “smart” rules could be established thorough data analysis and simulations. A notable outcome was the potential for collaboration with other industries, such as financial technologies. Finance data analysts, who demonstrated exceptional data analysis and modeling skills during the COVID-19 crisis, could contribute valuable expertise to the implementation of alarm delays.

The final solution direction focused on the need for smarter and more reliable sensors. Since faulty sensors account for a significant portion of false alarms, the group proposed developing sensors capable of detecting when they are producing artifacts and automatically suppressing alarms. Examples included sweat detectors for electrocardiogram (ECG) sensors and motion detectors for ECG, respiration, and SpO_2 sensors. The development of affordable wireless sensors was also highlighted as a strategy to reduce sensor-related artifacts and alarms.

Table 2. Solutions to enhance system capabilities

Solution Title	Solution Description	Design Elements
Insights On Alarming	Alarm dashboard displaying the number, type, and cause of alarms, per hour/shift/day. Offers insights on alarm limit and setting changes.	- A logging tool is very important to identify the problem causes and solution strategies. - Analyze nurse behavior and advise on alarm settings. Maybe even dB levels. This can be on all the time or selectively. **Key enablers:** - Collaboration between nurses & nurse managers: They can see what they can improve. This can also be used for training. - Dashboard (solution) - Monitor change management. Continuous improvement. - AI for recommendations / guidance for less experienced nurses. Specific to nurse profiles. - User research on better understanding nurse behavior / staff satisfaction.
Alarm Delays	Alarm delays based on configuration of individual measurements, based on time, or other smart rules (e.g., magnitude of deviation, repetitive patterns, trend-based)	- Implementing delays is not straightforward. Delay level decision depends on patient population and which parameters are relevant for them. **Key enablers:** - Identify smart rules through data analytics. - Partner with finance sector (FinTech): During COVID, it was realized that finance data analysts were well equipped to monitor patient traffic and observe and interpret data. Partnering with FinTech companies who are very good in big data analysis and filtering data might be beneficial to learn how to filter alarm signals.
Smart Sensors	Sensor itself determines any malfunctions and when it generates artifacts. Detect sweat (ECG), motion (ECG, RESP, SpO_2), levelling (Invasive BP)	- An example is detecting motion via accelerators and suppressing artifacts. **Key enablers:** - Sweat measurement. Loosening of ECG leads/ electrodes. Sweat detection can have the side benefit of providing additional physiological clinical info. - Sensors, algorithms. - Research - Wireless sensors: Wireless sensors currently exist but are highly costly – price reduction is needed for large scale implementation.

7.3.3. Contextual Concerns – Group 3

Factors related to patient populations and unit cultures revealed that while some alarm-related issues and solutions are context-specific, others are applicable across all types of ICUs. For example, in the NICU at Erasmus MC, strict protocols on alarm limits and limited nurse autonomy in adjusting settings resulted in significantly more alarms compared to the PICU and Adult ICUs. Additionally, the high number of alarms in the NICU was partly due to the difficulty in securing SpO_2 sensors on neonates, whose skin is more sensitive to pressure and chemicals. Given these challenges, the importance of context-aware patient monitoring systems that can adapt alarming algorithms was identified as a crucial solution. The group identified improved SpO_2 sensors as the solution with the highest potential impact on reducing the number of alarms.

Across all units, it was recognized that the current practice of having all ICU medical equipment (e.g., ventilators, beds, infusion pumps) generate audible alarms—even for simple interactions like confirmation beeps—contributes to sound pollution in the ICU environment, negatively affecting both patients and staff. To address this, participants suggested a shift to multimodal alerts that leverage haptics, lights, colors, and sound cancellation. For example, some signals could be directed solely at healthcare staff through methods like light blinking or alarms based on nurse location, thereby reducing sound pollution and improving the ICU soundscape. Multimodal alarms and reduction of the audible alerts was identified as the solution with the second most potential impact.

Design solutions addressing context-related challenges

Table 3 outlines the solutions derived from context-based insights. The first strategy focused on enhancing SpO_2 sensors and improving their fixation, particularly for younger patients with sensitive skin. This approach entails further research at the intersection of medical and engineering disciplines, with a strong emphasis on material science. Collaboration between manufacturer and medical centers was deemed crucial, as this would facilitate rapid validation cycles for the developed solutions.

The second strategy involves reevaluating the necessity of audible signals for alerts and confirmations in ICU medical devices. While current protocols often mandate these audible signals, the consensus was that this approach is outdated and in need of revision. The initial step is to compile a comprehensive inventory of all sounds in the ICU, including their acoustic characteristics. Multidisciplinary teams should then assess which system features truly require audible signals, balancing risks and benefits within the soundscape. Features deemed unnecessary for audible alerts should leverage other modalities, such as visual cues or haptic feedback. Simulation rooms and labs could support this research, enabling quick iteration and validation cycles.

The third solution builds on the second by addressing the potential of existing wearable devices, such as pagers that ICU nurses already carry. Participants suggested extending the functionality of these pagers to include haptic feedback. Increasing the informativeness of pagers could reduce the need for certain alerts, such as technical alarms. The development of such pagers should consider the body part to which the device will be attached, with attention to hygiene and contamination concerns.

The fourth solution focused on extending the functionalities of the acknowledge button, which is currently used to mute alarms for two minutes. Participants agreed that this duration is often too short. To address this, it was suggested that nurses should have the option to extend the mute duration in real-time. The most relevant use-case was identified as the nursing and grooming activities, such as drawing blood or cleaning the patient, where the pressure on sensors generates many false alarms. A proposed solution was to introduce a 'nursing mode' in patient monitoring systems, similar to the feature found in dialysis machines. This mode would suppress alarms generated during standard procedures, potentially by shifting them to visual-only alerts if eliminating them entirely is too risky. Development of this functionality entails determining which alarms are typically generated during such standard procedures.

The last solution consisted of an overall context-aware system design. Factors such as time of day, nurse location, patient history, presence of family, and nursing procedures should be considered while designing the alarming algorithm. System features such as brightness, information display, and sound levels can be altered based on such factors, such as lower sound levels during night shifts. The system can automatically adjust such settings, with the option for nurses to customize settings as needed.

Table 3. Solutions addressing context-related challenges

Solution Title	Solution Description	Design Elements
Optimizing SpO_2 Sensors	New securing for SpO2 sensors. Especially considering neonates and factors such as movement, sweat, pressure. This is a low hanging fruit to reduce many false alarms.	**Key enablers:** - Research on how to measure SpO_2, both medical and engineering. - Research new materials to optimize skin fixation. - Utilize extra tools/accessory to make sure it stays in place. For example, a wristband is not suitable for babies. - Clinical studies for rapid validation cycles. Manufacturers and hospitals work together to validate new designs.
Reassess Necessity of Audible Alerts	Currently many devices in the room make audible signals. Eliminate some of these and communicate information through other modalities: lights, colors, haptics. Get together with multidisciplinary teams determine which devices and alerts need to have audible signal.	**Key enablers:** - Get together: Patients, nurses, doctors, designers, engineers, risk expert, perception expert, sound expert… Multidisciplinary collaboration is needed for this research. - Clear list and inventory of all the sounds in the patient room and around the bed. Not only the patient monitoring device but the ventilator: How high is the sound of the air coming in and out the infusion pump, dB of the patient bed etc. - Simulation rooms and labs to support quick development: At the manufacturer site, hospital, university etc. - Quick iterations and rapid validation cycles.
Haptics	Haptic modality and vibrations can be implemented on already-used pagers in the adult IC.	**Key enablers:** - Explore specific embodiments for body-worn devices. Determine which device type would be optimal for this modality: pagers, wristbands, anklets? - Research on which type of device - Research on which part of the nurse body to place - Consider concerns for contamination and hygiene

Extended Mute/Acknowledge Option	More options to mute/acknowledge alarms. Flexible time windows to extend mute time to 2, 5, or 10 minutes. This should take nurse decision into consideration.	**Key enablers:** - "Nursing mode" already exists on the dialysis machine. Develop similar features to suppress alarms while nurses are busy tending to the patient. - Determine which alarms are typically generated during certain nursing and grooming activities. Research alarms being generated during various procedures. - Visual information can stay during this time period in the form of lights. It is more crucial to eliminate the unwanted sounds. - Latching an alarm to haptic modality can be an option.
Context Awareness	Make the system aware of certain factors related to the context and act accordingly. Automatic mode changes based on day and night. Links to the previous solution opportunity, where certain alarms are suppressed, and the information being presented is altered based on the context.	**Key enablers:** - Research needed on which factors are relevant to incorporate: time of day, nurse in/out of the room, patient medical condition (e.g., heart rate alarms more crucial for cardiac patients), family present/absent, procedures being conducted… - System features that can change: brightness, information presented, sounds and sound levels.

Table 4. Comprehensive Solutions for Alarm Fatigue: Enhancements in Design, Technology, and Approach

Solution Category	**Patient Monitoring System Design**
Solution Description	Enhancing system functionalities, incorporating context-awareness, and improving on-device alarm management features.
Solution Opportunities	1) **Flexible system for user needs:** Transition from one-size-fits-all system to tailored user profiles – address various nurse profiles, levels of experience, unit types.
	2) **Multiparameter alarms:** Make alarming decisions based on the synthesis of multiple parameters instead of conventional single parameter alarms.
	3) **Trend alarms:** Observe the evolution of vital parameters and generate alarms based on trends in the data and repetition of alarming conditions.
	4) **Context awareness:** Adapt system behavior to contextual factors such as patient profiles, time of day, nurse proximity, nursing procedures.
	5) **Alarm advisor:** Provide on-device advice and guidance on alarm settings based on patient data, nurse preferences, and expected alarm load.
	6) **Multimodal alarms:** Not all information needs to be communicated through sounds. Explore modalities like lights, colors, haptics to reduce unwanted sounds.
Solution Category	**Supportive Technologies**
Solution Description	Innovations in sensor technology and integration of alarm dashboards.
Solution Opportunities	7) **Alarm dashboard:** Log, monitor and visualize the alarm load in the unit to identify problems. Encourage discussing solutions among nurses and nurse managers based on the observations.
	8) **Improved sensors:** Large number of non-actionable alarms and artifacts can be eliminated by improving the sensors and how they are attached to the patients.
Solution Category	**Building Awareness and Expertise**
Solution Description	Promoting interdisciplinary collaborations, increasing awareness, and providing targeted training for nurses.
Solution Opportunities	9) **Multidisciplinary and holistic approach:** Multifaceted challenge requires collaborations between engineers, healthcare professionals, researchers, UX design, data analysts, psychophysics experts
	10) **Awareness and Training:** Create awareness in nurses towards the problem and empower and train to realize their behavior can contribute to the solution. Create peer support systems.
	11) **Learning:** Implement incremental changes, monitor change continuously, learn, and adapt quickly through rapid validation cycles

7

Comprehensive and Integrated Solutions for Alarm Fatigue

Three workshop groups approached the issue from the three perspectives of user, system, and context. While the approaches were distinct, some solutions strategies were found to be recurring across the groups and formed patterns. Outcomes of thematic analysis summarizing synthesizing the solutions strategies are presented in the Table 4 encompassing enhancements in patient monitoring system design, supportive technologies, and approach to collaborations, development, and training.

7.4. Discussion

Through a multidisciplinary co-creation workshop using the sound-driven design approach, we identified key solution opportunities for the issue of alarm fatigue ICUs. Results indicate that the solution space is broad, requiring enhancements across multiple aspects of patient monitoring. These include enhancements on the system design of patient monitoring systems, development of supportive technologies, and building awareness and expertise at multiple levels of healthcare infrastructure.

Identified solution strategies align with exiting literature and consolidate previous insights. Previous studies have highlighted the influence of nurses' individual characteristics on their alarm management and patient monitoring practices (Deb & Claudio, 2015; Ruppel et al., 2019), supporting the need for flexible systems tailored to varied user needs (Bostan et al., 2024b; Özcan et al., 2018). Similarly, the integration of multiparameter alarms that provide system-level insights, rather than relying on conventional individual-device alarms, has been proposed as a solution (Koomen et al., 2021; Pater et al., 2020). The concept of trend alarms, which track the evolution and recurrence of alarming medical conditions, has also been explored as a viable strategy (Charbonnier & Gentil, 2007; Paul et al., 2016). Furthermore, the detrimental effects of standard alarm sounds have been well-documented (Özcan et al., 2018; Phansalkar et al., 2010), inspiring investigations into the effectiveness of multimodal alarms (Cobus & Heuten, 2019; Garot et al., 2020). Our findings consolidate these solutions into a practical package aimed at enhancing patient monitoring systems, further expanding the approach by incorporating novel elements such as context-awareness.

The second set of opportunities focused on supportive technologies to aid alarm reduction, such as improving sensors and introducing alarm dashboard displays. Faulty sensors and poor fixation on the patient's skin are major contributors to false alarms, making sensor enhancement a straightforward target for reducing alarm frequency (Özcan et al., 2018). Participants also emphasized the value of logging, monitoring, and visually displaying alarm data to nurses and nurse managers to pinpoint issues and facilitate quick solutions. These dashboards, grounded in thorough data analysis of alarm load in the unit, would reveal the patterns that often lead to excessive number of alarms, and highlight the areas for improvement. Recent studies on ICU alarm load demonstrate various effective strategies that could guide such efforts (Bostan et al., 2024b; Poncette et al., 2021).

The final line of opportunities focused on enhancing awareness and expertise. Previous studies have shown that nurse training can significantly reduce the number of alarms and mitigate the effects of alarm fatigue (Bi et al., 2020; Dewan et al., 2019; Phillips et al., 2020). In this study, the potential for ongoing education in best practices for alarm management was explored, emphasizing peer support models and empowering nurses to play an active role in solutions. The importance of iterative, incremental changes was highlighted as essential for continuous improvement. Lastly, adopting a multidisciplinary and holistic approach was recognized as the foundational strategy for all future initiatives (Koomen et al., 2021; Özcan et al., 2018; Sanz-Segura et al., 2022).

7.5. Conclusions

In this study, we adopted a multidisciplinary approach to gather perspectives and expertise from stakeholders across various fields, an effective strategy in sound-driven design processes (Monache et al., 2022). This workshop brought together ICU nurses, doctors, industry experts in health technologies, and researchers with backgrounds in design and cognitive sciences. The value of this collaboration became clear during the workshop, as informal conversations showed how enthusiastic participants were to be involved in such an effort. The diverse perspectives of ICU stakeholders provided unique insights crucial for enhancing the overall situation and sparked inspiring discussions. This study highlights the crucial role of multidisciplinary collaboration in tackling complex challenges like alarm fatigue. Involving diverse stakeholders is critical in designing solutions which are practical, impactful, and widely supported.

7.5.1. Limitations

This study's findings are context-specific and may not fully generalize to ICUs with different patient populations, technologies, or cultural practices. For example, requirements in cardiac or surgical ICUs may differ from those of regular adult ICUs. The design directions proposed in this study are still conceptual and require validation through empirical testing in real ICU environments. Additionally, some proposed solutions, particularly those involving changes to medical device regulations or hospital policies, may face significant implementation challenges beyond the scope of this study. These highlight the need for further interdisciplinary collaboration and policy support. Furthermore, the patient perspective was not represented in this workshop. Similar co-creation sessions in the future can expand the solution space by including ICU patients as participants.

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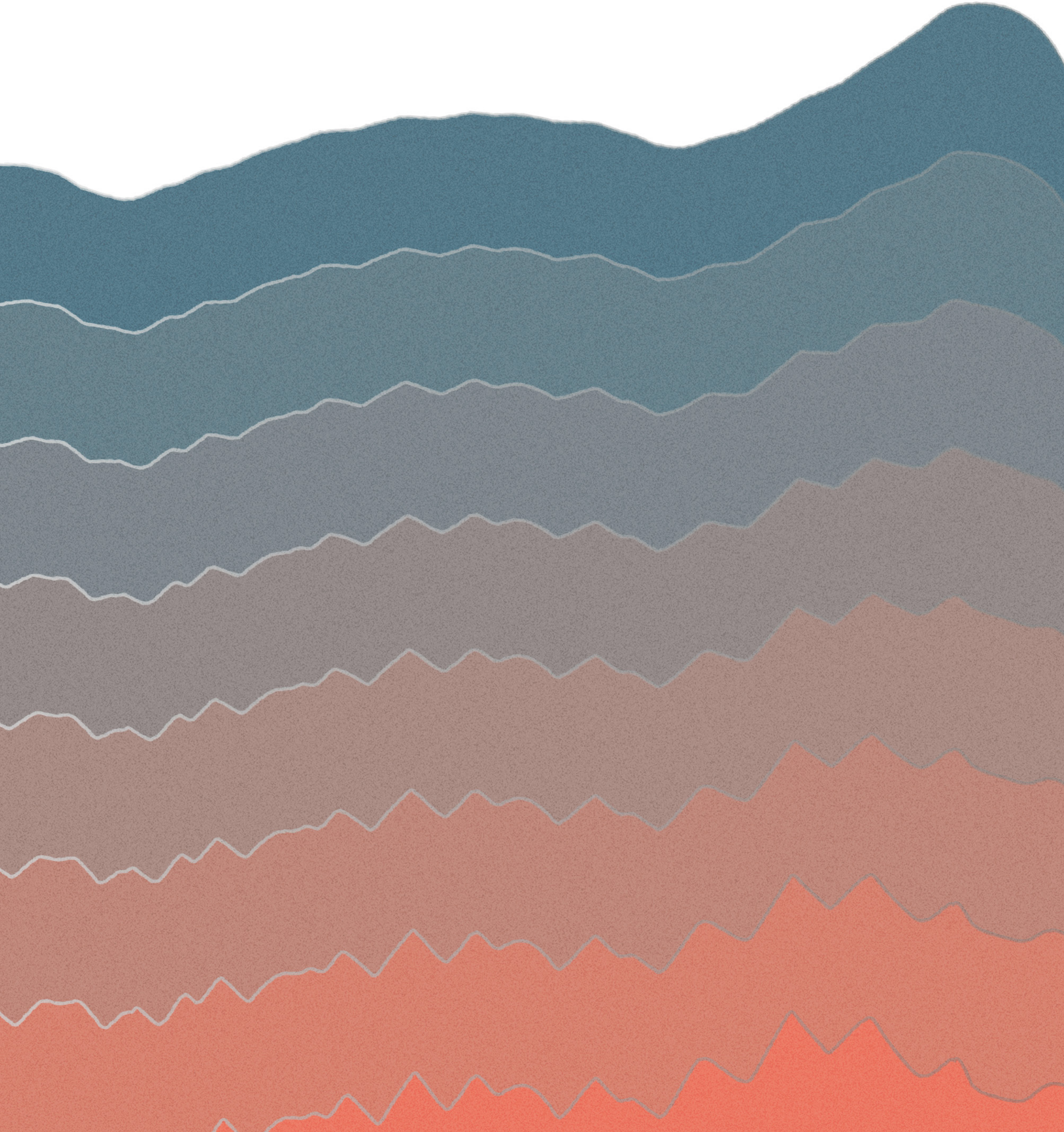

8

Discussion and Conclusion

8.1 Understanding the Tension between too Few and too Many Alarms

The work in this dissertation focuses on how patient monitoring systems intersect with the cognitive, affective, and workflow dynamics of ICU nurses. By examining the design and function of monitoring systems through the lens of usability and human factors, this research shifts attention toward creating systems that empower nurses, streamline workflows, and mitigate stress. It acknowledges that while patient safety is always the end goal, the path to achieving it must account for the broader ecosystem of human and technological interactions in the ICU.

In the ICU, patient safety has always been the primary concern. The rapid progress of technology has introduced a wide range of new sensors for monitoring patient vitals, along with highly sensitive detectors capable of detecting even subtle changes. Medical device regulations are designed to enhance safety by requiring patient monitoring devices to flag every event, regardless of its scale or relevance. The assumption is that capturing and announcing each event ensures it will be noticed by a healthcare provider who can then take appropriate action. As a result, current patient monitoring systems generate an overwhelming number of alarms. However, since many of these events are not critical or even relevant, majority of the alarms do not require action, leading to frequent 'false' alarms. While sensitive alarming algorithms are intended to minimize risk, the excessive number of non-actionable alarms creates a paradoxical effect. Nurses grow tired and become desensitized to frequent alarms, leading to slower or inappropriate responses (Sanz-Segura et al., 2019). This reduced responsiveness increases patient risk (Ruskin & Hüske-Kraus, 2015). Patient safety has a reverse u-shaped relationship with alarm frequency: too many alarms can be just as dangerous as too few.

Alarm fatigue stems from the disconnect between highly sensitive alarming algorithms and human factors. Humans, regardless of how well they are trained in their expertise, are ultimately bound by biological limitations. ICU nurses have limited attention spans, memory capacity, and tolerance for stress. These cognitive limitations make it impossible to respond to every alarm. As patient monitoring devices generate alarms continuously, a nurse's ability to respond diminishes over time. This tension between technological output and human capabilities is experienced by ICU nurses as alarm fatigue.

The work in this dissertation reveals that increasing patient safety does not mean announcing every minor incident. A mode of alarming that can account for human cognitive limits is needed to find the sensitive balance point between too few and too many alarms. Cognitive ergonomics emphasizes designing systems that work with, not against, human cognitive capabilities. Achieving this is possible by suppressing, selecting, delaying, and prioritizing alarming events. Such ways of organizing information reduce the cognitive load for nurses. Instead of being notified about irrelevant incidents, nurses can now be notified about insights based on patterns and trends. This could mean that patient monitoring devices do not generate alarms based on data, but on information. Making alarms fewer but more informative will increase nurse well-being, which ultimately will translate to patient safety (Edworthy & Hellier, 2005).

In order to take a step in this direction, this dissertation had the aim to identify design directions for nurse-centered patient monitoring systems. The ICU context, the underlying technology of patient monitoring systems, and nurses as the primary users were investigated to identify the friction points in the use of patient monitoring systems. This knowledge was then used to generate nurse-centered design directions for improved patient monitoring systems.

8.2. Main Findings of the Thesis

8.2.1. ICU context-related findings

Investigations of the ICU context revealed that factors relating to patient physiology, unit cultures, standard routine practices, and unit layout influence the number of alarms. Number of alarms is lower in units where the patients are adults, nurses are allowed to customize alarm limits, and unit layout consists of single-patient rooms. These findings are in line with previous studies (Cvach et al., 2017; Joshi et al., 2018), expanding their scope by comparing alarm load across unit types within one medical center. In addition to unit characteristics, some factors increase alarms in all types of units. Daily routines, standard practices, and patient physiology are known contributors to the number of alarms, as documented by existing work (Poncette et al., 2021). Alarms can be reduced if patient monitoring systems are designed to account for such predictable patterns. This can be achieved by implementing nursing modes during daily routines, extended muting options during standard procedures, and improved sensors targeting diverse patient populations. Such features can make patient monitoring systems more context-aware, thereby limiting the irrelevant output. In summary, a significant proportion of alarms can be eliminated if systems are equipped to address contextual needs.

8.2.2. Findings related to the monitoring system architecture

Investigations of the technology of the patient monitoring systems revealed the sheer frequency of alarms. In an open-bay layout, almost constant alarm noise driven by both medical and technical events was found. Despite the high volume of alarms, the majority are of low to medium priority, which do not require immediate intervention. This highlights an imbalance in the system's design, where critical alarms are obscured by less urgent notifications. These insights emphasize the need for more targeted alarm management strategies. Allowing nurses to customize alarm limits and leveraging intelligent algorithms to suppress or prioritize alarms are highlighted as concrete opportunities, following previous literature (Ansari et al., 2016; Chromik et al., 2022; Koomen et al., 2021; Manna et al., 2019; Piri et al., 2022). These findings contribute to the understanding of the causes of alarm fatigue, and inform the design of context-sensitive and user-centered patient monitoring systems (Wilken et al., 2017).

Further research on the alarming algorithm contributed to our understanding of how alarm management strategies can improve the ICU environment by reducing alarm overload and enhancing nurses' ability to respond to critical events. Frequent non-actionable alarms pollute and clutter the acoustic environment. Nurses often delay their response to alarms, anticipating false alarms to auto-correct before intervention. This presents an opportunity to delay the alarm signals, with a potential 10-second delay eliminating more than half of the alarms, similar to findings over a decade ago (Welch, 2011). Selectively implemented alarm delays can make systems smarter, reducing the cognitive load on nurses and improving their trust in patient monitoring systems. However, implementing delays are not straightforward as risks on patient safety need to be eliminated. Risks can be minimized by accounting for factors such as the variation in the monitored vital parameters, priority levels of alarms, and patient medical conditions while implementing delays. Nurse adaptation to a novel dynamic in which alarms are delayed can be facilitated by trainings and new alarm sounds. Furthermore, it is essential for such considerations to be part of a broader institutional strategies, with regular audits and updates based on data and feedback from healthcare providers. Developing such solutions require collaboration across multiple disciplines, from healthcare providers to engineers and policymakers. Overall, this research advanced our knowledge of how system design can align more effectively with human factors.

8.2.3. Findings related to the ICU nurses users

Studying ICU nurses as the primary users of patient monitoring devices has allowed us to adopt a user-centered approach, focusing on the needs and capabilities of nurses. Conventional monitoring system design does not accommodate human factors and user needs (Phansalkar et al., 2010; Ruppel et al., 2019). Research in this dissertation revealed this to be a patient safety hazard, as well as a burden on nurse well-being. Providing the relevant information in a digestible manner holds the potential to support an effective and healthy workflow. The shift in healthcare towards more personalized care for patients can extend to address the distinct needs of healthcare staff. Work in this dissertation highlights diversity in nurses and their interactions with monitoring systems, revealing distinct personalities and nurse profiles. While individual characteristics have been explored in existing literature (Deb & Claudio, 2015; Ruppel et al., 2019; Sanz-Segura et al., 2019), this thesis contributes by highlighting their impact on interactions with patient monitoring systems. Identifying and addressing the unique needs of user groups can minimize the cognitive load during system use. Overall, this approach reveals the issues with conventional top-down system design. Design process informed by input and feedback from the users holds the potential to improve patient safety and the quality of care.

Exploring the cognitive processes during alarm interactions allows us to position non-actionable alarms as task interruptions, and highlights their impact on cognitive and emotional states. By triangulating the subjective affects, objective cognitive stress, and behavioral outcomes, this work deepens the understanding of how frequent disruptions compromise both performance and well-being. Findings indicate that task interruptions are annoying and stressful, and the effect intensifies with increasing frequency and complexity of interruptions. These findings reveal the broader impact of sustained stress and reduced focus in critical environments like healthcare, where clear and timely decision-making is vital. Outcomes of this work challenge the established conventions of alarm design. By revealing the risks associated with frequent alarms that disrupt the workflow, the need for systems that reduce unnecessary interruptions and better support sustained cognitive performance is highlighted (Sitterding et al., 2014). The implications for design practice extends beyond the ICU. Across various high-stakes fields such as healthcare and aviation, it is essential for interface design to minimize technology-induced interruptions (Cheng et al., 2020). More thoughtful, human-centered solutions reduce risks and enhance the workflow.

8.3. Contributions to Design Research

This thesis contributes to design research by bridging the gap between theoretical insights and practical applications within high-stakes environments like intensive care units. The findings inform us of the challenges of designing for high impact societal issues (i.e., alarm fatigue) within complex socio-technological environments (critical care). It integrates human-centered design principles with a focus on cognitive ergonomics to address alarm fatigue, a pressing issue in healthcare. The sound-driven design approach reveals solutions that are beyond designing sounds for alarm (Monache et al., 2022). Following this framework to mitigate unwanted alarms through systems engineering, integrating nurse needs and identities through design for experience and finding new purposes to alarms within nurse clinical workflows holds the potential for solutions that are more inclusive, sustainable, and impactful. Overall, the thesis exemplified how to approach a complex societal issue with a systematic approach.

The research emphasizes the importance of designing and engineering systems that respect human cognitive limitations and offers strategies to leverage them for more effective workflows in healthcare (Koomen et al., 2021). By integrating cognitive processes such as attention, annoyance, and stress into the design process, it advances the alignment of system characteristics with human needs. Additionally, uncovering the individual traits of nurses as operators of monitoring systems enriches human factors research by highlighting the nuanced interplay between user behavior and system interaction. This paves the way for customizable system settings that cater to diverse user profiles, enhancing both usability and effectiveness.

A key contribution lies in its evidence-based methodological approach to design, combining qualitative insights from diverse stakeholders with empirical data from user behavior and cognitive load studies. This interdisciplinary perspective enriches design research by showcasing how participatory methods can lead to actionable and scalable solutions. Additionally, the thesis highlights the value of longitudinal and iterative research in healthcare design. By advocating for sustained validation cycles and in-situ testing, it sets a precedent for integrating real-world constraints and dynamic user needs into the design process. This thesis offers an example of how collaborative and holistic approach provides consolidate design solutions for healthcare (Özcan et al., 2018).

8.4. Implications for Better Patient Monitoring

Current systems are often designed from an engineering and regulatory perspective, without prioritizing the needs of the user. Improving patient monitoring to be more nurse-centered holds the potential to support effective workflows, improve healthcare staff well-being, and reduce patient risks. In explorations of how to achieve this, improvements to the patient monitoring system design ranks in top priority. Improvements in this area can enhance the strained relationship between ICU nurses and patient monitoring systems to become one of effective collaboration. This shift should be supported by the integration of supportive technologies and continuous expertise development to ensure sustainable improvements. The design strategies supported by this thesis are presented below, and are illustrated in Figure 1.

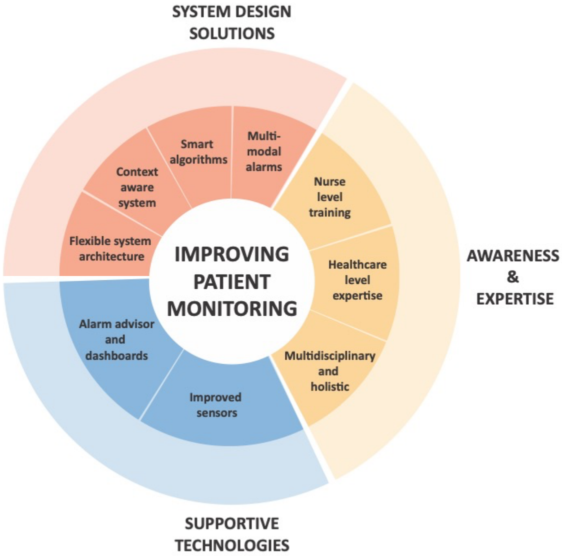

Figure 1. Implications for improving patient monitoring supported by the work in this thesis.

8.4.1. System design solutions

Flexible system architecture to address diverse ICU needs

One-size-fits-all monitoring systems fail to account for the complexities and diversity across different ICU environments, patient populations, and nursing practices. System architecture allowing for tailored configurations is essential to address these diverse needs. Some features critical to enhance usability and safety are customizable alarm parameters, adaptable user interfaces, and context-specific alert hierarchies. Medical device regulations often favor rigid, universal designs to ensure compliance. Designers and manufacturers need to navigate these regulatory constraints by integrating flexibility in ways that adhere to safety standards. Furthermore, involving end-users during the design and testing phases is crucial. Nurses and clinicians can provide insights into workflows, enabling iterative development that captures realistic challenges.

Context-aware systems to reduce cognitive burden

Current systems operate in a vacuum, treating every data point as equally important without considering the broader clinical context. They don't adapt to changes in the environment, the nurse workflow, or the patients' condition. This lack of context-awareness increases the cognitive burden on ICU nurses, who must manually filter through irrelevant alarms. Patient monitoring systems need to be more adaptable to effectively support nurse workflows. An example system feature can be 'nursing mode', where systems suppress predictable non-actionable alarms during known procedures, reducing unnecessary interruptions. Features like extended mute options could allow nurses to temporarily silence alarms during these known activities while keeping critical alerts active.

Patient monitoring systems could also take cues from their environment: adjusting alarm thresholds based on patient profiles, the time of day, or the proximity of a nurse. A context-aware approach would ensure that alarms are more meaningful, actionable, and aligned with the dynamic nature of ICU care.

Smarter algorithms, smarter alarms

The concept of smarter alarms has been on the table for decades, yet progress remains slow. While medical device regulations limit how far we can go with optimizing alarm algorithms, change has to start somewhere. This dissertation highlights the need for smarter systems once more. Research has repeatedly shown that flooding nurses with scattered and irrelevant data points does not enhance patient safety—it diminishes it. Instead, it is essential to supply nurses with relevant information and actionable insights to support their decision making.

Several strategies can enhance system intelligence and create smarter alarms. One effective approach is integrating carefully calibrated alarm delays. Nurses already apply this concept informally, waiting briefly to see if an alarm resolves itself before responding. Systematically incorporating such delays could significantly reduce non-actionable alarms while maintaining safety. Advanced delay algorithms could intelligently assess alarm priority, the criticality of vital signs, and other parameters to determine the appropriate delay duration and application.

Another idea is multiparameter alarms, which synthesize data from multiple parameters rather than relying on conventional single metrics. By integrating trends across vitals like heart rate, blood pressure, and oxygen saturation, these alarms provide a more comprehensive assessment of the patient's condition. This reduces the likelihood of triggering alarms for clinically insignificant fluctuations, and presents nurses a fuller picture of the patient's condition.

Trend-based alarms offer a third solution. Nurses often use the frequency of fluctuation alarms as a metric of patient stability, even if these fluctuations don't require immediate action. Incorporating trend analysis directly into the system would enable alarms to reflect such meaningful patterns in the data, alerting nurses to significant trends or repeated issues.

Multimodal alarms

Current ICU environments are dominated by audible signals from various devices, leading to cognitive overload for all inhabitants of the ICU. Not all information needs to be conveyed through sound. By adopting multimodal alarms, information can be distributed across other sensory channels, such as visual indicators (lights and colors) or haptic feedback, significantly reducing noise pollution while preserving critical communication.

A multidisciplinary approach is essential for the research and implementation. Teams including clinicians, biomedical engineers, designers, and human factors experts should collaborate to determine which devices and alerts require audible signals and which can be conveyed through other means. Developing an inventory of all sounds in patient rooms, from ventilator noises to infusion pump alerts and even the hum of patient beds, is the first step. Simulation rooms at hospitals, universities, and manufacturer sites can play a critical role in this transformation. These controlled environments enable iterative testing and development with active involvement from end users. Such collaboration ensures that new alarm strategies align with real-world workflows and improve both usability and patient safety.

8.4.2. Supportive technologies

Alarm advisor: Data-driven support for alarm management

A central dashboard logging, monitoring, and visualizing the alarm load within the unit would help nurses and managers identify problem areas. Including insights related to the number, type, and cause of alarms per hour, per shift, or per day holds the potential to increase nurse awareness about their alarm customizations. Simple and effective visualizations would serve as a starting point for collaborative discussions on potential solutions.

On-device alarm advisor could offer guidance tailored to the environment for newer or less experienced nurses. System recommendations may include alarm settings based on patient data, nurse preferences, and predicted alarm load. For example, it could suggest optimal parameter ranges, highlight trends, or flag repetitive false alarms. By transforming raw alarm data into actionable insights, this approach reduces cognitive burden and empowers nurses to make informed decisions.

Better sensors

Faulty sensor readings remain a persistent challenge in managing alarm fatigue. Particularly in pediatric and neonatal ICUs where patient movement and physiological nuances often complicate measurements, blood oxygen saturation alarms dominate the sound environment. One crucial improvement lies in developing smarter sensors that can detect and respond to artifacts directly. For instance, sensors equipped with accelerometers to identify motion-related interference, or those capable of detecting sweat and poor attachment can filter out erroneous signals before they trigger an alarm. Advanced designs could integrate self-monitoring features to enable sensors to signal when they are malfunctioning. Wireless sensor technology offers another avenue for innovation, minimizing physical clutter at the patient bedside. However, their high cost remains a barrier to widespread use. Reducing the price of wireless solutions would make these technologies more accessible across healthcare systems.

8.4.3. Awareness and expertise

Training at the nurse level

Addressing alarm fatigue requires empowering ICU nurses as active participants in the solution. This begins with creating awareness of the problem through transparent communication and data-sharing tools, such as alarm load dashboards. Nurses and nurse managers can identify patterns and discuss actionable strategies within their teams. It is essential for effective training programs to emphasize the role nurses play in mitigating alarm fatigue. Education sessions can focus on practical approaches, such as customizing alarm settings, recognizing non-actionable alerts, and adopting best practices for managing alarm thresholds. Training should aim to empower nurses and highlight how individual and collective behaviors can contribute to a more manageable alarm environment. Peer support systems can be established to support sustained learning. This could include mentorship opportunities, where experienced staff guide newer team members in navigating alarm-related challenges.

Learning at the broader healthcare level

Addressing alarm fatigue requires action beyond the efforts of individual ICU nurses. This is a systemic issue that demands changes at institutional and organizational levels. Solutions should focus on creating a culture of continuous improvement, beginning with small, incremental changes. The implemented adjustments should be monitored closely to evaluate their impact, ensuring the system evolves based on real-world findings.

Quantifying alarm load through tools such as alarm dashboards play a critical role in identifying patterns over time. It is essential to complement these insights with qualitative methods, like staff interviews and feedback sessions. Rapid validation cycles are essential for refining strategies. These learning outcomes not only inform immediate practices, but also influence earlier stages of design, education, and policy-making, creating a comprehensive framework.

Multidisciplinary and holistic approach

Alarm fatigue is a complex, multifaceted problem that extends beyond simple technical fixes. Comprehensive solutions require collaboration across disciplines, bringing together expertise in engineering, healthcare, psychology, design, and data analysis. Engineers and designers can collaborate with healthcare professionals to create systems that are functional and intuitive. Researchers, psychologists, and psychophysics experts can provide insights into human cognition and behavior that influence alarm perception and response through cognitive and emotional processes. Data analysts can further refine these efforts by identifying patterns and opportunities for improvement.

Additionally, it is crucial to consider the broader infrastructure in which patient monitoring systems operate. They are embedded in a larger network of institutional practices, workflows, and the physical ICU environment. Effective solutions must take this context into account, ensuring that any changes made align with existing systems and workflows. Only through a holistic, team-based approach can we make meaningful progress in reducing alarm fatigue and improving patient care.

8.5. Limitations and Recommendations for Future Research

Recommendations made in this dissertation include significant changes to the patient monitoring system architecture. Suggestions such as alarm delays, nursing mode, multimodal alarms, and improved sensors need to be developed, tested, and refined to ensure real world applicability without compromising patient safety. As implementing these directly in the ICU poses risks to patient safety, development of ICU simulation rooms at hospitals, universities, and manufacturer sites can play a critical role in this transformation. Building such simulators requires diverse expertise, including insights from the previously mentioned disciplines as well as fields such as architecture.

Longitudinal studies that track the long-term outcomes of alarm management interventions are needed to understand the lasting impact of alarm system modifications on nurse well-being and patient safety. This is needed to identify whether improvements in alarm systems lead to sustained reductions in fatigue and errors, providing more evidence for effective system-wide changes. To support this, hospitals may establish in-house research mechanisms, such as dedicated research teams or collaborative partnerships with academic institutions. By embedding research within the hospital setting, it is possible to gather real-time data, address hospital-specific challenges, and ensure the ongoing evolution of alarm management practices. Additionally, hospitals could implement pilot programs for alarm system modifications and track their effectiveness through controlled trials, with iterative adjustments based on nurse feedback and patient outcomes.

The work reported in this dissertation took place during the COVID-19 pandemic, limiting access to the ICU environment and healthcare staff significantly. To address these challenges, avenues of research and chosen methods were adapted dynamically to investigate the issues related to alarms from various perspectives. Due to these circumstances, some findings are solely grounded in controlled studies, which may not reflect the full complexity of real-world ICU conditions. Furthermore, implementing the changes suggested in this dissertation within the constraints of current medical device regulations and available technology presents significant challenges. Integration into existing regulatory frameworks and system architectures restrict the speed at which novel alarm management strategies can be adopted. Exploring ways to bridge the gap between research findings and practical implementation in real-world healthcare settings is crucial for ensuring their success. Translating the insights in this dissertation into daily practice will require iterative testing and validations in actual ICU environments.

A natural next step is investigating the nurse profiles identified in this thesis to reveal their alarm management habits and system use. Such research is needed to refine the nurse profiles as user types of patient monitoring systems and ensure the applicability of the recommendations. It is important to recognize that these profiles are likely to vary significantly across different geographical locations and cultures. Therefore, future research should aim to replicate similar studies in varied settings to capture cultural nuances and generate broader, more globally relevant insights.

The work throughout this thesis revealed the challenges of multidisciplinary collaboration. The terminology and approaches used by psychologists and designers can sound quite foreign in the raw realities of the ICU. Similarly, the healthcare staff may be skeptical of novelty brought in by non-medical experts. Bridging gaps across fields requires stakeholders from diverse backgrounds to engage one another with curiosity and a shared focus on the ultimate goal of improvement. Adopting an open mindset to learn and grow together is crucial for researchers tackling such multifaceted challenges. Future research can expand the multidisciplinary approach adopted here further by systematically exploring collaborations across fields such as machine learning, cognitive psychology, and human factors engineering to develop more adaptive alarm systems.

Finally, this thesis did not study the effect of alarms on patients. Design directions were not consolidated by patients, who are also listeners in the ICU acoustic environment. Future research could explore how changing alarm management practices impact patient well-being, recovery, and stress levels. Additionally, involving patients in co-creation workshops could provide valuable insights into how alarm systems can be designed to minimize disturbance while maintaining safety. As this kind of work requires heavy involvement with patients — who may be currently admitted, recently discharged, or still experiencing lasting effects of their ICU stay — it is essential that researchers in this field are deeply familiar with the clinical environment and workflows.

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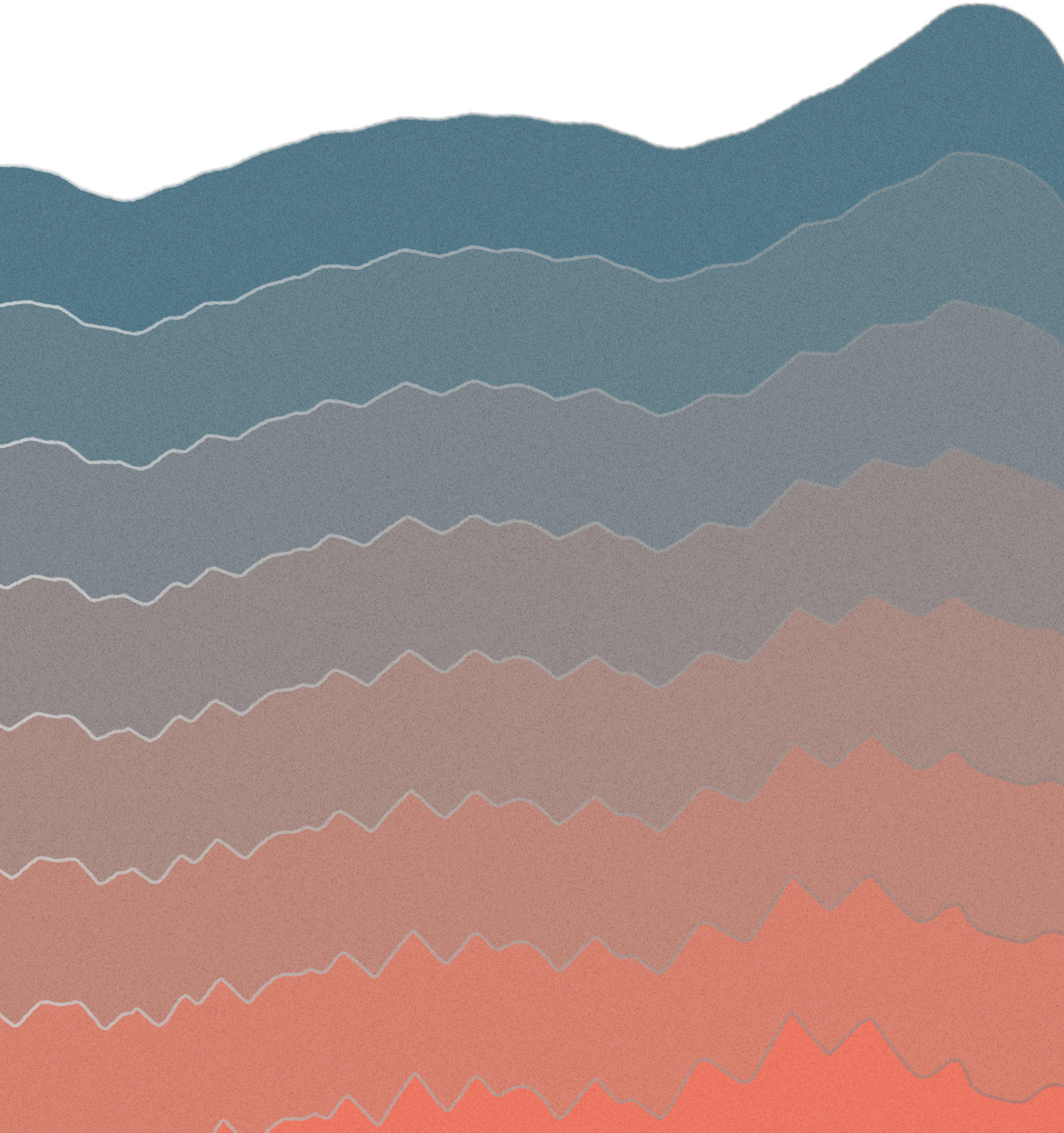

9 Appendices

List of Publications

Bostan, I., Özcan, E., Gommers, D., & van Egmond, R. (2022). Annoyance by Alarms in the ICU: A Cognitive Approach to the Role of Interruptions by Patient Monitoring Alarms. *Proceedings of the Human Factors and Ergonomics Society Europe Chapter 2022 Annual Conference*.

Bostan, I., van Egmond, R., Gommers, D., & Özcan, E. (2024). Customizing ICU patient monitoring: a user-centered approach informed by nurse profiles. *Cognition, Technology and Work*. https://doi.org/10.1007/s10111-024-00763-9

Bostan, I., van Egmond, R., Gommers, D., & Özcan, E. (2024). ICU alarm management reimagined: Sound-driven design and the role of acoustic biotope. *Design Research Society*. https://doi.org/10.21606/drs.2024.553

Bostan, I., Özcan, E., Gommers, D., van Egmond, R. (*submitted*). Annoyance by Task Interruptions in Healthcare Workflows: Underlying Cognitive Mechanisms

Bostan, I., Goos, T., van Egmond, R., Gommers, D., Özcan, E. (*submitted*). A Tale of Three ICUs: Documenting Alarm Loads in Adult, Pediatric, and Neonatal Intensive Care Units to Reveal Implications for Design and Practice

Bostan, I., van Egmond, R., Gommers, D., Özcan, E. (2025). From Research to Practice: A Collaborative Approach to Tackling Alarm Fatigue in ICUs. *Proceedings of the Forum Acousticum Conference*.

ACKNOWLEDGEMENTS

The work in this thesis would not have been possible without the support of a constellation of people around me. I would like to take a moment to extend them my gratitude.

First and foremost, I would like to thank my promotors, **Elif Özcan** and **René van Egmond**, for their guidance and support throughout this journey. Your advice kept me on track and pushed me to keep going, even when the road was challenging. We faced numerous obstacles along this journey until the very last days, and still we made it through. Your supervision has shaped me into an independent researcher, sharpening my analytical reasoning and clarifying my voice as a scientist. I enjoyed every freedom I was given to explore and actualize myself. I have been inspired by your ability to look from a distance and see the directions the field is flowing in. I truly appreciated all the feedback and the support. The perspective I've gained and lessons I've learned under your guidance will stay with me for the rest of my life. Thank you very much.

I would also like to express my gratitude to **Diederik Gommers** for providing me with the opportunity and space to conduct my research. Under your guidance, I was introduced to the dynamic world of healthcare. Your perspective has helped me maintain focus on the bigger picture and has deepened my appreciation for the contributions I can make to this evolving field.

Gijs Louwers, you have a special place in this work. Perhaps in a parallel universe I started this PhD alone, and I am not sure there the PhD is completed. I have been lucky to be in this universe with you alongside me throughout the journey. You have been my mirror, my anchor, my accomplice. Words cannot express the relief I felt on brief moments of eye contact amidst violent storms. We complemented each other perfectly, covering each other's shortcomings with our strengths. Every step of the way I felt that you got my back, and I hope I made you feel the same. Thank you so much for being a great partner in crime. I'm looking forward to being inspired by rest of your journey.

Two people who made my time in TU Delft an entertaining journey are **Soyeon Kim** and **Nicolas Chaves de Plaza**. Your friendship made work feel not like work, but a fun project I was doing with friends. Our trip to Torino has been a landmark in our story together. I'm grateful for all the food we've shared, all the humour and laughter, all the moments of nerding out. I have also relied on your scientific support in this journey, turning scary new tasks into exciting challenges. I couldn't have asked for better companions. Thank you for always being there, for lifting my spirits during tough times, and for making every success feel even more rewarding. I see the pure and ambitious souls you both are, and I feel very lucky to be a part of your journeys. I look forward to our adventures ahead.

Ela Fasllija was a crucial character that appeared at the very end of this story. I am grateful we caught each other in a brief window of time, and that I had a chance to appreciate your commitment to work, your honesty, and your thorough approach while maintaining focus on the big picture. I watched you being incredibly resilient in the face of massive struggles and still remaining an optimist. I will continue to be impressed by the great heights you are destined to reach in life.

I would like to express my gratitude to colleagues from the CAL. **Stefano Delle Monache** has been the academic big brother I turned to when I was confused. And surely every time, I left his side even more confused. Thank you for challenging my thinking, and for always being there to offer a new perspective. The rest of our Italian team was represented by **Salvo Cucinella**, **Sara Lenzi**, and **Simone Spagnol**. Thank you all for the Mediterranean warmth you brought into the cold winters. You eased my transition into the world of design, and I'm grateful for your friendly support.

I have been fortunate to have **Yuguang Zhao** and **Cehao Yu** as my office mates. Our room was never a formal setting for distant colleagues, but a safe space to gossip our hearts out. I enjoyed the cozy and comfortable setting we created together. Yuguang, I feel that four years were not enough to know you, as you surprised me with inspiring new depths at every corner. I can see that your creative perspective will bring you the wonders you deserve in life.

Throughout my PhD I was lucky to be part of the Perceptual Intelligence Lab. **Sylvia Pont** you embody the scientist I had in mind growing up, and I am thankful I got a real-life example on how to be one. I am truly inspired by your ability to set up a lab around your interests and get to play with colourful lights for science! In addition, I will forever be grateful for your support in the darkest moments of this journey. Having you on board was sometimes the only ground I felt under my feet. Your support has been critical to the completion of this work, and I thank you for the role you played.

Jan Jaap Assen has not been a colleague for a long time, but this doesn't mean we have not been drinking jenever in the meantime. I have always enjoyed your colourful personality and the light heartedness you bring to science. Looking forward to hearing countless more travel stories from you. **Christina Schneegass** you have been my cognitive accomplice and sparring partner among all the voices of design. I have deeply appreciated your quick mind, your sharp opinions, and always so helpful attitude. Every conversation with you has left me inspired, and I often wish we had the chance to work more closely together. **Maarten Wijntjes** has been a great colleague with his easy-going nature yet sharp competence. It's been a pleasure working alongside you.

I appreciated the support of my Philips colleagues along the way. Thank you, **Andreas Walden** and **Vitor Antunes**, for welcoming me into the world of alarms with joy. Your extensive expertise on the topic always inspired me to dig deeper in my research. I met **Benjamin Lopez** and **Marlieke Overdijk** later in my PhD journey, yet their contribution has steered the strategic direction of my work. I enjoyed the fun day of workshop we created together and have learned from your skills. I also would like to thank **Esther van Heide** for the few instances of advice I got from her, which were always sharp and insightful. I deeply appreciated the company of **Yoko Sen** and **Avery Sen** along this journey. Your creative perspective and personal touch to the topic has brought such a breath of fresh air to my mind. Among all the highly technical work which can sometimes feel grey, your approach has brought in the colors and showed me how research can reflect personal passion. And finally, I would like to thank **Dirk Hüske-Kraus**. Our work together has been brief, but had a lasting impact on me. I admired your profound expertise on the topic and comprehensive understanding of the research space. In the short time we got to work together, I enjoyed your mastery in your skills and felt my perspective widening with every conversation.

I would like to thank the members of the defence committee who have spent time and effort contributing to this work. Meeting **Judy Edworthy** at a conference and discussing my experiment ideas motivated me to jump into the last year of my research with confidence. I feel proud to have her in my committee as her sharp and critical mind provide a fun challenge for me to push my reasoning. I also appreciate the support of **Iris Wallenburg**, **John van der Dobbelsteen**, and **Marijke Melles** in shaping this work to the highest standards.

Beyond colleagues, there have been other scientists who have been critical in the completion of this work. I never officially worked with **Alper Çevirgel**, yet no one has contributed more to this PhD journey than him, both scientifically and personally. The scientist that you are, the creative perspective you have in analytical reasoning, and your endless curiosity are inspirations I will carry with me for the rest of my life. Alper, sen filmlerde görüp özendiğim bilim insanlarındansın. Konulara geniş açıdan bakışın, doğru bildiklerinin peşinden tutkuyla koşuşun, bir yandan yakınındakilere yardıma eğilmen ve tüm bunları yaparken rengârenk bir eğlenceden geri kalmaman bu hayatta tüm insanlara örnek olacak erdemler. Sabahlara kadar uzay zamandan konuşabilecek ortamımız ve akademideki en büyük yoldaşlarımdan biri olman başlı başına hayatımı çok zenginleştirdi. Ancak bunların yanında derin arkadaşlığın asıl paha biçilemez destekti. Modelleme kodundan salçaya kadar her şeyi paylaşabileceğin arkadaş az bulunur. Çelik gibi birileri varsa, bu gerçekten sensin. Hayatının geri kalanını hangi renklerle boyayacağını merakla izliyorum. I can't think of any other paranymph to accompany me on the final day of this PhD.

Melina Timplalexi has been another invaluable comrade on the academic path, stretching my mind with her playful curiosity from the very beginning. You came into my life with your open heart, sharp attitude, and bright mind to show that it is possible to share a close friendship and scientific curiosities with a single person. Our conversations have freed my mind of limits I had not even known were there. I am grateful that I got the chance to witness the passionate and creative person that you are. The distance between us has been difficult to get used to, but we were born with a sea between us anyway. We will one day sit on the same side of that sea and laugh at all the waves we've ridden.

Another great mind accompanying me along this journey has been **Charlotte Fraza**. Your endless curiosity for neuroscience and ambition to deliver work on the highest standards have been great motivators for my own work. More importantly, you always seek ways to braid creativity into your science. Your ambition for finding alternate ways of engaging with science, and the confidence in putting yourself out there for the whole wide world to see are truly admirable. I enjoy the entrepreneurial attitude you bring to science, and love seeing that it does not have to be confined into the gray boundaries of office rooms.

I would like to express my gratitude to my old colleagues from KUAR Design Lab. This is where I met and fell in love with the field of industrial design. **Oğuzhan Özcan**, **Evren Yantaç**, **Oğuz Buruk**, **Ahmet Börütecene**, **Muhammet Ramoğlu**, **Çağlar Genç, Hayati Havlucu, Güncel Kırlangıç, Doğa Gatos,** and **Damla Çay** have shown me that I can combine scientific methods with colorful research to design a better life for real people. I will always be grateful for the fun time we spent together that has fundamentally shaped my career.

I was fortunate to meet **Tilbe Göksun** early in my career. Her mentorship gave me the first tools and perspective I needed in academia. She supported me as a young researcher and set me on the path of becoming an independent researcher. I am grateful that you believed in my potential that early on, and I hope to pay your favor forward to other bright young minds.

Bunların yanında arkadaşlarıma da teşekkür etmek istiyorum. Şimdiye kadar ismi geçen herkesle bilimsel ve profesyonel bir kesişimim oldu ama sizlerin sağladığınız destek bundan çok daha ayrıydı. Hangi kadın kızlar grubu olmadan tüm bunları başarabilir ki? Birlikte büyüdüğüm **Selin Başeren**, **Simge Tuşur** ve **Merve Tekin** bana bir ömür destek oldular. Yürüdüğümüz yollarda, ulaştığımız her yeni aşamada birlikteydik. Hayatı sizinle keşfettiğim ve herkesin bambaşka bakış açılarından beslenebildiğim için çok şanslıyım. **Cansu Çankayalı** doğanın ve evrenin büyüsünü içinin derinliklerinde hisseden, ışığın vuruşunu dakikalarca izleyip içinde kaybolabilecek ender insanlardan. Hollanda maceramız birlikte başladı ve senin arkadaşlığının yarattığı sıcaklık olmasa belki bu ülkeye bir daha asla dönmez, bu çalışmaya asla başlamazdım. Tüm kadın arkadaşlarıma içtenlikle teşekkür ediyorum.

Jules van Damme is another name who was critical to the completion of this work. You came into my life as a tornado, turning everything around and changing the flow of things forever. You have one of the most unique minds I have ever met, and I am endlessly grateful that I get the privilege of experiencing it every day. Countless days I came home as a raincloud, and your bright sunshine always filled my mind with rainbows. You amaze me with your creative perspective to life and never letting one boring moment pass by. You have been my greatest support in countless ways. I feel blessed to walk alongside you as you carve out surprising paths in life with your brilliant mind. I look forward to all the castles we will build in the sky.

Herkesten öte, sevgili ailemin desteği bu çalışmadaki en büyük katkıdır. Annem ve babam beni büyük fedakârlıklarla bugünlere getirdiler, dürüstlükleriyle bana örnek oldular. Seçtiğim yolda beni hep desteklediler ve arkamda sapasağlam durdular. Sizlere burada kelimelerle teşekkür etmem mümkün değil. Kardeşim doğru yoldan ayrılmayan tavrıyla beni dinledi, objektif bakış açısıyla eleştirmenim oldu ve yanımda durdu. Burada ismini anamayacağım kadar kalabalık olan geniş ailem bana her zaman güvenli bir liman sundu, kendimi bildim bileli sıcaklığı hiç sönmeyen bir ocak oldu. Hiç bitmeyen yardımseverliğiniz hep ayaklarımın altındaki sapasağlam zemindi. Ne yaptıysam, her şey sizlerle paylaştığım sürece değerli ve anlamlı. Sonsuz teşekkürler.

Thank you all for accompanying me on this journey!

ABOUT THE AUTHOR

Idil Bostan was born in Istanbul in July 4th, 1992. She developed a curiosity towards nature from an early age. This curiosity was accompanied by a strong desire to read every book in the world. Following these interests set her on the academic path. She completed her Bachelor's degree in Psychology and English Literature at Koç University in Istanbul. Discovering her passion for research, she got her first job as a researcher and was introduced to the world of design. After a few enjoyable years at this role, she wanted to dig deeper into the human mind. In 2018, she moved to the Netherlands to pursue a Master's degree in Cognitive Neuroscience at the Donders Institute in Radboud University. Here she explored the endless mysteries of human consciousness, grappled with the challenges of neuroimaging, and finalized her thesis on the effects of curiosity in decision-making. Completing her Master's degree, she moved to Amsterdam. She started her PhD in 2020 at TU Delft in collaboration with Philips and Erasmus Medical Center. The project faced challenges due to the global pandemic, but was completed in the festive atmosphere of December 2024.

Idil is an explorer of the human mind, and is on a journey to experience its depths in every light. Her dream is to be an author living by the beach, surrounded by a big family and countless animals.