Cognition, Technology & Work
https://doi.org/10.1007/s10111-024-00763-9

ORIGINAL ARTICLE

Customizing ICU patient monitoring: a user-centered approach informed by nurse profiles

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Received: 19 October 2023 / Accepted: 9 April 2024

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.

Keywords ICU nurses · Patient monitoring systems · Nurse profiles · Personality · Stress · Nursing experience

1 Introduction

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 and Funk 2013). Nurses become desensitised 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 and 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 and 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.

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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 and La Calle 2020). By considering the needs and preferences of nurses through a user-centred 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.

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 (Fig. 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; Edworthy and Hellier 2005; 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 (Fig. 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 and 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.

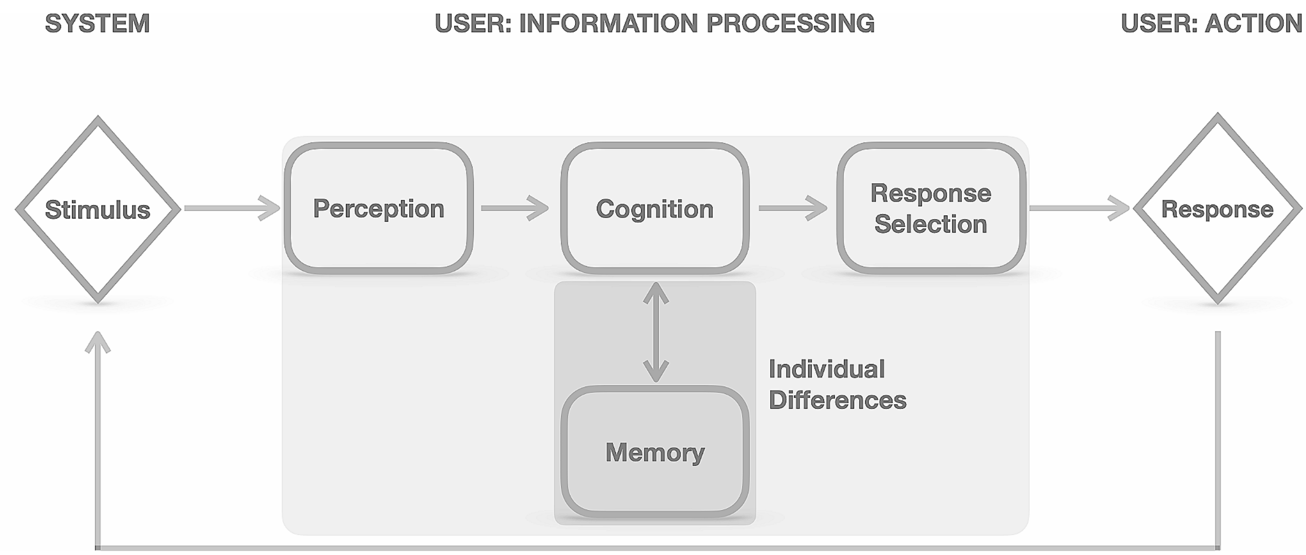

Fig. 1 HIP model simplified and adapted from Wickens, illustrating the cognitive processing of information during human-system interaction. Audio-visual stimulus is generated by the system and processed by the user. Processing involves the stages of perception, cognition, and response selection. Individual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

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.

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 Fig. 2. In the figure, observable behaviour 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 behaviour 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.

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 and 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.

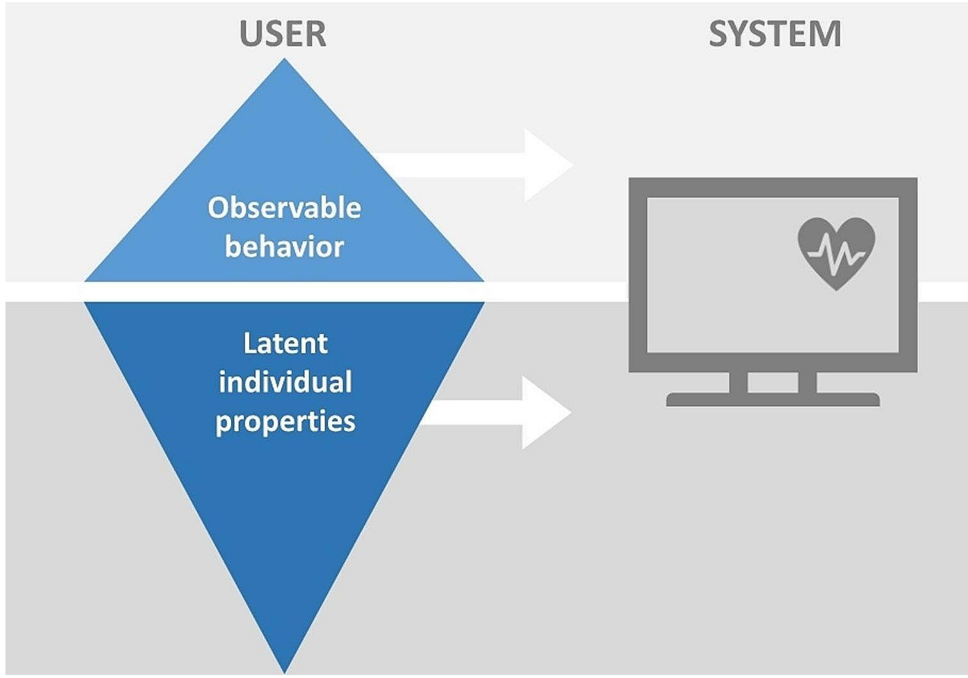

Fig. 2 Observable system interaction behaviors are driven by latent individual properties

1.2.1 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 and Gommers 2020; Ruppel et al. 2018; Wung and 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 and 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.

1.2.2 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 and 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 and 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 behaviour. Higher agreeableness is marked by considerate, nurturing, warm demeanour whereas lower scores suggest assertive, independent, direct disposition. Conscientiousness encompasses level of organization and goal-directed behaviour. 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 demeanour. 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 organised 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).

1.2.3 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 and Hüske-Kraus 2015; Wung and 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 and 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 and 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 and 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.

1.2.4 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.

2 Method

2.1 Study 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.

2.2 Participants

Nurses from *Paediatric* 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 *Paediatric* 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, 11 were males. Mean age was 37.80 years, $SD = 14.92$. Twenty-eight of participants were *Paediatric* 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, $r(14) = 0.97, p < .001$. Mean years of experience for females was 12.7, while for males it was 17.7. Mean years of ICU nursing experience for *Paediatric* was 15.9 years, and for *Adult* was 10.9 years. Difference in the years of experience between the units was not statistically significant, $p > .05$.

2.3 Setting

This study was conducted in two ICUs within the same medical centre. 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 Paediatric 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 centre 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.

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.

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

2.5 Measures

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.

2.6 Analysis

All data was processed and analysed 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 and 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 and 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 and 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 and 7, with 1 indicating the least musical association. Finally, risk was measured by a single item. Scores range between 1 and 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 0.05.

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 (*paediatric* and *adult*). Finally, Cronbach’s

Table 2 Mean and standard deviations (in parenthesis) for nine traits. Last line is Cronbach's alpha indicating internal consistency

	Extraversion	Agreeableness	Conscientious.	Neuroticism	Openness	Stress	Sensitivity	Musicality	Risk
Range	**1–5**					**20–100**	**1–7**		
Paedi.[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]	0.88	0.82	0.81	0.78	0.69	0.76	0.83	0.88	-

[a] Mean and *SD* values for paediatric and adult units

[b] Mean and *SD* for all nurses

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

alphas are listed for each trait, representing the internal consistency of each trait.

Figure 3 illustrates the mean scores of BFI traits for *Paediatric* 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 *Paediatric* nurses were higher for Extraversion, Agreeableness, and Conscientiousness. Mean scores of *Paediatric* 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 *Paediatric* nurses scored significantly higher on Extraversion, $t(51) = 2.65$, $p = .011$, Cohen's $d = 0.73$. Paediatric 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 Fig. 3 by the dashed line. For *Paediatric*, 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 $d = -1.05$.

Figure 4A illustrates the difference in mean Stress scores for *Paediatric* and *Adult* units; while 4B illustrates differences in the mean Sensitivity, Music, and Risk traits. 4 A 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, $p > .05$.

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, $p > .05$.

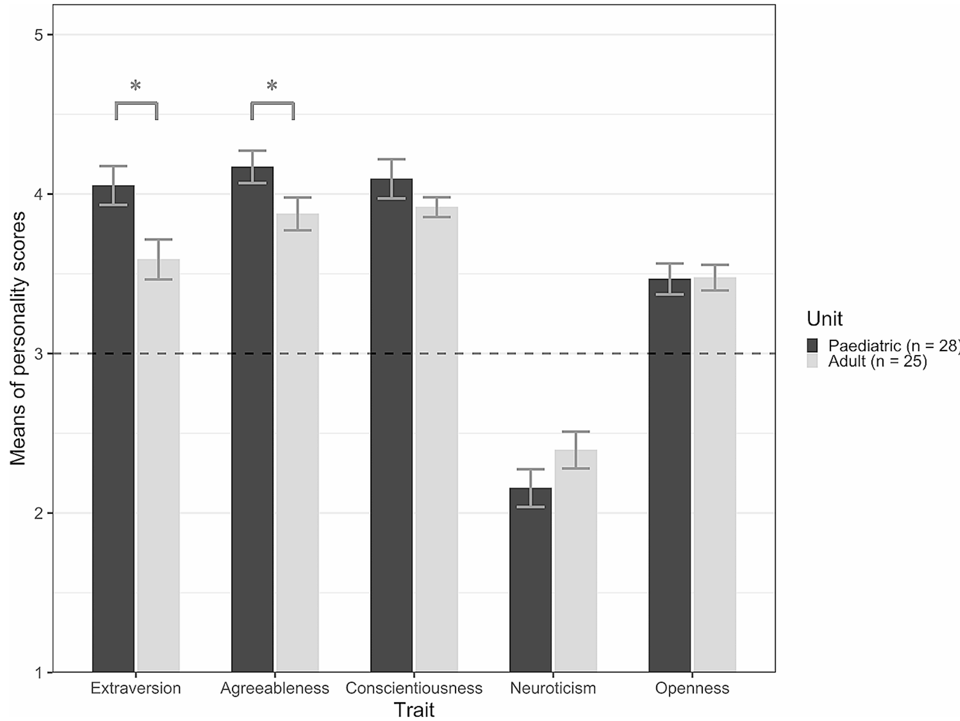

Fig. 3 Differences in personality scores between the units and from the mean of 3. Error bars are SEM. Only the difference in Extraversion and Agreeableness scores were statistically significant between the units. All trait scores were significantly different than the mean of 3

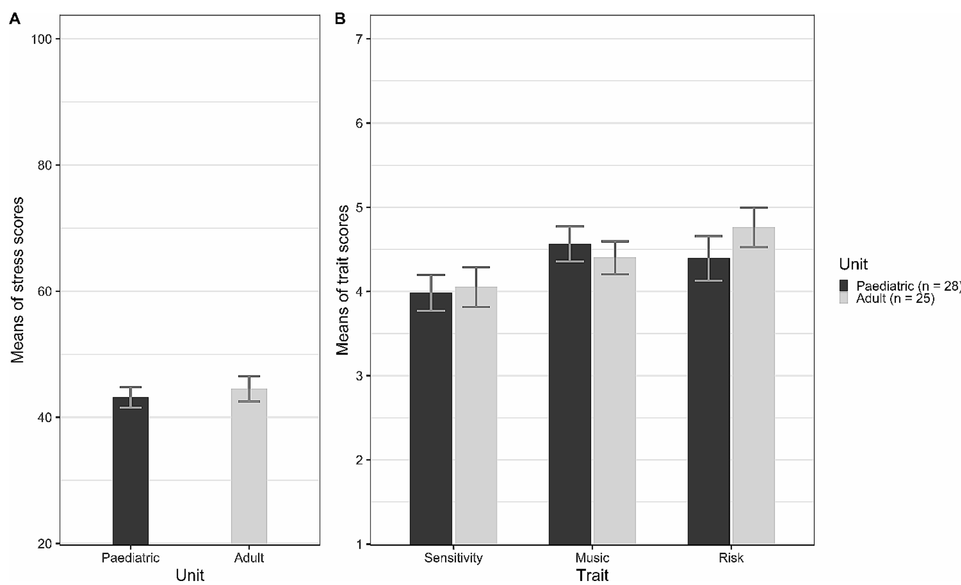

Fig. 4 Differences in trait scores between the units. Error bars are SEM. Differences between the units were not statistically significant

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 ($R^2=0.071$, $F(1, 51)=4.97$, $p=.030$). In other words, Extraversion predicted Stress Vulnerability (β = -4.10). This is illustrated in Fig. 5A. Black dots represent individual nurse scores and area around the regression line represents 95% confidence interval. Similarly, as seen in Fig. 5B, there was a statistically significant negative association between Stress Vulnerability and Risk, ($R^2=0.067$, $F(1, 51)=4.74$, $p=.034$), (β = -2.08). The other traits did not show statistically significant relations to Stress, $p>.05$.

3.1 Hierarchical cluster analysis

The obtained scores of the nine traits and years of Experience were analysed 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 centred

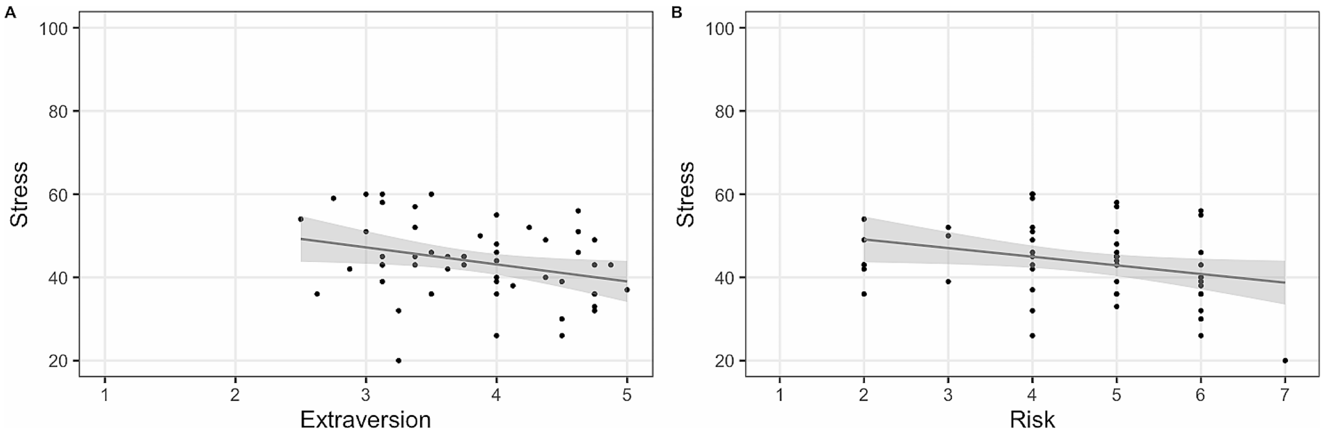

Fig. 5 Regression analysis indicated Extraversion and Risk were negatively associated to Stress Vulnerability

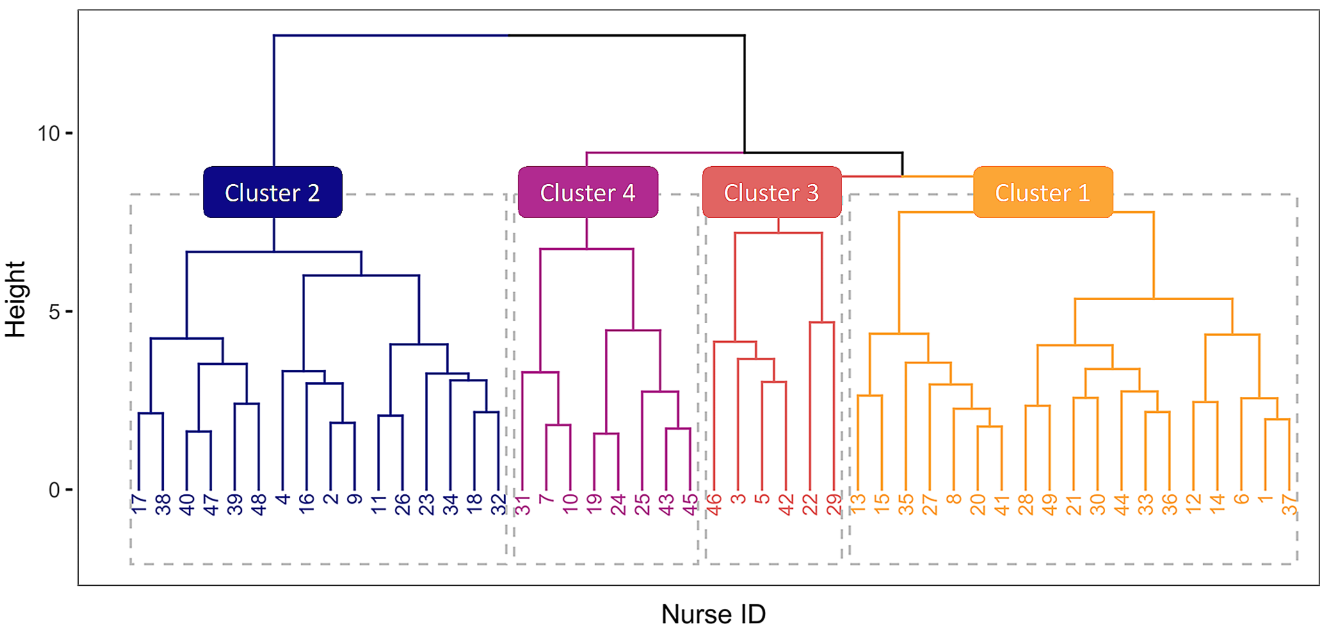

Fig. 6 Dendrogram illustrating nurse clusters generated by Hierarchical Cluster Analysis. Each participant number is illustrated as a leaf. Branches closer together indicate similarity in characteristics. Clusters 1 and 3 were the most closely associated, while Cluster 2 was the most distant. Resulting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

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 Fig. 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/Paediatric nurses, and cluster means for all traits are presented in Table 3.

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 Fig. 7. It is important to note that these scores are relative within the sample of nurses measured in this study.

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 Fig. 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 Fig. 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 (Fig. 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 Fig. 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.

Table 3 Mean trait scores for all clusters and overall nurses. Notice $N = 49$ due to exclusion

	Extraversion	Agreeableness	Conscientious.	Neuroticism	Openness	Stress	Sensitivity	Musicality	Risk	Experience	n Paediatric / n Adult
Range	**1–5**					**20–100**	**1–7**			**0–42**	
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

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

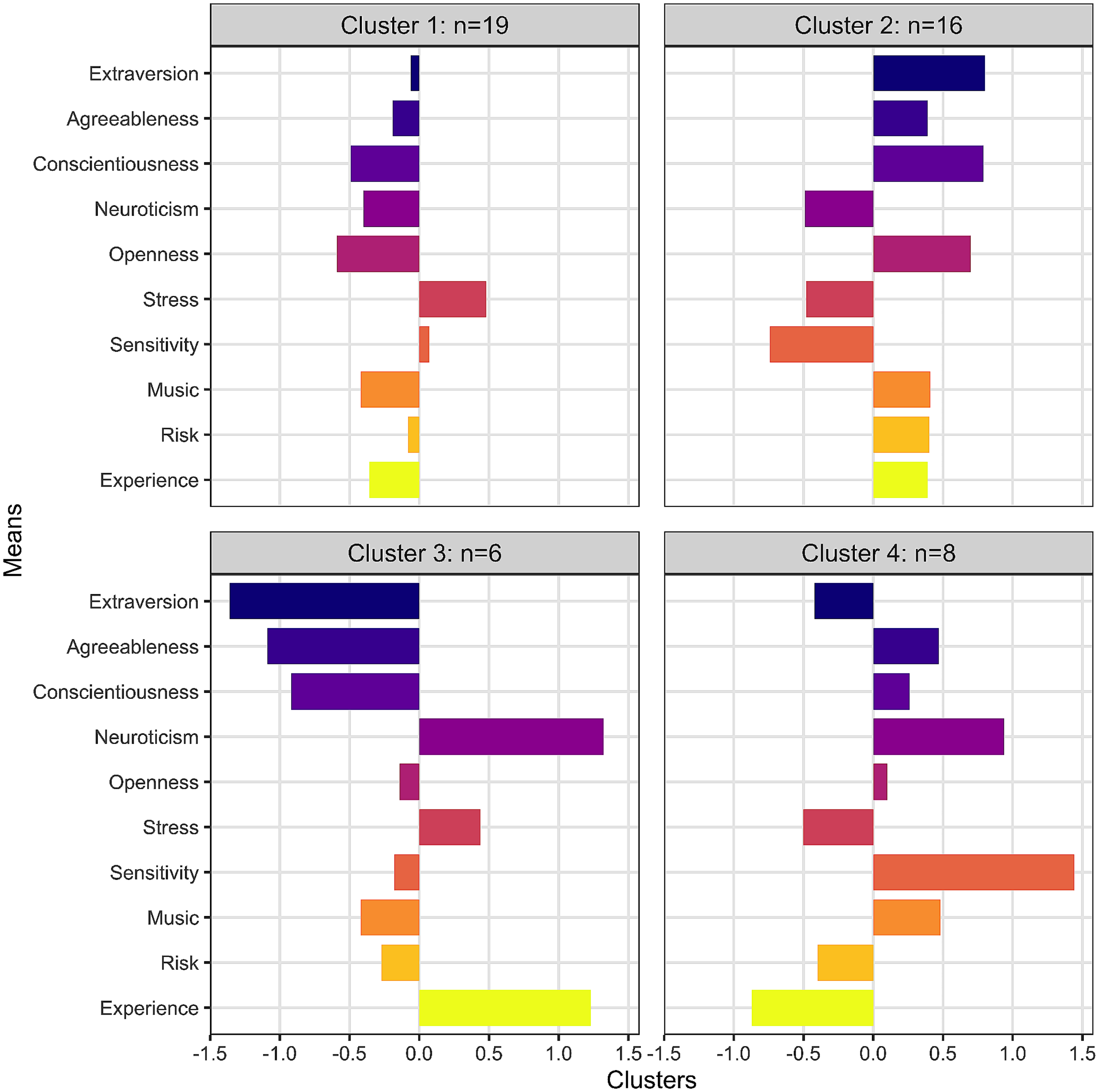

Fig. 7 Cluster mean scores illustrated in individual panel. Y-axis is the traits; x-axis is the corresponding z-scores of cluster trait means. Comparison demonstrates the differences among the clusters. For example, Cluster 3 had the highest level of experience while Cluster 4 had the lowest. Clusters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

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 paediatric 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 *Paediatric* nurses scoring higher in general. This points to a slightly more caring and nurturing personality for paediatric 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 paediatrics 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 midpoint scale. Sensitivity to physical stimulation, musicality, and risk-taking tendency appeared to be less defining characteristics between the units.

4.1 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.

4.2 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; Delle 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.

4.3 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.

4.4 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-centred design collaborations.

4.5 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.

4.6 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 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 (Fig. 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-centred 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-centred 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 centres and geographical locations can be useful in validating the findings of this research. In the future, we intend to measure the interaction behaviour 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.

Acknowledgements This study was part of the VitalAlarms project at the Critical Alarms Lab of Industrial Design Engineering TU Delft and Department of ICU at Erasmus Medical Center. The project received funding from Philips and Holland High Tech. We thank Dirk Hüske-Kraus for his insights in conceptualization and analysis. We further extend our gratitude to Jan Willem Kuiper, MD for his support in data collection. Finally, we thank the nurses in Adult and Paediatric IC units for their time and collaboration.

Author contributions I.B. conducted the data collection, analysis, wrote the main manuscript text, and prepared all figures and tables. E.O.and R.E. supervised research activities, such as the selection of the methods and analysis techniques. D.G. provided the data collection facility and access to participants involved in the study. E.O.and R.E. supported the writing process. All authors reviewed the manuscript.

Funding The research was conducted independently without any interference of the funding parties.

Declarations

Competing interests The authors declare no competing interests.

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