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

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Abstract

Intensive Care Unit (ICU) nurses are burdened by excessive number of false and irrelevant alarms generated by patient monitoring systems. Nurses rely on patient monitoring systems for timely and relevant information about patients. However, systems currently in place are not sensitive to nurse capabilities and fail to communicate information efficiently. Ensuring efficient communication and effective collaboration between patient monitoring systems and ICU nurses is possible through improving system design to be sensitive to nurse capabilities and preferences. Recognizing nurses as users of patient monitoring systems, we aim to gain in-depth understanding of the user group. We conducted a survey study involving nurses from two IC units to reveal their individual characteristics. Subsequently, we performed hierarchical cluster analysis to develop data-driven nurse profiles. We discuss the implications of nurse characteristics on system use. We suggest design recommendations tailored to four distinct user profiles to address their unique needs through system design. By optimizing the system interactions to match the natural tendencies of nurses, our aim to alleviate the cognitive burden induced by system use to ensure that healthcare providers receive relevant information, ultimately improving patient safety.

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 & 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 & Hüsk-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). We argue a mismatch exists between the interaction possibilities offered by patient monitoring systems and the capabilities of nurses. This mismatch results in burdened workload, stress, and fatigue, all of which can be mitigated by system design improvements (Nuamah & Mehta, 2020). Aligning system interaction possibilities with nurse capabilities necessitates an in-depth understanding of ICU nurses as system users. To gain deeper understanding of ICU nurses, this study scrutinizes individual characteristics of nurses to reveal distinct user groups. We identify four primary types of ICU nurses with the objective of informing future studies aimed at enhancing patient monitoring interactions. By doing so, we aim to reduce the mismatch between the systems and their users, and a take step towards symbiotic efficient collaboration (Grootjen et al., 2010).

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 functionalities that facilitate the interaction might vary among different types of users. Efforts so far have often targeted a generic ICU nurse. We propose this one-size-fits-all approach fails to capture the variation among different users and their interaction styles with the system. People appraise events and respond differently based on their individual backgrounds, memories, associations, and characteristics (Scherer et al., 2001). Recent studies point to this variation among nurses and suggest nursing styles differ based on personal differences (Ruppel et al., 2019). We argue that capturing this variation in nurses is valuable as it allows designing for distinct user groups in a more targeted 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. Addressing the individual differences through improved design has the potential to reduce the additional workload and stress induced by use of patient monitoring systems.

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-centred design approach, we take a step towards humanizing intensive care.

In this paper, our aim is to understand latent nurse needs that might be relevant in nurse-system interactions. 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.

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; J. Edworthy & Hellier, 2005; J. R. Edworthy et al., 2017; Foley et al., 2020; Pereira et al., 2021; Srietharan 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 & Funk, 2013). Personality and other individual differences have been shown to influence alarm responsivity (Claudio et al., 2021; Deb & Claudio, 2015). Feedback loop can also be influenced by 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.

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, and that their potential has yet not been explored from the human factors engineering perspective. 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. By understanding what drives the actions of the user, we can determine the most effective cognitive cues to optimize the interaction with the system.

We argue that several factors modulate the way alarms are cognitively processed and appraised. Level of noise annoyance hinges upon several individual factors (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 might be more inclined to decrease the number of alarms generated by the patient monitoring system by customizing system settings. Nurses vary in how they customize alarm settings (Özcan & Gommers, 2020; Ruppel et al., 2018). To capture this variation, we list several factors that we consider influential in how nurses process alarms and interact with the patient monitoring system.

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 introverted 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
innovative 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 might 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 might 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). We argue sensitivity to stimuli might determine how nurses evaluate alarms, and consequently 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 one’s abilities in perceiving musical and sound related attributes. Higher scores indicate higher perceptual ability for music.

A final factor that might 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 (Despines, 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. Another difference might lie 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 might 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.

Method

Study design

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

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 < 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 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.

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.

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.

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.
Similarly, for Extraversion, Openness, Sensitivity, Stress, Neuroticism, Agreeableness, Conscientiousness, 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 alphas are listed for each trait, representing the internal consistency of each trait.

<table>
<thead>
<tr>
<th>Questionnaire</th>
<th>Range</th>
<th>Number of Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personality</td>
<td>BFI</td>
<td>1–5</td>
</tr>
<tr>
<td>Stress</td>
<td>SVS</td>
<td>20–100</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>HSPS (subset)</td>
<td>1–7</td>
</tr>
<tr>
<td>Musicality</td>
<td>MSI (subset)</td>
<td>1–7</td>
</tr>
<tr>
<td>Risk-taking</td>
<td>-</td>
<td>1–7</td>
</tr>
</tbody>
</table>

### 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 1–5, 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 20–100, with 20 indicating the least vulnerability to stress. MSI scores were based on the means of 11 items. Scores of the negatively phrased items were reversed to positive. Final scores range between 1–5, 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.

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

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(51) = 8.66, p < .01, Cohen's d = 1.64; Agreeableness, t(51) = 11.53, p < .01, Cohen's d = 2.18; Conscientiousness, t(51) = 8.92, p < .01, Cohen's d = 1.69; and Openness, t(51) = 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 of nurses 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. 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 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, ($R^2 = .067, F(1, 51) = 4.74, p = .034$), ($\beta = -2.08$). The other traits did not show statistically significant relations to Stress, $p > .05$.

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 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.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>n</th>
<th>Range</th>
<th>Mean</th>
<th>20–100</th>
<th>1–7</th>
<th>0–42</th>
<th>Experience</th>
<th>Paediatric / Adult</th>
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</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>19</td>
<td>1–5</td>
<td>3.85</td>
<td>3.96</td>
<td>3.77</td>
<td>2.01</td>
<td>3.19</td>
<td>47.89</td>
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<tr>
<td>Cluster 2</td>
<td>16</td>
<td>4.42</td>
<td>4.26</td>
<td>4.45</td>
<td>1.95</td>
<td>3.79</td>
<td>38.94</td>
<td>3.19</td>
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<tr>
<td>Cluster 3</td>
<td>6</td>
<td>2.98</td>
<td>3.48</td>
<td>3.54</td>
<td>3.08</td>
<td>3.40</td>
<td>47.50</td>
<td>3.81</td>
</tr>
<tr>
<td>Cluster 4</td>
<td>8</td>
<td>3.61</td>
<td>4.31</td>
<td>4.17</td>
<td>2.84</td>
<td>3.51</td>
<td>38.75</td>
<td>5.64</td>
</tr>
<tr>
<td>Overall N=49</td>
<td></td>
<td>3.89</td>
<td>4.06</td>
<td>4.03</td>
<td>2.26</td>
<td>3.47</td>
<td>43.4</td>
<td>4.02</td>
</tr>
</tbody>
</table>

One of the main goals of this study was to reveal distinct user groups and gain an in-depth understanding of their characteristics. To this end, 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.

Discussion

In the following paragraphs, we first focus on the general nurse traits, and move onto differences between the nurses. In general, 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 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 conscientiousness 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 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 represented a unique user profile with their individual characteristics and preferences. The unique characteristics of profiles may be insightful for designing system affordances 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 needs through the interaction with the patient monitoring systems.

Although the nurse profiles showed significant differences in their traits, these differences should only be interpreted within the limits of the sample in this study and note 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 bounds 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.

Design Implications.

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). In this section, we present system design recommendations to align system affordances with the natural tendencies of each user profile.

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. Designing the system with features that help them complete tasks efficiently may be beneficial. This could include features such as shortcuts to system functions or automation tools. A well-organised system interface may help them adapt to the system more easily. Overall, designing the system to be simple, easy-to-use, and logically organized, with minimal distractions and clear guidance and support, may improve the user experience for this user group.

The Sociable & Flexible (Cluster 2)
The Young & Sensitive (Cluster 4)

This group is based on Cluster 2. Even though they represent the second largest group, they are the least like 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 might 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. Improving the user experience for this group may be achieved by providing opportunities for user feedback and incorporating it into future system updates.

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 distinguished by their high levels of experience and emotional reactivity. They score relatively lower on the social traits, indicating preference for personal time and quiet. These indicate that they may be vulnerable to stressful situations. To minimize the potential for stress and anxiety, it would be helpful to streamline the workflow within the system. This could involve simplifying the user interface, reducing the number of steps required to complete tasks, or automating certain processes to minimize cognitive load. A stable and resilient system such as the one proposed for Cluster 1 could be suited for their needs.

Overall, the majority of the nurse users belong to the "Moderate & Straightforward" and "Sociable & Flexible" profiles. The "Experienced & Short-tempered" and the "Young & Sensitive" profiles are users that are defined by their years of experience as an ICU nurse, either being at the end of their career or have just begun. A system that can cater for all different types of nurse profiles is challenging to design, however current technological developments will support some of the user needs. Generative AI techniques that could follow each nurse's interaction style and build up on their preferences and decisions could be of use here to improve the nurse-system interactions (e.g., Moderate & Straightforward and Experienced & Short-tempered). A system that co-designs with the users, where nurses have direct input during the design phase, could be interesting for device manufacturers and policy makers as they will get a first-hand insight from the expert users. Such system evaluations often done in the product testing phase could extend to actual use. Furthermore, the system can develop iteratively, such as regular software updates to allow novel functionalities while the system is in use. Moreover, the need for less sensory stimulation (e.g., Young & Sensitive) can be resolved by mitigating false alarms. Peripheral products tracking location could be incorporated to deliver the information to nurses where they are. Our results indicate that needs of the nurse groups do not compete and can be addressed by incorporating novel technology solutions to manage the flow of information in the ICU.

Conclusions

This study highlights the importance of considering individual properties of ICU nurses in the design of patient monitoring systems. The findings demonstrate that human factors studies should go beyond observable behaviour and consider the latent individual properties of users. By identifying and targeting the unique needs and preferences of distinct user groups, designers can create more effective and user-centred systems that minimize cognitive load during interaction with the system. 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.

Declarations

Competing Interests

This project was partially funded by Philips Patient Monitoring. The authors have no competing interests to declare that are relevant to the content of this article.

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References


Figures

Figure 1

HIP model adapted from Wickens, explaining cognitive processing of information during human-system interaction. Audio-visual signal is generated by the system and processed by the user. Individual differences modulate information processing. User responds by taking action.

Figure 2

Observable system interaction behaviors are driven by latent individual properties.

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 5

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

Figure 6

Dendrogram of nurses generated by Hierarchical Cluster Analysis. Clusters differed in their sizes. Clusters 1 and 3 were the most closely associated, while Cluster 2 was the most distant.
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.