An Eye-Tracking Assessment of Coronary Care Nurses during the Interpretation of Patient Monitoring Scenarios

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Abstract

Introduction: It has yet to be determined whether visual attention, measured via eye tracking metrics (ETMs) can be indicative of performance level in coronary care nursing when interpreting patient vitals.

Methods: This study captures the visual attention of nurses when interpreting five scenarios using simulated text and vital signs. Baseline performance was marked using detailed criteria and scored 0-10. Self-rated confidence from 1-10 was also collected for each scenario. Cognitive workload was assessed by measuring a participant's heart rate and post-performance NASA-TLX responses. Eleven coronary care nurses were recruited providing 55 interpretations/observations in total. 45 of which, post data quality filtering, were used to analyse ETMs.

Results: Mean performance score = 6.86±1.50 and mean confidence rating = 7.51±1.2. A subset of ETMs significantly correlate with performance across all scenarios. Individual scenarios also provide significant correlations. Three of six regression models were statistically significant with $R^2 \geq 0.5$.

Conclusion: Correlations between specific ETMs and performance have been found across all scenarios and for individual scenarios. Further work is needed to confirm the benefit of ETM in assessing simulation-based training performance.

1. Introduction

Patient safety and medical errors are a critical area of concern within healthcare [1]. Lack of knowledge and skill with clinical procedures, as well as decision-making can be significant factors with many of the errors that are reported [2].

Many healthcare tasks can be simulated using computer/web technology to provide trainees with a method to improve knowledge and skills [3]. Computer-based simulation still requires further research to demonstrate how it can provide a fully comparable training experience compared to other modalities, such as mannequin-based simulation, standardized patients etc.

Monitoring is a core competency in nursing involving surveillance of the patient and their physiological signals [4]. This is imperative for the early detection of patient deterioration [5]. There is a need for more consistent practice in patient surveillance [6] and effective assessment of patient vital signs [7].

Research into the understanding of visual attention during healthcare tasks has increased [8]–[10]. The mind-eye hypothesis states that measurements of visual attention may indicate underlying cognitive activity [11].

The objective of this study was to assess the role of eye tracking metrics (ETMs) and other psychophysiological measurements as independent assessors for a trainee performing interpretation of patient vital signs [12]. This work contributes to the viability of automated simulation based assessment in nursing.

2. Methods

Eleven coronary care nurses were recruited during a one-day ECG seminar at Altnagelvin Hospital. They were asked to verbally interpret five different monitoring scenarios while being eye-tracked and wearing a heart rate (photo-plethysmography) monitor. Visual attention during the task was captured using the Tobii X60 eye tracker (tobiipro.com) at a recording frequency of 30Hz and heart rate by wearing an Empatica E4 wristband (empatica.com). After performing the five interpretations, we asked each participant to complete a NASA-TLX (humansystems.arc.nasa.gov) survey, consisting of seven scaled questions related to task performance (e.g. mental demand, frustration etc.) to allow us to analyse their cognitive workload during the task.

2.1.   Patient scenarios

The vital signs scenarios were designed/validated by nursing experts (following work aimed at capturing these monitoring scenarios into digital format [13]) and then simulated using Laerdal's SimMan simulation software (laerdal.com). One minute of each set screen were recorded to use in the task. The patient vignettes settings were as follows: (1) medical ward, (2) cardiology ward, (3) surgical ward, (4) respiratory ward, (5) emergency department. Each scenario contained ten available marks for the interpretation.

Once the participant was ready, the next screen contained the patient's vital signs, for them to verbally interpret: Electrocardiogram and Heart Rate, Arterial Blood Pressure, Central Venous Pressure, Oxygen saturation, Respiratory Rate and Temperature. All provide areas of interest (AOI) for eye tracking metrics (ETM) used in the analysis, see Figure 1.
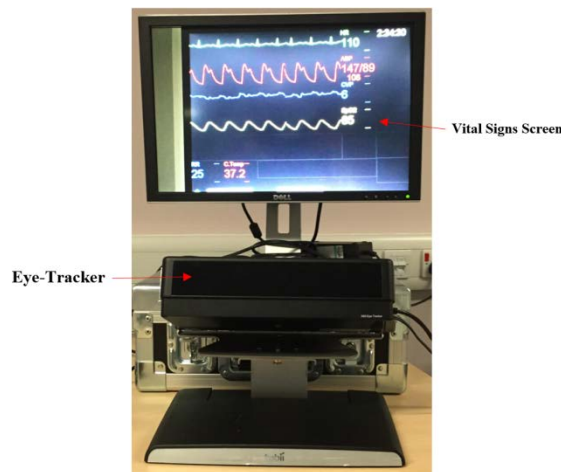

Figure 1. Tobii X60 Eye Tracker and Simulated Vital Signs Screen.

2.2.   Data analysis

The AOIs that ETMs would perform measurement on were coded as such: Electrocardiogram = *ECG*, Heart Rate = *HR*, Arterial Blood Pressure* = *ABP* + *[W]* or *[N]*, Central Venous Pressure* = *CVP* + *[W]* or *[N]*, Oxygen Saturation* = SpO_2 + *[W]* or *[N]*, Temperature = *TEMP*, Respiratory Rate = *RESP*. *These vital signs have both a wave and numeric component, with *[W]* = Wave and *[N]* = Number, analysed separately.

We also wished to analyse visual attention spent on non AOI areas of the screen – as we saw this as potentially indicative of uncertainty. This is coded as *NON-AOI* and ETMs measure it the same way as the AOIs.

The ETMs provided by the Tobii eye tracking software (tobiipro.com) are shown in Table 1.

Table 1. Eye tracking metrics (ETMs) used in analysis

ETM	Analysis Abbreviation	Description
Time to first fixation (s)	*TTFF*	Time elapsed before first fixation on area of interest.
First fixation duration (s)	*FFD*	Time elapsed during first fixation on area of interest.
Fixations before (number)	*FB*	Number of fixations (elsewhere) before first on area of interest during viewing.
Fixation duration (s)	*FD*	Mean elapsed time from all fixations.
Fixation count (number)	*FC*	Total number of fixations on area of interest.
Total fixation duration (s)	*TFD*	Total elapsed fixation time on area of interest.
Visit duration (s)	*VD*	Mean elapsed time from first fixation inside area of interest until eye gaze exits.
Visit count (number)	*VC*	Total number of visits on area of interest.
Total visit duration (s)	*TVD*	Total elapsed visit time on area of interest.

Manual operator quality control procedures were applied for eye tracking recordings and those that fell below 50% recording quality (e.g. participant looking away from the screen too much) were excluded from analysis. The analysis was performed using R programming in RStudio (rstudio.com) with core R functionality used for regression model building and with *dplyr/tidyr*, *Hmisc* and *DAAG* libraries used for data tidying, correlation testing and cross validating regression models respectively.

Our primary analysis here is to present moderate to strong correlating ETMs to performance score, both across all scenarios but also individual scenarios interpreted by participants. With significant correlations found we attempted simple linear or multiple linear regression to predict the score. Cross validation was performed on some of these models with mean squared error (MSE) given: due to limited sample size, only results presented are with regression models that produced R^2 or Multiple $R^2 \geq 0.80$.

We also present correlations amongst NASA-TLX and heart rate monitoring for task cognitive loading.

3.   Results

The nurses recruited had an age range 25-43 years, with a mean age of 32 years; experience range 5-17 years

with a mean of 9 years. Table 2 provides performance and confidence scores across all scenarios by all participants.

Table 2. Participant Performance: total score and confidence.

Measure	Mean ±SD	Min	Max
Total Score (0-10)	6.86 ±1.50	4	10
Confidence (1-10)	7.51 ±1.20	5	10

3.1. ETMs and performance score

Due to data quality filtering (see 2.2.), two of eleven participants were removed, resulting in the removal of ten interpretations. This leaves 45 total observations to analyse. Significant correlations for ETMs and performance score across all scenarios are presented in Table 3. The most significant model **(p=0.01)** used three of the five available predictors, with **Multiple R^2 = 0.34**. Three-fold cross validation produced **MSE = 1.35**. Figure 2 shows the cross validation prediction values against dataset performance scores.
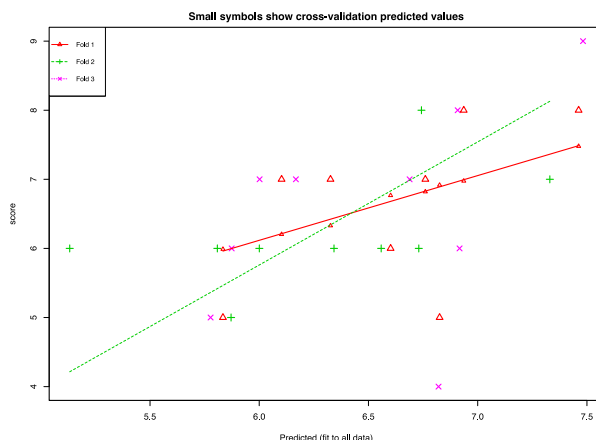

Figure 2. Predicting performance score across all scenarios using ETMs: three-fold cross validation plotted values (predictions) vs dataset scores

Correlation analysis of ETMs for the individual scenarios are shown in Table 4, including details of predictive model attempts.

Table 3. Correlating ETMs with score across all scenarios.

AOI	ETM	r	p
TEMP	TTFF	0.44	<0.01
RESP		0.43	<0.01
TEMP	FB	0.39	<0.05
NON-AOI	FFD	-0.35	<0.05
TEMP	VD	-0.31	<0.05

Table 4. Correlating ETMs and score for each scenario, with simple linear or multiple linear regression models and cross-validation on models with $R^2 \geq 0.8$.

	Scenario	AOI	ETM	r	p	Predictive Model Details
1	Medical Ward	NON-AOI	FD	-0.71	<0.05	Most significant model **(p=0.02)** using all available predictors with **Multiple R^2 = 0.72**.
			FB	0.68	<0.05	
2	Cardiology Ward	*No significant ETM correlations to performance score and no significant predictive regression models.*				
3	Surgical Ward	RESP	TTFF	0.80	<0.05	Most significant model **(p=0.02)** using 1 of the 2 available predictors with **R^2 = 0.64**.
		SpO$_2$ [W]		0.70	<0.05	
		TEMP	FFD	0.68	<0.05	
4	Respiratory Ward	ABP [W]	FB	-0.82	<0.01	Most significant model **(p=0.02)** using 2 from 8 available predictors with a **Multiple R^2= 0.83**. 3-fold cross validation produced **MSE= 0.32**.
			TTFF	-0.78	<0.01	
		NON-AOI	FFD	-0.80	<0.01	
		CVP [N]	FD	-0.78	<0.01	
			TFD	-0.77	<0.05	
			TVD	-0.77	<0.05	
			FC	-0.68	<0.05	
		TEMP	VC	0.69	<0.05	
5	Emergency Department	CVP [W]	TFD	-0.91	<0.001	Most significant model **(p<0.001)** using 1 from 7 available predictors with **R^2 = 0.83**. 3-fold cross validation produced **MSE= 0.25**.
			TVD	-0.90	<0.01	
			VD	-0.77	<0.05	
			FC	-0.68	<0.05	
			VC	-0.71	<0.05	
		ABP [W]	TFD	-0.79	<0.01	
			TVD	-0.77	<0.05	

3.2. NASA-TLX and heart rate

Fourteen significant correlating variables were found amongst NASA-TLX (both total score overall and individual questions responses), heart rate (bps), their mean confidence rating (1-10) and other demographic information. Neither NASA-TLX or heart rate values correlate strongly with performance score, see Table 5.

Table 5. Correlations between NASA-TLX and non-ETM measures.

Var. i	Var. ii	r	p
TLX: Mental Demand	TLX: Effort	0.61	<0.001
	TLX: Total	0.67	<0.001
	Age (yrs.)	-0.51	<0.001
	Experience (yrs.)	-0.56	<0.001
	Initial Heart Rate	-0.73	<0.001
	Mean Heart Rate	-0.63	<0.001
TLX: Temporal Demand	TLX: Total	0.73	<0.001
	Age (yrs.)	-0.62	<0.001
	Experience (yrs.)	-0.64	<0.001
TLX: Effort	Initial Heart Rate	-0.73	<0.001
	Δ Heart Rate	0.53	<0.001
TLX: Frustration	Final Heart Rate	0.55	<0.001
TLX: Total	Experience (yrs.)	-0.56	<0.001
Confidence	Mean Heart Rate	-0.55	<0.001

4. Discussion and conclusions

This study provides significant correlating ETMs to task performance. *TTFF* for both (1) *TEMP* and (2) *RESP* are the most significant with score across all scenarios. Notably both are situated at the bottom of the screen - suggesting better performers digest information from AOIs above for longer than poorer performers. Notably *CVP [W]/[N]* are strong negative correlators to score in scenarios four and five. In both scenarios *CVP* is normal with no significant relation to recommendations that would achieve higher scores. Eye-tracking appears to see a link between those who ignore this AOI and better performance. NASA-TLX and heart rate also provide some significant correlations with each other. Notably that both mental demand and effort have a negative but strong correlation with participant initial heart rate.

The results provide indicators for further research into ETMs and performance in simulated training for vital sign interpretation. A larger dataset could provide significantly more insight to the cognitive process of this task and lead to validated metrics for assessment of trainee nurses. Confirmation of discriminating metrics could lead to automatic classification between performance level - either low/high performance or at least uncertain/confident interpretations. The former providing a method to efficiently quantify training level of trainee, the latter to assess uncertainty of nurses at the bedside.

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