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A dynamic human reliability assessment approach for manned submersibles using PMV-CREAM

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ABSTRACT

Safety is always acritical focus of exploration of ocean resources, and it is well recognized that human factor is one of the major causes of accidents and breakdowns. Our research developed a dynamic human reliability assessment approach, Predicted Mean Vote-Cognitive Reliability and Error Analysis Method (PMV-CREAM), that is applicable to monitoring the cognitive reliability of oceanauts during deep-sea missions. Taking into account the difficult and variable operating environment of manned submersibles, this paper analyzed the cognitive actions of oceanauts during the various procedures required by deep-sea missions, and calculated the PMV index using human factors and dynamic environmental data. The Cognitive Failure Probabilities (CFP) were calculated using the extended CREAM approach. Finally, the CFP were corrected using the PMV index. This PMV-CREAM hybrid model can be utilized to avoid human error in deep-sea research, thereby preventing injury and loss of life during undersea work. This paper verified the method with “Jiaolong” manned submersible 7,000 m dive test. The“Jiaolong” oceanauts CR(Corrected CFP) is dynamic from 3.0615E-3 to 4.2948E-3, the CR caused by the environment is 1.2333E-3. The result shown the PMV-CREAM method could describe the dynamic human reliability of manned submersible caused by thermal environment.

1. Introduction

The goal of our research was to develop a dynamic human reliability assessment approach applicable for monitoring the cognitive actions and attitudes of oceanauts during deep-sea missions. To assess the impact of changes in the submersible environment on the diving teams, we utilized the extended Cognitive Reliability and Error Analysis Method (CREAM) method and Predicted Mean Vote (PMV) index, as explained in the following sections.

1.1. Safety and HRA at sea

Safety is an essential subject in the exploration and development of marine resources (Zhou et al., 2017). The human element has been identified and accepted as one of the main causes of maritime accidents (Zhang et al., 2014). Accordingly, Human Reliability Analysis (HRA) techniques are used widely for researching on-ship scenarios to provide a better understanding of human behavior in these situations (Pourzanjani and Zheng, 2001). For example, the available HRA methods provided assessment of the role of human reliability on the risk of capsizing (Webb and Lamoureux, 2003). In the study of ships navigating coastal waters, researchers used qualitative and quantitative tools to model human error and reliability while using on-board ship navigation (Sulaiman and Kader, 2012). Nonetheless, statistics concerning human failure in the maritime domain remain scarce or nonexistent, which causes challenges for the implementation of an effective quantitative HRA method (Yang et al., 2013). Deep ocean exploration teams should be fully aware of operational risks during the various stages of the diving and return procedures, including laying, diving, cruising, landing, and rising. During these stages, human reliability (operation without failure) plays a crucial role,

Abbreviations: ATHEANA, A technique for human error analysis; CFP, cognitive failure probabilities; CREAM, cognitive reliability and error analysis method; CPC, common performance conditions; CII, context influence index; HEART, human error assessment and reduction technique; HRA, human reliability analysis; PII, performance influence index; PMV, predicted mean vote; PPD, predicted percentage of dissatisfied; SPAR-H, standardized plant analysis risk – human reliability; SLIM, success likelihood index methodology; THERP, technique for human error rate prediction.

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but reliability is affected easily by heat, humidity, noise, lighting, and other environmental factors.

Since human ability is an essential factor for safety, reliability assessment is a critical issue for risk researchers, decision makers, safety engineers, and practitioners. Human reliability can be defined in terms of performance by demonstrating how consistently an individual/operator can complete a given action correctly, or how long the operator can perform an action without failure (Pyy, 2000). HRA has proven useful for the mitigation of human errors, particularly in the nuclear industry. Some widely used HRA methods include the Technique for Human Error Rate Prediction (THERP), Success Likelihood Index Methodology (SLIM), Human Error Assessment and Reduction Technique (HEART), Standardized Plant Analysis Risk – Human reliability (SPAR-H), A Technique for Human Error Analysis (ATHEANA), and the CREAM (Swain, 1963; Embrey et al., 1984; Williams, 1988; Blackman et al., 2008; Thompson et al., 1997; Hollnagel, 1998).

The duties performed by crew members onboard manned submersibles reveal an environment with highly contextual dependencies. Technological, environmental, and social factors often come together to form complex, interactive working conditions (Yang et al., 2013). The CREAM approach provides an HRA method that enables qualitative opinions from experts to be converted into quantitative human failure analysis results (Kohnen, 2009). The CREAM technique starts with the construction of an event sequence for a specific situation. The next step is to describe the actions and cognitive activities for each of the various performance segments to determine the relevant cognitive functions. Finally, the likely error modes are identified (Hollnagel, 1998). The core of CREAM is that human error is not stochastic, but rather errors are shaped by the context of the task. CREAM identifies nine Common Performance Conditions (CPC) that together provide a comprehensive and well-structured basis for characterizing the conditions under which the performance is expected to take place. The term 'control mode' is used to reflect the general character of the various conditions. Four kinds of control modes are defined in CREAM: scrambled control, opportunistic control, tactical control, and strategic control, with the error probability reduced gradually. Finally, quantification of the Cognitive Failure Probability (CFP) is attained by calculation.

1.2. Manned submersibles and their working environment

Manned submersibles are handy tools for deep-sea scientific research and resource exploration (Zhou et al., 2017; Zhang et al., 2014). Deep sea explorations are essential for the investigation of marine creatures, micro-organisms, minerals, and other resources hidden under deep water, as well as for geophysical research into the structure and behavior of the earth (Walden and Brown, 2004). Since the 1960s, numerous models of manned submersibles have been developed that can dive to extreme depths, including the Alvin (Boulègue et al., 1987) of the USA (4,500 m), Nautile (Iwai et al., 1990) of France (6,000 m), Shinkai 6500 (Sagalevitch, 1998) of Japan (6,500 m), MIR (Liu et al., 2010) of Russia (6,000 m), and Jiaolong (Ashley, 1993) of China (7,000 m). In recent years, China's manned diving program has been among the most active. In addition to the Jiaolong manned submersible, other Chinese projects are growing fast, such as the 4,500 m application-level manned submersibles, and the myriametric manned submersibles for full-ocean depth (Walden and Brown, 2004). At the same time, the United States, Japan, and other countries have similar projects in the so-called deep-sea challenge. Among the full ocean depth manned submersibles are the Deepsea Challenger of James Cameron's team, Deepsearch of DOER Marine, and DeepFlight Challenger of Hawkes Ocean Technologies (Hardy et al., 2013; Taylor and Lawson, 2009; Tingle, 2009).

The manned submersible cabin is a very complicated operations center, as shown in Fig. 1. It contains a propulsion system, underwater communications system, life support system, mechanical arm, display system, detection system, and emergency system, among others. As deep-sea operating equipment, the manned submersible operation system has certain characteristics and requirements.

(a) Long working time: The average speed of submergence is about 40 m/min. In addition to sea surface preparation time and underwater operation time, a 3,000 m deep-sea mission takes 7–9 h, so the average time required for a 5,000–7,000 m deep-sea mission is over 12 h.
(b) Small working space: The manned submersible generally features a 2.1 m titanium alloy spherical cabin that must carry three team members (a pilot and two scientists). In addition, the manned submersible is equipped with large quantities of equipment. For these reasons, the operating space is very narrow.
(c) Task intensity: Each launching task involves 8 stages (A–H). A deep-sea mission includes many related scientific missions, such as sample collection, terrain mapping, equipment arrangement and recovery, and so on. Consequently, the oceanauts are required to maintain intense concentration during various phases of their work.

The environment of the manned submersible cabin is complex and variable. For example, the temperature and humidity change with depth. These conditions are tightly controlled by atmospheric control technology. As mentioned above, the small cabin must accommodate three team members plus a large amount of equipment for the performance of various tasks, so the internal space is very tight. In addition, the limitations of battery power further constrain the ability to provide conventional ventilation. Consequently, there is no air conditioning system in the manned cabin.

The procedures for diving and returning the manned submersible to the surface constitute a complex operational environment for seafloor resource exploration. The exploration team must bear extreme temperatures and humidity. During a deep-sea mission, oceanauts must endure the physical tests that arise while working long hours in an enclosed space, as well as psychology challenges that result from the isolated environment.

Because of this special work environment, there are always potential hazards and instances of submarine accidents (Ung, 2015). In the future, manned submersible technology will be improved in terms of its ability to support long missions and provide more comfortable workspace. A key problem to be solved in the field of manned submersibles is how to ensure the safety and efficiency of the underwater cabin. In this connection, researchers are examining the influence of the cabin environment on exploration teams.

1.3. Thermal comfort and labor productivity

Over the past few decades, the topic of indoor thermal comfort has been debated frequently, in part because of its effects on the comfort, health, and productivity of occupants in the workplace (Luo et al., 2016). Factors that influence the indoor thermal environment include air temperature, relative humidity, wind speed, and radiation temperature. While all of these factors have an impact on worker efficiency, air temperature has the greatest impact (Jin et al., 2017). In manned submersibles, the indoor thermal environment can influence the performance of various aspects of required tasks in different ways. Therefore, for research purposes, it is necessary to use a metric of thermal comfort that

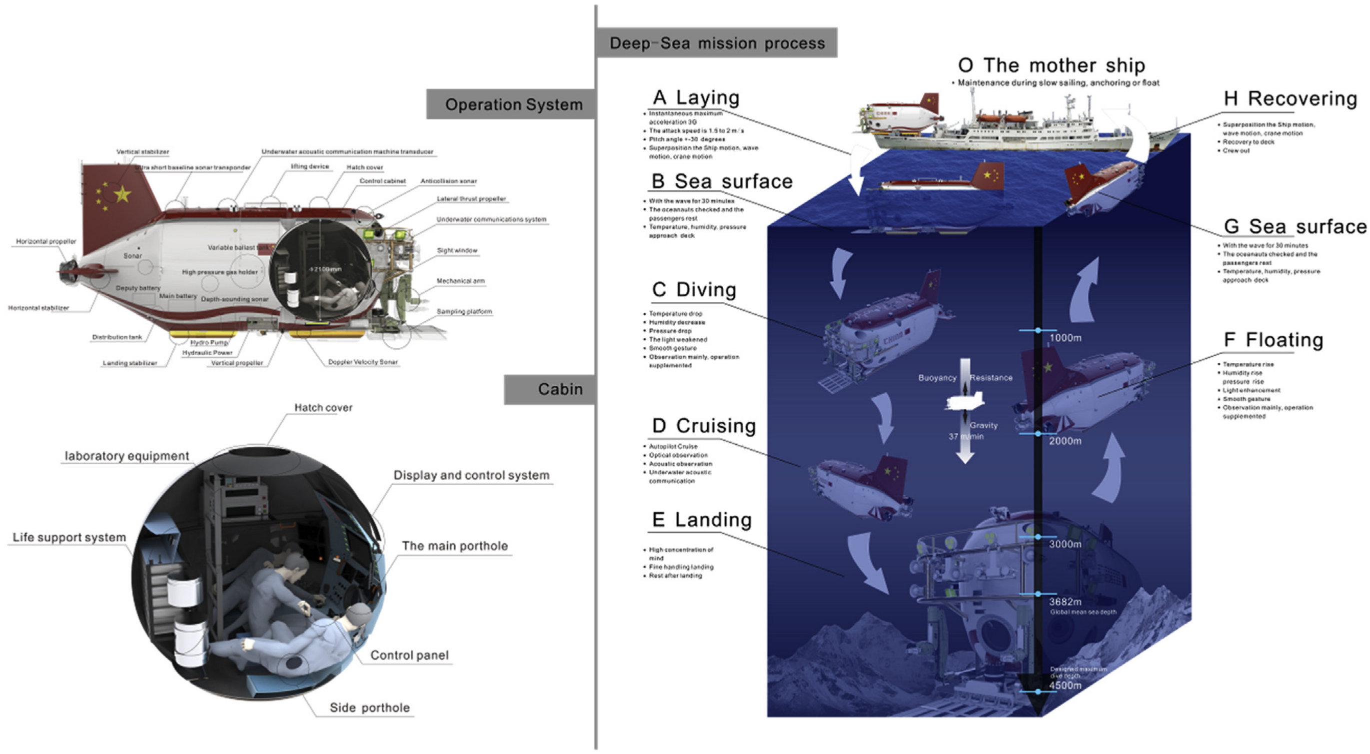


Fig. 1. Manned submersible operating system.

considers all factors, including the level of activity undertaken.

The Predicted Mean Vote (PMV) index is based on extensive American and European experiments conducted by Fanger in 1970, whose work involved studying over 1,000 subjects in well-controlled environments (Fanger, 1970; Kosonen and Tan, 2004; ISO, 2005; Ole Fanger and Toftum, 2002). The PMV index predicts the mean value of the votes of a large group of individuals on a 7-point thermal sensation scale (see Table 1) (ISO, 2005). For the PMV, thermal sensation is measured as a function of six heat balance parameters: the subject's metabolic activity level and clothing insulation, the immediate environment's air temperature, mean radiant temperature, air velocity, and relative humidity. The Predicted Percentage of Dissatisfied (PPD) is an index that establishes a quantitative prediction of the percentage of thermally dissatisfied people who feel too cool or too warm. Both the PMV and PPD were found to be highly relevant as tools in the assessment of productivity loss for the rate of change in thermal comfort criteria (Kosonen and Tan, 2004) The PMV-PDD model has since been established as the official method of evaluating thermal comfort by many national and international standards organizations (Van Hoof, 2008), including ISO standard 7730 (ISO, 2005), ASHRAE Standard 55 (ASHRAE, 2004), CEN 15251 (CEN, 2007), and Chinese GB/T 50785 (GB/T, 2012).

In recent years, many researchers have performed numerous experiments to study the relationship between air temperature variations and changes in productivity. Schellen et al., 2012 discussed gender differences in chronophysiology, thermal comfort, and productivity by comparing convective and radiant cooling (Geng et al., 2017). Through repeated experimental investigation, Jin et al. researched the effects of higher temperature setpoints during the summer on office workers' cognitive load and thermal comfort (Jin et al., 2017). Geng et al. discussed the impact of the thermal environment on occupant IEQ perception and productivity, establishing the quantitative relationship between productivity and the thermal environment (Geng et al., 2017).

Koehn and Brown (1985), Thomas and Yiakoumis (Randolph Thomas and Yiakoumis, 1987), Hancher and Abd-Elkhalek (1998), Mohamed and Srinavin (2005), Akimoto et al. (2010) and Lan et al. (2011) have conducted different experiments to investigate the relationship between thermal environment and labor productivity. They also established mathematical models to forecast the change of productivity due to air temperature variations. Despite of the different models, these studies all revealed that deviation from thermal neutral condition led to productivity loss.

For our research, we used the CREAM method and PMV index to develop a dynamic human reliability assessment approach applicable for monitoring the cognitive actions and attitudes of oceanauts during deep-sea missions. In this paper, we provided an in-depth analysis of the cabin environment of manned submersibles, and collected the characteristics of thermal environment change. The dynamic PMV-PPD index was obtained through human factors and the dynamic data of the thermal environment, and included the cabin temperature data, humidity data, and the rate of individual personnel metabolism, among other factors. Based on the PMV-PPD index, we optimized the CREAM approach for manned submersible human reliability analysis.

The remainder of this paper is presented as follows. Section 2 describes our research methodology. Section 3 provides a demonstration of our methods. Section 4 discusses our findings, and Section 5 provides our conclusions and recommendations for future work.

Table 1
7-Point thermal sensation scale (ISO, 2005).

Hot	Warm	Slightly warm	Neutral	Slightly cool	Cool	Cold
+3	+2	+1	0	−1	−2	−3

2. Research methodology

The assessment method presented in this paper covers both environment and task analysis. Our aim was to assess human performance reliability under the difficult and variable working conditions found in the cabin of manned submersibles used for ocean resource exploration. This portion of the paper presents the details of our methodology.

2.1. PMV method

Based on the ISO 7730 standard, the PMV and PPD indices provide a thermal environment assessment through calculations using the measurement of six quantities: two subjective measures (the subject's clothing thermal insulation and metabolic rate) and four external physical measures (the immediate environment's air temperature, mean radiant temperature, air velocity, and air humidity). The procedure used in our work was as follows.

We calculated the PMV using Eqs. (1)–(5) (Koehn and Brown, 1985):

$$PMV = [0.303\times\exp(-0.036M)+0.028]\times\left\{\begin{array}{l}(M-W)-3.05\times10^{-3}\times[5733-6.99(M-W)-P_a]-0.42\times[(M-W)-58.15]\\ -1.7\times10^{-5}\times M\times(5867-P_a)-0.0014\times M\times(34-t_a)\\ -3.96\times10^{-8}\times f_{cl}\times\left[(t_{cl}+273)^4-\left(\overline{t_r}+273\right)^4\right]-f_{cl}\times h_c\times(t_{cl}-t_a)\end{array}\right\}, \quad (1)$$

$$t_{cl}=35.7-0.028\times(M-W)-I_{cl}\times\left\{3.96\times10^{-8}\times f_{cl}\times\left[(t_{cl}+273)^4-\left(\overline{t_r}+273\right)^4\right]+f_{cl}\times h_c\times(t_{cl}-t_a)\right\}, \quad (2)$$

$$h_c=\left\{\begin{array}{ll}2.38\times\left|t_{cl}-t_a\right|^{0.25} & for\ \ 2.38\times\left|t_{cl}-t_a\right|^{0.25}>12.1\times\sqrt{v_{ar}}\\ 12.1\times\sqrt{v_{ar}} & for\ \ 2.38\times\left|t_{cl}-t_a\right|^{0.25}<12.1\times\sqrt{v_{ar}}\end{array}\right., \quad (3)$$

$$f_{cl}=\left\{\begin{array}{l}1.00+1.290\times I_{cl}\ \ for\ \ I_{cl}\le 0.078m^2K/W\\ 1.05+0.645\times I_{cl}\ \ for\ \ I_{cl}>0.078m^2K/W\end{array}\right., \quad (4)$$

$$P_a=\varphi_a\times P_s=\varphi_a\times610.6\times\exp\left(\frac{17.260\times t_a}{273.3+t_a}\right), \quad (5)$$

where M is the metabolic rate (W/m^2), W is the effective mechanical power (W/m^2), I_{cl} is the clothing insulation (m^2·K/W), f_{cl} is the clothing surface area factor, t_a is the air temperature (°C), $\overline{t_r}$ is the mean radiant temperature (°C), v_{ar} is the relative air velocity (m/s), p_a is the partial vapor pressure (Pa), h_c is the convective heat transfer coefficient (W/m^2 °C), t_{cl} is the surface temperature of clothing (°C), and φ_a is the relative humidity.

The PMV predicts the mean value of the votes of a large group of people exposed to the same environment on a 7-level scale of thermal sensations, i.e. from −3 to +3. PPD predicts the percentage of thermally dissatisfied people. PPD may be more reliable than PMV, because individual votes show scatter as a result of human factors (ISO, 2005). Table 1 shows the relationship between PMV and a thermal sensation proposed by Fanger (1970), and Fig. 2 summarizes the relationship between PMV and PPD (Koehn and Brown, 1985).

PPD is determined by Eq. (6), which depends on PMV:

$$PPD=100-95\times\exp\left(-0.003353\times PMV^4-0.2179\times PMV^2\right) \quad (6)$$

2.2. Profile of the cognitive reliability of the task

In this step, the description of the event sequence is refined by identifying the cognitive activities that characterize each task step. The cognitive activities are then used to build a cognitive profile for the main task segments, based on the functions described by the underlying cognitive model (Taylor and Lawson, 2009).

Series-parallel hybrid systems are among the most widely used systems in engineering. Based on the characteristics of the tasks performed by the oceanauts, we constructed a cognitive demand model for each task that allowed us to calculate the CFP of the system.

The hybrid system consists of two modes: (a) the series-parallel system, and (b) the parallel-series system. The whole system is made up of n subsystems. Each subsystem i consists of m_i components, $i=1, 2, \ldots, n$. $R_i(t)$ is the failure probability of the components in subsystem i, as shown in Fig. 3.

$$R_{PS}=\prod_{i=1}^{n}\left(\prod_{j=1}^{m_i}R_{ij}\right) \quad (7)$$

Series–parallel system failure probability (Yalaoui et al., 2005):

$$R_{SP}=1-\prod_{i=1}^{n}\left(1-\prod_{j=1}^{m_i}R_{ij}\right) \quad (8)$$

where R_{PS} is the parallel-series system reliability, R_{SP} is the series-parallel system reliability, R_{ij} *is* the reliability of the jth component of subsystem i ($i=1, \ldots, n$ and $j=1, \ldots, m_i$).

For this research, we classified cognitive processes according to the cognitive activities of the oceanauts. Each task was considered to include seven major activities (P1–P7) as shown in Fig. 4. In summary, the cognitive challenge for oceanauts is to manage the dive activities by looking for or reading system indicators, judging the environment and dive state comprehensively, and making decisions in a timely manner based on the equipment feedback data. The current version of the list of characteristic cognitive activities is shown in Table 2.where R_P denotes the cognitive activities CFP, $\overline{R_P}$ is the coefficient of cognitive activities reliability correction, R_{Pi} is the critical cognitive activities CFP, and $i=1, 2, 3, \ldots, n$, $n=7$.

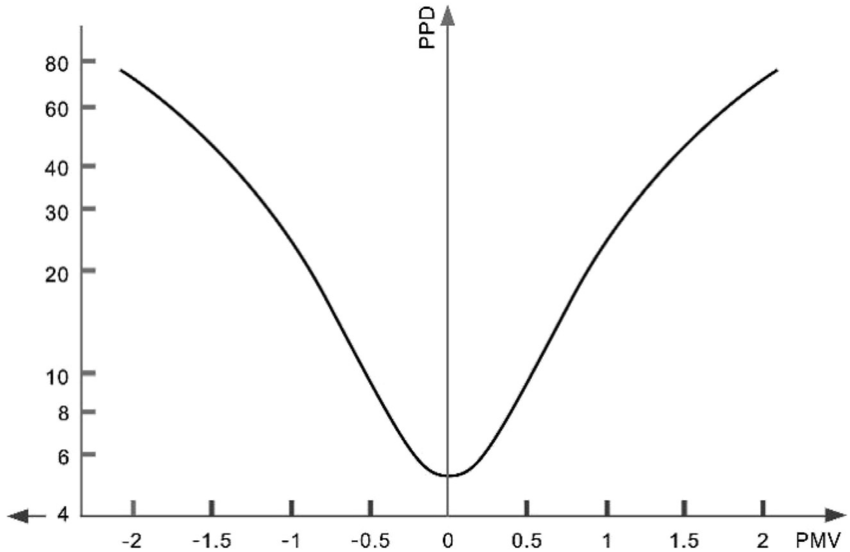
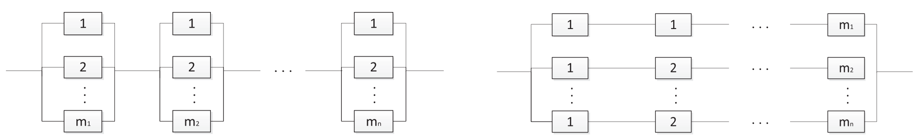


Fig. 2. PPD as function of PMV.



(a) Parallel – Series (b) Series–parallel

Fig. 3. Series–Parallel system structure and Parallel-Series system structure (Yalaoui et al., 2005; Sarhan et al., 2008).

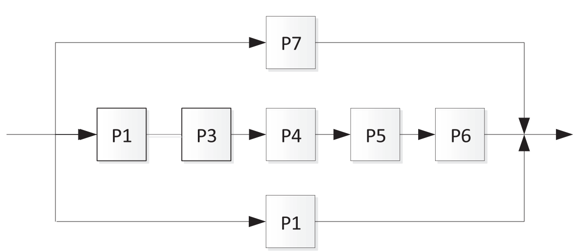


Fig. 4. Parallel-Series reliability mode of cognitive processes.

2.3. CFP with CREAM method

2.3.1. CFP evaluation

In the CREAM approach, the context influence index (β) is defined as the difference between the number of reduced CPC and the number of improved CPC. The performance influence index (ρ) is based on the expected effect of a CPC on the performance reliability, and is used to account for the specific quantitative influences of the CPC. The value of the ρ is based mainly on the weighting factor provided by the extended CREAM technique and adjusted by the expert judgments.

Thus, the CII could be written as follows (Hancher and Abd-Elkhalek, 1998):

Table 2
List of critical cognitive activities.

$$R_P = \overline{R_P}(1 - R_{P1})(1 - R_{P2}R_{P3}R_{P4}R_{P5}R_{P6})(1 - R_{P7}), \tag{9}$$

$$\overline{R_P} = \frac{\sum_{i=1}^{n} R_{Pi}}{n} \tag{10}$$

Cognitive activity	General definition
P1 Observe	Look for or read specific measurement values or system indicators.
P2 Identify	Analyze the sub-system (component) states.
P3 Diagnose	Recognize or determine the nature or cause of a condition by means of reasoning about signs or symptoms, or by the performance of appropriate tests.
P4 Plan	Formulate or organize a set of actions by which a goal will be achieved that addresses the diagnosed issue.
P5 Execute	Perform a previously specified action or plan. Execution comprises actions such as open/close, start/stop, fill/drain, etc.
P6 Verify	Confirm the correctness of a system condition or measurement, either by inspection or test.
P7 Co-ordinate	Bring system states and/or control configurations into the specific relations required to carry out a task or task step. This also includes checking the feedback from prior operations.

$$\beta = \sum_{n=1}^{9} \rho_n \tag{11}$$

$$CFP = CFP_0 \times 10^{0.25\beta} \tag{12}$$

where β is the context influence index, and ρ is the performance influence index.

2.3.2. CPC and performance influence index(ρ)

The CPC provide a well-structured, comprehensive basis for characterizing the conditions that influence working performance. The context for cognition and action for a given task is determined in accordance with the CPC. CPC are utilized by the CREAM technique to define sets of possible error modes and causes of errors. The CPC and related performance reliability are shown in Table 3 (Taylor and Lawson, 2009). Since the procedures used on the manned submersible deep-sea mission need extra attention from the oceanauts, maritime human reliability analysis is essential. Reliability analysis can be performed initially based on the CPC of the CREAM approach, but this analysis depends on identification of the nine CPC (Chen et al., 2017). For our research, we posed the subjective CPC questions to marine experts (marine engineers and HSEQ managers) and the ship's crew (Master and Chief Officer) to get the levels for the seven main steps of the cognitive processes. The result was reduced to one CPC level by finding the geometric means of all results. Table 3 shows the CPC assessment by selected respondents for the work performed in the manned submersible mission. Table 3 lists the ρ values in the CPC. It is noted that these values are flexible, rather than fixed and unchangeable, in order to be used in practical application to manned submersibles.

2.3.3. Control modes

As mentioned previously, there are four characteristic control modes defined in CREAM. They are connected with human cognition and action, and they are determined by the CPC. The four control modes—Scrambled, Opportunistic, Tactical, and Strategic—are linked with different failure probability intervals representing human action failure probabilities (Taylor and Lawson, 2009), as described in Table 4. The control modes can be used to characterize the performance of an individual, team, or group of people equally well.

2.3.4. Cognitive function failures recognition(CFP_0)

The purpose of this step of the extended CREAM technique is to identify likely cognitive function failures (Chen et al., 2017). Based on the phenotype-genotype classification of erroneous actions, it is possible to produce a complete list of cognitive function failures. As shown in Table 5 cognitive function failures are defined relative to the four cognitive functions in the associated model: observation errors (O), interpretation errors (I), planning errors (P), execution errors (E). The purpose of identifying the likely cognitive function failures is not to consider all the possible ways in which each step or a specific step of the task can fail, but rather to determine what predominant type of failure can be expected for the task as a whole. Table 5 shows the basic values of cognitive function failure probability. The characteristics of the nine CPC are used to adjust the nominal CFP values to get the final error probability. The basic CFP is noted as CFP_0.

Table 3
CPC level and performance weighting factor for manned submersible (Hollnagel, 1998).

n	CPC name	CPC level/description	Effects	ρ			
				O	I	P	E
CPC1	Adequacy of organization	Very efficient	Improved	−1.0	−1.0	−0.8	−0.7
		Efficient	Not significant	0	0	0	0
		Inefficient	Reduced	1	1	1.2	1.4
		Deficient	Reduced	1	1	1.8	2
CPC 2	Working conditions	Advantageous	Improved	−0.7	−0.8	−1	−0.7
		Compatible	Not significant	0	0	0	0
		Incompatible	Reduced	1.4	1.2	1	1.6
CPC 3	Adequacy of MMI and operational support	Supportive	Improved	−0.7	−1	−1	−0.6
		Adequate	Not significant	0	0	0	0
		Tolerable	Not significant	0	0	0	0
		Inappropriate	Reduced	2.2	1.2	0.9	2.4
CPC 4	Availability of procedures/plans	Appropriate	Improved	−0.8	−1	−0.5	−0.7
		Acceptable	Not significant	0	0	0	0
		Inappropriate	Reduced	1.5	1	3.1	2.1
CPC 5	Number of simultaneous goals	Fewer than capacity	Not significant	0	0	0	0
		Matching current capacity	Not significant	0	0	0	0
		More than capacity	Reduced	1.5	1.3	1.2	1.6
CPC 6	Available time	Adequate	Improved	−0.8	−0.5	−0.5	−0.6
		Temporarily inadequate	Not significant	0	0	0	0
		Continuously inadequate	Reduced	1.9	2.1	2.2	2.6
CPC 7	Time of day	Day-time (adjusted)	Not significant	0	0	0	0
		Night-time (unadjusted)	Reduced	1.5	1.2	1.4	1.3
CPC 8	Adequacy of training and experience	Adequate, high experience	Improved	−0.8	−0.5	−0.6	−0.8
		Adequate, limited experience	Not significant	0	0	0	0
		Inadequate	Reduced	1.5	2.8	2.6	2
CPC 9	Crew collaboration quality	Very efficient	Improved	−0.8	−0.9	−0.9	−0.6
		Efficient	Not significant	0	0	0	0
		Inefficient	Not significant	0	0	0	0
		Deficient	Reduced	1.5	1.2	1.3	2.2

Table 4
CPC control modes and their probability interval (Taylor and Lawson, 2009).

Control mode	Probability intervals.	Describe
Strategic	0.5E-5<P < 1.0E-2	the choice of next action is in practice unpredictable or haphazard.
Tactical	1.0E-3<P < 1.0E-1	the next action is determined by the salient features of the current context rather than on more stable intentions or goals. The
Opportunistic	1.0E-2<P < 0.5E-0	performance is based on planning, hence more or less follows a known procedure or rule.
Scrambled	1.0E-1<P < 1.0E-0	the person considers the global context, thus using a wider time horizon and looking ahead at higher level goals. The

Table 5
The basic values of cognitive function failure probability (Hollnagel, 1998).

Cognitive function	Potential cognitive function failure		CFP_0
Observation errors (O)	O1	Observation of wrong object. A response is given to the wrong stimulus or event.	1.0E-3
	O2	Wrong identification made, due to e.g. a mistaken cue or partial identification.	7.0 E-2
	O3	Observation not made, overlooking a signal or a measurement.	7.0 E-2
Interpretation errors (I)	I1	Faulty diagnosis, either a wrong diagnosis or an incomplete diagnosis.	2.0 E-1
	I2	Decision error, either not making a decision or making a wrong or incomplete decision.	1.0 E-2
	I3	Delayed interpretation, i.e., not made in time.	1.0 E-2
Planning errors (P)	P1	Priority error, as in selecting the wrong goal (intention)	1.0 E-2
	P2	Inadequate plan formulated, when the plan is either incomplete or directly wrong.	1.0 E-2
Execution errors (E)	E1	Execution of wrong type performed, with regard to force, distance, speed or direction.	3.0 E-3
	E2	Action performed at wrong time, either too early or too late.	3.0 E-3
	E3	Action on wrong object (neighbor, similar or unrelated)	5.0 E-4
	E4	Action performed out of sequence, such as repetitions, jumps, and reversals.	3.0 E-3
	E5	Action missed, not performed, including the omission of the last action in a series.	3.0 E-2

2.4. CFP in a dynamic environment

2.4.1. Correction factor

The CFP is a static evaluation in traditional CREAM method. The influence of a dynamic environment onboard a manned submersible can cause productivity loss. The mission reliability is under the influence of CFP and productivity. With R_0 is the initial CFP, CR is the corrected CFP, k is the correction factor. We assume that the CFP of mission reliability is proportional to productivity, thus:

$$CR = R_0 \times k \tag{13}$$

With $\triangle R$ is the variation of the CFP, P_0 is the initial productivity ($P_0 = 100$), P is the corrected productivity ($P < 100$), $\triangle P$ is the variation of the productivity. We assume that the CFP change rate is equal to productivity change rate. Then the relational model of the change rate and correction factor is the following:

$$\frac{\Delta R}{R_0} = \frac{\Delta P}{P_0} \tag{14}$$

$$\frac{|CR - R_0|}{R_0} = \frac{|P_0 - P|}{P_0} \tag{15}$$

$$k = 2 - P\% \tag{16}$$

2.4.2. Productivity loss

The PMV-Productivity method was proposed by Australian scholars Sherif Mohamed and Korb Srinavin (Mohamed and Srinavin, 2005). Depth-sea mission belong to light physical labor, use the mathematical regression models for light construction tasks. The PMV was selected to be the independent variable to establish Eq. (17):

$$P = 102 - 0.80PMV - 1.84PMV^2 \tag{17}$$

where P is the productivity of light physical labor, $\triangle P$ is productivity loss (Sun et al., 2012).

We make an assumption that uses the assumed productivity loss for the change of failure probability, and we use the PMV-PPD index to correct the CFP.

$$k = 2 - P\% = \frac{98 + 0.80PMV + 1.84PMV^2}{100} \tag{18}$$

3. Demonstration

In this section, we demonstrate how we used PMV-PPD and extended CREAM to conduct a human reliability assessment for a manned submersible.

3.1. Task cycle phase

According to the typical task characteristics, a deep-sea mission consists of eight stages, as shown in Table 6: (A) Laying, (B) Sea surface, (C) Diving, (D) Cruising, (E) Landing, (F) Floating, (G) Sea surface, and (H) Recovering. We used the average data that Jiaolong 7,000 m depth-sea mission (At lower latitudes). The whole process lasted more than 12 h, and ran from 06:30–18:50 for a total of 740 min, excluding ship preparation and inspection time. Fig. 5 shows the curve for depth and task segmentation during the mission process.

3.2. PPV dynamic data

3.2.1. Environmental change characteristics

For this paper, we took average dynamic environment data for the time period 06:30–07:50 in typical low-latitude seas of the Jiaolong manned submersible cabin (The data come from Director of China Ship Scientific Research Center). We selected 75 sets of dynamic data for a 10-min interval. The temperature data was $ta = \{ta_1, ta_2, ta_3 \ldots ta_{75}\}$, and the relative humidity data was $\varphi_a = \{\varphi_{a1}, \varphi_{a2}\varphi_{a3} \cdots \varphi_{a75}\}$.

Fig. 6 and Fig. 7 shows the 7000m tasks temperature curve and

Table 6
Typical task characteristics and time.

Stage (St)	A	B	C	D	E	F	G	H
n	1–3	4–6	7–16	17–25	26–38	39–70	68–72	73–75
Time	6:30–6:50	6:50–7:20	7:20–9:00	9:00–10:30	10:30–14:30	14:30–17:50	18:00–18:20	18:20–18:50
Duration	20 min	30 min	105 min	85 min	245 min	210 min	20 min	30 min

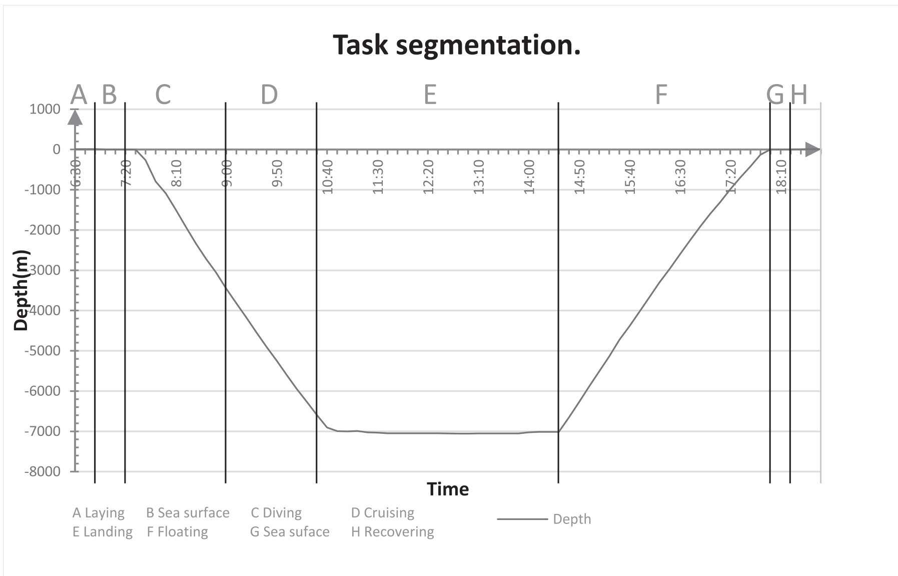


Fig. 5. Task segmentation.

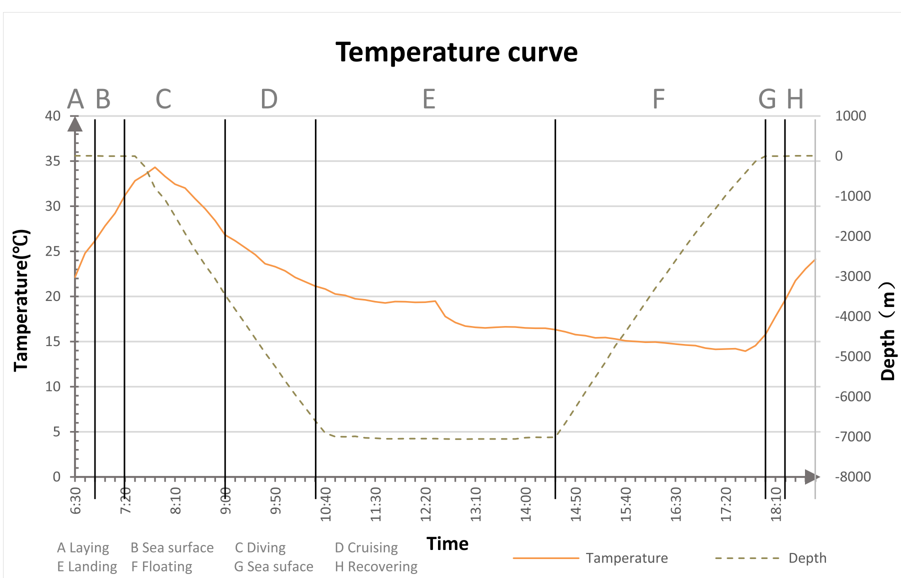


Fig. 6. Temperature curve.

the humidity curve in the cabin.

3.2.2. Human factors data

Human factors data may include different combinations of metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity, and air humidity (ISO, 2005). Based on the manned submersible cabin environment and personnel characteristics, our basic assumptions were as follows. Table 8 reports the results of the human factors data.

- Radiant temperature was assumed to be equal to the room temperature.
- Air velocity was 0.15 m/s. (According to the ASHRAE standard, air velocity below 0.15 m/s is considered "still air.") (ASHRAE, 2004)

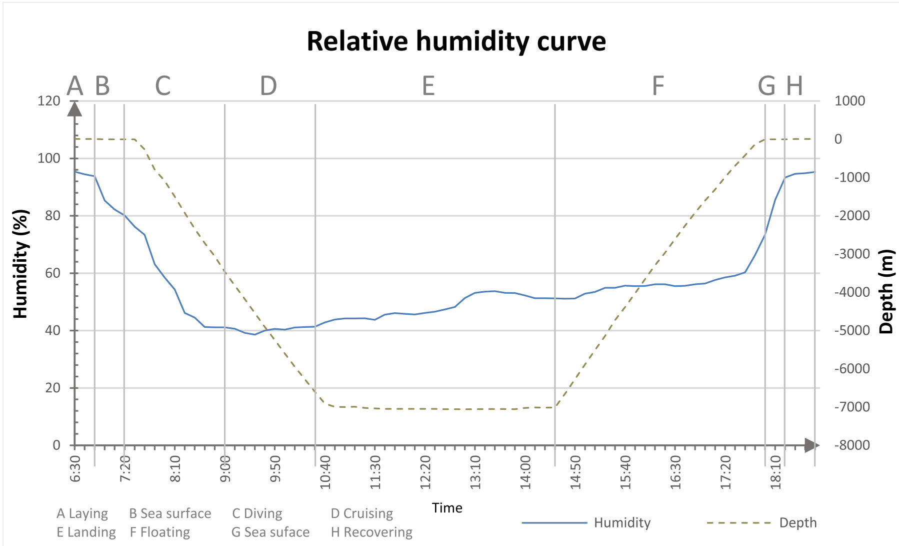


Fig. 7. Relative humidity curve.

Table 7
(I_{cl}) Clothing insulation.

Clothing	I_{cli}	
	clo	$m^2 \cdot K/W$
Panties	0.03	0.005
Short sleeves	0.15	0.023
Trousers/Normal	0.25	0.039
Outdoor clothing/Coat	0.60	0.093
Socks	0.02	0.003
Shoes (thin soled)	0.02	0.003
Standard office chair	0.1	0.016
SUBTOTAL	1.17	0.182

1.0 clo = 0.155 m^2 K/W = 0.133 m^2 h°C/kcal.
I_{cl} = sum (I_{cli}) = 1.17 clo = 0.182 m^2 K/W.
Clothing insulation $I_{cl} > 0.078m^2K/W$, using Eq. (4), Calculable $fcl = 1.16497125$.

Table 8
Human factors data.

Human factors	Data
(M) Metabolic rate	70 W/m^2
(W) Effective mechanical power	0
(f_{cl}) Clothing surface area factor	1.16497125
(t_a) Air temperature	Fig. 6
($\overline{t_r}$) Mean radiant temperature	ta
(v_{ar}) Air velocity	0.15 m/s
(p_a) Partial vapor pressure	Eq. (5)
(h_c) Convective heat transfer coefficient	5.1
(t_{cl}) Surface temperature of clothing	Eq. (2)

- Working conditions for the oceanauts were typical, mainly requiring mild activities or sitting, making observations, communicating, using operation buttons, operating "arms," or performing other similar tasks. According to the ISO7730 standard, the oceanauts' operation level was Sedentary activity, with a metabolic rate of $M = 70\ W/m^2 = 1.2$ Met.
- The cabin air temperature was as shown in Fig. 6:
  - $ta = \{ta_1, ta_2, ta_3 \ldots ta_{75}\}$
- The cabin relative humidity was as shown in Fig. 7:
  - $\varphi = \{\varphi_1, \varphi_2, \varphi_3 \ldots \varphi_{75}\}$
- The clothing insulation was calculated according to the current personnel clothing combination as shown in Table 7.
- The Partial vapor pressure was derived from Eq. (5), with *ta* and φ as shown in Figs. 6 and 7.
- Based on the characteristics of the manned submersible personnel and cabin environment, we obtained the following data as shown in Table 8: (t_{cl}) denotes the surface temperature of clothing using Eq. (2); (h_c) is the convective heat transfer coefficient using Eq. (3); (f_{cl}) is the clothing surface area factor using Eq. (4); and (P_a) is the partial vapor pressure using Eq. (5).

PMV and PPD were calculated to find the optimal air temperature for the cabin. In this calculation, we assumed that the mean radiant temperature of the environment was equal to the dry bulb air temperature, and the relative air velocity was 0.15 m/s.

3.2.3. PMV index calculation

We used a MATLAB software program to calculate the PMV index and draw curves.

$$PMV = \{PMV_1, PMV_2, PMV_3 \ldots, PMV_{75}\}.$$

Fig. 8 shows the PMV change curve.

3.3. CFP based on extended CREAM

3.3.1. Step 1 – calculating β using Eq. (11)

Cognitive function failures are defined relative to the four cognitive functions in the associated model: observation errors (o), interpretation errors (i), planning Errors (p), execution Errors (e). Each step of the cognitive process was divided into sub-steps for defining cognitive functions. In this way, the likely cognitive failure type for each cognitive activity could be identified and calculated in accordance with Eq. (11) by utilizing normal CFP values and CPC in Table 3.

$$\beta_i = \sum_{n=1}^{9} \rho_{in} = -1.7, \quad \beta_p = \sum_{n=1}^{9} \rho_{pn} = -1.8, \quad \beta_e = \sum_{n=1}^{9} \rho_{en} = -1.1$$

where *o, i, p, e* is the cognitive function. n is CPC number, ρ_{on} is the

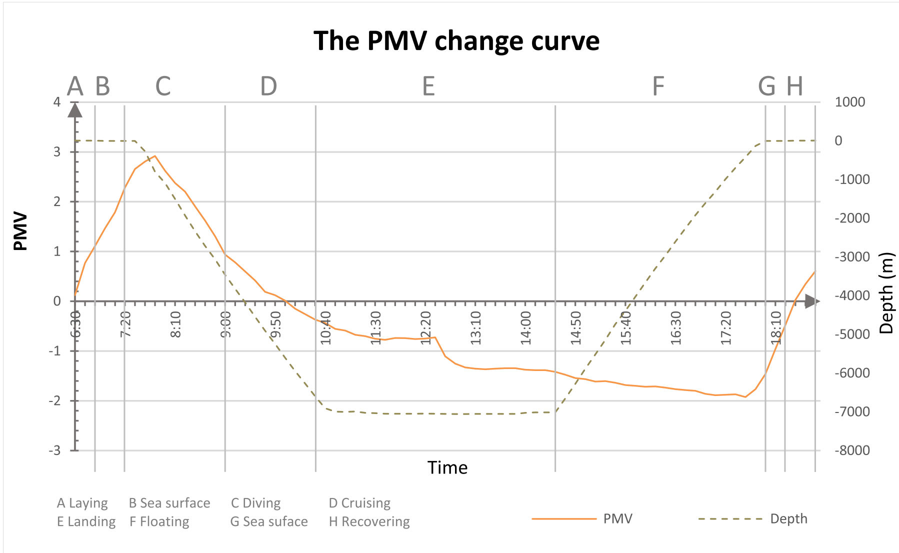


Fig. 8. The PMV change curve.

observation errors performance influence index of the CPC_n. (see Table 3)

3.3.2. Step 2 — finding the basic cognitive values of the 7 major activities (P1–P7)

Through the analysis of the cognitive processes of the oceanauts as shown in Fig. 4, we found the potential cognitive function failure and the basic value of the 7 major activities as shown in Table 9.

3.3.3. Step 3 — calculating the CFP of 7 major activities (P1–P7)

Reliability analysis based on an extended version for each cognitive process is illustrated in Table 10, including cognitive activity, cognitive function errors, potential cognitive function failure, basic value, the context influence index, and the CFP. Consequently, the adjusted CFP can be calculated in accordance with Eq. (12), as shown:

Table 9
List of critical cognitive activities.

Cognitive activity	General Definition	Potential cognitive function failure	Basic value (CFP_0)
P1 Observe	Look for or read specific measurement values or system indicators.	o2 Wrong identification made, because of e.g., a mistaken cue or partial identification.	7.0E-2
P2 Identify	Analyze the identity of sub-system (component) state.	i1 Faulty diagnosis, i.e., either a wrong diagnosis or incomplete diagnosis.	2.0E-1
P3 Diagnose	Recognize or determine the nature or cause of a condition by means of reasoning about signs or symptoms, or by the performance of appropriate tests.	i2 Decision error, i.e., either failing to make a decision, or making a wrong or incomplete decision.	1.0E-2
P4 Plan	Formulate or organize a set of actions by which a goal will be achieved successfully.	p2 Inadequate plan formulated, when the plan is either incomplete or directly wrong.	1.0E-2
P5 Execute	Perform a previously specified action or plan. Execution comprises actions such as open/close, start/stop, fill/drain, etc.	e1 Execution of the wrong type is performed regarding force, distance, speed, or direction.	3.0E-3
P6 Verify	Confirm the correctness of a system condition or measurement, either by inspection or test.	o3 Observation not made, e.g., overlooking a signal or a measurement.	7.0E-2
P7 Co-ordinate	Bring system states and/or control configurations into the specific relation required to carry out a task or task step. This also includes checking the feedback from prior operations.	e5 Action missed or not performed (omitted), including omission of the last actions in a series.	3.0E-3

Table 10
Recognition matching and error probability of cognitive function.

Cognitive Activity	Cognitive function errors				Potential cognitive function failure	Basic value (CFP_0)	Context influence index (β)	Cognitive failure probability (CFPx)
	Observation (o)	Interpretation (i)	Planning (p)	Execution (e)				
P1	√				o2	7.0E-2	−2	R_{P1}
P2		√			i1	2.0E-1	−1.7	R_{P2}
P3		√			i2	1.0E-2	−1.7	R_{P3}
P4			√		p2	1.0E-2	−1.8	R_{P4}
P5				√	e1	3.0E-3	−1.1	R_{P5}
P6	√				o3	7.0E-2	−2	R_{P6}
P7				√	e5	3.0E-3	−1.1	R_{P7}

$$R_{Pi} = CFP0_{Pi} \times 10^{0.25\beta_{Pi}}, \tag{19}$$

where Pi represents the 7 major cognitive activities, i = 1,2,3 …,7, β_{Pi} is the context influence index of Pi, and CFP_{0pi} is the basic CFP of Pi.

3.4. Dynamics of CR for the cognitive activities system

The traditional CREAM CFP is a statistical evaluation method. The influence of a dynamic environment as encountered on a manned submersible can cause a change in failure probability. We considered using the PMV-PPD index to correct for CFP, as follows.

With Eq. (18) and PMV = {PMV_1, …, PMV_{75}}, we can get the dynamic correction factor k_j.

$$k_j = \frac{98 + 0.80PMV_j + 1.84PMV_j^2}{100}, \tag{20}$$

where k_j is the correction factor, and $j = 1, \ldots, 75$.

Add the dynamic correction factor k to Eq. (13), and we get the corrected CFP (CR_{Pi}):

$$CR_{Pi} = R_{Pi} \times k_j, \tag{21}$$

where Pi productivity the 7 major cognitive activities, $i = 1, \ldots, 7$, CR_{Pi} is the corrected CFP of Pi, k_j is the correction factor, and $j = 1,2,3 \ldots, 75$.

Build the corrected CFP for the cognitive activities system with the correction factor k and the Eq. (9) and (13):

$$CR = \frac{\sum_{i=1}^{n} CR_{Pi}}{n}(1 - CR_{P1})(1 - CR_{P2}CR_{P3}CR_{P4}CR_{P5}CR_{P6})(1 - CR_{P7}), \tag{22}$$

$$CR_j = \frac{\sum_{i=1}^{n} R_{Pi} \times k_j}{n}\left[1 - R_{P1} \times k_j\right]\left[1 - R_{P2}R_{P3}R_{P4}R_{P5}R_{P6} \times k_j^5\right] \times \left[1 - R_{P7} \times k_j\right], \tag{23}$$

where CR is the corrected CFP of the cognitive activities system, Pi represents the 7 major cognitive activities, $0 < n \le 7$, CR_{Pi} is the corrected CFP of Pi, R_{Pi} is the CFP of Pi, k_j is the correction factor, and $j = 1, \ldots, 75$. Table 11 shows the main part of the calculation with Eqs. (20)–(22).

By comparing temperature, humidity, and depth with CR, our results showed that temperature was the main parameter that affected CR, and the effect of humidity was not apparent. As Table 11 shows, the maximum level of CR occurred in stage C, and the minimum level of CR occurred in stage D. During the stages E, F, and G, the CR oscillated at a low level. Finally, the CR fell back in stage H, as described below.

- At 07:50, the CR were 4.2948E-3 (max), the temperature was 34.32 °C (max), and the humidity was 63.14%. When the manned submersible was in stage C and started diving, the tasks of the oceanauts included checking the operation of various pieces of equipment and contacting the mother ship. During this time, the oceanauts faced high work intensity and multiple mission objectives. The environment had a greater impact on the tasks because the team members needed to pay close attention.
- At 10:20, the CR were 3.0615E-03 (min), the temperature was 21.63 °C, and the humidity was 41.23%. The manned submersible was in stage D, and the mission objectives included cruising, placing equipment, shooting, and sampling, among other operations. During this time, the temperature of the environment had the least influence on the operating conditions of the oceanauts.
- During the time period 10:20–12:40, the CR remained at a low level, and the temperature stayed at about 19.3°C–23 °C. At this point, the mission was in stage E, and the operating environment was suitable for work.
- During 12:50–17:40, the CR rose in a wave-like way as if affected by the temperature drop. The CR were 3.4052E-03 at 17:40 (the next to highest value reached by the CR), the temperature was 13.94 °C, and the humidity was 60.32%. Then the manned submersible was in stage F, and the low temperature affected the oceanauts' state to a certain extent. By this time, the oceanauts had already experienced 6 h of continuous work, and their physical and mental conditions were poor. Although the floating stage had no complicated tasks to complete, the oceanauts might be required to provide an emergency response in case adverse circumstances unexpectedly impacted the submerged floating process, such as equipment failure, lack of buoyancy, lack of oxygen, or energy shortage. Therefore, this stage required the attention of the team.
- By 18:30, the manned submersible had floated to the surface. It was in stage G. The CR were 3.0682E-03 (the next to lowest value reached by the CR), the temperature was 21.76 °C, and the humidity was 94.62%. At this point, the team was required to adjust the device status and wait for recovery. Under normal circumstances, by this time the oceanauts are generally in good condition. However, manned submersibles can drift on the surface of the sea for some time, because the recovery process involves waiting for outside personnel to coordinate their operations with the mother ship. The recovery could be affected adversely by the weather or equipment, so the recycling operation might not be completed in a timely fashion. Over a long time, the sea cabin temperature will continue to rise, and high temperatures and high humidity could deteriorate the oceanauts' status.

4. Sample analysis and discussion of the results

The first- and second-generation HRA methods, by any definition, have featured largely static task analyses of operating events as the underlying basis of performance modeling. These methods have also relied on performance estimations mapped to similar previous performance derived through empirical data or expert opinion. (Boring, 2007). Most these HRA methods are designed to capture human performance at a point in time. These models can be considered static HRA models, in that they do not explicate how an environment change affects CFPs and the event progression downstream. Simulation-based dynamic HRA may be called third generation HRA, The HRA carried out in this article is from the impact of the working environment on people.

The HRA methodology based on PMV-CREAM proposed in study is not confined to a specific task or procedure in manned submersible, but a generalized method in the maritime safety field used to evaluate CFP the human reliability of seafarers when the thermal comfort of their working environment is harsh and dynamic. To demonstrate the applicability of the PMV- CREAM proposed in this research, an example about manned submersible deep-sea mission is introduced in Section 3. Our results showed that the cognitive failure probabilities of oceanauts can be affected

Table 11
Key variation parameters.

n	Time	Depth(m)	Temperature(°C)	Humidity	CFP	States	Stage
1	6:30	8.17	22.13	95.37	3.0745E-03	Start	A
…	…	…	…	…	…	Up	
8	7:40	−267.13	33.51	73.38%	4.2015E-03	Up	C
9	7:50	−795.62	34.32	63.14%	4.2948E-03	max	C
10	8:00	−1088.37	33.31	58.48%	4.0586E-03	Down	C
…	…	…	…	…	…	Down	
23	10:10	−5946.83	22.12	41.08%	3.0618E-03	Down	D
24	10:20	−6268.95	21.63	41.23%	3.0615E-03	Min	D
25	10:30	−6596.55	21.15	41.31%	3.0639E-03	Up	D
…	…	…	…	…	…	Up	
32	11:40	−7047.37	19.28	45.53%	3.0970E-03	Up	E
33	11:50	−7047.28	19.43	46.10%	3.0924E-03	Down	E
34	12:00	−7046.96	19.42	45.81%	3.0929E-03	Up	E
35	12:10	−7046.94	19.35	45.62%	3.0949E-03	Up	E
36	12:20	−7046.58	19.37	46.12%	3.0941E-03	Down	E
37	12:30	−7046.92	19.48	46.58%	3.0908E-03	Down	E
38	12:40	−7053.22	17.78	47.38%	3.1526E-03	Up	E
39	12:50	−7054.83	17.11	48.25%	3.1858E-03	Up	F
40	13:00	−7056.73	16.72	51.34	3.2050E-03	Up	E
41	13:20	−7052.18	16.52	53.56%	3.2117E-03	Up	F
42	13:30	−7051.49	16.58	53.73%	3.2149E-03	Down	F
43	13:40	−7052.34	16.63	53.12%	3.2111E-03	Down	F
44	13:50	−7053.13	16.62	53.10%	3.2087E-03	Up	F
64	17:00	−1603.54	14.28	56.37%	3.3794E-03	Up	F
65	17:10	−1310.67	14.14	57.62%	3.3904E-03	Up	F
66	17:20	−988.92	14.17	58.53%	3.3865E-03	Down	F
67	17:30	−696.05	14.21	59.10%	3.3822E-03	Down	F
68	17:40	−418.76	13.94	60.32%	3.4052E-03	Up	F
69	17:50	−129.79	14.56	66.35%	3.3428E-03	Down	F
…	…	…	…	…	…	Down	
73	18:30	5.76	21.76	94.62%	3.0682E-03	Down	G
74	18:40	7.87	23.06	94.87%	3.0978E-03	Up	H
75	18:50	8.17	24.12	95.29%	3.1400E-03	END	H

by the dynamic and difficult environment aboard manned submersibles during deep-sea missions, as shown in Fig. 9. We found that the oceanauts provided good performance reliability. Typically, their performance followed planned procedures, but some temporal deviations were possible with changes in the temperature and relative humidity.

In section 3, the environment of manned submersible provides two favorable conditions for PMV-CREAM. First, the environment is a continuous dynamic change. During the deep-sea missions, Significant changes in thermal environment have obvious effect on oceanaut's work. Second, The operating mission in the closed cabin is light physical activity of the sitting position, use the PMV-Productivity method evaluate productivity loss is valid. Although the proposed PMV-CREAM can predict the effects of dynamic thermal environment on CR, however, in practice, it is not always easy to do this forecast since the accident development process

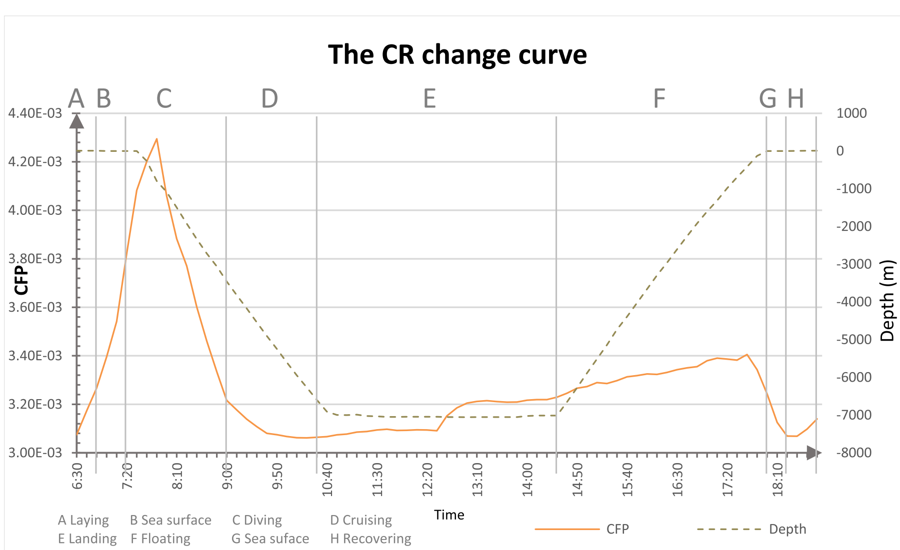


Fig. 9. The CR change curve.

varies in terms of the changeable navigational environment factors and unknown crew actions. In addition to thermal comfort, there are many factors that affect the working efficiency and reliability of people for ocean operation, such as lighting, noise, waves and working time. So the key to further study is the influence of other factors on human reliability.

For this research, we describe the general task process through cognitive processes to guaranteed application of the PMV-CREAM method in other fields. Get instant CR through calculation of cognitive process nodes based on extended CREAM. As described in this paper, human performance simulation in dynamic environment reveals important new data sources and possibilities for exploring human reliability. These data sources hold tremendous promise for HRA, but there are significant challenges to be resolved, particularly with regard to the dynamic nature of people performance status vs. the mostly static nature of conventional.

5. Conclusion

For both safety and loss prevention, the performance reliability of oceanauts must be at its highest level when exploring ocean resources. This paper provided a dynamic quantified human reliability assessment for manned submersibles by utilizing an extended CREAM approach based on the PMV-PPD indices.

To demonstrate our proposed application of PMV-PPD and CREAM, we conducted a human reliability assessment using a Jiaolong 7,000 m manned test dive. Our results showed that the CR during the manned submersible's operation ranged from 3.0615E-3 to 4.2948E-3, The largest CR difference of value caused by the environment is 1.2333E-3. Based on this finding, we conclude that the performance reliability of the manned submersible team was reliable. Typically, their performance followed planned procedures, but some temporal deviations were possible.

Because the submersible has a changing environment, the various procedures have a relatively high level of complexity. To explore the implications of the changing features on performance, we analyzed the manned submersible's operation process. The results of our research demonstrated that human performance reliability was at the desired level throughout the operation. The available statistical data also confirmed that the results were consistent and reasonable.

This research is expected to yield an original contribution that can be used by the submersible design institutes, marine resources development organizations, and safety engineers to evaluate the performance reliability of oceanauts on manned submersibles. Our work focused on performing quantified data analysis to prove the applicability of the extended CREAM approach to the procedures involved in manned submersible deep-sea missions. We highlight the following aspects of the research:

i. The dynamic PMV-CREAM model can utilize both qualitative and quantitative data to enhance safety parameters for the process of conducting deep-sea scientific research and resource exploration in 99.8 percent of the world's oceans.
ii. This research is expected to contribute to the efforts to develop assessments of oceanauts' performance reliability, thereby helping to increase efficiency while improving loss prevention in manned submersibles.
iii. The quantified outcomes of the research, such as the CR corrected by the PMV index, can be utilized to avoid human error and ensure safety in deep-sea research, thereby preventing human injury and loss of life.
iv. In the future, data about the influence of the changeable character of the submersible environment will be used to guide and optimize task allocation, as well as improve the design of the cabin layout and cabin environment.

In conclusion, this research developed a dynamic human reliability assessment approach applicable to monitoring the cognitive actions and attitudes of oceanauts during deep-sea missions. The model can be applied to any other critical operational process in a similar environment, such as a deep-space station, airtight cabin of a ship, or sightseeing submersible, where crew reliability has a high level of importance. Further investigations may be concerned with enhancing consistency in the PMV-CREAM approach by focusing on task operation characteristics and environmental influences on various cognitive behaviors.

Declarations of interest

None.

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