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A new approach to human error assessment in financial service based on the modified CREAM and DANP

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Abstract

The main purpose of this study is to identify and determine the most important sub-tasks of stockbroking that affect the reliability of human resources. The cognitive reliability and error analysis (CREAM) method has been used to calculate the human error. To consider the different effects of work condition factors for each condition performance common (CPC), they are weighted using the decision analytical network process (DANP) method. The highest amount of the detected errors related to execution error, interpretation error, and planning error are 67%, 25%, 8%, respectively and probability of total cognitive error in the task of "stockbroker" is 0.1414. Considering equal impact for all CPCs on performance reliability is the most important gap and limitation in most previous studies. In this study, the relationship between CPCs has been investigated using the DANP. Moreover, the relationship between HEP and the work environment error are calculated by humans with the Napierian logarithm function.

Keywords: Human reliability, cognitive reliability and error analysis method (CREAM), decision analytical network process (DANP), financial service

1-Introduction

Investment in the economic growth and development of countries is of vital important and is one of the effective factors in determining the type risk, and Return on Investment (ROI). Most economists and financial experts put their efforts into identifying and measuring the investment risk (Arthur, et al., 2018). The financial and capital market enables long-term investment by raising funds and presenting them to investors (Arthur, et al., 2018). Liquidity and productivity risk that investors are faced with in financial markets varies, and obtaining information about them will be costly for investors. Therefore, the presence of stockbrokers to provide information for investing in low-risk projects and having economic justification will be very effective so that resources flow properly and efficiently to the real sectors of the economy. The stock market can have very complex time series data. The complexity and importance of financial risks in investment markets, reveals the vital role of stockbrokers in financial and economic processes. However, considering that human errors are inevitable, it seems necessary to analyze the stock broker's errors and devise appropriate control strategies to reduce these errors. One of the sectors in the financial industry that can lead to financial losses due to human error is stock exchange brokerage.

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The nature of activities in stock brokerage is such that it imposes a lot of mental work load on people and makes them prone to error (Meshkati, 1991). Stockbrokers are responsible for the technical analysis of past trades and also predict the movement of future market prices with the help of various indicators (Aouni, et al., 2018). They also study the behavioral aspects of financial markets to develop models for predicting future stock value (Cavalcante, et al., 2016; Whittingham, 2004). Given that people's behavior is affected by specific working conditions, it is necessary to pay more attention to the problem of human error and evaluate the working conditions affecting these errors. Human errors are assumed to be unintentional, and that the actions leading to failure are taken purposefully to achieve an expected result, but the result is not achieved within its permissible range (Whittingham, 2004). There are a variety of methods and techniques for reducing human errors. These techniques are divided into two main categories: first-generation methods and second-generation methods. One of the most well-known approaches of the second category is Cognitive reliability and error analysis method (CREAM). This method was first introduced in 1998 by Hollnagel (Hollnagel, 1998a). One of the features of this method is that it focuses on the cognitive contexts of human behavior. This technique also provides a procedure-based classification and a position-based cognitive control model based on human factors, organization, and technology (Kim, 2000).

In the CREAM method, after a job activity, working conditions affecting the user's performance are also considered. Common Performance Conditions (CPCs) are a basic and comprehensive structure of workplace characteristics that are expected to affect an individual's performance, thus affecting the probability of error (Hollnagel, 1998a; Phillips & Sagberg, 2014). To evaluate the working conditions affecting the performance and determine the probability of human error in this research, the CREAM has been used to analyze the reliability of human resources. This study aims at determining the reliability of human resources and errors in the duties of stockbrokers. To consider the different effects for each CPC, these factors are weighted using the DANP method. The DANP technique was introduced as a combination of Analytical Network Process (ANP) and Decision-Making Trial Evaluation Laboratory (DEMATEL) techniques. This approach is a suitable method for solving problems with dependent criteria and feedback (Chiu, et al., 2013). Due to the sensitivity of the stockbrokers 'duty and the effect of their actions and suggestions on clients' investment, in this study, the CREAM technique is used to identify cognitive errors and calculate the reliability of stockbrokers. Also, some of the limitations and shortcomings of the CREAM technique are examined and a solution is proposed for it. For all studies in this field, most existing approaches have only examined the possible cognitive errors either based on the CPCs introduced by Hollnagel or based on the proposed basic method that assumes the weights of all CPCs on the performance are the same. Consequently, based on conducted studies, the main contribution and motivation in this study is following:

Considering equal impact for all CPCs on performance reliability is the most important gap and limitation in most previous studies. Given that the effects of all CPCs are not the same and they must be adjusted appropriately to the intended work environment, the present study tries to overcome this limitation using the DANP technique. Also, in previous studies, five of the CPCs were defined as independent, and four of the CPCs were dependent on the others constantly. But in the present study, the dependence and relationship between CPCs have been investigated using the DANP technique. Although in some previous research, CPC weights have been calculated using MADM methods, the dependence between CPCs has not been considered. More specifically, the effect or non-effect of each CPC on performance has been investigated according to the opinion of experts and also different effects of each CPC have been considered. Therefore, in contrast to previous research, in this paper, the weight and independence of each CPC in real conditions are investigated through the DANP technique, simultaneously.

Moreover, the relationship between HEP and the work environment error and mean time to human error are calculated using the napierian logarithm function.

From a practical contribution, the majority of studies associated with human resource reliability have been concluded in industrial and transportation environments, and human resource reliability has not been investigated in financial environments and markets.

The rest of the paper is organized as follows. Section 2 describes the literature. Section 3 addresses conceptual background of the subject. Section 4 discusses the research method. The findings are presented in section 5. Finally, the conclusion and suggestions are given in section 6.

2-Literature review

Existing studies on the assessment of human resource reliability using this technique in various manufacturing and service organizations and for sensitive jobs, for which the error analysis is required, are limited and are summarized as follows:

Kubota et al. (2001) used the extended CREAM to analyze errors related to organizational committees in six sections. Furthermore, in Konstandinidou et al. (2006) the probability of the error human was calculated using CREAM for maintenance work and control room of operators in the chemical industry. The aim of this study, which deals with human uncertainty, was to show the main origin of cognitive errors and their impact using the knowledge of experts. He et al. (2008) considered human error probability based on human inherent factors' assessments that contained psychological and physiological factor tests, including CREAM was selected as a framework. In addition, Yoshimura et al. (2014) adapted the human reliability method for marine disasters. This study provided an overview of the findings and the results of the questionnaire and also discussed the prioritization of the CPCs that cause the accident. In Kumar et al. (2015), the basic and extended CREAM method was used to assess human reliability and find human Reliability in the liquid gas discharge station. Zhou et al. (2018) developed a method that provides point estimates of the human error probability (HEP) in tanker operational safety. Human reliability and the mean time to human error were calculated by the Markov method. They proposed a quantitative human reliability analysis (HRA) model based on the Bayesian network, fuzzy logic theory, and cognitive reliability & error analysis method (CREAM) for the tanker shipping industry. The presented HRA model provided the ability to conduct more reliable results.

Zhang and Tan (2018) presented a human reliability support model based on a safety promotion plan for a power supply system in a liquefied natural gas terminal. They looked at a model that was mathematically treated by Fuzzy CREAM in combination with Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithms (GA). In this paper, the GA identified the target level of membership of each CREAM control mode when the HEP does not meet the safety promotion requirement. Petruni et al. (2019) addressed a method to support the evaluation and selection of an appropriate HRA method for the automotive sector using the Analytic Hierarchy Process (AHP) technique. This technique provides a way to assist risk assessors and safety managers in selecting the HRA methodology. Zhang et al. (2019) presented a dynamic human reliability assessment approach using PMV-CREAM for manned submersibles. In this research, the cognitive failure probabilities were calculated using the extended CREAM approach. Ung (2019) estimated the collision probability of oil tankers using a modified fuzzy Bayesian Network based on CREAM and Fault Tree Analysis. This research appointed the quantitative effects and weights caused by the ambient elements. Shirali et al. (2019) used CREAM Bayesian Network (BN) in the real world to identify the limitations associated with CPCs. The results of this study showed that there are miscellaneous values of control modes in CREAM BN compared with the basic CREAM. They provided a plain and practical method for the calculation of HEP in the wrapped industries.

Mahdi Rezaie et al. (2020) analyzed the reliability of human resources using the extended CREAM to reduce human errors. This study was conducted for the task of "communication and licensing operator" in Mashhad urban railway Company. Zheng et al. (2020) developed a new human reliability analysis (HRA) called the Systems Analysis for Formal Pharmaceutical Human Reliability (SAFPH℞). They presented suggestions for improving the reliability of community pharmacies by HRA based on the CREAM. Ahn and Emek Kurt (2020) introduced a new approach based on the CREAM method that provided a framework with maritime human errors for evaluating specific scenarios associated. Chen et al. (2021) designed a human reliability analysis model by integrating the internal type-2 fuzzy sets, CREAM, and analytic network process to overcome the uncertainty of CREAM in high-speed trains32. Lin (2021) analyzed the interface design of medical equipment based on human error using Operator Action Tree and CREAM. The aim of this study is created an ergonomic reliability evaluation modeling, and specify the development sequence of significant human factors events.

He et al. (2021) used CREAM to assess the probability of human reliability errors. They test within one pharmaceutical company to indicate its applicability and reliability so that it will be used more widely in other diverse companies in HEP measures. Yao et al. (2022) proposed a fuzzy CREAM method to analyze the human error in a nuclear power plant factory. They found that CREAM may be suitable for this goal. Lin, et al. (2022) evaluated human reliability by reducing human error in a nuclear power plant enterprise. They used the hesitant fuzzy matrix (HFM) and cognitive reliability and CREAM. Also, Asadayoobi et al. (2022) estimated human reliability based on probabilistic mission completion time using a Bayesian network. They predicted an employee's reliability and time to complete a time-sensitive mission when the workforce is working in an unsafe environment. Although Human Reliability Analysis (HRA) was developed for nuclear energy, it has various applications in other areas. Ciani et al. (2022) applied HRA to improve human reliability in railway engineering. Uflaz et al. (2022) and Ilke Sezer, et al. (2022) used HRA to evaluate ship managers. Zare et al. (2022) examined human reliability in the petrochemical industry. They used AHP to weigh and rank performance-shaping factors (PSFs) and human errors. The Failure Likelihood Index (FLI) was then determined for each of the human errors found in the transferred work. They found that the AHP-FLI technique is a reasonable approach to assessing human reliability. Morais et al. (2022) provided an automatic classification of accident reports related to human error using the machine learning algorithm. They created the Multi-Attribute Technological Accidents Dataset (MATA-D) using a taxonomy focused on the relationship between human error and its drivers. Elidolu et al. (2022) focused on cargo operations on tankers with high risks for the crew and the marine environment. This study addressed the issue of static electricity, which could cause huge explosions under hazardous conditions when a discharge makes contact. They made an important contribution by providing information on the risks of static electricity to tanker safety supervisors, ships' officers, and other maritime authorities to improve the safety of cargo operations.

3-Conceptual background

3-1-Human error

Melchers (1995) stated that human error can be defined as an event or procedure that deviates from an accepted competent action. Human errors are assumed to be unintentional, and the actions leading to failure are taken purposefully to achieve an expected result, but the result is not achieved within its permissible range (Whittingham, 2004). Therefore, human error can occur if should be no intention of error when operating, the action is purposeful; the expected outcome of the action is not within the specified range. The consequences of human error that bring about major catastrophes around the world include the Chernobyl nuclear disaster, the Space Shuttle Challenger disaster, Tenerife airport, an oil spill at the Depriz Partizan oil rig, a Chemical Leak at LG Plant in India, the destruction of the sea Aral and other items. Occupations and processes are considered critical from a human error perspective, where an error can have catastrophic consequences such as death, severe economic damage, and widespread environmental pollution (Wiegmann, Shappell, 2001).

3-2-Human resource reliability

Reliability is one of the most important characteristics of complex systems, which in todays' competitive world is great importance of companies (Fakoor Saghih & Modares, 2021; Modares, et al., 2022a; Modares, et al., 2022b; Ramazanian & Modares, 2011; Modares, et al., 2021; Modares, et al., 2022c; Bafandegan Emroozi, et al., 2022). One of the types of reliability is the reliability of human resource. Human reliability is related to contexts such as human factor engineering and refers to human reliability in areas such as manufacturing, military transportation, and medicine. Human performance can be affected by many factors such as age, physical health, emotions, making some common mistakes, cognitive errors and biases, etc. Human reliability is defined as the probability of a human being performing a particular task at the stage of the operating system over a period of time (Dhillon, 2009). Taking into account Meister (1996), the probability of success in the efficiency of those human resources whose activities require the reliability of the system and its availability can be interpreted as the reliability of human resources. Human resource reliability is defined as the probability that a task will be performed successfully by an individual at any given stage of system operation and in the shortest amount of time.

3-3-Human resource reliability assessment methods

Human error is an important factor in many industrial failures, which it is accounted for about 60% to 70% of accidents (De Felice et al, 2012). Therefore, human reliability analysis (HRA) approaches have been presented to assess the human contribution to failures and errors. HRAs are generally classified into two generations, which depend on risk assessment or cognitive activity, respectively. The first-generation of human reliability assessment techniques include human error prediction (THERP) (Swain and Guttmann, 1983; Swain, 1987) and human error assessment and reduction (HEART) (Williams, 1986, 1988). Human cognitive reliability (HCR) (Hannaman et al., 1984) and Optometry Admission Test (OAT) (Wreathall, 1982). In first-generation techniques, humans are considered as mechanical components and therefore human errors are considered as equipment defects. In these methods, analysts break down operator tasks into components and then consider the potential impact of performance-shaping factors (PSFs) such as equipment design, time pressure and stress (Bell and Holroyd, 2009). By combining these elements, the analyst calculates the probability of a human nominal error. Second-generation techniques focus more on the content of human performance with a deeper insight into the intrinsic features of human performance, which seek to find errors in cognitive processes (Hollnagel, 1998. Reer, 2008, & Kim, 2000). Second-generation techniques are also improved by calculating socio-technical factors in predicting their error rates (Fujita and Hollnagel, 2004; Zheng et al., 2017; Reer, 2008).

The techniques of this generation show the interaction between human operators, production processes, organization, and environment and how they affect human cognition models (Hollnagel, 1998a; Bye et al., 1999; Kim and Jung, 2003; Kim et al., 2006; Lee et al., 2011; Di Pasquale et al., 2013; Zhao and Smidts, 2019). CREAM has been considered to a large extent in advanced second-generation techniques. The CREAM method considers the main criteria and provides qualitative results (Bell & Holroyd, 2009). The method does not require historical and statistical data and considers the impact of the work environment on the operator's performance is comprehensive and significant. Most articles discussing the CREAM method in the literature suggest various mathematical methods for improving the quantity of HEP. The reasons for choosing the CREAM approach are: the analysis is based on the knowledge and evaluation of experts, no need to have a lot of historical and statistical data, and the CREAM method considers factors that can affect human performance. In addition to the well-known results (possibility of human error), there are two qualitative reasons for using this method:

1. A cognitive demand for tasks creates that represent the activities of each cognitive function.
2. A cognitive error profile extends that presents the types of possible errors for an assignment.

The CREAM method states that human performance is more related to the situational conditions of the task than to the intrinsic characteristics of the task itself. Accordingly, the CREAM method considers the range of human error probabilities based on assessed values of social and technical factors called CPCs. These factors are selected in such a way that the number of CPCs can describe the criteria that affect the effectiveness of human performance. The CPCs are assessed by experts for each task.

After adjustments, the number of CPCs that improve or reduce performance is investigated. Finally, one of the four control modes is selected (Text Pattern Control (COCOM)), each of which considers the range of probabilities of human error (Hollnagel, 1998a)

4- Methodology

Due to the growing trend of exchange and the extent of cognitive errors, this study attempts to develop quantitative models for understanding and controlling error. This research is applied in terms of purpose. Error analysis method with emphasis on human cognitive reliability CREAM was presented by Eric Hollnagel in 1998. This method is part of the second-generation techniques of the human reliability assessment (HRA) process, which has a detailed theoretical background and focus on the cognitive contexts of human behavior, as well as the structure and cognitive contexts of the task as an effective, Useful method has been selected for the study of human error (Hollnagel, 1998a; Bell & Holroyd, 2009). The decision team consists of fifteen stock exchange brokers' experts who are fully acquainted with the tasks of stock exchange brokerage and were used to collect data related to the DANP and the CREAM method. These experts have at least five years of related experience. The gender of this group includes both man and female and has an age range of 25 to 45 years. In this study, the results of the presented calculations are more reliable than using the conventional CREAM method because the DANP method has been modified in determining the coefficients related to CPCs.

So, the relationship between CPCs is closer to the real situation than the parity of weights in all conditions. The use of the overall probability of cognitive error to perform the stockbroker task and identifies the current control mode of this task as opportunistic control that should move towards tactic control. After human resource reliability, and mean time to human error can be calculated using the relationship between HEP and the work environment through the Napierian logarithm function. The steps for conducting the research are illustrated in figure 1.

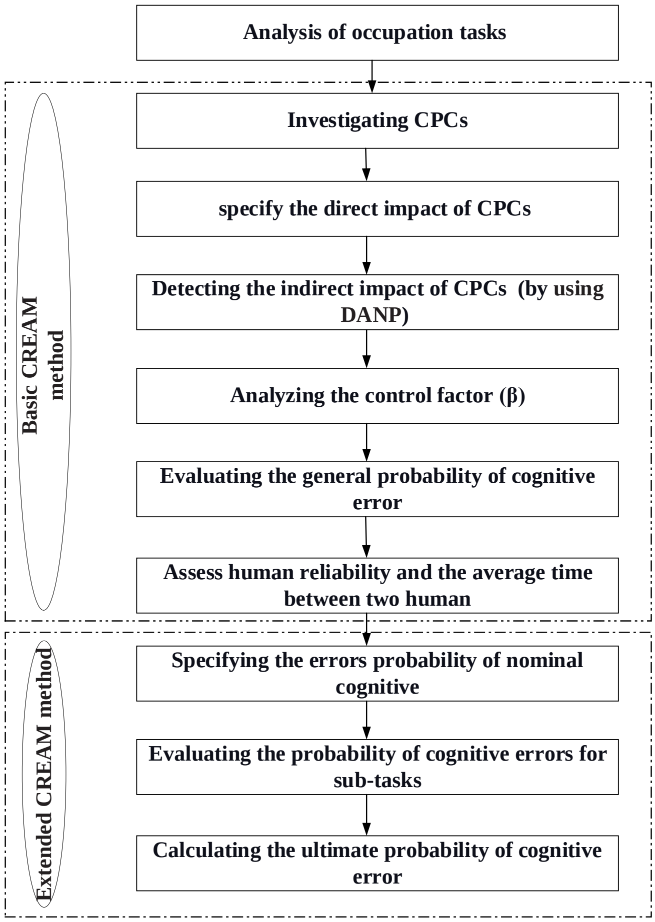

Fig.1. Research flowchart

5-Research steps and findings

In the present paper, ten steps were suggested as follows:
Each stage of the approach is explained in a separate subsection. In parallel, we investigate the complete analysis of the implementation method for financial service (stock market).

5-1-Step 1: Analysis of occupation tasks

In this stage, to analyze the reliability for all activities, the HTA method is used to identifying the event sequence for the principal task. The result of the hierarchical task analysis for the stockbroker task is presented in the following list:

- ✓ Write stock purchase orders
- ✓ Calculation of transfers
- ✓ Control of stock transactions, acceptance, and delivery of securities
- ✓ Calculation of parity rate, profit distribution
- ✓ Recording of data of transactions and transfers performed daily
- ✓ Presentation of suitable investment areas to individuals and companies
- ✓ Evaluation of current and past financial data and investment markets
- ✓ Study of economic and political trends affectingly financial markets
- ✓ Checking of financial statements and analyze the prices of goods, sales, costs

- ✓ Preparing written reports and present them to your contacts
- ✓ Meeting with investors to explain offers and recommendations
- ✓ Performing administrative duties related to the purchase and sale of securities

As mentioned, this list shows all the basic steps that a stockbroker performs to perform a task. Using the HTA method, the sub-tasks related to the main task (stockbroker) are identified. Figure 2 shows the sub-functions as well as the relationships between them.

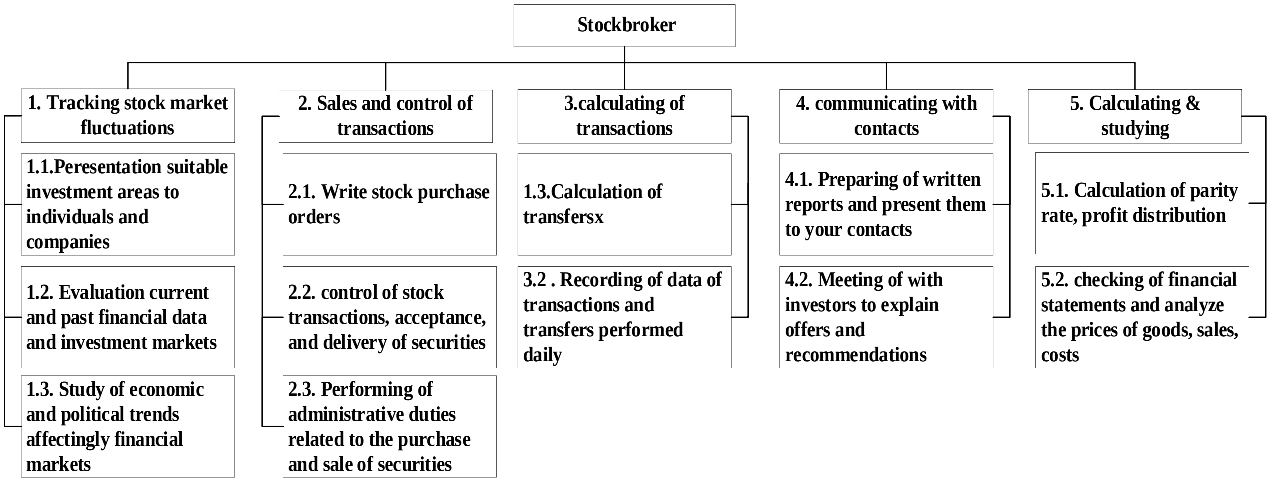

Fig.2. Hierarchical task analysis

5-2- Step 2: Investigating CPCs

Investigating the CPCs must be performed by experts with general knowledge of the system under review to evaluate the CPCs in the CREAM method. CPCs include nine items, and each degree indicates the extent to which that parameter affects the operator's performance. Different techniques such as questionnaires, observation, and interviews are used to determine the level of each CPC (Hollnagel, 1998a). Based on Hollnagel's book, each range of CPCs has a different impact on performance. Each CPC can affect reliability in three ways: increase (improve), neutral (ineffective), and decrease. At the end of the work environment study, the CPC level is indicated in the third column of table 1.

5-3- Step 3: specify the direct impact of CPCs

There are three types of CPC effects on PR: improvement, reduction, and not significant. Not significant means that the impact is relatively small and it is generally not possible to determine whether the impact on performance reliability is positive or negative. The direct effect of CPC status on performance is assessed. In this section, a questionnaire is designed to assess CPCs. The results of the questionnaire are given in the fourth column of table 2.

Table 2. Expected impact on reliability for the task of stockbroker

Symbol	CPCs	CPCs level	Expected impact on reliability
CPC1	1. Adequacy of organization	Efficient	Not significant
CPC2	2. Working conditions	Incompatible	Reduction
CPC3	3.Adequacy of MMI and operational support	Tolerable	Not significant
CPC4	4.Availability of procedures/plans	Inappropriate	Reduction
CPC5	5.Number of simultaneous goals	Matching current capacity	Not significant
CPC6	6. Available time	Temporarily inadequate	Not significant
CPC7	7.Time of day (circadian rhythm)	Day-time (adjusted)	Not significant
CPC8	8. Adequacy of training and preparation	Adequate, limited	Not significant
CPC9	9. Crew collaboration quality	Deficient	Reduction

5-4- Step 4: Detecting the indirect impact of CPCs

In this paper, direct and indirect relationships among the criteria and dimensions of the problem are determined through the DEMATEL method, then the weight of the criteria and dimensions is calculated using the concept of ANP. This step is only for CPCs that do not affect the performance reliability. The CPCs interdependence should be evaluated to assess their indirect effect on reliability.

5-4-1- Introduction of DANP technique

The DANP method was introduced as a combination of DEMATEL and ANP techniques in 2008 by Yang et al. The DANP is a suitable method for solving problems with dependent criteria and feedback (Chiu, Tzeng, & Li, 2013). The steps to perform this technique are as follows: (Lee, Huang, Chang, Cheng, 2011. Xia, Xu, 2011).

Step a: In this step, a direct effect matrix is formed like the DEMATEL method. Data are obtained using a questionnaire and the scale used (the questionnaire included a correct score of 0, 1, 2, 3, or 4, which 0 indicates that the two factors do not affect each other and 4 based on natural language criteria of linguistics show a very high impact). The experts should be aware of the field under discussion and use the pairwise comparison method to evaluate the effect of the criteria and show the effect of each criterion i on each criterion j. This matrix must be a non-negative n × n matrix. On the basis of the experts' opinion, the direct impact relationship matrix is shown in equation (1), the direct impact relationship matrix:

$E_h = \left[e_{ij}\right]_{n\times n}$, h = 1, 2, …, H, where E1, …, Eh, …, EH

$$E = \begin{bmatrix} e11 & . & . & . & e1j & . & . & . & e1n \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ ei1 & . & . & . & eij & . & . & . & ein \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ en1 & & . & . & enj & . & . & . & enn \end{bmatrix} \quad (1)$$

Step b: The average matrix of the direct relationship

Matrix A is the average score of experts. This matrix presents the influence degree of each criterion on others, as shown equation (2).

$$A = \begin{bmatrix} a11 & . & . & . & a1j & . & . & . & a1n \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ ai1 & . & . & . & aij & . & . & . & ain \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ an1 & & . & . & anj & . & . & . & ann \end{bmatrix} \quad (2)$$

Step c: The matrix is directly related to the direct effect of matrix D on the normalization of matrix A. The matrix D is easily obtained from equations (3) and (4), where all the major diagonals of the criteria are equal to 0:

$$\mathbf{D} = \mathrm{b} \cdot \mathbf{A} \quad (3)$$

$$b = \min\left\{ \frac{1}{max\, 1 \le i \le n \sum_{j=1}^{n} = aij}, \frac{1}{max\, 1 \le j \le n \sum_{i=1}^{n} = aij} \right\} \quad (4)$$

Step d: In this step, the direct and indirect relationships of relative intensity matrix is constructed. In this step, the set of unlimited sequences of direct and indirect effects of the criteria on each other is calculated as a geometric progression. In this relation i represents the unit matrix**.**

$T = D + D^2 + \ldots + D^q = D\,(I + D + D^2 + \ldots + D^{q-1}) = D\,(I + D + D^2 + \ldots + D^{q-1})\,(I - D)\,(I - D)^{-1} = D(I - D)^{-1}$, when $\lim_{q\to\infty} D^q = [0]_{n\times n}$

Step e: the sum-row and the sum-column of T matrix elements are calculated, the relations between the criteria are evaluated:

$$O = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = (O_1, \ldots, O_i, \ldots, O_n) \quad (5)$$

$$r = \left[\sum_{j=1}^{n} t_{ij}\right]'_{n\times 1} = (r_1, \ldots, r_i, \ldots, r_n) \quad (6)$$

Where *Oi* the sum of the rows in the whole matrix is the penetration relation T, which represents the total effects (direct and indirect) of criterion i in all other criteria. Similarly, r_j is the sum of the columns in the whole matrix of the penetration relation T, which represents the total effects (direct and indirect) of the criterion j obtained from the other criteria. O_i indicates the overall effect that criterion i has on other criteria and r_j indicates the effect that criterion j has on other criteria. Therefore $(O_i + r_i)$ and $(O_i - r_i)$ present the degree of importance and causality of criterion i, respectively. If $(O_i - r_i)$ is positive, the relevant criterion is a definite influencer (related to the group of causes), and if $(O_i - r_i)$ is negative, the criterion is a definite influential (corresponding to the group of causes).

Step f: In this step, by combining the DEMATEL method and ANP, an unbalanced super matrix is obtained, first the T matrix is normalized in order to normalize this matrix, each member is divided by the total number of members' rows in the corresponding block of that member, so that the total effect matrix is normalized.

$$
\begin{array}{cc|c}
 & & \begin{array}{cccccc} \multicolumn{2}{c}{D1} & \multicolumn{2}{c}{Dj} & \multicolumn{2}{c}{Dm} \\ c11. & c1m_1 & cj1. & cjm_j & cm1. & cmm_m \end{array} \\
\begin{array}{c} D1 \\ . \\ . \\ . \\ E = Dj \\ . \\ . \\ . \\ Dm \end{array} & \begin{array}{c} c11 \\ . \\ c1m_1 \\ . \\ cj2 \\ . \\ cjm_j \\ . \\ cmm_m \end{array} & \begin{bmatrix} T_c^{11} & . & . & . & T_c^{1j} & . & . & . & T_c^{1m} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ T_c^{i1} & . & . & . & T_c^{ij} & . & . & . & T_c^{im} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ T_c^{m1} & . & . & . & T_c^{mj} & . & . & . & T_c^{mm} \end{bmatrix}_{n \times n \mid m < n, \sum mj = 1mj = n,}
\end{array} \quad (7)
$$

By calculating the matrix transpose, the normalized total effect and then weighted super matrix is obtained. In addition, if the i^{th} dimension has no effect on the j^{th} dimension, the subset Tijc = [0] is a representation of the independence (without the effect relation) of each criterion over the other criteria, and in addition, the relational matrix of the total effect of T_D dimensions on the equation (8) shown

$$
T_D = \begin{bmatrix} t11 & . & . & . & t1j & . & . & . & t1m \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ ti1 & . & . & . & tij & . & . & . & tim \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ tm1 & & . & . & tmj & . & . & . & tmm \end{bmatrix}_{m \times m} \quad (8)
$$

Step g: In this step, the weighted super matrix is calculated, for this purpose, the general effect matrix related to the dimensions of the problem must be calculated. Each of the elements of this matrix is equal to the average of all the elements of the matrix related to the general effect matrix of the criteria, if the general effect matrix of the criteria is as follows**:**

$$
\begin{array}{cc|c}
 & & \begin{array}{cccccc} \multicolumn{2}{c}{D1} & \multicolumn{2}{c}{Di} & \multicolumn{2}{c}{Dm} \\ c11. & c1m_1 & cj1. & cjm_j & cn_1 & cmm_m \end{array} \\
\begin{array}{c} D1 \\ . \\ . \\ . \\ E = Di \\ . \\ . \\ . \\ Dm \end{array} & \begin{array}{c} c11 \\ . \\ c1m_1 \\ . \\ ci1 \\ . \\ cim_i \\ . \\ cmm_m \end{array} & \begin{bmatrix} T_c^{\alpha 11} & . & . & . & T_c^{\alpha 1j} & . & . & . & T_c^{\alpha 1m} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ T_c^{\alpha i1} & . & . & . & T_c^{\alpha ij} & . & . & . & T_c^{\alpha im} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ T_c^{\alpha m1} & . & . & . & T_c^{\alpha mj} & . & . & . & T_c^{\alpha mm} \end{bmatrix}_{n \times n \mid m < n, \sum mj = 1mj = n}
\end{array} \quad (9)
$$

The total effect of the dimensions is calculated based on equation 10. Where T_c^{α} represents the generalized normalized effect relationship matrix in the dimensions of the criteria.

$$
t_D^{ij} = \frac{\sum_{h=1}^{m_i} \sum_{k=1}^{m_j} t_{hk}^{ij}}{m_i m_j} \tag{10}
$$

$$
T_D = \begin{bmatrix}
t_D^{11} & . & . & . & t_D^{1j} & . & . & . & t_D^{1m} \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
t_D^{i1} & . & . & . & t_D^{ij} & . & . & . & t_D^{im} \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
t_D^{m1} & & . & . & t_D^{mj} & . & . & . & t_D^{mm}
\end{bmatrix} \tag{11}
$$

The resulting matrix is normalized as a row and then each element of this matrix is multiplied of all the blocks elements of the corresponding element in the un-weighted super matrix:

$$
W^{\alpha} = (T_c^{\alpha})' \tag{12}
$$

Step h: In this step, the weighted super matrix is calculated. In this matrix, the total effect relationship of T_D^{α} dimensions can be calculated by T_D.

$d_i = \sum m_j = t_D^{ij}$, i = 1, 2, …, m, as shown in equation (13).

$$
E = \begin{array}{cc}
 & \begin{array}{ccccccccc} & D1 & & & Di & & & Dm & \\ c11 & . & c1m_1 & ci1 & . & cim_i & cm_1 & . & cmm_m \end{array} \\
\begin{array}{cc}
D1 & c11 \\
. & . \\
. & c1m_1 \\
. & . \\
Dj & cj2 \\
. & . \\
. & cjm_j \\
. & . \\
Dm & cmm_m
\end{array} &
\begin{bmatrix}
W^{11} & . & . & . & W^{i1} & . & . & . & W^{m1} \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
W^{1j} & . & . & . & W^{ij} & . & . & . & W^{mj} \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
. & & & & . & & & & . \\
W^{1m} & . & . & . & W^{im} & . & . & . & W^{mm}
\end{bmatrix}
\end{array}_{n \times n \mid m < n, \sum mj = 1mj = n} \tag{13}
$$

The matrix T_D^{α} and the super matrix W the weight vector W^{α} and the weighted super matrix can be easily obtained by equation (14), where $t_{ij}^{\alpha D}$ is scalable and:

$$
W = T_D^{\alpha} W^{\alpha} \tag{14}
$$

$$
\begin{array}{ccc}
 & & \begin{matrix} D1 & & & Di & & & Dm \\ c11 & . & c1m_1 & ci1 & . & cim_i & cm_1 & . & cmm_m \end{matrix} \\
\begin{matrix} D1 \\ . \\ . \\ . \\ = Dj \\ . \\ . \\ . \\ Dm \end{matrix} & \begin{matrix} c11 \\ . \\ c1m_1 \\ . \\ cj2 \\ . \\ cjm_j \\ . \\ cmm_m \end{matrix} & \begin{bmatrix} t_{11}^{\alpha D} \times W^{11} & . & . & . & t_{i1}^{\alpha D} \times W^{i1} & . & . & . & t_{m1}^{\alpha D} \times W^{m1} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ t_{1j}^{\alpha D} \times W^{1j} & . & . & . & t_{ij}^{\alpha D} \times W^{ij} & . & . & . & t_{mj}^{\alpha D} \times W^{mj} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ t_{1m}^{\alpha D} \times W^{1m} & . & . & . & t_{im}^{\alpha D} \times W^{im} & . & . & . & t_{mm}^{\alpha D} \times W^{mm} \end{bmatrix}
\end{array}
\tag{15}
$$

$$
\begin{array}{ccc}
 & & \begin{matrix} D1 & & & Di & & & Dm \\ c11 & . & c1m_1 & ci1 & . & cim_i & cm_1 & . & cmm_m \end{matrix} \\
\begin{matrix} D1 \\ . \\ . \\ . \\ = Dj \\ . \\ . \\ . \\ Dm \end{matrix} & \begin{matrix} c11 \\ . \\ c1m_1 \\ . \\ cj2 \\ . \\ cjm_j \\ . \\ cmm_m \end{matrix} & \begin{bmatrix} t_{11}^{\alpha D} \times W^{11} & . & . & . & t_{i1}^{\alpha D} \times W^{i1} & . & . & . & t_{m1}^{\alpha D} \times W^{m1} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ t_{1j}^{\alpha D} \times W^{1j} & . & . & . & t_{ij}^{\alpha D} \times W^{ij} & . & . & . & t_{mj}^{\alpha D} \times W^{mj} \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ . & & & & . & & & & . \\ t_{1m}^{\alpha D} \times W^{1m} & . & . & . & t_{im}^{\alpha D} \times W^{im} & . & . & . & t_{mm}^{\alpha D} \times W^{mm} \end{bmatrix}
\end{array}
\tag{16}
$$

The resulting weighted super matrix is powered until all the elements converge and becomes a stable super matrix, according to equation 17 and the weight of the elements is calculated:

$$\mathrm{Lim}_{z\rightarrow\infty} (\mathbf{W})^{z} \tag{17}$$

Where z shows the amount of power, and by adding the relative weight of each criterion in each dimension, the local weight of the dimensions can be obtained. Then, the total weight of each criterion can be divided by the local weight of its dimension to obtain the local weight of the criteria.

5-4-2- Findings of DANP technique

The weight of the factors was calculated after collecting the data obtained from the questionnaire, using EXCEL and MATLAB software. Table 3 and figure 3 show the weights obtained from this method for each factor.

Table 3. Influential weights related to criteria by DANP

CPCs	Normal weight
CPC1	0.05
CPC2	0.156
CPC3	0.05
CPC4	0.027
CPC5	0.01
CPC6	0.134
CPC7	0.162
CPC8	0.361
CPC9	0.05

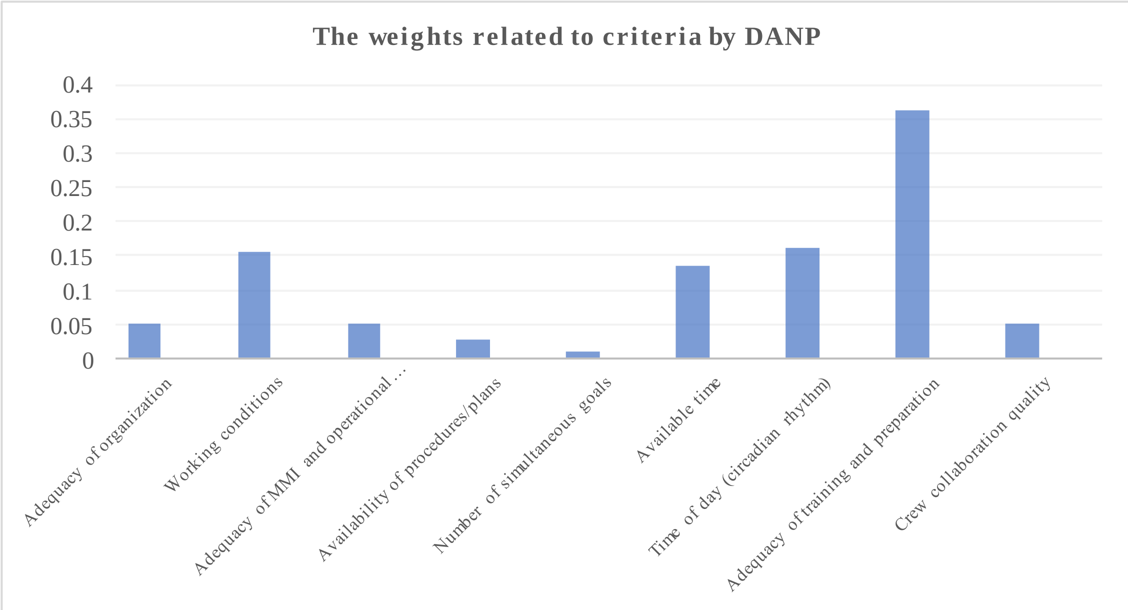

Fig. 3. Influential weights related to criteria by DANP

Based on the results, the six presented CPCs need to measure their indirect impact on performance that have highlighted in Table 1. Following figure 4, this has been done to calculate the indirect effect of the "organizational adequacy" factor. This CPC is dependent on the other five CPCs and therefore, based on weights obtained from the DANP method, if 80% of the factors affecting this CPC have a similar direction on performance reliability. As shown in Table 3, two factors affecting the "Adequacy of an organization" have a decreasing effect (27.43%) and three factors (72.57%) don't affect performance reliability. As regards, 80% of these factors are not in one direction, the effect of this factor remains unchanged.

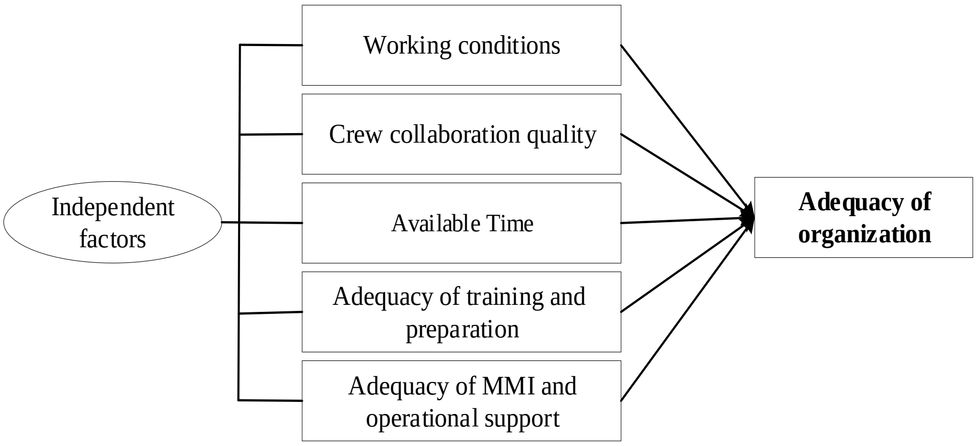

Fig. 4. Influencing factors of the “Adequacy of the organization” factor

These percentages for "time of day", "available time", "Number of simultaneous goals", "Adequacy of training and preparation" and finally "Adequacy of MMI and operational support" are 66%, 75%, 83%, 50%, respectively. In this article, "Working conditions", "Availability of procedures/plans"," Crew collaboration quality" are among the factors that reduce reliability and do not need to be adjusted. Also, the results of the adjustment show that the factors of " Adequacy of an organization", " Time of day"," Adequacy of training and preparation " Number of simultaneous goals" and" Adequacy of MMI and operational support" do not affect reduce performance reliability. Also, 82.33% of the factors affecting" available time "have operational reliability. Therefore, the impact of this factor on performance reliability is diminishing. Calculations related to the results mentioned in tables 4-10 are expressed. The final evaluation of each CPCs for the stockbroker task is shown in table 9.

Table 4. Adjusted effect of " Adequacy of organization " factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Adequacy of organization	Working conditions	Reduced	0.156	0.274301	Not significant
	Crew collaboration quality		0.05		
	Available time	Not significant	0.134	0.725699	
	Adequacy of training and preparation		0.361		
	Adequacy of MMI and operational support		0.05		

Table 5. Adjusted effect of "Available time" factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Available time	Crew collaboration quality	Reduced	0.05	0.823322	Reduced
	Working conditions		0.156		
	Availability of procedures /plans	Not significant	0.027	0.176678	
	Adequacy of organization		0.05		

Table 6. Adjusted effect of "Time of day" factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Working conditions	Working conditions	Reduced	0.156	0.614	Not significant
	Availability of procedures /plans		0.027		
	Adequacy of organization		0.05		
	Available time	Not significant	0.134	0.386	
	Adequacy of training and preparation		0.361		

Table 7. Adjusted effect of " Adequacy of MMI and operational support " factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Adequacy of MMI and operational support	Working conditions	Reduced	0.156	0.3017	Not significant
	Adequacy of training and preparation	Not significant	0.361	0.6983	

Table 8. Adjusted effect of " Number of simultaneous goals " factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Number of simultaneous goals	Working conditions	Reduced	0.156	0.308081	Not significant
	Availability of procedures /plans		0.027		
	Adequacy of organization	Not significant	0.05	0.691919	
	Adequacy of training and preparation		0.361		

Table 9. Adjusted effect of " Adequacy of training and preparation " factor

Dependent factor	Influencing CPCs	The effect on performance reliability	The weight of affecting CPCs	Normalized weight	Modified effect
Working conditions	Crew collaboration quality	Reduced	0.05	0.545667	Not significant
	Working conditions		0.156		
	Availability of procedures /plans		0.027		
	Time of day	Not significant	0.134	0.454333	
	Number of simultaneous goals		0.01		
	Adequacy of organization		0.05		

Table 10. Final evaluation of CPCs for the main task of "Stock brokerage"

CPCs	CPCs weight	CPCs levels	The expected effect on performance reliability
CPC1	0.05	Efficient	Not significant
CPC2	0.156	Incompatible	Reduced
CPC3	0.05	Tolerable	Not significant
CPC4	0.027	Inappropriate	Reduced
CPC5	0.01	Matching current capacity	Not significant
CPC6	0.134	Temporarily inadequate	Reduced
CPC7	0.162	Day-time (adjusted)	Not significant
CPC8	0.361	Adequate, limited	Not significant
CPC9	0.05	Deficient	Reduced

5-5- Step 5: Analyzing the control factor (β)

In the CREAM method, the β value represents the conversion of CPC values to control states (Hollnagel, 1998a). To achieve the β score and error probability interval, taking into account figure 5, the desired interval on the horizontal and vertical axis be selected, and based on the β value is determined. The x-axis illustrates the total activity that reduces performance and the y-axis represents the total activity that improves performance, and the β index is equal to the difference between component X and component Y. On the basis of the β value, the control style is determined.

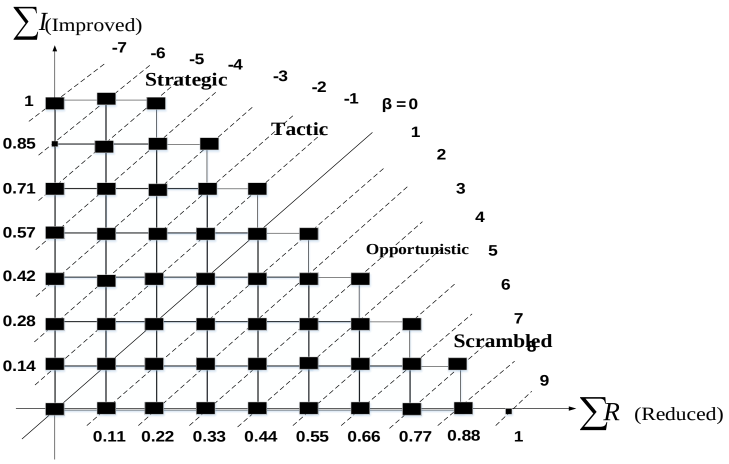

Fig.5. β score determining diagram & control modes (He, et al., 2008)

Taking into account figure 4, to attain the value of β and the error probability distance, the total weight values relationship for the main task is shown in figure 8.

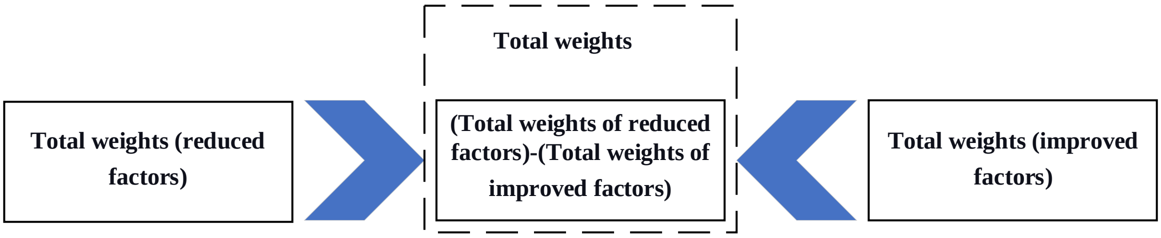

Fig. 6. Total weight

5-6- Step 6: Evaluating the generalized cognitive error Probability

In this step, the level of control is determined by amount of β, and then the cognitive error probability is calculated. The four levels of control and their cognitive error probability for Strategic control (β= -4 to -7) equal to: 0.00005 < P < 0.01, Tactic control (β= -3 to 1) in the range 0.001 < P < 0.1, Opportunistic control (β= 2 to 5) in the range 0.01 < P < 0.5 and finally to Scrambled control (β= 6 to 9) is between 0.1 to 1 (0.1 < P < 1) (He, et al., 2008; Konstandinidou, et al., 2006). The total weight value of reducing factors is 0.367 (0.156+0.027+0.134+0.05=0.367) and for improved factors is 0, taking into account figure 5. Given that 36.7% of CPCs are to reduce performance reliability, this value is in the range (0.44-0.33) and β is between 3 and 4. Accordingly, the value of β = 3.336. Therefore, the error probability interval is in the range of 0.01 to 0.5 (0.01<p<0.5), and the control mode is "Opportunistic control".

5-7- Step 7: Assess the average time between two human errors

The basic CREAM method has overlooked the weight of each CPC, while the effect of each CPC on human reliability is different. The weight of each CPC should be assessed taking into account the specific work environment, which can make the effect of CPCs on the workplace more accurate and make quantitative HRA results more reliable (Kumar, et al., 2015). CREAM assumes that human reliability increases as the work environment improves. The relationship between HEP and the work environment can be modeled with a Napierian logarithm function (He, et al., 2008; Chai, et al., 2011). k is a permanent number in the following equation and is calculated as follows, and following the previous step, β is equal to 3.336.

$$\ln(P_{HEP} / P_{HEP,0}) = k\,\beta \tag{18}$$

Where k is permanent, calculated by:

$$k = -0.7629, P_{HEP,0} = 0.002236 \tag{19}$$

$$\ln(P_{HEP,Max} / P_{HEP,0}) = k\,\beta_{Min},\ \ln(P_{HEP,Min} / P_{HEP,0}) = k\,\beta_{Max} \tag{20}$$

$$P_{HEP} = P_{HEP,0}\,e^{k\beta} = 0.002236e^{-0.7629\beta} \tag{21}$$

If the work shift on-board is every 8 h, The reliability is given by:

$$R_h(8) = exp[-8\times 0.002236.\exp(-0.7629\beta)] \tag{22}$$

Mean time to human error:

$$T_R = \frac{1}{P_{HEP}} = \frac{1}{0.002236.\exp(-0.7629\beta)} \tag{23}$$

The weight of each CPC is evaluated following the study environment, which makes the description of CPCs from the work environment more accurate and the quantitative results of HRA more reliable (Yoshimura, et al., 2014). The work environment has a significant impact on human reliability in the CREAM model. CREAM assumes that human reliability increases as the work environment improves. Based on equations 5 and 6, The human resource reliability and Mean time to human error are the following:

$$R_h(8) = exp[-8 \times 0.002236.\exp(-0.7629 * 3.336)] = 0.9986 \tag{24}$$

$$T_R = \frac{1}{P_{HEP}} = \frac{1}{0.002236.\exp(-0.7629\beta)} = 5699.3 \tag{25}$$

Taking into account the research previous steps of results, the reliability of human resources by the basic CREAM method is equal to 0.9986.

5-8- Step 8: Specifying numerical cognitive failure probability (CFP)

The extended CREAM technique includes four basic types of cognitive function: observation, planning, interpretation and execution. Each of the described cognitive activities can be described based on a combination of the four basic cognitive functions required. The cognitive function needs proportionate to each of the tasks analyzed are presented in table 11. For example, coordination requires planning in addition to implementation. The fact that cognitive activities are part of cognitive function does not mean that they are 1. For example, cognition and evaluation both refer to interpretation and planning, and the reason why these cognitive activities are distinct is to refer to the different characteristics of tasks at some level of their performance. Different models may be used to express cognitive function that represents different layers of cognitive activity. But there are many benefits to using this model, so it is less likely to be incorrect.

Table 11. Relationship between activity type and cognitive function (Hollnagel, 1998a)

The type of activity	Cognitive Function
Co-ordinate	Planning, Execution
Communicate	Execution
Compare	Interpretation
Diagnose	Interpretation, Planning
Evaluate	Interpretation, Planning
Execute	Execution
Identify	Interpretation
Maintain	Planning, Execution
Monitor	Observation, Interpretation
Observe	Observation
Plan	Planning
Record	Interpretation, Execution
Regulate	Observation, Execution
Scan	Observation
verify	Observation, Interpretation

The aim of this phase is determining the predominant types of failures expected for the entire task. At this stage, first, the critical cognitive activities for each of the sub-tasks and their cognitive functions are determined, and subsequently, following the defined cognitive functions, the types of cognitive errors related to them are determined. At the end of this step, the probability of any cognitive failures is presented (Hollnagel, 1998a). With regard to the opinion experts, each of the sub-tasks was linked to the cognitive activities, which is shown in table 12.

Table 12. Cognitive function failures

Cognitive Function		Potential cognitive function failure	Basic Value for Failure Probability
Observation errors	O1	Observation of the wrong object	0.001
	O2	Wrong identification made	0.007
	O3	Observation not made	0.007
Interpretation errors	I1	Faulty diagnosis	0.2
	I2	Decision error	0.01
	I3	Delayed interpretation	0.01
Planning errors	P1	Priority error	0.01
	P2	Inadequate plan formulated	0.001
Execution errors	E1	Execution of the wrong type performed	0.003
	E2	Action performed at the wrong time	0.003
	E3	Action on the wrong object	0.0005
	E4	Action performed out of sequence	0.003
	E5	Actin missed, not performed	0.03

Regarding to the results of this step for the five sub-tasks related to the "stockbroker" show that the type of cognitive activity and the type of cognitive failure are communication, execution, and performance, respectively. Considering the frequency observed in the type of cognitive activity for the subdivisions of "stock broker", it can be noted: 67% of the subgroups have cognitive activity "execution", 25% interpretation error, and 8% planning error. Likewise, 67% of cognitive error for subtasks is related to an execution error. These results have provided in figure 7.

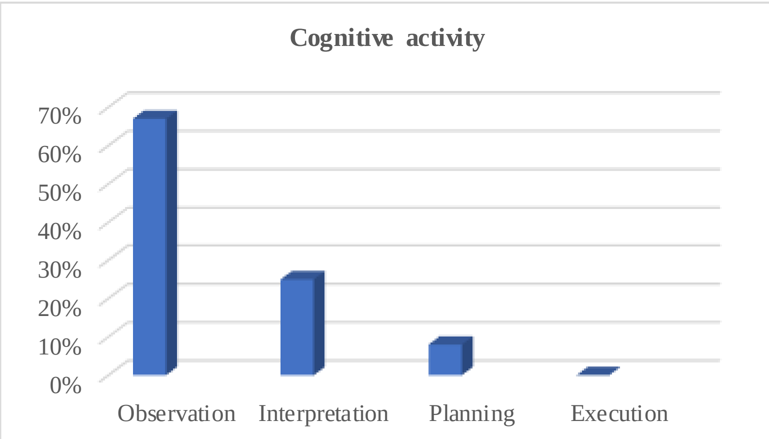

Fig. 7. Cognitive activity

5-9- Step 9: Evaluating the probability of cognitive errors for sub-tasks

This step was calculated the adjusted each cognitive failure probability in each of the sub-tasks. The total weights of the factors of cognitive failures are calculated for all CPCs. Finally, the error is multiplied by its nominal probability. The weight of factors for cognitive error is calculated based on the provided in Hollnagel's book. The obtained results in the basic CREAM are used to calculate the probability of modified cognitive failures. Therefore, following the results of CPCs and related cognitive functions in Hollnagel's book, the probability of cognitive errors for each sub-task is calculated. Table 13 is shown how to calculate this error for the tracking stock market fluctuations sub-task. The total effect of CPCs on the cognitive failure probability for each of the tasks was presented in tables 14-17, respectively.

Table 13. The effect of CPCs on the cognitive errors of the" Tracking stock market fluctuations"

Level	CPCs	Sub-task	1.1	1.2	1.3
		Functions of COCOM	I_2	I_2	I_2
Adequacy of organization	Efficient		1	1	1
Working conditions	Incompatible		2	2	2
Adequacy of MMI and operational support	Tolerable		1	1	1
Availability of procedures/plans	Inappropriate		1	1	1
Number of simultaneous goals	Matching current capacity		1	1	1
Available time	Temporarily inadequate		1	1	1
Time of day (circadian rhythm)	Day-time (adjusted)		1	1	1
Adequacy of training and preparation	Adequate, limited		1	1	1
Crew collaboration quality	Deficient		1	1	1
The total effect of CPCs			2	2	2
CFP0			0.01	0.01	0.01
Adjusted CFP			0.02	0.02	0.02

Table 14. The effect of CPCs on the cognitive errors of the "Sales and control of transactions"

Level	Sub-task	2.1	2.2	2.3
	Functions of COCOM	E_1	E_1	E_1
The total effect of CPCs	4		4	4
CFP0	0.003		0.003	0.003
Adjusted CFP	0.012		0.012	0.012

Table 15. The effect of CPCs on the cognitive errors of the "Calculating transfusion"

Level	Sub-task	3.1	3.2
	Functions of COCOM	E_1	E_3
The total effect of CPCs	4		4
CFP0	0.003		0.0005
Adjusted CFP	0.012		0.002

Table 16. The effect of CPCs on the cognitive errors of the "Communicating with contacts"

Level	Sub-task	4.1	4.2
	Functions of COCOM	E_1	P_2
Crew collaboration quality	1		1
The total effect of CPCs	4		5
CFP0	0.003		0.003
Adjusted CFP	0.012		0.015

Table 17. The effect of CPCs on the cognitive errors of the" Calculating and studying"

Level	Sub-task	5.1	5.2
	Functions of COCOM	E_1	E_3
The total effect of CPCs	4		4
CFP0	0.003		0.0005
Adjusted CFP	0.012		0.002

5-10- Step 10: Calculating the ultimate cognitive error probability

In the final step of the extended CREAM method, the justified CFP values must be combined with the task event sequence to obtain a single number. For this purpose, the event sequence in the first step of the initial method must be considered. After calculating the probability of cognitive error for each of the sub-tasks, using the formulas presented in table 18 and the rules governing the interdependence between tasks, the probability of cognitive error for the main task is calculated. Table 18 explains how to calculate the final CFP (CFPT).

Table 18. The calculating of total cognitive error probability

Relationship among sub-tasks	*CFPt*	Dependence among sub-tasks
parallel subtasks	$CFPt \approx Min(CFP_i)$	High
	$CFPt = \prod(CFP_i)$	low
sequential subtasks	$CFPt \approx Max(CFP_i)$	High
	$CFPt = 1 - \prod(1 - CFP_i)$	low

In the last phase of the CREAM technique, the probability of total error for the main task of the "stockbroker" is detected based on the equations presented in table 8. In the case of sequential tasks, a sub-task error can lead to a primary task error. In the case of parallel tasks, the failure of all tasks brings about the main error of the task. Table 18 shows this probability for the five subgroups of the second level of the HTA chart. In the last row of the table, the probability of total error for the "stockbroker" task is calculated.

Table 19. Adjusted Cognitive Failure Probability

Sub-task	CFPt
Tracking stock market fluctuations	0.0588
Sales and control of transactions	0.0356
Calculating transfusion	0.014
Communicating with contacts	0.0268
Calculating and studying	0.014
The main task	$CFPt = 1 - \prod(1 - CFPi)$
stockbroker	0.1412

Research findings based on extended CRREAM (step 10) present that the reliability of human resource is equal to 0.8588 ($R = 0.8588$). However, the human resource reliability by the basic CREAM (steps 6 and 7) is equal to 0.9986. Furthermore, findings of extended CREAM (step 10) presented that total cognitive error probability is equal to 0.1412.

6- Conclusion and suggestions

This study attempts to extend quantitative models for understanding and controlling errors and makes the results of the calculations presented using the CREAM method more reliable; Because in determining the coefficients related to CPCs by the DANP method, corrections have been made. With this change, the relationship between CPCs is closer to the real situation than the weight parity condition in all conditions. The relationship between HEP and the work environment is modeled using a Napierian logarithm function, which after the basic CREAM method can evaluate the amount of human resource error and the time between two human errors. Taking into account the results, the highest amount of the identified errors for the stockbroker's duty includes execution error (67%), interpretation error (25%), and planning error (8%), respectively. Based on these results, as well as the results obtained from the quantitative steps of the CREAM method, the probability of total cognitive error for the task is 0.1412, and the highest probability of cognitive error related to sub-tasks with 0.0588 is assigned to the "tracking stock market fluctuations" sub-task.

Based on the obtained results, sub-tasks of tracking stock market fluctuation, Sales and control of transactions, communicating with contacts, calculating transfusion, calculating and studying have the highest probability of cognitive error, respectively. Therefore, to improve the performance and increase the reliability of stockbrokers, decision-makers should focus on sub-tasks with a higher probability of cognitive failure. This will reduce the human error of stockbrokers and will lead to better decision-making on profitable companies. Also, among the tasks with a higher probability of cognitive error, attention should be paid to communication, execution, and performance errors, respectively. It is suggested that in future research, system dynamics be used to identify effective CPCs as well as environmental factors that somehow deal with human reliability. In this study, common operating conditions are statically investigated and the nature of the data is definitive. In future research, common performance conditions can be classified into static and dynamic groups and several scenarios can be designed to relate CPCs to performance and their effect on cognitive functional errors, and then each of the proposed scenarios can be rank using decision-making methods.

In this research, the common performance conditions related to the stockbroker's task have been considered, which can be done separately for each of the sub-tasks. Also, the number of CPCs is defined in nine different sections. In future studies, CPCs that affect performance can be modified based on the study and defined in more or fewer categories. Also, each of the CPC can define in such a way that instead of defining their impact on performance in general, their relationship is considered to depend on a series of factors. These factors can be affected with different (or identical) weights on performance.

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