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Expanding the Occupational Health Psychology Methodology: An Artificial Neural Network Approach

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Abstract

Burnout in the healthcare sector is usually seen as a three-dimensional construct consisting of emotional exhaustion, depersonalization, and lack of personal accomplishment. The term has become increasingly common since the second half of the last century and can be described essentially as a state of emotional and mental exhaustion. In the long run, people who suffer from burnout invest more energy than they get back, according to the model of demands and rewards. In other words, burnout is a long-term process of exhaustion that results from an imbalance between effort (demands) and results.

Nurses are highly exposed to psychosocial stressors such as role ambiguity, contact with pain and death, or workload and are therefore particularly susceptible to developing burnout. Hardiness is a personality construct that consists of three variables: commitment, challenge, and control. The three variables work together synchronously and create an attitude that is very effective in alleviating stress conditions and reducing burnout.

Many relationships between variables are not linear, yet researchers use linear methods such as Pearson correlation or linear regression to analyze these relationships. Artificial neural networks are sophisticated modeling and prediction tools that are capable of extracting complex nonlinear relationships between variables. From this perspective, the first study with a sample of 465 Chinese nurses explores this ability by modeling nonlinearities in the hardiness-

modulated burnout process with an artificial neural network. Specifically, two multi-layer feed-forward artificial neural networks are concatenated to model the composite nonlinear burnout process. The results show that this approach of a concatenated artificial neural network is feasible to model the burnout process and that the relationships between stress, hardiness, burnout variables, and their consequences are nonlinear to varying degrees.

Most research has used a variable-centered approach (e.g., regression, SEM) to study the additive and interactive effects of hardiness on stressors and their consequences. In this type of research, the main focus is to investigate the different levels of the overall hardiness construct, such as high or low in all dimensions. Person-centered research, on the other hand, investigates the effect of the combination of different levels on all dimensions (i.e., profiles), such as high levels of commitment and challenge and low levels of control.

In the second study, an investigation was conducted by applying a k-means cluster analysis (a type of person-centered analysis) to a sample of 325 Chinese nurses. Three profiles were identified, composed of individuals who scored: (1) average in terms of commitment and control and high in terms of challenge, classified as the novelty-seeker profile, (2) average in terms of commitment and challenge and high in terms of control, classified as the rigid-control profile, and (3) high in terms of all hardiness dimensions, classified as the hardy profile. It is important to note that this result shows that the non-hardy nurses do not form a homogenous group. The study found that nurses with a hardy profile had the lowest burnout rates and consequences. As for the other two profiles, nurses with the novelty-seeking profile were more likely to have burnout than nurses with a rigid control profile.

To further improve our understanding of the mitigating effect of hardiness profiles on stressors and burnout as a consequence, the three hardiness profiles found in the second study were examined for their different effects on stressors and burnout using an artificial neural network and OLS regression analysis. The results of these analyses showed that the relationships between stressors and burnout worked differently in the three profiles. Nurses with the burnout profile had the highest probability of burnout. In contrast, the hardy nurses, as expected, were the least likely to be affected by burnout. In addition, some of these relationships were nonlinear and therefore not statistically significant when analyzed by regression analysis. However, the same relationships were recognized as important by the artificial neural network. The results obtained through the different investigations, show the need to continue exploring the nonlinear relations between the variables used in this work to have a greater knowledge of the problem. This non-linear approach helps to understand the complexity of burnout and allows establishing precise and specific prevention measures based on the different profiles. Furthermore, the hardy personality profiles enable us to concretely identify the more or less high susceptibility of nurses to burnout. In this way, it is possible to develop specific prevention programs based on these risk factors and promote hardy attitudes among nurses.

Resumen

El burnout es un riesgo psicosocial de las profesiones sanitarias. Habitualmente se considera un constructo tridimensional que consiste en el agotamiento emocional, la despersonalización y la falta de realización personal. El término se ha vuelto cada vez más común desde la segunda mitad del siglo pasado y puede describirse esencialmente como un estado de agotamiento emocional y mental. A largo plazo, las personas que sufren burnout invierten más energía de la que reciben, según los modelos de demandas y recompensas. En otras palabras, el burnout es un proceso de desgaste a largo plazo que resulta de un desequilibrio entre el esfuerzo (las demandas) y los resultados.

Las enfermeras están muy expuestas a factores de estrés psicosocial como la ambigüedad de rol, el contacto con el dolor y la muerte o la carga de trabajo y, por lo tanto, son particularmente susceptibles de desarrollar burnout o desgaste profesional. Hardiness es un constructo de personalidad que consiste en tres variables fundamentales: compromiso, reto y control. Las tres variables actúan de forma sincronizada, favoreciendo una actitud que es muy eficaz para aliviar las condiciones de estrés y reducir el burnout, así como utilizar un afrontamiento eficaz frente a este riesgo psicosocial.

Además, importantes relaciones entre las variables que explican el burnout no son lineales, pero los investigadores utilizan métodos lineales como la correlación de Pearson o la regresión lineal para analizar estas relaciones

complejas. Las redes neuronales artificiales son herramientas sofisticadas de modelado y predicción que son capaces de extraer relaciones no lineales complejas entre las variables. Desde esta perspectiva, el primer estudio realizado en la tesis con una muestra de 465 enfermeras chinas explora esta capacidad mediante la modelización de las no-linealidades en el proceso de burnout modulado por hardiness con una red neuronal artificial. Específicamente, se concatenan dos redes neuronales artificiales de tipo feed-forward de varias capas para modelar el proceso de burnout compuesto no lineal. Los resultados muestran que este enfoque de una red neuronal artificial concatenada es factible para modelar el proceso de burnout y que las relaciones entre las variables de estrés, hardiness, burnout y sus consecuencias son no lineales en diversos grados. La mayoría de las investigaciones han utilizado un enfoque centrado en las variables (por ejemplo, regresión, SEM) para estudiar los efectos aditivos e interactivos de hardiness en los factores de estrés y sus consecuencias. En este tipo de investigación, el enfoque principal consiste en investigar los diferentes niveles del constructo de hardiness global, como alto o bajo en todas las dimensiones. La investigación centrada en la persona, por otra parte, investiga el efecto de la combinación de diferentes niveles en todas las dimensiones (es decir, los perfiles), como altos niveles de compromiso y reto y bajos niveles de control.

En el segundo estudio, se ha realizado una investigación centrada en la persona mediante la aplicación del algoritmo k-medias a una muestra de 325 enfermeras chinas, se identificaron tres perfiles, compuestos por individuos que obtuvieron una puntuación: 1) promedio en cuanto a compromiso y control y alto en cuanto a reto, clasificado como perfil de búsqueda de novedades, 2) promedio en cuanto a compromiso y reto y alto en cuanto a control, clasificado como perfil de control rígido, y 3) alto en cuanto a todas las dimensiones de resistencia, clasificado como perfil de resistencia. Es importante señalar que este resultado muestra que las enfermeras menos resistentes no forman un grupo homogéneo. En el estudio se observó que las enfermeras con un perfil resistente tenían las tasas de burnout y consecuencias más bajas. En cuanto a los otros dos perfiles, las enfermeras con el perfil de búsqueda de novedades tenían más probabilidades de sufrir burnout que las enfermeras con un perfil de control rígido.

Para mejorar aún más nuestra comprensión del efecto mitigador de los perfiles de hardiness sobre los factores de estrés y el burnout como consecuencia, los tres perfiles de hardiness encontrados en el segundo estudio fueron examinados por sus diferentes efectos sobre los factores de estrés y el burnout utilizando una red neuronal artificial y un análisis de regresión múltiple. Los resultados de estos análisis mostraron que las relaciones entre los factores de estrés y el burnout funcionaban de manera diferente en los tres perfiles. El personal de enfermería con el perfil de búsqueda de novedades tenía la mayor probabilidad de tener burnout. Por el contrario, las enfermeras más resistentes, como se esperaba, eran las que menos probabilidades tenían de verse afectadas por el burnout. Además, algunas de estas relaciones no eran lineales y por lo tanto, no eran estadísticamente significativas cuando se analizaban mediante el análisis de regresión. Sin embargo, las mismas relaciones fueron reconocidas como importantes por la red neuronal artificial. Los resultados obtenidos a través de las diferentes investigaciones, muestran la necesidad de seguir explorando las relaciones no lineales entre las diversas variables para tener mayor conocimiento del problema. Este enfoque ayuda a entender la complejidad del burnout y permite establecer medidas de prevención precisas y específicas en función de la no linealidad. Además, los perfiles de personalidad resistente, permiten conocer de manera concreta la mayor o menor vulnerabilidad respecto al burnout de las enfermeras. Así como, comprobar que el perfil de baja personalidad resistente no es un grupo homogéneo. De esta manera, podremos desarrollar programas de prevención específicos en función de estos factores de riesgos y elaborar propuestas preventivas para el desarrollo organizacional en los hospitales y promover actitudes de resistencia en las enfermeras.

Chapter 1
Introduction

1. Burnout

In recent decades, the word burnout has become increasingly common as a colloquial term for mental exhaustion. Originally used by professionals in the auxiliary, service, and support sector, it is now used in almost all areas of work. It can be described as a state of exhaustion comparable to smothering a fire or extinguishing a candle, although a better explanation would be a broken battery that can no longer be charged to its full capacity.

Something very similar happens to people who are burned-out. In the long run, they invest more energy than they get back. In summary, burnout is a long-term exhaustion process stemming from an imbalance between investments (requirements) and results.

1.1 The Origin and Uncovering of Burnout

In the early years of the 20th century, still before the psychological burnout was mentioned, the slang expression, ‘to burn oneself out’, which means ‘to work too hard and die early’ (Partridge, 1961) emerged. In other countries, similar terms appear about the same time. For example in Japanese, ‘karoshi’, signifies ‘death by overwork’. In 1961, Graham Greene, an English author, published his novel ‘*A Burnt-out Case’* which tells the tragic story about a well-known architect but the perhaps best example of burnout *ante literam* is the case study of a psychiatric nurse (Schwartz & Will, 1953).

Burnout was first mentioned by Bradley (1969) as a psychological phenomenon that occurs in the helping professions. He proposed a new organizational structure intending to counteract burnout among probation officers. Nevertheless, Herbert Freudenberger, a US-American psychiatrist born in Germany, is generally regarded as the discoverer of the burnout syndrome. In his influential paper entitled ‘Staff burn-out’ Freudenberger (1974) described many aspects of the syndrome and made the term burnout widely known and popular. At that time, Freudenberger worked as an unpaid psychiatrist at an alternative health care center in New York. Together with many other young idealistic volunteers, he was very involved in helping young drug addicts. Over time, he observed a gradual loss of energy and a loss of motivation and commitment among the volunteers, accompanied by various psychological and physical symptoms. One of the main reasons for Freudenberger to examine his observations more deeply was the fact that he had fallen victim to burnout twice.

About the same time but independently, Christina Maslach (1976), an American social psychologist, studied the ways in which people in stressful jobs cope with their emotions in the workplace. She was particularly interested in the dehumanization as a cognitive strategy in self-defense. The results demonstrated three phenomena:

- Manifestations of emotional exhaustion
- Development of negative perceptions and feelings about their patients
- Crisis in professional competence as a result of emotional disorder

To describe these phenomena Maslach adopted the term burnout (Wilmar B Schaufeli, Maslach, & Marek, 1993).

1.2 Burnout as a Global Problem

As already mentioned, burnout has its origins in the USA in the 1970s. However, it spread rapidly to other countries around the world. At first, the term burnout was not used as a clinical diagnosis. Instead, it was seen as an almost inevitable phenomenon affecting highly motivated individuals in the field of human services. In other words: a normal reaction to an abnormal situation. When it arrived in Europe, the concept of burnout changed from a psychological phenomenon to a medical diagnosis. This is largely due to the social security systems that cover sickness and disability pensions. Since 2018 the WHO classifies burnout (code Z73.0) in its ICD-11 (International Classification of Diseases) as a diagnosable condition (World Health Organization, 2018). This change is a further step in the recognition of the importance of psychosocial risks of occupational origin and contributes to making burnout visible, facilitating diagnosis and prevention. However, it is not included in the DSM-5 (Diagnostic and Statistical Manual of Mental Disorders).

1.3 Why is Burnout Increasing?

To understand the noticeable increase in occupational stress and burnout, not only work-related factors must be considered, but also the social, cultural, and ideological changes in our society. According to Wilmar B. Schaufeli and Enzmann (1998), six factors might explain the augmenting occupational stress and burnout. These factors are interrelated and demonstrate the aspects of a transformation process towards a globalized society.

1. **The growing service sector**
   The commercial and not-for-profit service sector has expanded rapidly in all industrialized countries in recent decades, and human services such as nursing, education, and social work are among the fastest-growing occupational groups. As mentioned above, workers in service occupations are at high risk of developing burnout because of the emotional demands they face in their daily work with people.

2. **Labeling**

   Compared to previous decades, people today use psychological terms to a greater extent to describe their problems, concerns, ailments, and difficulties. There are two reasons why stress plays a key role in this labeling process. Firstly, stress is considered the cause of many symptoms, and secondly, the term stress is particularly suitable for labeling because of its ambiguity and vagueness. As a result, in recent decades the use of the term stress has spread from the scientific and professional community to the general public.

3. **Individualization**

   Social roles are no longer fixed in modern society because traditional communities such as church, neighborhood, and even family have lost their importance. Instead, people must build and maintain their own social networks. This requires considerable effort and social skills that a growing number of people do not possess, leading to the development of narcissistic, selfish, and manipulative individuals who demand immediate satisfaction of their wishes but remain constantly unsatisfied.

4. **Increased emotional and mental workload**

   In many professions, the new technology has caused a shift from physical to mental workload. Many people work in a highly developed hi-tech environment that requires complex cognitive skills such as alertness, accuracy, and quick decision-making. These requirements increase the mental workload of workers and can contribute to burnout. Furthermore, due to the competitiveness of our society, an increasing emotional workload can be observed. Employees are forced to constantly show "consumer-friendly" attitudes that contradict the expression of their real feelings. In addition to the growing qualitative workload, there is also the increasing quantitative workload, which employees are confronted with.

5. **Diminished professional authority**
   Traditionally, professionals were valued members of society, who possessed considerable prestige and social status. This changed dramatically in the 1970s so that in the 1980s the "heroes" were no longer idealistic teachers or doctors, but stockbrokers and managers. Moreover, the general public began to question the knowledge, skills, and even the social institutions they represented. Professionals were accused of misusing public funds, as they were constantly creating new demands and service areas just to secure their own professional existence (Cherniss, 1995). The emergence of social media in the 21st century and the appearance of the influencer only a few years later has further reduced the reputation and influence of professionals.
6. **Unrealistic expectations in experts**
   The general population has several beliefs, expectations, or opinions about experts. These are communicated through the mass-media and most professional training programs. This reinforces unrealistic expectations, especially of novices. This inevitably collides with the harsh reality with which professionals are confronted. The result is disillusionment and burnout (Cherniss, 1980).

1.4 Possible Burnout Symptoms

In order to illustrate the almost all-encompassing meaning of the term burnout, Wilmar B. Schaufeli and Enzmann (1998) compiled all syndromes that they could find from uncontrolled clinical observations and interview studies and from designed questionnaire studies. They then categorized the symptoms according to the common classification of psychological symptoms into five groups: affective, cognitive, physical, behavioral, and motivational.

1.4.1 Affective Symptoms

People who suffer from burnout usually have a tearful and depressive mood. The mood can change quickly, but generally, it is low. The emotional resources of the individual are exhausted and emotional control may decrease, leading to undefined anxiety and nervousness.

1.4.2 Cognitive Symptoms

The main cognitive symptoms are the feeling of helplessness, hopelessness, and powerlessness. In addition, a feeling of failure is experienced together with a feeling of inadequacy and impotence, which can lead to poor job-related self-esteem. The individual's ability to concentrate over a longer period of time is diminished, he or she is forgetful and makes all kinds of small and big mistakes. Occasionally individuals suffering from burnout feel out of control and even have the fear of "going crazy".

1.4.3 Physical Symptoms

Physical symptoms can be divided into three categories:

The first includes all types of undefined physical ailments such as headaches, nausea, or dizziness. In addition, persons suffering from burnout are observed to experience sudden weight loss or gain, sleep disturbances, and sexual problems. However, the most common physical symptom is chronic fatigue. People who are burned-out feel extremely tired and exhausted.

The second category includes psychosomatic disorders such as ulcers and coronary heart disease. Less severe, but more frequently registered colds are extended colds from which one cannot recover.
The last category includes typical physiological stress reactions such as increased heart and breathing rate, high blood pressure, and increased sweating.

1.4.4 Behavioral Symptoms

A burned-out individual has a tendency to run around hyperactive without knowing what to do and where to go. She or he is not able to focus on anything specific and acts directly and spontaneously without considering alternative possibilities. Interestingly, the opposite - hesitation, doubt, and indecision - can also be observed. There are reports of increased consumption of stimulants such as coffee and tobacco, as well as alcohol, tranquilizers, or illegal drugs. Another behavioral symptom is over- and malnutrition, which results from reduced impulse control. Burned-out persons may also experience an increased number of accidents due to risky behavior such as speeding, diving, or paragliding.

1.4.5 Motivational Symptoms

Professionals who suffer from burnout have usually lost their true motivation, and zeal, passion, interest, and ideals have disappeared. Instead, disillusionment, disappointment, and resignation set in.

Despite this systematic classification, the mere listing of all these symptoms, which, as already mentioned, mostly result from clinical impressions, is not an adequate definition of the syndrome. Above all, it illustrates the almost all-encompassing meaning of the term and underlines the need for an operational definition.

1.5 What is Burnout?

As mentioned before, there are numerous burnout symptoms and as a consequence, many possible burnout definitions exist. In the first years after the discovery of burnout, the syndrome was "defined" by simply summarizing the symptoms. However, it is quite obvious that simply listing all the symptoms gives a rather static picture of burnout, namely that of a negative mental state and not that of a process that develops over time. The scientists tried to overcome this problem by developing a process definition in addition to the state definition.

1.5.1 State Definition

State definitions attempt to explain the burnout syndrome through the targeted selection of the most characteristic core symptoms. Although they differ in scope, precision, and dimensionality, three elements relating to the symptomatology, preconditions, and area of burnout syndrome appear to be essential:

- Dysphoric symptoms, especially emotional or mental exhaustion, negative attitudes towards others, decreased effectiveness and performance.
- Improper expectations and emotional demands.
- Work-related. Burnout occurs in individuals who do not suffer from psychopathology and who did their jobs at adequate levels before.

1.5.2 Process Definitions

Process definitions attempt to describe the syndrome as a dynamic process and allow three conclusions to be drawn:

- Burnout begins with tensions resulting from the imbalance between the expectations, intentions, and ideals of the individual and the challenges of rough everyday life.

- The stress resulting from this discrepancy develops slowly and can either be consciously experienced by the individual or remain unobserved for a long time.
- The way the individual deals with stress is decisive for the development of burnout.

However, the two types of definitions are not mutually exclusive. On the contrary, they complement each other in the sense that state definitions represent the final state of the burnout process. However, it must be mentioned that in recent years burnout has been considered as a process rather than a state, taking into account previous and subsequent factors (Neckel, Schaffner, & Wagner, 2017).

The World Health Organization (2019) describes burnout in their International Statistical Classification of Diseases and Related Health Problems (ICD-11) as:

> "Burn-out is a syndrome conceptualized as resulting from chronic workplace stress that has not been successfully managed. It is characterized by three dimensions: 1) feelings of energy depletion or exhaustion; 2) increased mental distance from one's job, or feelings of negativism or cynicism related to one's job; and 3) reduced professional efficacy. Burn-out refers specifically to phenomena in the occupational context and should not be applied to describe experiences in other areas of life."

With regard to the historical and socio-cultural context of burnout, two types of conclusions can be drawn. Firstly, the core symptom of burnout - exhaustion - is a context-free, universal, psychological experience that does not seem to be limited to a specific historical period or culture. The meaning of the exhaustion symptom also seems to establish a connection between burnout and depression, which also counts exhaustion among its core symptoms. The most telling historical example of burnout is the neurasthenia of the 19th century, but burnout-like phenomena have also been observed in non-Western cultures among indigenous peoples from the Andes and the Himalayas. Second, burnout, as "discovered" in the US in the 1970s, seems to be more specific to modern, advanced societies characterized by social fragmentation and individualization. Moreover, burnout is equated with occupational burnout (i.e., a work and context-related condition) and is thus a culture-specific term. This means that by definition it occurs exclusively in those cultures where jobs and professions exist. However, even within Western culture, burnout can have different meanings in different countries, ranging from a slight psychological strain to a medically diagnosed inability to work. It can be argued that the specificity of burnout, which lies in the combination of exhaustion with other symptoms such as mental distancing (depersonalization, cynicism) and reduced personal performance, is lost when it is reduced to mere exhaustion. This would lead to the final conclusion that burnout is indeed a mental state rooted in a specific historical and socio-cultural context (Wilmar B. Schaufeli, 2017).

1.6 Relationship Between Burnout and Other Conditions

1.6.1 Burnout vs. Job Stress

Burnout can be seen as a special kind of occupational stress, which means that the demands exceed the resources of an individual. The difference between burnout and work stress lies in the longer time perspective. According to Brill (1984), stress refers to a temporary process of adjustment accompanied by psychological and physical symptoms. In Figure 1. curve A represents people who have experienced stress and have returned to normal performance levels. Individuals who respond like Curve B are on the right track but have not yet reached their normal level.

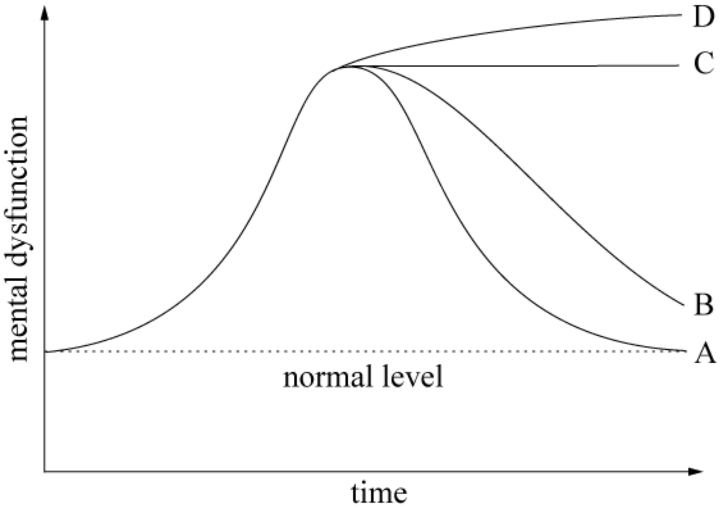

Figure 1 Stress Curve (A, B) vs. Burnout Curve (C, D)

Burnout, on the other hand, refers to a breakdown in the adaptation that is associated with chronic dysfunction at work. This is illustrated by C and D. Curve C represents someone who has collapsed and is no longer functioning at a stable level, while D is still in the process of deteriorating.

There is a further difference between burnout and stress at work when burnout is defined as a multidimensional syndrome which, as in the working definition of Wilmar B. Schaufeli and Enzmann (1998), includes the development of negative, dysfunctional attitudes and/or behavior at work. Stress reactions at work include physical, psychological, and behavioral symptoms similar to those listed in Chapter 1.4 on page 7 but not dysfunctional attitudes and behaviors (Jonathon R. Halbesleben, 2008; Pines & Keinan, 2005).

1.6.2 Burnout vs. Depression

The connection between burnout and depression has been discussed since the discovery of burnout. Freudenberger and Richelson (1981) found that burnout usually occurs in connection with anger, while depression is associated with feelings of guilt. Furthermore, the symptoms of burnout are probably job- and situation-specific, and especially in the early stages of burnout people are productive in other areas and still experience happiness. Depression conversely is characterized by a generalization of the person's symptoms across all life situations (Neckel et al., 2017). Nevertheless, work-specific burnout symptoms can generalize across all situations and areas of life and thus lead to real depression (Hakanen & Schaufeli, 2012).

1.6.3 Burnout vs. Chronic Fatigue

Although early descriptions of chronic fatigue go back to the 1930s, it is only since the 1980s that there has been a great deal of growing interest in the so-called Chronic Fatigue Syndrome (CFS). The best-known symptom of CFS is persistent unexplained fatigue, but there are many other symptoms such as sore throat, general muscle weakness, mild fever or chills, painful lymph nodes, joint pain, sleep disturbances, and general headaches. In contrast to burnout, CFS is ubiquitous and includes mainly physical symptoms, although accompanying psychological symptoms are also observed. On the contrary, burnout symptoms are primarily psychological symptoms, although accompanying physical symptoms are not unusual. Furthermore, burnout is work-related, whereas CFS can be found in all areas of life (Huibers et al., 2003; Neckel et al., 2017; Van Heugten, 2011).

1.7 Assessment and Prevalence

Psychological characteristics can be assessed through observations, interviews, or questionnaires. In addition, physiological parameters such as heart rate, blood pressure, and different hormone levels can be used. Grossi, Perski, Evengård, Blomkvist, and Orth-Gomér (2003) found in a study on physiological correlates of burnout in women that female individuals with high burnout had higher levels of tumor necrosis factor-alpha (TNF-α) and glycated hemoglobin (HbA1C) in whole blood, independent of disturbing factors such as depression. The research team concluded that burnout in women is apparently associated with increased inflammatory reactions and oxidative stress. The authors of another study (Lennartsson, Sjörs, Währborg, Ljung, & Jonsdottir, 2015) found that individuals who had higher burnout levels responded with less salivary cortisol than individuals with little or no salivary cortisol, suggesting that more severe burnout symptoms may be related to hypocortisolism. In addition, individuals with more severe burnout symptoms tended to have lower Adrenocorticotropic hormone (ACTH) responses than the control group. Langelaan, Schaufeli, van Doornen, Bakker, and van Rhenen (2007) conversely found no differences between burned-out managers and healthy managers in the assessment of the allostatic stress index, which is made up of the following eight parameters: High-density lipoprotein (HDL), cholesterol, body mass index (BMI), systolic and diastolic blood pressure (SBP and DBP), C-reactive protein (CRP), glycosylated hemoglobin (HbA1C) and glucose.

1.7.1 Interview

The interview is the method most frequently used by doctors, counselors, and social workers to assess the mental state of their clients or patients. The problem with this approach is that if the interviewer does not structure the interview well, it is inaccurate for the purposes of individual assessment. Furthermore, interviews are time-consuming and therefore not very efficient. Another problem is their unavoidable subjectivity. However, this subjectivity is also a strength. For example, the respondent may be asked to clarify statements or explain inconsistencies. Therefore, more in-depth insights can be obtained through an interview.

1.7.2 Questionnaires

Questionnaires are quite popular because of some practical advantages: First, they can be managed quickly in large groups and are therefore very efficient and cost-effective. Secondly, they are easy to evaluate and interpret and therefore reliable tools, as standardization eliminates the subjectivity of the evaluators. The negative aspect of this standardization is the inflexibility of the self-reports and the tendency to fake good answers or avoid extreme answers. Thus, although self-reports are reliable tools, their validity is not beyond question. One can never be quite sure which psychological feature is being investigated.
Since the discovery of burnout, various questionnaires have been developed, some with different areas of application and/or other conceptualizations of burnout. Some of the questionnaires frequently used in research are described below.

Maslach Burnout Inventory (MBI)

The instrument was first introduced in 1981 by Christina Maslach and Jackson (1981). The second edition was published five years later (C. Maslach & Jackson, 1986), and in 1996 the last edition, for the time being, was published (Christina Maslach, Jackson, & Leiter, 1996). The MBI is still the most frequently used tool for assessing burnout. The authors of the questionnaire describe burnout as a three-dimensional syndrome characterized by emotional exhaustion, depersonalization, and reduced personal performance. The MBI comprises consequently three subscales: (a) Mental exhaustion, (b) dysfunctional attitudes or/and behaviour (i.e., depersonalisation) and (c) reduced effectiveness. A score is calculated for each of these subscales. The test consists of 22 items, graded from 0 to 6, and it takes about seven minutes to complete the MBI. The latest edition of the MBI includes the traditional MBI-Human Services Survey (MBI-HSS) and the MBI-Educators Survey (MBI-ES) as well as the MBI-General Survey (MBI-GS), which can be used in any professional environment as the items do not explicitly refer to the health care system.

Pines Burnout Measure

The Pines Burnout Measure is a questionnaire with 21 items for assessing physical, emotional, and cognitive exhaustion (Pines & Aronson, 1988; Pines, Aronson, & Kafry, 1981). The items are answered on a seven-level scale from "never" to "always". It has been shown that the Pines Burnout Measure has very good psychometric characteristics.

Oldenburg Burnout Inventory

The Oldenburg Burnout Inventory assesses only the two dimensions of exhaustion and disengagement from work and has shown high convergent validity with the MBI. (J. R. B. Halbesleben & Demerouti, 2005)

Nursing Burnout Scale (NBS)

The Nursing Burnout Scale (Moreno-Jiménez, Garrosa, & Gutiérrez, 2000) is a specific measure of nursing burnout with particular precursor factors (occupational stressors), and includes the personality variable hardiness that, according to current studies on occupational stress and burnout, represents a relevant element in the burnout process.

The NBS comprises 78 items. The burnout block corresponds to the three dimensions: emotional exhaustion, depersonalization, and personal accomplishment, as proposed by C. Maslach and Jackson (1986), although the dimension of personal accomplishment has been replaced by the opposite dimension, namely lack of personal accomplishment, to facilitate the interpretation of the profiles and the calculation of an overall burnout index. Each item is scored on a 4-point scale, ranging from 1 ‘totally disagree’ to 4 ‘totally agree’. The NBS has been found to have very good reliability and validity (Garrosa, 2006; Ladstätter, Garrosa, Badea, & Moreno-Jiménez, 2010)

Copenhagen Burnout Inventory (CBI)

The Copenhagen Burnout Inventory is designed to overcome some of the disadvantages of MBI and measures burnout using 19 items in the following three scales: (a) Extent of personal experience of exhaustion (physical and mental), (b) Stress and exhaustion attributed to work, and (c) Frustration and exhaustion resulting from working with clients. (Kristensen, Borritz, Villadsen, & Christensen, 2005)

Shirom–Melamed Burnout Questionnaire

The instrument comprises 22 items that measure different aspects of the burnout syndrome as expressed by the subscales burnout, tension, listlessness, and cognitive difficulties. The items are answered on a seven-level scale from "never" to "always". (Melamed, Kushnir, & Shirom, 1992; Melamed et al., 1999; Shirom, Westman, Shamai, & Carel, 1997)

1.8 Variables Related to Burnout

According to Web of Science, the number of existing studies containing the keyword ‘burnout’ in the title exceeds 10.000 entries. More than 63% of them have been published in professional journals, the rest are book chapters or books, research documents, conference papers, and doctoral or master’s theses.

1.8.1 Possible Antecedents of Burnout

Potential causes of burnout which are shown in Table 1 can be categorized into personality variables, work-related attitudes and work, and organizational variables. Additionally, Table 1 shows socio-demographic variables which, although they are not causes of burnout, may be related to other factors such as gender, role assumption, role expectations, or "feeling type". Similarly, age is not a cause of burnout, but it can be related to age-related factors such as professional socialization.

Socio-Demographic Variables

The socio-demographic variable most closely associated with burnout is age (Christina Maslach, Schaufeli, & Leiter, 2001). Younger workers have a higher rate of burnout than those over 30, or in other words, it seems that burnout tends to occur at the beginning of a career. This reinforces the finding that burnout is negatively correlated with work experience. Some authors interpret the higher burnout rate among younger and less experienced people as a shock to reality.
The other socio-demographic variables do not show such a clear relationship with burnout, although some studies show that burnout occurs more often among women than among men. One explanation for this could be that working women experience a higher total workload than working men due to the additional responsibilities at home, and the workload is in turn positively related to burnout.

Personality Variables

As far as personality variables are concerned, it is quite difficult to explain the relevance of correlations with burnout, since people interact in complex ways in

Table 1 Possible Correlates and Causes of Burnout

socio-demographic variables
age
gender
work experience
marital status
level of education
personality variables
hardiness
external control orientation
confronting coping style
self-esteem
‘feeling type’
optimism
emotional competence
Type A behavior
neuroticism (anxiety)
extroversion
work-related attitudes
high (unrealistic) expectations
work and organizational variables
workload
time pressure
role stress, role conflict, and role ambiguity
hours worked
direct client contact
number of clients
the severity of clients’ problems
work & family balance
social support from colleagues or superiors
lack of feedback
participation in decision making
autonomy

situations. Even a high correlation of a certain personality trait is not necessarily associated with causality. However, there are many studies that show that a "hardy personality" characterized by participation in daily activities, a sense of control over events, and openness to change is consistently associated with all three dimensions of the MBI. In other words, the more hardy a person is, the less burned-out they are (Garrosa, Rainho, Moreno-Jiménez, & Monteiro, 2010; Christina Maslach et al., 2001). Another strong personal trait is neuroticism, which includes fear, hostility, depression, self-confidence, and vulnerability. A neurotic person is emotionally unstable and seems predisposed to experience burnout (Anvari, Kalali, & Gholipour, 2011; Wilmar B. Schaufeli & Enzmann, 1998).

The control orientation or locus of control of a person can be either external or internal. Persons with an external locus of control attribute events and performance to powerful others or chance, while persons with an internal locus of control attribute events and performance to their own effort, ability, and willingness to take risks. Individuals with an external locus of control are emotionally exhausted, depersonalized, and experience feelings of low personal achievement compared to those with an internal locus of control (Akça & Yaman, 2010; Glass & McKnight, 1996).

The relationship between a person’s coping style and burnout is another example of the importance of personality variables in burnout research. Burned-out individuals cope with stressful events in a rather passive, defensive way, whereas an active and confronting coping style is used by individuals with a lower level of burnout (Ding et al., 2015).

Work and Organizational Variables

Workload and time pressure are highly related to the burnout dimension emotional exhaustion, but, and this is striking, practically not to personal accomplishment.

Role stress, role conflict, and role ambiguity have been found to be moderately associated with burnout. Role theory suggests that role conflicts or tensions often make it increasingly difficult for individuals to successfully perform each of their roles because of limited resources (e.g., energy, time) or the incompatibility between different roles such as work vs. family roles (Boles, Johnston, & Hair Jr, 1997; Jackson & Schuler, 1985). Role stress arises in particular from the influence of the environment on an individual's ability to fulfill role expectations (Beehr & Glazer, 2005). During the last decades, the number of (especially female) individuals who have two or more jobs (for economic reasons) has been steadily increasing. In the light of role theory, this development, which implies role stress, since these persons have to fulfill two or if the family role is included, three roles, is associated with negative consequences for individuals and organizations. An enormous amount of research documents the effects of role stressors (E. M. Chang, Hancock, Johnson, Daly, & Jackson, 2005; Örtqvist & Wincent, 2006; Piko, 2006).

Role ambiguity reflects the uncertainty that employees experience regarding the expectations of their work. It has been shown that this stress factor is strongly related to burnout (Day & Livingstone, 2001; Tunc & Kutanis, 2009).

Direct client contact is positively correlated with burnout, but this relationship is somewhat weaker than that which burnout has with the variables workload, time pressure, or role conflicts. (Wilmar B. Schaufeli & Enzmann, 1998). Client-related stress factors include interaction with difficult clients, problems in dealing with clients, the frequency of contact with chronically or terminally ill patients, or the confrontation with death and dying. Therefore, the hypothesis that burnout is largely related to emotionally charged interactions with clients must be refuted, at least empirically.

There is clear evidence for a negative correlation between social support and burnout, especially support from supervisors. Social support might buffer the consequences of stress factors such that workers who obtain more support are better able to cope with their job demands (Ben-Zur & Michael, 2007).

Another positively related characteristic is lack of feedback. Various study results show a consistent positive correlation to all three burnout dimensions (R. T. Lee & Ashforth, 1996; Christina Maslach & Jackson, 1984). Lastly, involvement in decision making is negatively correlated with burnout (Pretorius, 1994).

1.8.2 Potential Consequences of Burnout

Throughout the last decades, the majority of burnout research has studied possible causes for burnout. Far fewer studies have looked at the effects of burnout syndrome. The possible consequences of the burnout syndrome can be divided into individual consequences, effects on work orientation and attitude, and organizational consequences.

On the individual level, depression is a likely consequence of burnout. However, it is not entirely clear whether burnout can only be seen as a consequence or also as a cause of depression. The strong correlation between depression and burnout, especially with the dimension of emotional exhaustion, can be explained in various ways: a) burnout and depression have common symptoms such as low energy, poor work motivation, and negative attitudes. (b) neuroticism catalyzes both depression and emotional exhaustion, and (c) there may be common external causes such as stressful working conditions which can independently lead to both burnout and depression (Neckel et al., 2017).

Table 2 Potential Consequences of Burnout

Individual consequences
Depression
Psychosomatic complaints
Health problems
Substance use
Spillover to private life
Work orientation and attitudes
Job satisfaction
Organizational commitment
Conflicts with coworkers
Intention to quit
Organizational consequences
Absenteeism and sick-leave
Job turnover
Performance and quality of services

On the individual level, depression is a likely consequence of burnout. However, it is not entirely clear whether burnout can only be seen as a consequence or also as a cause of depression. The strong correlation between depression and burnout, especially with the dimension of emotional exhaustion, can be explained in various ways: a) burnout and depression have common symptoms such as low energy, poor work motivation, and negative attitudes. (b) neuroticism catalyzes both depression and emotional exhaustion, and (c) there may be common external causes such as stressful working conditions which can independently lead to both burnout and depression (Neckel et al., 2017).

Research has also found a strong positive correlation between psychosomatic complaints and burnout. Psychosomatic complaints indicate subjectively measured symptoms, but these are objectively difficult to verify. By contrast, health problems are based on factual diagnoses. Complaints that can be verified without difficulty, however, have a weaker correlation with burnout. Psychosomatic complaints and health problems are regarded as somatic stress responses that result from frequent and/or persistent psychophysiological agitation, and it appears that both are likely to be associated with burnout (Dittner, Wessely, & Brown, 2004).

In Table 2 we find the variables job satisfaction, organizational commitment, and intention to quit the job under the label work orientation and attitudes. The first entry, job satisfaction, correlates strongly with all burnout dimensions, especially depersonalization (Aiken, Clarke, Sloane, Sochalski, & Silber, 2002; Piko, 2006). Organizational commitment also correlates strongly but inversely with the two burnout dimensions of emotional exhaustion and depersonalization. In comparison, the relationship between reduced personal performance and organizational commitment is much weaker (Hakanen, Bakker, & Schaufeli, 2006).

Almost the same results are found for the variable intention to quit. For all three items considered there is a striking correlation between burnout and work orientation and attitudes (Armstrong Stassen, Al Ma'Aitah, Cameron, & Horsburgh, 1994).

Important organizational consequences of burnout are absenteeism, fluctuation, reduced performance, and service quality. Research has shown a rather low correlation between burnout and absenteeism despite popular assumptions to the contrary (Iverson, Olekalns, & Erwin, 1998). There is a positive correlation between job turnover and depersonalization, but a distinction must be made between the much stronger relationship between turnover intentions and the somewhat weaker relationship between actual turnover. This fact implies that a large number of burned-out skilled workers continue their work involuntarily, which in turn could have negative consequences for the employee and the organization (H. Kim & Stoner, 2008; Lu & Gursoy, 2016). The results regarding the relationship between performance and burnout are not very consistent. In theory, a significant negative relationship should be found, and several studies have shown such a relationship. However, other studies found only statistically non-significant or even positive correlations with burnout

(Jonathon R. Halbesleben & Bowler, 2007; Wilmar B. Schaufeli & Enzmann, 1998).

1.9 Prevention and Intervention of Burnout

A large number of burnout interventions have been developed in recent decades because of the urgent need to do something about the syndrome. Some try to treat burnout after it has already occurred, while others focus on how burnout can be prevented. Interventions can be classified into two groups: (1) focus or level of intervention and (2) purpose (Awa, Plaumann, & Walter, 2010; Jonathon R. Halbesleben, 2008; Le Blanc & Schaufeli, 2008; Söderback, 2015).

1.9.1 Focus

The focus or level of intervention can be divided into three groups: (1) The individual level, at which the person should learn to cope better with stress, and prevent the occurrence of negative psychological and physiological effects. This class focuses on the reactions of individuals to stressful circumstances without taking into account their specific context. (2) Interactions at the individual and organizational levels. The aim is to increase the resistance of the employee to certain stressors at work. (3) Interventions at the organizational level with the aim of tackling the root cause of the problem, i.e., changing the work situation through organizational interventions. However, many of them are mainly aimed at increasing efficiency, improving quality, or reducing costs (Wilmar B. Schaufeli & Enzmann, 1998).

1.9.2 Purpose

In addition to the focus, the interventions can be classified according to their purpose, four of which exist: (1) The identification. At first glance, it does not appear to be an intervention, but it is nevertheless taken into account, as early detection is essential for combating burnout. (2) Primary prevention, which aims to reduce risk factors and change the nature of the stressors. (3) Secondary prevention, which seeks to change the way individuals respond to stressors. In principle, primary prevention can be used for all employees, while secondary prevention is used for people at risk of burning out. (4) A treatment whose purpose is to heal those who are traumatized.

1.9.3 Individual-Level Interventions

Interventions aimed at the individual level are quite general and focus on dealing with stress rather than burnout. However, most of them have their roots in clinical or health psychology. Table 3 on page 28 distinguishes six interventions at the individual level (Leiter, Maslach, & Frame, 2014).

Self-Monitoring

Self-monitoring is a very good instrument to strengthen the self-awareness of the individual by focusing on warnings and symptoms of distress. To operationalize self-monitoring a stress diary or personal record can be used, which should include: the stress symptoms, when they occurred, the occasion and place, the feelings and thoughts you had, and what you did afterward. Such a diary should be kept for about a month. It has been shown that the number of stressful events was positively related to the negative effects at the end of the working day (Jonathon R. Halbesleben, 2008).

Table 3 Burnout Interventions (adapted from Wilmar B. Schaufeli and Enzmann (1998))

<table>
<tr><th rowspan="2">Purpose</th><th colspan="3">Focus on</th></tr>
<tr><th>Individual</th><th>Individual/ Organizational Interface</th><th>Organization</th></tr>
<tr><td>Identifi-cation</td><td>Self-monitoring

Self-assessment</td><td>Personal screening</td><td>Stress audit

Psychosocial check-up</td></tr>
<tr><td>Primary Prevention</td><td>Didactic stress management

Promoting a healthy lifestyle</td><td>Time-management

Interpersonal skills training

Promoting a realistic image of the job

Balancing work and private life</td><td>Improving the job content and environment

Time scheduling

Management development

Career management

Retraining

Corporate Fitness and wellness programs</td></tr>
<tr><td>Secondary Prevention</td><td>Cognitive-behavioral techniques

Relaxation</td><td>Peer-support groups

Individual peer-support

Coaching and consultation

Career planning</td><td>Anticipatory socialization

Conflict management, communication, and decision-making

Organizational development</td></tr>
<tr><td>Treatment</td><td></td><td>Specialized counseling

Psychotherapy

Referral</td><td>Institutionalization of Occupational Health and Safety Services

Employee Assistance Programs</td></tr>
</table>

Self-Assessment

There are numerous questionnaires available for self-assessment of burnout. Although such tests can raise awareness of certain burnout symptoms, valid statements about the degree of burnout a person experiences cannot and should not be made.

Didactic Stress Management

In order to raise awareness of burnout and stress and to improve self-care, all kinds of information such as the internet, books, TV shows, newspapers, etc. can be used. This didactic coping strategy should not only deal with symptoms or causes, but also with treatments and solutions. There is, however, a serious negative aspect called "medical student syndrome". When people are confronted with symptoms of any kind, they have a high risk of mistakenly associating them with themselves and assuming that they actually suffer from them (Waterman & Weinman, 2014).

Encouraging a Healthy Lifestyle

Physical well-being is an important part of emotional well-being and can make a person more resistant to stress. 'Mens sana in corpore sano', a commentary that Homer wrote more than 2700 years ago, is still, or more than ever, valid for the prevention of burnout. There are many ways to improve one's physical health, such as proper nutrition, weight control, physical exercise, smoking bans, getting enough sleep or rest during the working day and afterward. Perhaps the most effective way to resist stress is regular physical exercise such as walking, cycling, and swimming (Jones III, Norman, & Wier, 2010; Kravits, McAllister-Black, Grant, & Kirk, 2010).

Cognitive Behavioral Techniques

Individuals do not react directly to events, but to their own interpretation of these events. This well-known fact signifies that an emotional reaction such as anxiety, anger, depression, etc. is not caused by an event itself, but by the cognitive marker associated with the event. Researchers in the field of cognition and behavior believe that emotions (feelings), cognitions (thoughts), and behaviors (actions) are interconnected, as shown in Figure 2. According to this reasoning, an individual who changes his interpretation of an event reduces negative feelings and ultimately eliminates unwanted behavior. Cognitive-behavioral techniques use this logic to prevent stress and burnout by changing an individual's thoughts about things instead of the things themselves (Cheek, Bradley, Parr, & Lan, 2003; Zielhorst et al., 2015).

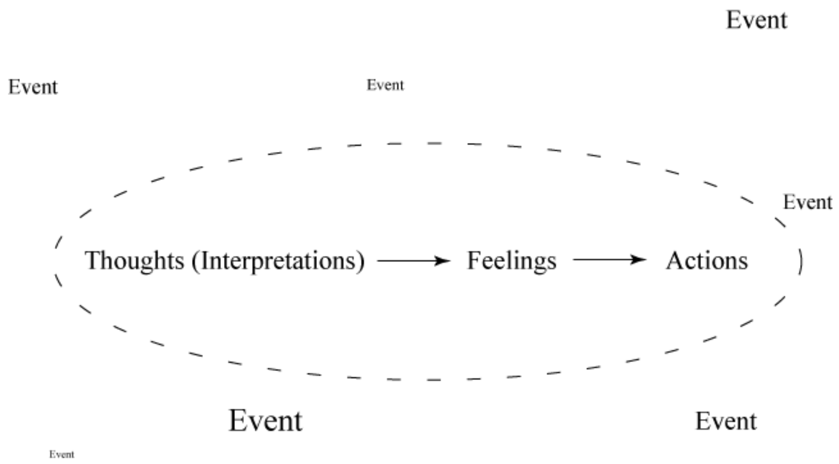

Figure 2 Cognitive Behavioral Chain

Relaxation

People suffering from burnout are usually unable to relax, which inevitably leads to a vicious circle of exhaustion. Strenuous work can trigger such a state, but so can recreational activities if they are carried out in a performance-oriented manner. As it is assumed that relaxation is a general solution to stress, it is included in every stress management program in training. There are various relaxation techniques such as deep breathing, muscle relaxation, biofeedback, or meditation but they all rely on the active involvement of the individual, which is not easy, especially in the beginning. Relaxation can cause strange and frightening feelings like dizziness, unexpected muscle contractions, or loss of control. In spite of these rather negative side effects, research suggests that the degree of emotional exhaustion is reduced after several sessions with different relaxation techniques (Higgins, 1986).

1.9.4 Individual/Organizational-Level Interventions

If one considers that burnout is strongly related to work, it becomes clear that a large part of the interventions does not only concern individual but also organizational issues. The focus of these interventions is at the intersection between employee and organization, and attempts are made to raise awareness, develop or improve individual coping skills, provide emotional and instrumental support at work, or cure stress and burnout symptoms through intensive treatment.

Screening

Screening tools such as the Occupational Stress Indicator (OSI) are used to assess the exposure of workers to workplace stressors and the link to burnout (Cooper, Sloan, & Williams, 1988; Davis, 1996). In general, such tools cover a range of occupational stressors, ways of coping with stress, and psychological and physical stress responses. In addition to the burnout intensity of workers compared to other members of the organization or occupational group, the tool identifies specific causes of stress, stress reactions, and individual tactics for coping with stress.

Time Management

In today's organizations and companies, many employees are exposed to time pressure and feel that they are not able to perform their main tasks at the expected level (Nyssen, Hansez, Baele, Lamy, & De Keyser, 2003; Peeters & Rutte, 2005). Although time pressure is a structural problem of the organization, the individual employee must deal with it by using his time efficiently. There are various strategies that try to prevent employees from burning out under time pressure, such as: working smarter instead of harder, taking a short break, etc. But the reality shows that it is often more difficult than it seems to achieve the wanted outcome. Three areas are important to focus on:

Knowledge acquisition - The employee's tasks, duties, and powers can be clarified by recording the time spent on specific tasks and matching it to the tasks and responsibilities of the workplace.

Priority setting - Employees must set priorities in their work.

Identification of "time thieves" - such as meetings, visitors, returning calls. Time can then be (1) saved by, for example, a quick reading, (2) controlled by realistic planning, and (3) used by effective delegation.

Interpersonal Skills Training

There seems to be a broad consensus that demanding interpersonal relationships with customers, recipients, employees, and superiors have a major impact on the development of burnout. Nevertheless, in most professions, professional skills are much more valued than interpersonal skills. This is a big mistake, especially in helping professions, because it is crucial to know how to handle the different phases of the help process (e.g., "breaking the ice"), how to deal with non-cooperation, or how to treat people according to gender, race, age, cultural background, personality, values, and attitudes. Even learning to say "no" seems difficult, although it is very important to control your own quantitative workload and thus prevent burnout. Various studies found a negative relationship between burnout and interpersonal skills (Corcoran & Bryce, 1984; Wilmar B. Schaufeli, 1995; Taormina & Law, 2000).

Avoiding Unrealistic Job Expectations

When professionals start their first job, they are usually very optimistic and have high ambitions and expectations. This idealistic view represents a risk factor in the development of burnout, as these high expectations that newcomers to the profession have inevitably collided with the harsh reality. In order to avoid this so-called "reality shock", supporting and promoting more realistic job expectations is an effective prevention strategy (Cherniss, 1980; Dalal et al., 2015; Kahill, 1986; J. H. Meyer, 1982).

Maintaining a Healthy Work-Life Balance

Many scientists believe that the majority of burned-out employees are very involved in their work and some of them have hardly any life outside of work, which leads to a high susceptibility to burnout (Brauchli, Bauer, & Hämmig, 2011). To avoid this, a lively and varied private life is essential, as it complements the public working life. Dynerman and Hayes (1992) describe some simple and practical ideas on how to balance work and private life: Drawing physical and mental boundaries between work and home, limiting the spillover into the workplace, engaging in leisure activities that are fun and rewarding. Another concept called "decompression", proposed by Christina Maslach (2003) pays special attention to the transition from work to home, which can be any activity (e.g., window-shopping, reading a book, gardening, daydreaming, walking or taking a nap) that takes place between working and non-working hours and allows you to leave work behind and relax before getting involved in your private life.

Specialized Career Counseling

The interventions presented so far all fall into the category of prevention. However, people who are actually suffering from burnout, i.e., who either have serious difficulties in doing their job or are on sick leave, require somewhat more extensive treatment in addition to the prevention strategies. One of these treatments is specialized career counseling, which is carried out by professionals such as general practitioners, social workers, or occupational health practitioners (Gorter, Eijkman, & Hoogstraten, 2001; Le Blanc & Schaufeli, 2008). In severe cases, psychotherapeutic treatment of burnout by highly specialized professionals such as psychiatrists, psychotherapists, or clinical psychologists is required. Klink and Terluin (1996) recommend an active approach to burnout control. Instead of withdrawing from one's duties, resting, and passively waiting for the healing to simply happen, they recommend that employees take active control of their lives (working and/or private) again and take responsibility for their own behavior.

1.9.5 Organizational-Level Interventions

Interventions at the organizational level focus entirely on the organization. Such interventions may include monitoring stress in the organization, eliminating or reducing work stressors, improving coordination between employees and organization, guiding the managerial style, or setting up health projects and services (Beehr & O'Driscoll, 2002; Sutherland, 2005).

Stress Audit

An important tool for assessing the stress level of an organization is the stress audit. There are different types such as company opinion polls, climate surveys, safety surveys, or attitude surveys but all of them are used to analyze departments, units, etc. The results of such audits can be used by management to improve organizational performance and the well-being of the workforce. When conducting a stress audit, several aspects must be taken into account: (1) The survey should be conducted during working hours and anonymously. (2) Surveys should be carried out regularly to identify changes over time. (3) It is very important that the results are discussed openly with the participants. (4) Management should not only identify problems but also look for concrete measures to eliminate or improve them (Cooper & Cartwright, 1994).

Refining Job Content and Setting

Many organizations and companies do not have formal job descriptions, but simply summarize the duties and responsibilities of the employee, which increases the probability of role ambiguity and can lead to burnout. To improve the working environment, detailed job descriptions could be formulated and written down. To improve the work content, a strategy called job redesign or job crafting can be applied, which contains three elements:

1. Job extension - replacing assembly line work, where only one activity is performed at a time, with modular work. Including tasks in the current workplace could improve the resistance of employees to burnout.
2. Work enrichment - is the restructuring of a job so that it becomes more meaningful and challenging and therefore worthwhile in itself. Instead of simply increasing the number of tasks, as is the case with job extension, job enrichment involves more decision-making and responsibility.
3. Job rotation - is an approach that aims to give an employee a comprehensive overview of the whole company. Another purpose of job rotation can be to distribute the "dirty work" equally among all employees by rotating tasks (Gordon et al., 2018; Yip & Rowlinson, 2009).

Management Development Training

The results of management development training programs must be seen in terms of multi-level results (Tyler, 2004). Beyond the individual level, training outcomes contribute to related group outcomes and to the overall results of the organization. To develop a healthy working environment, managers should have two skills:

1. Managers must be role models for a healthy lifestyle, with skills in stress management, self-confidence, communication and conflict management, and time management.
2. Managers must be able to identify when employees need help and refer them to an adequate service (e.g., the occupational health and safety service).

However, instead of reducing, many managers and supervisors increase burnout because they are not aware of the psychological consequences of many of their decisions. Some of them even lack general management skills such as setting priorities or delegating tasks, and they lack specific interpersonal skills such as active listening or expressing strong concerns. Finally, but no less importantly, they work under considerable pressure and therefore run the risk of burning themselves out. Management development programs such as management education or management training can solve at least some of these problems (Gold, Thorpe, & Mumford, 2016; McGurk, 2010; Storey, 2004).

Corporate Fitness and Wellness Programs

By institutionalizing fitness and wellness programs, various organizational aspects might be improved: Reduction of health care expenditures, positive development of the employees' health status, increased productivity, and stronger labor-management relations. Besides these general aspects, corporate fitness and wellness programs can focus on control of high blood pressure, cessation of smoking, weight reduction, physical fitness, reduction of lower back pain, health and safety education reduction of alcohol use, and stress management (Burke, 2014; Schreurs, Winnubst, & Cooper, 2003). However, despite the general idea that healthy people are associated with healthy and productive businesses the results of a review of eleven studies on wellness programs of companies in Europe were contradictory in terms of economic impact (Martínez-Lemos, 2015).

2. Hardiness

There are various ways of dealing with (negatively perceived) stressors and strains including burnout. Hardiness is one of these ways. More than 40 years ago, Suzanne Kobasa, a graduate student, named the set of personality variables that distinguished leaders who developed stress-related health problems from those who were not as "hardiness" (Kobasa, 1979). Only a few years later, Paul Bartone (1984) found that bus drivers who were less hardy were more likely to have various health problems such as high blood pressure, heart disease, etc. than hardy bus drivers. Since then numerous researchers have found more and more evidence of the positive effect of hardiness on health and performance (Eschleman, Bowling, & Alarcon, 2010; Maddi, 2013; Stein & Bartone, 2020).

2.1 The Three Cs

A hardy person combines the three hardiness dimensions: Commitment, challenge, and control. They work together synchronously and create an attitude that is highly effective in alleviating stressful conditions. This construct of hardiness is found in people who perform well in life despite a range of stressful conditions. More than that, they strive under these conditions.

Commitment

People with a high level of commitment see life as a whole as meaningful and valuable, even if it is painful and/or disappointing at times. Highly committed individuals are motivated and strive for personal competence. This sense of competence which was first described by White (1959) helps the person to realistically assess new and therefore stressful situations. Having high levels of commitment means to see the world as interesting and useful, no matter how difficult things become. Highly committed persons pursue their interest with vigor. They are socially engaged with other people and profoundly involved in their work.

On the other hand, people with low levels of commitment are often bored and find little meaning in life. They do whatever they do without a real game plan or an idea of where they want to be in the future. In general, they are rather unreflective and distant, have little interest in their work, in themselves or other people. When faced with a challenge, poorly commitment people tend to give up easily.

Challenge

Hardy persons have high challenge levels. This means they like variety and in general see change and disruptions as opportunities to personally learn and grow which in turn generates increased self-confidence (Fiske & Maddi, 1961). For these individuals, problems are part of life and instead of running away from them, they try to find a solution.

People with a low level of challenge do not like anything new that might interfere with their lives. They prefer stability and tend to avoid challenging situations. They seem to be reliable but when faced with change they tend to not be able to adapt to the new situation.

Control

People high in control believe that their actions make a difference in the outcomes. They see themselves as being in charge not only of their present situation but also of their always somewhat uncertain future. They choose to be active and involved in whatever they do, are willing to make choices, and accept that these choices come with responsibility.

In contrast, people low on the control dimension tend to feel that they have no influence or control over the things that happen around them. They tend to choose the relative safety of inaction.

2.2 How Does Hardiness Work

Stress in its different forms can cause burnout and the consequences thereof. Hardiness helps to stay healthy and to perform better when exposed to stressors. Since the emergence of hardiness (Kobasa, 1979) many studies found a correlation between hardiness and less burnout (DePew, Gordon, Yoder, & Goodwin, 1999; Garrosa, Moreno-Jiménez, Liang, & González, 2008; Jonathon

R. Halbesleben, 2010; Maddi & Kobasa, 1984) and hardiness and better performance. So how does hardiness work?

Situation Assessment

Hardiness affects the stress reaction process already at the onset of stress, namely when the situation in which someone finds oneself is assessed or sized-up. In this first stage of the process which includes situation appraisal, thinking about possible response options, and evaluation of their outcomes. This first stage is based on what skills and capabilities someone has or thinks she or he has. Persons with high levels of hardiness generally appraise stressful situations more positively. They recognize the difficulty and challenge they are in but also believe they are capable to deal with the situation. There is evidence that hardy people have slightly higher baseline levels of the stress hormones (Zorrilla, DeRubeis, & Redei, 1995). This means that these people have a heightened awareness and can react more quickly to a stressful event. Persons with a low level of hardiness tend to see stressful situations as more threatening or negative because they have less confidence in their abilities.

Stress Reaction

This differential way of assessing a situation leads to a different stress response. (Folkman & Lazarus, 1984). The hormone level rises rapidly when a stress situation exists and the heart rate and blood pressure increase. In hardy persons, hormone levels increase more quickly than in non-hardy persons (Asle M

Sandvik et al., 2019; Zorrilla et al., 1995). This is good for a quick reaction. However, if this situation continues for a longer period of time, it will have negative consequences for the heart and other parts of the body. Howard, Cunningham, and Rechnitzer (1986) found that hardiness acts as a buffer for stress, which means that hardy people are better protected compared to non-hardy people.

Recovery

There are indications that hardy persons recover faster from stressful situations. The hormones released during a stressful situation are broken down more quickly and earlier. This is accompanied by an earlier decrease in heart rate after someone has been exposed to stress. (Asle M. Sandvik et al., 2013; Asle M Sandvik et al., 2019; Zorrilla et al., 1995). People with low hardiness take longer to return to baseline levels, which means that they are exposed to stress hormones for longer, with all the negative consequences that this entails.

3. Artificial Neural Networks

For thousands of years philosophers have tried to answer two questions: (1) How does the human mind work and (2) can non-humans have minds and/or emotions? Despite all technological progress, these questions have not been answered until today.
Many scientists have tried to clarify and solve these questions with the help of computer-aided models. Some of them accepted the idea that machines can do everything that humans can do, while others vehemently opposed this idea. The latter group argued that such sophisticated behaviors and emotions as love, creativity, and moral decisions will always go beyond the scope of a machine (Bigman & Gray, 2018; Negnevitsky, 2011; Wallach, Allen, & Smit, 2008).

3.1 What is Neurocomputing

All our lives, we humans use a complex biological neural network: the brain. It consists of a highly interconnected system of about 10^{11} special nerve cells, the neurons. Much of how the brain works is still not understood, but it is generally accepted that information is stored and processed simultaneously throughout the network, not just in specific locations. Learning is a fundamental and crucial feature of biological neural networks and is seen as strengthening or weakening existing connections and creating new connections between neurons (Beale, Demuth, Hagan, & De Jess, 2014; Rioult-Pedotti, Friedman, Hess, & Donoghue, 1998). Artificial neural networks (ANNs) mimic on a very rudimentary level our brain because they do not require programming of tasks, but generalize and learn from experience. ANNs are composed of a number of very basic processing elements (artificial neurons) and a certain number of connections between them. An ANN does not execute commands, but reacts in parallel to the information presented and can function correctly even if an artificial neuron or connection stops working or if the information has a certain noise level. Therefore, an ANN is an error- and noise-tolerant system that is capable of learning through a training process. The knowledge and performance of an ANN are based on its topology, the values of connections (weights) between neurons, and the functions built into the neurons (Porto & Pazos, 2006).

3.1.1 History of Artificial Neural Networks

ANNs, also known as "connectionist models" or "parallel distributed processing", are not a new development. This field of research was established even before the invention of the computer, but real progress has been made with the significant increase in computing power. There are six important periods in ANN's history:

1. Initiation: The modern age of ANNs began in 1943 with the work of McCulloch and Pitts (1943). The two researchers developed models of ANNs based on their understanding of neurology. Their artificial networks were based on a few neurons, which were regarded as binary tools with invariable thresholds. The results of their models were simple logical functions like AND and OR. The McCulloch-Pitts neuron model formed the basis for the subsequent advances in ANNs.
2. Emerging technology: Not only neuroscientists played an important role in the development of ANNs. Psychologists and engineers also played a major role in the development of ANNs. Hebb (1949) described a learning process that was postulated from a neurobiological point of view.

He found that information is stored in the connections between neurons and proposed a learning strategy based on weight changes of the connections. Rosenblatt (1958) attracted considerable interest and activated the research area when he drafted and developed the perceptron. It was the first well-defined and computationally-oriented ANN, a device that could be trained to categorize certain patterns.

3. Deception and frustration: Minsky and Seymour (1969) slowed down ANN research considerably in the 1970s with their book Perceptrons, in which they mistakenly generalized the limits of single-layer perceptrons to multi-layer systems. The impact of their book was so great that research funds were cut off and many scientists lost interest and confidence in the field.
4. Quiet decade: Despite the slowdown in ANN research in the 1970s, some scientists continued their research. In 1972 Kohonen published his work on correlation matrix storage (Kohonen, 1972). Two years later, Werbos (1974) completed a basic description of the back-propagation algorithm used for the training of multi-layer feed-forward perceptrons.
5. Return and progress of ANN in the late 1970s and early 1980s was stimulated by three factors: (1) Several significant breakthroughs in research have been achieved, such as a comprehensive description of a recurrent ANN; How it worked and what it was actually capable of achieving (Hopfield, 1982). At the same time, Kohonen (1982) published an unsupervised, competitive learning, and clustering network the Self-Organizing Feature Map (SOFM). (2) Comprehensive books and conferences provided an encouraging environment for researchers in various fields. Several specialized computer languages were developed to meet different needs. Academic programs and courses were introduced at most major universities as a result of the major breakthroughs in the field of ANN. (3) The development of faster processors and larger RAMs

made it possible to use computationally intensive algorithms for the first time.

6. Since then, considerable progress has been made in the field of ANN. At least enough to attract a lot of attention and fund further research. Research is extending the area on many fronts and applications of ANNs can now be found not only in many research areas but also in industry and even in the consumer goods sector. Examples are face recognition systems (Deshpande & Ravishankar, 2017) or neural machine language translation (Johnson et al., 2017). There is no doubt that ANN technology is currently in a transitional phase.

3.1.2 Types of Artificial Neural Networks

ANNs can be classified in various ways. For instance, according to how they learn (i.e., supervised vs. unsupervised) if they are hardware or software implemented, the different tasks they can perform (e.g., pattern recognition, function approximation, etc.), whether they are recurrent or non-recurrent if the ANN is static or adaptive, etc. Consequently, the organization of ANNs into specific groups is not an easy exercise and may lead to overlaps in certain networks. For example, both LVQ networks and Hopfield networks cannot be clearly classified as unsupervised or supervised learning networks (Ham & Kostanic, 2001).
The following is a list of different types of ANNs:

- Feedforward (incl. autoencoder, group method of data handling, convolutional, etc.)
- Regulatory feedback
- Radial basis function (general regression neural network, deep belief network)
- Recurrent neural (fully recurrent, simple recurrent, hierarchical, etc.)

- Modular (Committee of machines, associative)
- Physical
- Dynamic (e.g., cascading network, neuro-fuzzy)
- Memory networks (e.g., one-shot associative memory, neural Turing machine, Pointer networks, etc.)
- Hybrids

3.2 Artificial Neuron Model

The ANNs research field is relatively new. This can be seen from the fact that there is no uniform mathematical standard notation and standard architecture representations for them. So far they are not yet firmly established. Besides, papers and books on ANNs come from a wide range of research areas such as engineering, physics, psychology, and mathematics, and almost all authors use vocabulary typical of their field. Because MATLAB was the primary tool used to perform ANN data analysis in the present work, the following section uses MATLAB notation.

3.2.1 Notation and Terminology

Scalars – small italic letters: *a,b,c*
Vectors – small bold letters: **a,b,c**
Matrices – capital bold letters: **A,B,C**

The following terms are used interchangeably in the field of ANNs to express the same characteristic:

- Bias, threshold, offset

  An additional network input adapted by the learning rule.
- Summer, linear combiner

  The mathematical function Σ.
- Summer output, net input

  The result of the summer. A scalar that is often labeled with n. (Note: The net input is not the network input.)
- Activation function, transfer function

  A linear or non-linear function $F(n)$, where n is the net input.
- Training algorithm, learning rule

  A procedure that modifies the weights and biases of an ANN in order to train the ANN to perform a specific task.
- Correct output, desired output, target output

  The correct output is the second term ($\mathbf{t}_n$) in a training example [$\mathbf{p}_n$,$\mathbf{t}_n$], where n denotes the n^{th} training example.
- Network output, actual output

  The output of an ANN denoted with **a**.

3.2.2 Single-Input Neuron

In Figure 3 on page 51, a single-input neuron (the simplest form of an ANN) is represented. The neuron receives the input p and multiplies it by the weight w which gives the $w \cdot p$ term This term is then transferred to the summer (linear combiner) together with a "dummy" input 1, multiplied by a bias θ. The output of the summer, n, is often referred to as net input and goes through a transfer function F, which transforms the net input n into the neuron output a. (Beale et al., 2014).

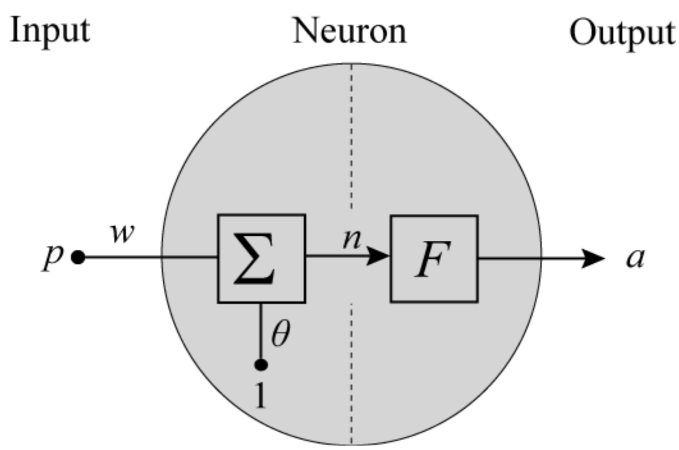

Figure 3 Single-Input Neuron

The output *a*, of the neuron is calculated as:

$$a = F\left(w \cdot p + \theta\right) \qquad 1$$

This output will vary depending on the specific transfer function that is selected. The bias θ can be considered as additional weight, but with the distinguishing feature that it has a constant input 1. The bias as a parameter of a neuron is not necessary but gives the neuron more flexibility. The weight *w* and the bias are both adjustable scalar parameters of the neuron. Typically, the transfer function is chosen by the network designer, and then the parameters *w* and θ are modified by a training function so that the neuron input/output relationship corresponds to a given target (Beale et al., 2014).

3.3 Basic Transfer Functions

The transfer function *F* in Figure 3 can be either a linear or a non-linear function of the net input n. The special transfer/activation function used in the network is chosen to meet the problem specification. Two of the most commonly applied functions are described below.

3.3.1 Linear Transfer Function

The linear transfer function is the simplest function and even though it appears to be a trivial function it is necessary in the output layer of multi-layer networks. The output of a linear transfer function is identical to its input (Beale et al., 2014):

$$a = F(n) = n, \qquad 2$$

This is also illustrated in Figure 4 .

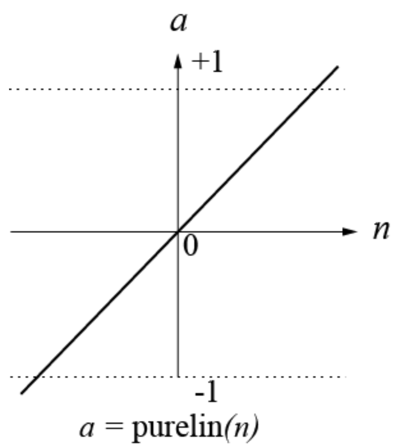

Figure 4 Linear Transfer Function

3.3.2 Sigmoid Transfer Function

One of the most commonly used non-linear transfer functions is the sigmoid transfer function which is shown in Figure 5. It takes the net input *n* and transforms it into a value in the range between 0 and 1, according to the following equation:

$$a = F(n) = \frac{1}{1 + e^{-\beta \cdot n}} \qquad 3$$

where β>0 is the slope parameter. By adjusting this parameter, different forms and properties of the function can be obtained. Figure 5, shows the sigmoid transfer function.

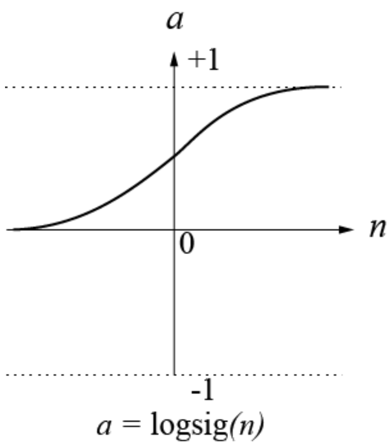

Figure 5 Sigmoid Transfer Function

The sigmoid transfer function is usually used in multilayer networks that are trained with the back-propagation algorithm because it is a mathematically well behaved, strictly increasing, and differentiable function. The differentiability of an activation function plays an important role in neurocomputing (Ham & Kostanic, 2001; Negnevitsky, 2011).

3.4 Multiple-Input Neuron

If several inputs have to be processed, a neuron with a single input, (i.e., a scalar), is not sufficient. A neuron with multiple inputs capable of processing vectors is needed. Figure 6 shows a neuron with an S-dimensional input vector.

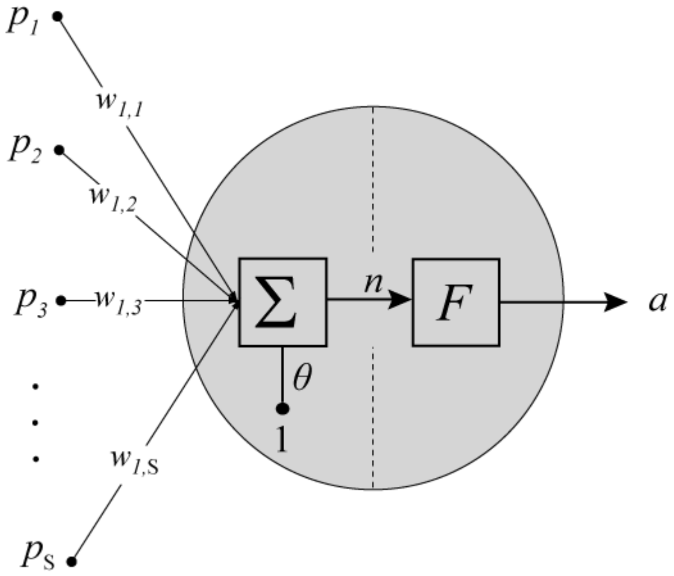

Figure 6 Multiple-Input Neuron

The individual elements $p_1, p_2, p_3,\ldots,p_S$ of the input vector **p** on the left side of the neuron are each weighted (i.e., multiplied) with the corresponding elements $w_{1,1}$, $w_{1,2}$, $w_{1,3},\ldots,w_{1,S}$ of the weight vector **w**. Then, the bias θ, is added to the weighted inputs and the net input n leaves the summer:

$$n = w_{1,1} \cdot p_1 + w_{1,2} \cdot p_2 + w_{1,3} \cdot p_3 + \ldots + w_{1,S} \cdot p_S + \theta \qquad 4$$

This expression can be rewritten as:

$$n = \mathbf{w} \cdot \mathbf{p} + \theta \qquad 5$$

The neuron output a can be written as:

$$a = F(\mathbf{w} \cdot \mathbf{p} + \theta) \qquad 6$$

where F is a transfer function like the sigmoid function. The weights are frequently defined as vectors or matrices. This is a convenient way to calculate the outcome. The following convention is used to assign the indices of the elements of the weighting vectors/matrices:

- The first index specifies the neuron to which a specific weight is connected to.
- The second index specifies the source of the signal that goes into the neuron.

Therefore, the indices in the weight $w_{1,2}$, indicate that this is the connection from the second source to the first neuron.

3.5 Training Algorithms

A training algorithm or learning rule is a procedure that adapts the weights and biases of ANNs. This is done in such a way that it generates the desired set of outputs from a set of inputs. There are different types of learning rules that can be divided into two categories: supervised learning and unsupervised learning (Beale et al., 2014; Krose & Van Der Smagt, 1996; Negnevitsky, 2011):

3.5.1 Supervised Learning

The ANN learns its task by providing it with a set of examples (the training set) of correct network behavior:

$$\{\mathbf{p}_1, \mathbf{t}_1\}\ , \{\mathbf{p}_2, \mathbf{t}_2\}\ , \ldots, \{\mathbf{p}_m, \mathbf{t}_m\} \qquad 7$$

where $\mathbf{p}_i$ is an input vector to the ANN, $\mathbf{t}_i$ is the corresponding target (desired) output vector, and m is the number of training pairs (not to be confused with the dimension of the input or output vector). The input data are forwarded through the ANN where the necessary calculations (of the summer and the transfer function) are performed. Finally, a network output $\mathbf{a}_i$ is generated which is compared to the target output. Then, the training algorithm modifies the network weights and biases to reduce the difference (error) between the network outputs and the targets.

3.5.2 Unsupervised Learning

In unsupervised learning, sometimes referred to as self-organization, the weights and biases of the ANN are only modified in response to the input. No target outputs are available. Instead, the ANN should independently identify relevant characteristics in the input data. Since there is no a priori set of categories into which the patterns can be placed, the system must develop its own particular representation of the input vectors. Most of these unsupervised learning rules perform a kind of clustering procedure.

3.6 Network Architectures

In most cases one neuron, even with many inputs, as described in chapter 3.4 is not sufficient for practical problems. Many neurons working in parallel are needed, i.e., they perform the same operation at the same time.

3.6.1 A Single Layer of Neurons

Figure 7, shows a single layer of Q neurons. Each element of the S-dimensional input vector is connected to each neuron of the layer. Thus, we now have a weight matrix with Q rows and S columns, rather than a weight vector, like in the case of a single neuron.

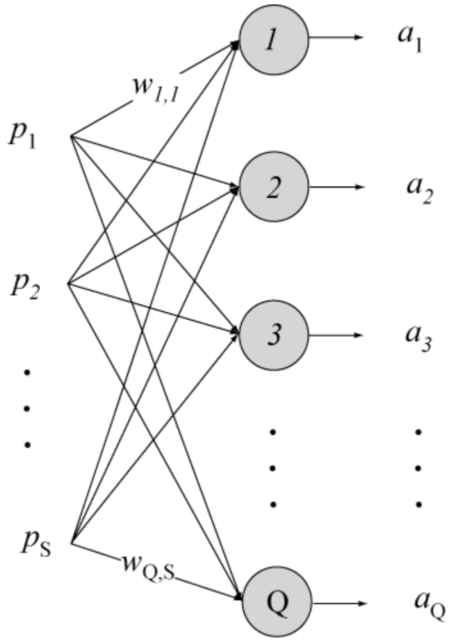

Figure 7 A Single Layer of Neurons

Each of the neurons in the layer has the same shape and works in the same way as the single neuron in Figure 6 on page 54. This means that each neuron has a bias θ_i, a summer Σ, a transfer function F and an output a_i. Since there are Q neurons in the layer, the output is now a vector with Q elements and not a scalar as in the case of a single neuron. This output vector is calculated as:

$$\mathbf{a} = F(\mathbf{W} \cdot \mathbf{p} + \boldsymbol{\theta}) \qquad 8$$

Generally, the number of inputs to a layer is not equal to the number of neurons. For Figure 7 this means that $S \neq Q$. Such a single layer of neurons is also referred to as a perceptron.

3.6.2 Multiple Layers of Neurons

More effective than a single layer of neurons like the one in Figure 7 are ANNs with multiple layers. Each of these layers has its own weighting matrix **W**, its own bias vector **θ,** and its own output vector **y**. Superscript values are applied to differentiate the three layers. To illustrate this, the weight matrix for the first layer is written as $\mathbf{W}^1$ and the second output vector as $\mathbf{y}^2$. Figure 8 shows an ANN with three layers using this concept. From left to right: S inputs are fed into the ANN. The first layer consists of Q neurons, the second layer has R neurons and the third has U neurons. The outputs of one layer become inputs for the next layer so that the second layer can be seen as a single-layer network with Q inputs, R neurons, and a $Q \times R$ weight matrix. The input of the second layer is y^1 and the output is y^2.

The forwarding procedure of outputs of one layer as inputs for the next layer can be written as:

$$\mathbf{y}^{m+1} = F^{m+1}\left(\mathbf{W}^{m+1} \cdot \mathbf{y}^{m} + \boldsymbol{\theta}^{m+1}\right) \quad 9$$

for $m = 0,1,\ldots,M-1$, where M is the number of layers in the network and F is the transfer function (Beale et al., 2014).

The neurons of layer one are fed with external inputs (i.e., the data to be analyzed):

$$\mathbf{y}^{0} = \mathbf{p} \quad 10$$

This is the starting point for Equation 9.

The output of the neurons in the last layer is considered the ANN outputs:

$$\mathbf{a} = \mathbf{y}^{\mathrm{M}} \qquad 11$$

The layer whose output is the ANN output is called the output layer. The other layers are called the input layer (the first layer) and the hidden layer (the layer between the other two). Therefore, the ANN in Figure 8 has one output layer one hidden layer, and one input layer.

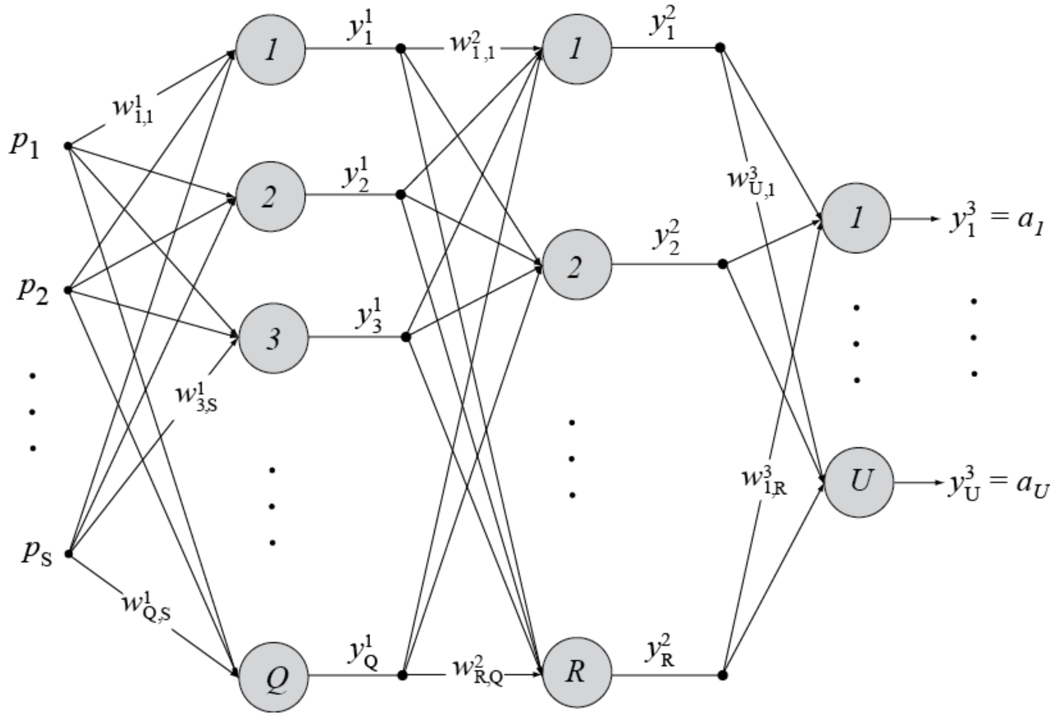

Figure 8 Three-Layer Network

The output of this three-layer ANN is calculated according to the following equation:

$$\mathbf{a} = \mathbf{y}^3 = F^3\left(\mathbf{W}^3 \cdot F^2\left(\mathbf{W}^2 \cdot F^1\left(\mathbf{W}^1 \cdot \mathbf{p} + \boldsymbol{\theta}^1\right) + \boldsymbol{\theta}^2\right) + \boldsymbol{\theta}^3\right) \qquad 12$$

Specifying the Network

In an ANN numerous parameters must be set. At first, it seems complicated to specify all these parameters in a way that the ANN is able to perform the desired operation. Fortunately, the problem only seems to be so complicated. In reality, it is much simpler. The inputs and outputs of an ANN are defined by the external problem specification. More concretely, if there are five external variables to be used as inputs, five neurons in the input layer must be specified. The same happens with the outputs. If there are to be three outputs from the ANN, there must be three neurons in the output layer. The choice for the number of hidden layers and the number of neurons in each of the hidden layers is not as transparent and is discussed in the next chapter about multi-layer feed-forward networks. As for the bias θ, it must be said that it is not necessary to use it. However, because it gives the ANN an additional variable, networks with bias are more powerful than those without bias. This can be seen when an input p of zero is used. A network without bias will always have a net input n of zero, which may not be desirable.

3.7 Multi-Layer Feed-Forward Network

A multi-layer feed-forward network consists of several successive layers of neurons such as in Figure 8 or Figure 9. The neurons of each layer, except the input layer, receive their input from neurons of the layer immediately in front of it and route their output to neurons of the layer immediately following. The output of the neurons of the output layer is finally passed on to the outside world. Within a layer, there are no connections between the neurons. Usually, an ANN consists of one input layer, at least one hidden layer, sometimes called the middle layer and one output layer. Multi-layer feed-forward networks are used to perform a nonlinear input/output mapping also known as function approximation. Figure 9 shows a multi-layer feed-forward network with S neurons in the input-layer, M-1 hidden-layers, and U neurons in the output-layer (Negnevitsky, 2011). Such a multi-layer network can be seen as a concatenation of several single-layer networks, such as perceptrons.

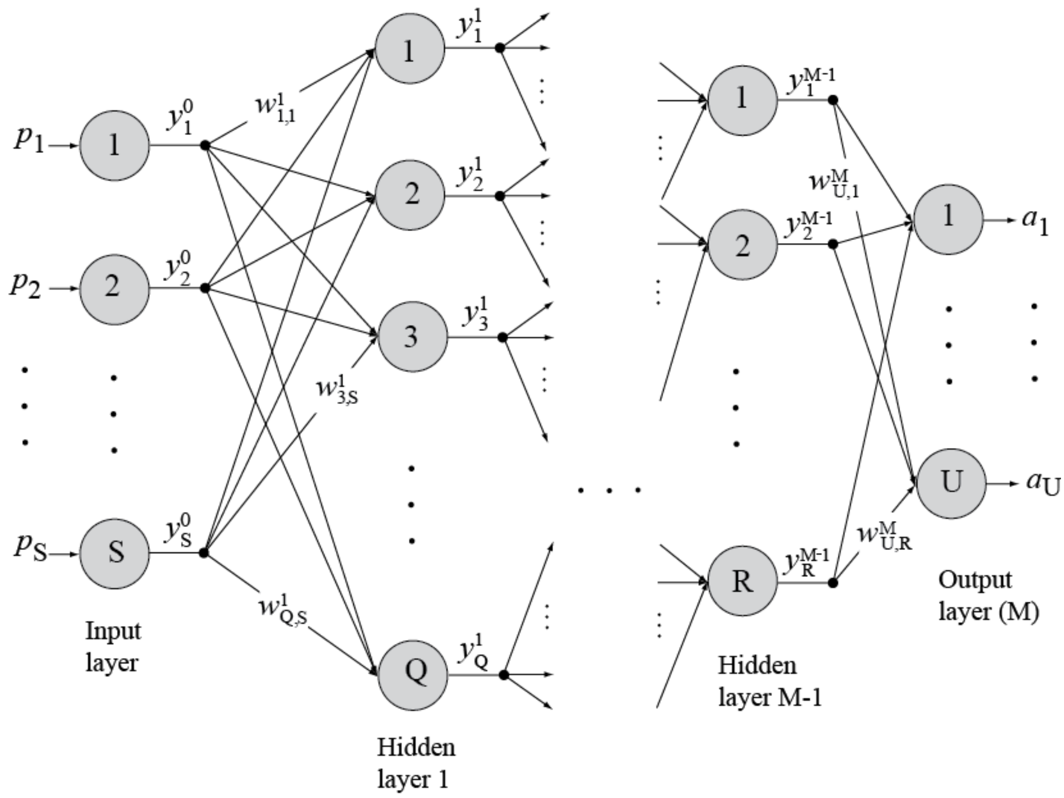

Figure 9 Multi-Layer Feed-Forward ANN

For this reason, multi-layer feed-forward networks are often referred to as multi-layer perceptrons (MLPs). Each layer in an MLP has its own specific purpose.

3.7.1 Input-Layer

The purpose of the input layer (and its neurons) is simple: it receives the input signals and distributes them without any processing to all neurons of the hidden layer. Input layer neurons generally have neither a summer nor a transfer function. Figure 10 depicts a typical input-layer neuron. Its output is calculated as:

$$y_n^o = p_n \qquad 13$$

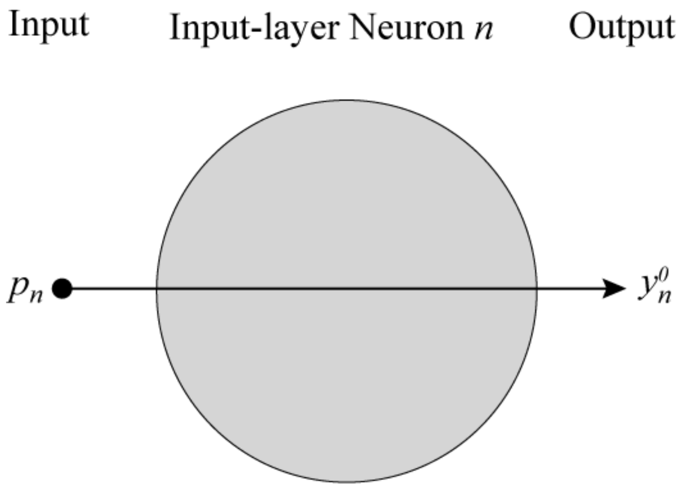

Figure 10 Input-Layer Neuron

where the superscript 0 (zero) indicates that this is the output of an input-layer neuron.

3.7.2 Output-Layer

In contrast to input neurons, output neurons are computational neurons and form the output signals of the entire ANN. The transfer function F of an output layer neuron is linear as explained in chapter 3.3. Figure 11 shows such an output neuron.

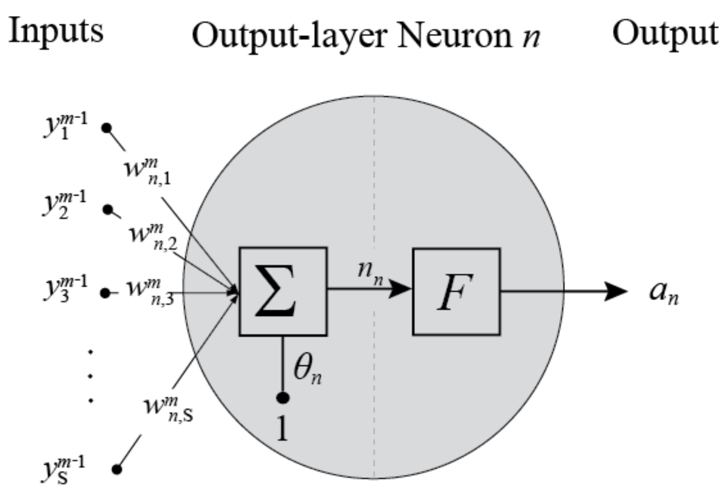

Figure 11 Output-Layer Neuron

The output a_n is calculated as:

$$a_n = n_n = F\left(n_n\right) = F\left(\sum_{i=1}^{S} \mathrm{w}_{n,i}^{m} \cdot y_i^{m-1} + \theta_n\right) \qquad 14$$

where F is the linear transfer function.

3.7.3 Hidden-Layer

The neurons in the hidden-layer 'hide' their desired output. This means that there is no obvious way to know and understand what the desired output of the hidden-layer (neurons) should look like since it is determined by the layer itself. The most commonly used transfer function in the hidden-layer neurons is the sigmoid transfer function. Figure 12 shows neuron n in hidden-layer m. The output of a hidden-layer neuron is computed as:

$$y_n^m = F(n_n^m) = F\left(\sum_{i=1}^{\mathrm{S}} \mathrm{w}_{n,i}^m \cdot y_i^{m-1} + \theta_n^m\right) \qquad 15$$

where F is a non-linear transfer function (e.g., the sigmoid transfer function) and S is the number of neurons in the hidden-layer m.

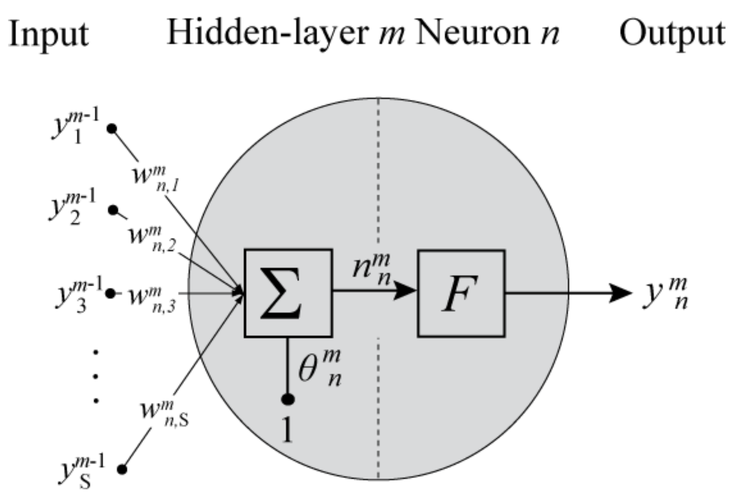

Figure 12 Hidden-Layer Neuron

3.7.4 Back-Propagation

There are various training algorithms to train an MLP, but the most common is back-propagation. This technique was first introduced by Bryson and Ho (1969) but was ignored because of the high computational cost. Ten years later, in the mid-1980s, the back-propagation algorithm was rediscovered by Rumelhart, Hinton, and Williams (1986). The central point behind this technique is that the errors needed to calculate the weight changes in the hidden layers and the output layer are propagated backward, starting with the output errors of the neurons in the output layer. Therefore, the method is called backward propagation.

The back-propagation training algorithm can be used in ANNs with any number of hidden layers. However, it has been demonstrated (Cybenko, 1989; Funahashi, 1989; Hornik, Stinchcombe, & White, 1989) that only one layer of hidden neurons is required to approximate each function with a finite number of discontinuities as long as the activation functions of the hidden neurons are nonlinear. This finding is called the universal approximation theorem and is the reason why only one hidden layer is built into most ANNs (Beale et al., 2014; Krose & Van Der Smagt, 1996).

As already mentioned, MLPs are used to perform nonlinear input/output mapping such as function approximation. However, before such an ANN is able to do this, it must be trained. In other words, the network must learn the task it is to perform. The back-propagation training algorithm consists of two phases: (1) A training input vector **p** is presented to the input layer, which the network then propagates forward from layer to layer, performing the appropriate calculations until the output **a** is generated by the output layer. (2) If the actual output **a** differs from the desired output **t**, an error **e** is calculated as:

$$\mathbf{e} = \mathbf{t} - \mathbf{a} \qquad 16$$

During this phase, this error is propagated backward from the output layer to the input layer and the weights **W** are modified. Figure 13 shows a three-layer ANN which explains graphically how the back-propagation training algorithm works.

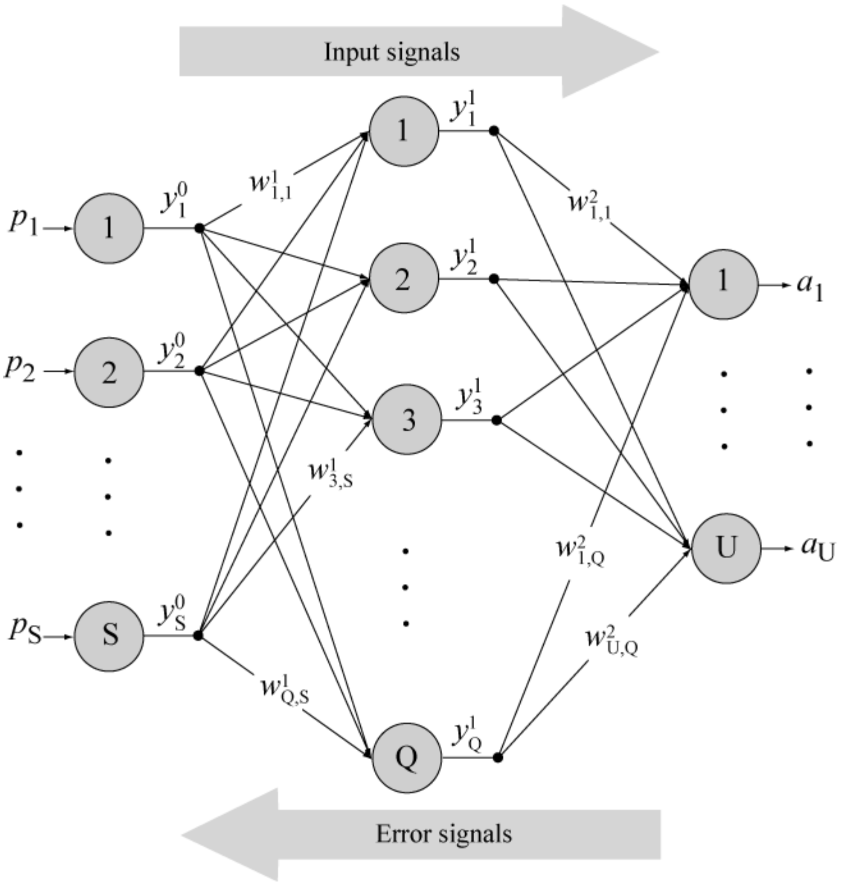

Figure 13 Three-Layer Feed-Forward Back-Propagation Network

The input signals $p_1, p_2, \ldots, p_n = \mathbf{p}$ are propagated forward through the ANN and the error signals, $e_1, e_2, \ldots, e_U = \boldsymbol{e}$ backward through the ANN.

Learning Rate

The learning rate α defines the size of the correction steps that the ANN performs to correct errors in each iteration. A high learning rate (usually a value close to 1) shortens the training time but with lower final accuracy, while a lower learning rate (a value close to 0) takes longer but has the potential for greater accuracy. Optimizations are primarily aimed at faster error minimization, while other improvements are mainly aimed at increasing reliability. To avoid oscillations within the ANN, such as changing connection weights, and to improve the convergence rate, refinements use an adaptive learning rate that increases or decreases as needed (Li, Fu, Li, & Zhang, 2009).

3.7.5 The Back-Propagation Training Algorithm

The back-propagation training algorithm works as follows (Beale et al., 2014; Negnevitsky, 2011):

Step 1: **Initialization**

The weights and biases of all neurons of the ANN are set to random numbers, evenly distributed within a small range of values (e.g., [-1,1]). The learning rate parameter α responsible for the learning speed is set to a value in the range [0,1]. The iteration number q is set to 0.

Step 2: **Propagation**

The input vector $\mathbf{p}(q) = p_1(q), p_2(q),\ldots, p_n(q)$ and the desired output vector $\mathbf{t}(q) = t_1(q), t_2(q),\ldots, t_m(q)$ are passed to the ANN and the following calculations have to be performed:

(1) The output of the input-layer is computed as:

$$\mathbf{y}^0(q) = \mathbf{p}(q) \tag{17}$$

(2) The outputs of the hidden-layers are calculated as:

$$\mathbf{y}^{m+1}(q) = F\left[\mathbf{W}^{m+1}(q) \cdot \mathbf{y}^m(q) + \boldsymbol{\theta}^{m+1}(q)\right], \tag{18}$$

for m = 0,1,…,M-2, where m is the m^{th} hidden-layer, M the total number of hidden-layers and F is a nonlinear transfer function like the sigmoid function.

(3) The output of the output-layer is calculated as:

$$\mathbf{a}(q) = F\left[\mathbf{W}^{\mathrm{M}-1}(q) \cdot \mathbf{y}^{\mathrm{M}-2}(q) + \boldsymbol{\theta}^{\mathrm{M}-1}(q)\right], \tag{19}$$

where F is the linear transfer function

Step 3: **Weight update**

The weights have to be updated, propagating backward the errors associated with the output neurons.

(1) Output-layer calculations:

Error:

$$\mathbf{e}^{\mathrm{M}}(q) = \left(\mathbf{t}(q) - \mathbf{a}(q)\right) \tag{20}$$

Weight and bias correction:

$$\Delta\mathbf{W}^{\mathrm{M}}(q) = -\alpha \cdot \mathbf{e}^{\mathrm{M}}(q) \cdot \left(\mathbf{y}^{\mathrm{M}-1}(q)\right)^{\mathrm{T}} \tag{21}$$

$$\Delta\boldsymbol{\theta}^{\mathrm{M}}(q) = -\alpha \cdot \mathbf{e}^{\mathrm{M}}(q) \tag{22}$$

Weight and bias update:

$$\mathbf{W}^{\mathrm{M}}(q+1) = \mathbf{W}^{\mathrm{M}}(q) + \Delta\mathbf{W}^{\mathrm{M}}(q) \tag{23}$$

$$\boldsymbol{\theta}^{\mathrm{M}}(q+1) = \boldsymbol{\theta}^{\mathrm{M}}(q) + \Delta\boldsymbol{\theta}^{\mathrm{M}}(q) \tag{24}$$

(2) Hidden-layers calculations m (m = 1,2,…,M-2):

Error:

$$\mathbf{e}^{m}(q) = \left(1 - \mathbf{y}^{m}(q)\right) \cdot \mathbf{y}^{m}(q) \cdot \left(\mathbf{W}^{m+1}(q)\right)^{\mathrm{T}} \cdot \mathbf{e}^{m+1}(q) \tag{25}$$

Weight and bias correction:

$$\Delta\mathbf{W}^{m}(q) = -\alpha \cdot \mathbf{e}^{m}(q) \cdot \left(\mathbf{y}^{m-1}(q)\right)^{\mathrm{T}} \tag{26}$$

$$\Delta\boldsymbol{\theta}^{m}(q) = -\alpha \cdot \mathbf{e}^{m}(q) \tag{27}$$

Weight and bias update:

$$\mathbf{W}^m(q+1) = \mathbf{W}^m(q) + \Delta\mathbf{W}^m(q) \tag{28}$$

$$\boldsymbol{\theta}^m(q+1) = \boldsymbol{\theta}^m(q) + \Delta\boldsymbol{\theta}^m(q) \tag{29}$$

Step 4: **Iteration**

The iteration variable q is increased by one and the whole process is repeated from step 2 until any end criterion is met.

The end criterion can be an error criterion (e.g., e < 0.01), the number of iterations (e.g., q = 10000) etc.

3.7.6 Example Back-Propagation Training

To illustrate the back-propagation training algorithm, a simple ANN with two neurons in the hidden-layer depicted in Figure 14 is used to solve the following function approximation problem:

$$g(p) = 1 + \sin\left(\frac{\pi}{4} \cdot p\right) \qquad 30$$

for -2 ≤ $p \leq 2$.

Only one value is required for this example calculation. If the value p=1 is chosen, the result of the function is:

$$g(p) = 1 + \sin\left(\frac{\pi}{4} \cdot p\right) = 1 + \sin\left(\frac{\pi}{4} \cdot 1\right) = 1.707 \qquad 31$$

Therefore the training pair (input p and desired output t) for the backpropagation example is $\{\ \mathbf{p}(0),\ \mathbf{t}(0)\ \} = \{\ [1],\ [1.707]\ \}$. Even if **p** and **t** are actually scalars, they are written as vectors since a scalar can be considered a one-element vector and the back-propagation algorithm described above works with vectors.

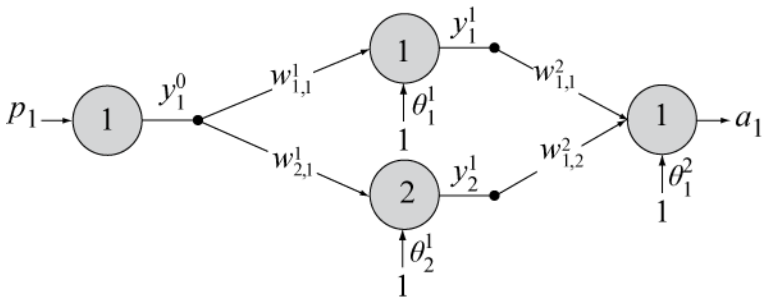

Figure 14 Example 1-2-1 Network

Following the steps of the back-propagation algorithm described before, the weights, and biases of the different ANN layers need to be initialized with values within the range (-1, 1), and the iteration variable q is set to 0.

Hidden-layer weights and biases:

$$\mathbf{W}^1(0) = \begin{bmatrix} -0.30 \\ 0.46 \end{bmatrix}, \qquad \boldsymbol{\theta}^1(0) = \begin{bmatrix} -0.51 \\ -0.19 \end{bmatrix}$$

Output-layer weights and bias:

$$\mathbf{W}^2(0) = \begin{bmatrix} 0.13 & -0.08 \end{bmatrix}, \quad \boldsymbol{\theta}^2(0) = \begin{bmatrix} 0.37 \end{bmatrix}$$

Learning rate variable α is set to:

$$\alpha = 0.1$$

The next step is the propagation of the input $\mathbf{p}(0) = [1]$ of the first training pair. The output of the input-layer is:

$$\mathbf{y}^0(0) = \mathbf{p}(\mathbf{0}) = [1]$$

The output of the hidden-layer is:

$$\mathbf{y}^1(0) = F\left(\mathbf{W}^1(0)\cdot\mathbf{y}^0(0) + \boldsymbol{\theta}^1(0)\right) =$$

$$= \text{logsig}\left(\begin{bmatrix}-0.30\\0.46\end{bmatrix}\cdot[1] + \begin{bmatrix}-0.51\\-0.19\end{bmatrix}\right) =$$

$$= \text{logsig}\left(\begin{bmatrix}-0.81\\0.27\end{bmatrix}\right) = \begin{bmatrix}\dfrac{1}{1+e^{0.81}}\\\dfrac{1}{1+e^{-0.27}}\end{bmatrix} = \begin{bmatrix}0.308\\0.567\end{bmatrix}$$

The output of the output-layer is:

$$\mathbf{a}(0) = \mathbf{y}^2(0) = F\left(\mathbf{W}^2(0)\cdot\mathbf{y}^1(0) + \boldsymbol{\theta}^2(0)\right) =$$

$$= \text{purelin}\left(\begin{bmatrix}0.13 & -0.08\end{bmatrix}\cdot\begin{bmatrix}0.308\\0.567\end{bmatrix} + [0.37]\right) = [0.365]$$

The output layer error would then be:

$$\mathbf{e}^2(0) = \left[\mathbf{t}(0) - \mathbf{a}(0)\right] = [1.707 - 0.365] = [1.342]$$

and the error for the hidden-layer is calculated as:

$$\mathbf{e}^1(0) = \left(1-\mathbf{y}^1(0)\right)\cdot \mathbf{y}^1(0)\cdot\left(\mathbf{W}^2(0)\right)^{\mathrm{T}}\cdot \mathbf{e}^2(0) =$$

$$= \begin{bmatrix} \left(1-y_1^1(0)\right)\cdot y_1^1(0) & 0 \\ 0 & \left(1-y_2^1(0)\right)\cdot y_2^1(0) \end{bmatrix} \cdot \begin{bmatrix} 0.13 \\ -0.08 \end{bmatrix} \cdot \begin{bmatrix} -1.342 \end{bmatrix} =$$

$$= \begin{bmatrix} (1-0.308)\cdot 0.308 & 0 \\ 0 & (1-0.567)\cdot 0.567 \end{bmatrix} \cdot \begin{bmatrix} 0.13 \\ -0.08 \end{bmatrix} \cdot \begin{bmatrix} -1.342 \end{bmatrix} =$$

$$= \begin{bmatrix} 0.213 & 0 \\ 0 & 0.246 \end{bmatrix} \cdot \begin{bmatrix} -0.175 \\ 0.107 \end{bmatrix} = \begin{bmatrix} -0.037 \\ 0.026 \end{bmatrix}$$

Now the weights and bias corrections can be calculated:

$$\Delta\mathbf{W}^2(0) = -\alpha\cdot \mathbf{e}^2(0)\cdot\left(\mathbf{y}^1(0)\right)^{\mathrm{T}} = -0.1\cdot\begin{bmatrix} -1.342 \end{bmatrix}\cdot\begin{bmatrix} 0.308 & 0.567 \end{bmatrix} =$$

$$= \begin{bmatrix} 0.041 & 0.076 \end{bmatrix}$$

$$\Delta\boldsymbol{\theta}^2 = -\alpha\cdot \mathbf{e}^2(0) = -0.1\cdot\begin{bmatrix} -1.342 \end{bmatrix} = \begin{bmatrix} 0.1342 \end{bmatrix}$$

$$\Delta\mathbf{W}^1(0) = -\alpha\cdot \mathbf{e}^1(0)\cdot\left(\mathbf{y}^0(0)\right)^{\mathrm{T}} = -0.1\cdot\begin{bmatrix} -0.037 \\ 0.026 \end{bmatrix}\cdot\begin{bmatrix} 1 \end{bmatrix} = \begin{bmatrix} 0.0037 \\ -0.0026 \end{bmatrix}$$

$$\Delta\boldsymbol{\theta}^1(0) = -\alpha\cdot \mathbf{e}^1(0) = -0.1\cdot\begin{bmatrix} -0.037 \\ 0.026 \end{bmatrix} = \begin{bmatrix} 0.0037 \\ -0.0026 \end{bmatrix}$$

The final step is the update of the weights and biases:

$$\mathbf{W}^2(1) = \mathbf{W}^2(0) + \Delta\mathbf{W}^2(0) = \begin{bmatrix} 0.13 & -0.08 \end{bmatrix} + \begin{bmatrix} 0.041 & 0.076 \end{bmatrix} =$$

$$= \begin{bmatrix} 0.171 & -0.004 \end{bmatrix}$$

$$\boldsymbol{\theta}^2(1) = \boldsymbol{\theta}^2(0) + \Delta\boldsymbol{\theta}^2(0) = \begin{bmatrix} 0.37 \end{bmatrix} + \begin{bmatrix} 0.134 \end{bmatrix} = \begin{bmatrix} 0.504 \end{bmatrix}$$

$$\mathbf{W}^1(1) = \mathbf{W}^1(0) + \Delta\mathbf{W}^1(0) = \begin{bmatrix} -0.30 \\ 0.46 \end{bmatrix} + \begin{bmatrix} 0.0037 \\ -0.0026 \end{bmatrix} = \begin{bmatrix} -0.296 \\ 0.457 \end{bmatrix}$$

$$\boldsymbol{\theta}^1(1) = \boldsymbol{\theta}^1(0) + \Delta\boldsymbol{\theta}^1(0) = \begin{bmatrix} -0.51 \\ -0.19 \end{bmatrix} + \begin{bmatrix} 0.0037 \\ -0.0026 \end{bmatrix} = \begin{bmatrix} -0.506 \\ -0.193 \end{bmatrix}$$

This completes the first iteration of the back-propagation algorithm. In the next iteration, the same procedure must be repeated with the updated weights and biases. The algorithm must continue until an end criterion such as a sufficiently small error or the maximum number of iterations is reached.
The ANN parameters in Table 4 show that the algorithm indeed converges after 50 iterations.

Table 4 Weights, Biases, Outputs, and Errors of the Example ANN for 50 Iterations

	Hidden Layer						Output Layer					
q	$w_{1,1}$	$w_{2,1}$	θ_1	θ_2	y_1	y_2	$w_{1,1}$	$w_{1,2}$	θ_1	a	t	e
0	-0.300	0.460	-0.510	-0.190	0.308	0.567	0.130	-0.080	0.370	0.365	1.707	1.342
1	-0.296	0.457	-0.506	-0.193	0.309	0.566	0.171	-0.004	0.504	0.555	1.707	1.152
2	-0.292	0.457	-0.502	-0.193	0.311	0.566	0.207	0.061	0.619	0.719	1.707	0.988
3	-0.288	0.459	-0.498	-0.191	0.313	0.566	0.238	0.117	0.718	0.859	1.707	0.848
4	-0.283	0.461	-0.493	-0.189	0.315	0.568	0.264	0.165	0.803	0.980	1.707	0.727
5	-0.279	0.464	-0.489	-0.186	0.317	0.569	0.287	0.207	0.876	1.084	1.707	0.623
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
45	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.451	1.301	1.706	1.707	0.001
46	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.451	1.301	1.706	1.707	0.001
47	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.452	1.301	1.706	1.707	0.001
48	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.452	1.301	1.706	1.707	0.001
49	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.452	1.302	1.706	1.707	0.001
50	-0.247	0.497	-0.457	-0.153	0.331	0.585	0.425	0.452	1.302	1.707	1.707	0.000

Chapter 2

ANN Analysis of Nursing Burnout and Hardiness

1. Introduction

ANNs have been used successfully in many different applications such as aerospace, robotics, banking and finance, voice and face recognition, telecommunications, transportation, manufacturing, entertainment, defense, etc. One of the fastest-growing areas of application in recent years has been the healthcare sector and the increasing number of hospitalizations together with the encouraging results of ANN in this field around the world will lead to further progress. The reasons for the growing popularity of ANNs are manifold: modern computers today are powerful enough to solve large, real-world problems with ANNs. Many powerful software packages such as GMDH, MATLAB, SPSS, GENESIS, etc. are now available (P. Kim, 2017; Marvin, 2016; McCormick, Salcedo, Peck, Wheeler, & Verlen, 2017). Furthermore, ANNs are able to learn with real data. Therefore they do not need the a priori knowledge necessary for expert systems and related methods. ANNs have also shown their superior properties in several problem areas compared to multiple regression in data analysis (Benbouras, Kettab, Zedira, Debiche, & Zaidi, 2018; Jamal & Nodehi, 2017; Somers, 2001).

Additionally, ANNs offer capabilities beyond those of regression, such as the capability to deal with nonlinear relationships (Akdeniz, Egrioglu, Bas, & Yolcu, 2018), missing data (Cabeza, Viciedo, Prieto-Moreno, & Vega, 2016), and outliers (Khamis, Ismail, Haron, & Mohammed, 2005; Scarborough & Somers, 2006). ANNs can be used as well in combination with regression, giving researchers the advantages of the strengths of both techniques (Detienne,

Detienne, & Joshi, 2003; Ladstätter et al., 2010). However, the application of ANNs in the field of occupational health has been sparse.

1.1 The Nursing Profession

The work of nurses includes not only the care of patients but also work related to disease prevention and public health. This is particularly evident in the current COVID 19 crisis (World Health Organization, 2020). Without the tireless efforts of nurses worldwide, the crisis would be much more serious. In most countries, nursing is considered a qualified profession requiring special training. This training usually lasts three years and includes general knowledge of medicine, practical experience of working with patients under the supervision of nursing veterans. After passing the final examination, nurses receive their diploma and are free to practice their profession. Some of the various duties of the nursing profession are technical in nature, such as measuring blood pressure, maintaining the life-support system of patients in intensive care units, etc. In recent decades, information technology has also taken over an increasingly large part of the nursing profession (Houston, Dieckhaus, Kircher, & Lardner, 2018) but the majority of their tasks are interpersonal in nature, such as being a kind of teacher, adviser, and administrator, who is responsible for promoting and maintaining the health of patients (Benson & Latter, 1998; Stein-Parbury, 2013). Some of the tasks of nurses can be decided and performed autonomously and individually, while others are instructed by doctors. Autonomous tasks include activities such as maintaining the patient's personal hygiene, positioning the patient in his or her hospital bed to avoid muscle or joint contractions, and sore spots caused by lying in bed for long periods of time. In addition, the activities of nurses include providing information to patients and their families, ranging from simple things like changing unhealthy behavior to simple treatments that patients can carry out independently at home to maintain their health after leaving the hospital. They are also responsible for administering medication, bandaging or sewing up injuries, etc., as instructed by the nurses' superiors. During the last decades, progressive development and specialization have made the nursing profession an autonomous and interdependent profession in relation to the medical profession (McGee & Inman, 2019). A summary of some specific characteristics is presented in Table 5 on page 80.

1.2 Burnout in Nurses

The nursing profession is a particularly stressful occupation. It is characterized by a continuous physical and emotional effort that is demanded of the patients (Hayes, Douglas, & Bonner, 2015; Kennedy, 2005). Nurses are constantly confronted with the pain and suffering of the patients and regularly find themselves in difficult situations in which they are forced to make critical decisions, even if in some cases only incomplete or unclear information is available (Braithwaite, 2008). Contact with patients who are in the final stages of their lives, or their death, are additional and critical stress factors (Peterson et al., 2010). Taking all factors into account, working in a hospital is not only a physical and mental effort, but also an emotional one, and it is therefore clear that nurses are at high risk of burnout (Hetzel-Riggin, Swords, Tuang, Deck, & Spurgeon, 2019).

1.2.1 Burnout Antecedents in Nursing

The main burnout antecedents of the nursing profession can be divided into two groups: (1) organizational factors and (2) interpersonal factors. Some specific organizational factors investigated and described in various studies are work

Table 5 Specific Characteristics of the Nursing Profession

Task-related and organizational factors	Work-schedule characteristics	Social and emotional factors
Responsibility	Night-work	Helping profession
Contact with pain and death	Shift-work	Little appreciation and acknowledgment for their work
Hierarchical and rigid organizational structure	Overtime	Conflicts with doctors, patients, and family members of the patient
Consequences of the decisions		Scarce emotional support
Time pressure		
Little participation in decision-making		
Interferences with tasks		
Work overload		
Role ambiguity		
A lot of and fluctuating information		

overload, lack of clarity, task ambiguity, and supervision problems (E. Chang & Hancock, 2003; E. M. Chang et al., 2005; Kitaoka-Higashiguchi, 2005; X. Liu et al., 2018). Some authors have highlighted the increasing complexity of tasks and lack of clarity of care functions as reasons for overload and role ambiguity (Tunc & Kutanis, 2009).

The interpersonal factors result mainly from the emotional demands of the patients and their relatives but also from conflicts with colleagues and superiors (Montgomery, Spânu, Băban, & Panagopoulou, 2015; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007).

The most consistently to burnout related socio-demographic factor is the age (Cañadas-De la Fuente et al., 2015; Gómez-Urquiza, Vargas, De la Fuente, Fernández-Castillo, & Cañadas-De la Fuente, 2017).
McVicar (2003) found that one of the reasons for the wide variety of stress reactions such as burnout among nursing professionals lies in the many possible combinations of their personality and coping strategies (Simoni & Paterson, 1997; Van der Colff & Rothmann, 2009).

1.2.2 The Effect of Hardiness on Nurses' Burnout

One of the personality traits to which nurses attribute a protective function in the burnout process is hardiness. It mitigates the negative consequences of stress. In recent years, the hardiness model has been widely used in nursing studies (Abdollahi, Abu Talib, Yaacob, & Ismail, 2014; Henderson, 2015). The importance of hardiness for the successful practice of nursing has also been confirmed in various Chinese studies on stress and burnout (Lambert, Lambert, Petrini, Li, & Zhang, 2007a; Liang & Miao, 2012).

1.3 Objectives

The main objectives of this work are twofold: First, to use ANNs as an instrument for data analysis in the field of nurse burnout and to compare the results to those of OLS regression. Second, to see how ANNs in their simple and concatenated form are useful to analyze the nurse burnout process and the effect of hardiness on it. Specific objectives are summarized below:

1. To show that simple and concatenated ANNs are effective methods on their own but especially in combination with OLS regression to analyze the antecedents–burnout–consequences process.

2. That ANNs give better results in burnout prediction compared to OLS regression when the relationships between variables are nonlinear.
3. That some of the relationships between variables of the antecedents–burnout–consequences process, including the effect of hardiness on these relationships, are nonlinear.
4. That ANNs allow researchers to find important relationships even if they are nonlinear and statistically not significant in OLS regression analysis.
5. To improve our understanding of hardiness through a person-centered method that is used to find different hardiness profiles such as a profile with an average level on commitment and control, and a high level on challenge or a profile with a high level of commitment and challenge and a low level of control.

2. Studies

2.1 Study 1:

Expanding the Occupational Health Methodology: A Concatenated Artificial Neural Network Approach to Model the Burnout Process in Chinese Nurses

Ladstätter, F., Garrosa, E., Moreno-Jiménez, B., Ponsoda, V., Reales, J., & Dai, J. (2016). Expanding the occupational health methodology: A concatenated artificial neural network approach to model the burnout process in Chinese nurses. *Ergonomics, 59*(2), 207-221.
doi:https://doi.org/10.1080/00140139.2015.1061141

Abstract

Artificial neural networks are sophisticated modelling and prediction tools capable of extracting complex, nonlinear relationships between predictor (input) and predicted (output) variables. The present study explores this capacity by modelling nonlinearities in the hardiness-modulated burnout process with a neural network. Specifically, two multi-layer feed-forward artificial neural networks are concatenated in an attempt to model the composite nonlinear burnout process. Sensitivity analysis, a Monte Carlo based global simulation technique, is then utilized to examine the first-order effects of the predictor variables on the burnout sub-dimensions and consequences. Results show that (1) this concatenated artificial neural network approach is feasible to model the burnout process, (2) sensitivity analysis is a prolific method to study the relative importance of predictor variables, (3) the relationships among variables involved in the development of burnout and its consequences are to different degrees nonlinear.

Keywords: burnout; artificial neural network; hardiness; health services; sensitivity analysis

Practitioner Summary: Many relationships among variables (e.g. stressors and strains) are not linear, yet researchers use linear methods such as Pearson correlation or linear regression to analyse these relationships. Artificial neural network analysis is an innovative method to analyse nonlinear relationships and in combination with sensitivity analysis superior to linear methods.

1. Introduction

1.1. Nursing and Health Care System Changes

Amongst the diverse health professions, nursing is considered to be an occupation highly vulnerable to stress and it is believed that the stressors nurses are exposed to are a problem that affects the practice of nursing globally (Butterworth, Carson, Jeacock, White, & Clements, 1999; Peterson, Arnetz, Arnetz, & Hörte, 1995; Pisanti, van der Doef, Maes, Lazzari, & Bertini, 2011; Schaufeli & Enzmann, 1998; Xie, Wang, & Chen, 2011). During the past two decades, the health care system has experienced important changes that include growing readmission rates, the ever-increasing emphasis on efficiency, and the demands of patients with acute and chronic diseases (Hanrahan, Aiken, McClaine, & Hanlon, 2010; Lindberg, 2007). These rising stressor levels are affecting nurses' job satisfaction, and may ultimately influence the quality of nursing care for patients (Lim, Bogossian, & Ahern, 2010; Tourangeau & Cranley, 2006). The People's Republic of China (PRC) faces a considerable set of challenges in health services delivery. It has been over 30 years since the PRC embarked on its new economic development strategy, which has resulted in impressive and sustained economic growth rates unparalleled for large economies throughout the last five decades. However, the rapid transformation towards a modern working life has been associated with growing demands of learning new skills, the requirement to adapt to new forms of work, pressure of higher productivity and quality of work, hustle, and growing psychological workload among the workforce, especially in the health professions (Garrosa, Moreno-Jiménez, Ladstätter, & Liang, 2006; Xie et al., 2011; Wang et al., 2012). Comparatively little has been published (in English) about how the economic transformation in the PRC is influencing changes in the health service labour environment, working conditions, and their consequences on employees (Lambert, Lambert, Petrini, Li, & Zhang, 2007a, 2007b). A partial explanation of the relative absence of research on these relevant labour issues originates from some degree of self-censorship by PRC-based academics, as the subject might spark some kind of labour activism, which is a sensitive issue for the Chinese government.

1.2. The Role of Hardiness in the Development of Burnout

Burnout in human services is understood as a specific occupational stress. In health-related professions, this results in psychologically and emotionally challenging interactions between caregivers and their patients (Gil-Monte & Moreno-Jiménez, 2007; Maslach & Jackson, 1986; Schaufeli, Maassen, Bakker, & Sixma, 2011). The operational definition of burnout in human services has three dimensions: (a) emotional exhaustion, which refers to feelings of being overextended and drained by the emotional demands of one's work, is commonly considered the core symptom of the burnout syndrome (Schirom, 2003), (b) depersonalization is specified as the evolvement of negative, cynical attitudes toward patients, and (c) lack of personal accomplishment, defined as the tendency to believe that one is no longer effective in working with patients

(Maslach & Jackson,1986). On the basis of these three dimensions, the occurrence of burnout can be alleviated by the availability of personal resources (Garrosa, Moreno-Jiménez, Rodríguez-Muñoz, & Rodríguez-Carvajal, 2011; Laschinger & Grau, 2012) such as hardiness, which was proposed by Kobasa (1979) as an idiosyncratic and active way of understanding a person's relationships with others, with goals, and with problems (Kobasa-Ouellette & Di Placido, 2001; Maddi, Harvey, Khoshaba, Lu, & Brow, 2006). Hardiness has been characterized by high levels of the three interrelated dimensions (Kobasa, 1979): (1) Commitment (vs. alienation) epitomizes persons who are committed to and feel deeply involved in the activities of their lives. (2) Control (vs. powerlessness) typifies a desire to having a continuous influence on the outcomes taking place around someone, regardless of how difficult this becomes. (3) Challenge (vs. security) reflects the expectation that life is capricious, that changes will encourage personal development, and that potentially stressful situations are assessed as exciting and stimulating rather than intimidating (Maddi, 2006). Extensive evidence reveals that hardy persons perform better and remain healthier in the presence of stress (e.g., Dolan & Adler, 2006; Eschleman, Bowling, & Alarcon, 2010; Garrosa, Moreno-Jiménez, Liang, & González, 2008; Hystad, Eid, Laberg, Johnsen, & Bartone, 2009).

Several studies provide support for the hypothesis that higher levels of hardiness are correlated with less stress and burnout (Duquette, Keruac, Sandhu, & Ducharme, 1995; Kobasa-Ouellette & Di Placido, 2001; Michielsen, Willemsen, Croon, De Vries, & Van Heck, 2004) and there is empirical evidence (Ladstätter, Garrosa, Badea, & Moreno, 2010) that the process of burnout (antecedents – burnout – consequences), including the modulating impact of hardiness on the development of burnout, involves nonlinear relationships. Ladstätter et al. identified, for example, that the relationship between the variables conflictive interaction (a burnout antecedent), hardiness, and lack of personal accomplishment is of an S-shaped nature. This means that there are large areas with low variation of the dependent variable lack of personal accomplishment corresponding to large variations of the independent variables conflictive interaction and hardiness, and relatively small areas in which most of the variation of the variable lack of personal accomplishment occurs. In other words, the effect of the independent variables on the dependent variable is limited to a rather small range of values. Within this range, however, the effect is quite strong.

Concerning a potential effect on organizational issues, hardiness appears to be positively related to organizational effectiveness (Garrosa et al., 2011; Fullick et al., 2009). In contrast to the quantity of studies on possible causes of burnout in the realm of nursing, only a few studies can be found on burnout-related consequences (Hakanen & Schaufeli, 2012; Lee, Lim, Yang, & Lee, 2011), which can be classified as consequences for the individual, effects on work orientation and attitudes, and effects for the organization or company (Schaufeli & Enzmann, 1998).

The above-mentioned information is included in the theoretical model (Figure 1) that is evaluated in this study. This model analyses burnout and the consequences of burnout as a function of job stressors and hardiness.

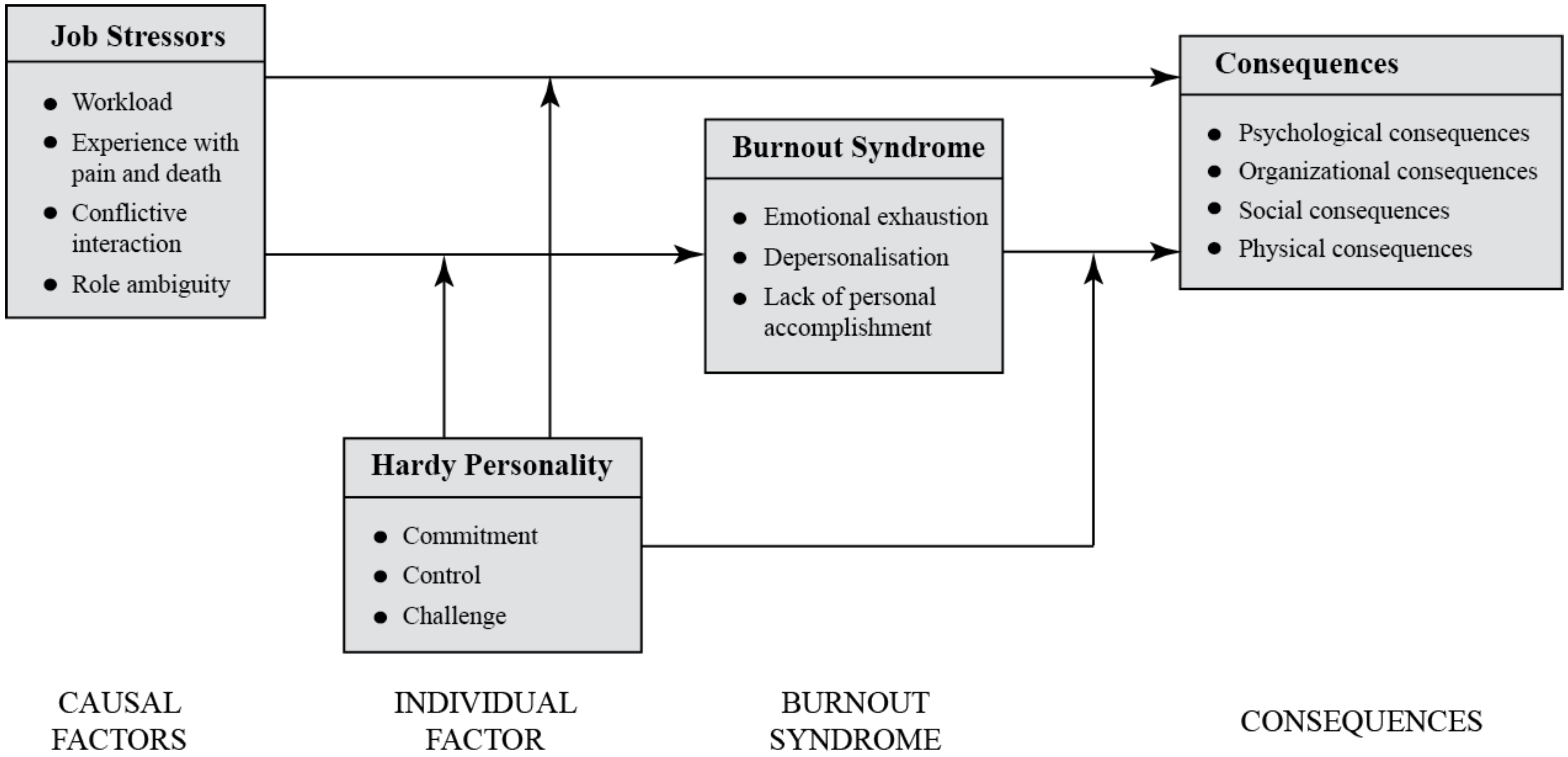

Figure 1. Theoretical model of the hardiness-modulated burnout process.

1.3. Neural Networks and Nonlinearity

With the purpose of deepening our understanding of how burnout is related to its antecedents, consequences, and to gain knowledge about how the distinct hardiness dimensions modulate the intensity of burnout and its consequences, artificial neural networks (ANNs), a comparatively new methodology, are probably the most appropriate instrument (Caudill, 1989; Hagan, Demuth, & Beale, 2002). Together with expert systems, fuzzy logic, and genetic algorithms, ANNs belong to the domain of artificial intelligence (Negnevitsky, 2005) and offer characteristics beyond those of linear and classical statistical methods, such as the capacity to deal with outliers and nonlinear relationships between variables (Garson, 1998; Karanika-Murray & Cox, 2010; Ladstätter, Garrosa, & Dai, 2014; Ladstätter et al., 2010; Palocsay & White, 2004; Somers, 2001). Due to their superiority, especially with regard to their predictive capacity, ANNs have found their way into many fields, such as aerospace, automotive, defence, medical or robotics. However, ANNs' improved predictive accuracy is not sufficient to justify their wider use in occupational health research. Scarborough and Somers support the requirement of defining a role for ANNs that includes a clear attachment to theory development and testing because these networks are exploratory pattern-recognition algorithms, which means that it is critical to assess the plausibility and relevance of the relationships that they extract. Thus, the discussion has to start with why ANNs should be incorporated into occupational health research and then move on to consider how they can be useful in modelling nonlinear relationships.

ANNs are especially well suited to study burnout and the environment in which it evolves for several reasons. First, burnout, as well as hardiness, is not seen as a single variable but as a three-dimensional construct (Eschleman et al., 2010; Kobasa, 1979), which creates a problem for conventional statistical methods that must analyse each of the three dimensions separately. ANNs, however, are capable of analyzing the whole burnout construct and its consequences simultaneously, generating results that are not exclusively based on the independent burnout sub-dimensions and the individual consequences but that also take into account intra- and inter-dependencies between their respective dimensions. Second, it is questionable whether the relationships between burnout antecedents, burnout, and consequences of burnout, as well as the moderating effect of hardiness on the afore-mentioned relationships, are linear. Ladstätter et al. (2010) found that the relationships between burnout antecedents and the burnout sub-dimensions, as well as the effect of hardiness on the process of burnout, are of nonlinear nature. ANNs are better suited to evaluate the burnout process than classical statistical methods because they are nonparametric and, therefore, do not underlie the various assumptions of the general linear model (DeTienne, DeTienne, & Joshi, 2003), which makes them capable of approximating any (linear and nonlinear) function or model (Hornik, Stinchcombe, & White, 1989) limited solely by the generalization capability of the generated model. Finally, but perhaps most importantly, we might commit a mistake by applying linear methods as an all-purpose approach to possibly non-linear problems. This might generate unexpected outcomes in the sense that one would not find a significant relationship between variables (not because there is none but only because of its nonlinear nature, which makes it impossible to detect with a linear method) despite that, theoretically, it would make sense to find one. Unfortunately, until now, researchers scarcely took advantage of the benefits of ANNs in their studies (Karanika-Murray & Cox, 2010; Ladstätter et al., 2010; Lord, Hanges, & Godfrey, 2003; Quinn, Rycraft, & Schoech, 2002; Thomas, 2006), despite their potential to improve both explanations and predictions compared to more familiar methods (Scarborough & Somers, 2006). In occupational health, just a few investigations using ANNs (Collins & Murray, 1993; Karanika-Murray & Cox, 2010; Ladstätter et al., 2010; Somers, 1999, 2001; Somers & Casal, 2009) are known. Karanika-Murray and Cox (2010) studied the application of ANNs to modelling the relationships between work characteristics and employee health, comparing the outcomes of the ANN analysis with the outcome of a multiple linear regression analysis. They revealed that the ANN results outperformed the linear regression models and that the predictors in the two approaches differed in their relative importance for predicting outcomes. Somers and Casal (2009) investigated the capabilities of ANNs by modelling nonlinearities in the job satisfaction–job performance relationship with two different ANN paradigms: a multi-layer perceptron and a radial basis function neural network, comparing the results with those of a Tobit regression and an OLS regression analysis. Both ANN paradigms showed substantially better results in predictive accuracy. Specifically, the multi-layer perceptron explained more than twice as much variance in job performance as the regression analysis. Ladstätter et al. (2010) employed a radial basis function (RBF) network to study burnout using socio-demographic variables, job stressors and hardiness as predictors of burnout. However, their research model did not include the consequences of burnout. In order to investigate the whole process of burnout, that is, antecedents → burnout → consequences, a more complex network has to be created. Concretely, two ANNs need to be concatenated. The output of the first ANN, that is, the three burnout sub-dimensions, is part of the inputs for the second ANN. The ANN architecture utilized in the present study to model the whole burnout process is shown in Figure 2.

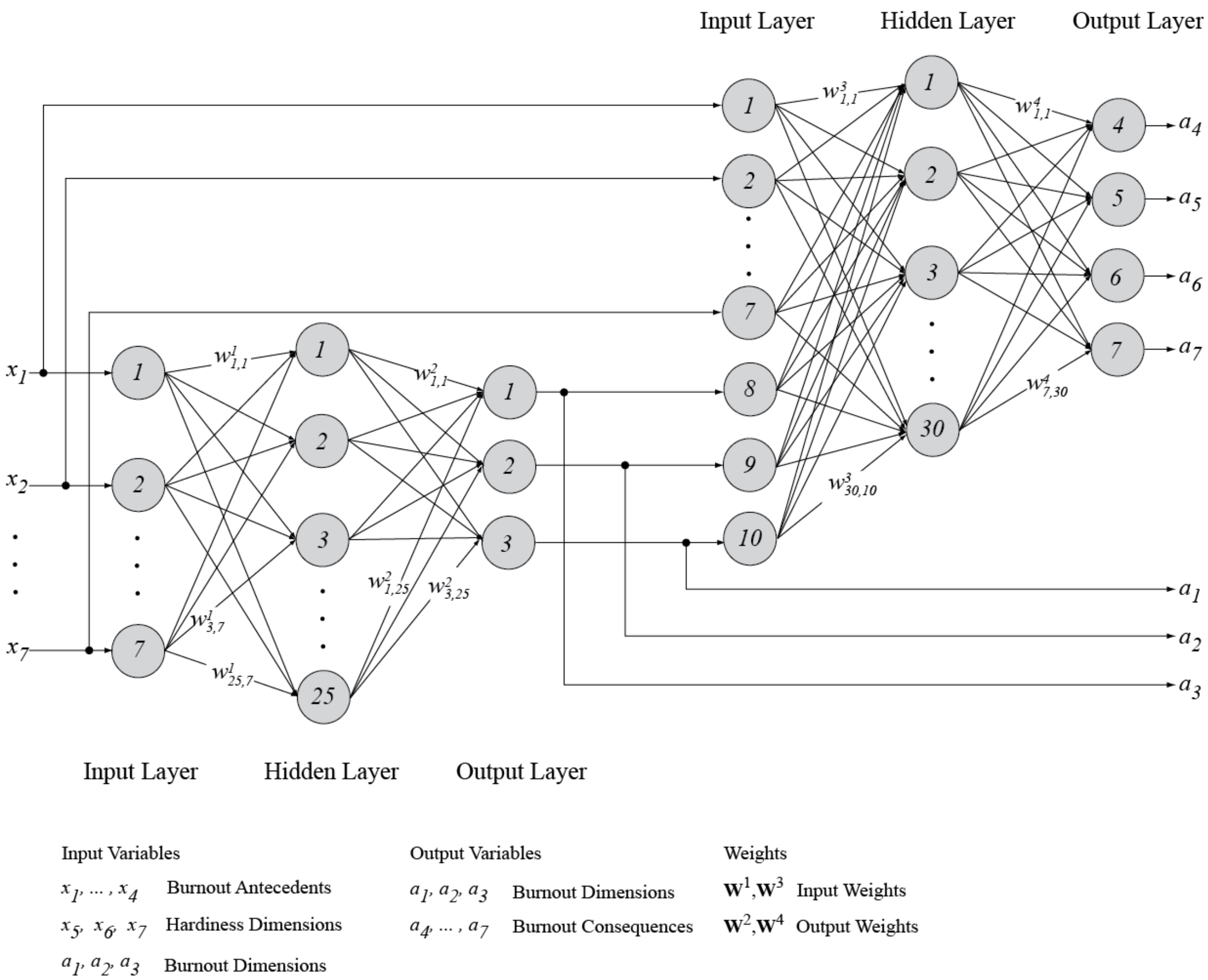

Figure 2. Concatenated ANN architecture applied in the hardiness-modulation antecedents –burnout – consequences model.

Various ANN paradigms capable of function or model approximation and prediction exist. The network selection process that is necessary to guarantee best results is based on trial and error and, therefore, time consuming. For the present study, we tested two different ANN paradigms: a multi layer perceptron (MLP), also known as multi-layer feed-forward network (Negnevitsky, 2005) and a radial basis function (RBF) network (Hagan, Demuth, & Beale, 2002). After several test runs, we chose the MLP network due to superior and more stable prediction results. Besides the selection of the ANN paradigm, several other parameters such as the training algorithm, the number of layers, the number of neurons in each layer, the connection structure between the layers and its neurons. must be chosen, which will be discussed in the analysis section of the present article.

1.4. Sensitivity and Visual Analysis

In spite of the enormous success in numerous areas, ANNs are still regarded as black-box methods (Sjoberg, et al., 1995) where it is hard for the user to comprehend the nature of the internal representations, that is, the weights, generated by the ANN in order to respond to a given problem. To overcome this limitation, a trained ANN has to be understood as a model of the process under investigation, which can be simulated. Then, various rule extraction and numerical methods can be used to study the contribution of the involved input variables to the output variables in the model (ANN). Sensitivity analysis (SA) is one of the most broadly used methods (Gevrey, Dimopoulos, & Lek, 2003) in this regard. According to Saltelli, Chan and Scott (2000), SA can be used to: (1) assess whether a model sufficiently represents the process under study, (2) identify factors which strongly contribute to output variability (and potentially require additional research to improve the knowledge base), (3) distinguish between significant and insignificant model parameters, (4) highlight the numeric ranges within the Likert range of the input variables which are associated with a maximum numeric variation in the output variables, and (5) determine factor interaction.

There are different techniques, which have different requirements (e.g., existence of correlations between the input variables, known linear or non-linear relationships between input and output variables.), and aims (e.g., determination of uncertainty of a specific input variable in connection to the overall output) to conduct SA (Saltelli, Tarantola, Campolongo, & Ratto, 2004). In the present study, we applied a Monte Carlo (MC) based global technique that performs multiple model evaluations using probabilistically generated pseudorandom numbers as model input. This technique produces sensitivity measures which can be interpreted like other variance-based statistical methods. As the input variables are correlated, we used a replicated Latin hypercube sample (r-LHS), which is generated by replicating r times a base sample set created using the Latin hypercube sample (LHS) algorithm (McKay, 1995; McKay, Beckman, & Conover, 1979) to estimate the importance indices (first-order effects) of the input variables (Saltelli et al.).

Apart from estimating the first-order effects of the variables that strongly contribute to output variability, it is very important to know the shape of relationships among variables, and the ranges where small changes have large effects (high sensitivity) as this helps to understand how certain variables affect others. Various authors (Ladstätter et al., 2010; Somers & Casal, 2009) suggested using three-dimensional surface plots extracted through the simulation of a trained ANN to comprehend how input variables affect the output variable and to identify areas of high sensitivity. This technique generates graphical models of the nonlinearity and provides an indication of its pervasiveness. In addition, it addresses the question of interpretability by evaluating whether or not the ANN has extracted conceptually reasonable relationships.

The present study verifies the following hypotheses:

1. The concatenated ANN approach is feasible to model and analyse the antecedents–burnout–consequences process and provides better results than multiple linear regression analysis.
2. The relationships between the variables of the antecedents–burnout–consequences process, including hardiness, are of a nonlinear nature.
3. SA is a suitable method to analyse the relative importance of the input variables utilized in the present ANN study.

2. Method

2.1. Sample

A convenience sample of nurses was obtained from four Chinese hospitals: Beijing hospital, Peking University First hospital, Qingdao MCH, and Binzhou Medical University Hospital. The response rate was 87%. After excluding 11 cases from the original sample due to missing data, the final sample comprised 465 participants of which 97% were females and whose age ranged from 20 to 54 years (M = 28.9, SD = 6.3). The majority of the sample (62%) was single or lived with a partner and had no children (65%). In terms of education, 60% of the respondents had a special nursing degree, 30% held a bachelor's degree and about 5% had graduated from University. Concerning the employment terms, participants were classified into three different categories: permanent nurses (28%), contractors (67%), and temporary nurses (5%). Weekly working hours ranged from 4 to 60 hours (M = 39.8, SD = 8.4) and 62% of the participants spent more than 75% of their working time caring for patients.

2.2. Measures

The process of burnout, including the effect of hardiness, was measured with the Nursing Burnout Scale Short Form (NBS-SF) (Garrosa et al., 2008; Moreno-Jiménez, Garrosa Hernández, & González-Gutiérrez, 2000; Tang, Garrosa, Lei, & Liang, 2007). The survey offers measures of specific nursing job stressors, identified as antecedents of burnout, burnout, and consequences of burnout, as well as hardiness and coping, totalling 65 items.

Burnout is measured by 12 items and is consistent with the classical dimensions in human services: emotional exhaustion (4 items, $\alpha = .82$) (e.g. 'In my work, I often feel emotionally and physically exhausted'), depersonalization (4 items, $\alpha = .76$) (e.g. 'With regard to my patients, I do not involve myself in their problems; it is as if they do not exist'), and lack of personal accomplishment (4 items, $\alpha = .75$) (e.g. 'Nobody considers me, I feel like "an all-purpose maid"'). Confirmatory factor analysis revealed that the hypothesized three-factor structure of burnout fits the data well, $\chi^2(47) = 199.71$, $p < .001$, goodness-of-fit index (GFI) = .93, adjusted goodness-of-fit index (AGFI) = .89, root mean square error of approximation (RMSEA) = .08, normed fit index (NFI) = .91, Tucker-Lewis index (TLI) = .90, comparative fit index (CFI) = .93).

Hardiness is a 12-item measure of commitment (4 items, $\alpha = .77$) (e.g. 'My daily work satisfies me and makes me totally devoted to it'), challenge (4 items, $\alpha = .71$) (e.g. 'Whenever possible, I try to have new experiences in my daily work'), and control (4 items, $\alpha = .74$) (e.g. 'Though I strain, I do not obtain my goals at work'). Confirmatory factor analysis revealed that the hypothesized three-factor structure of hardiness fits the data well, $\chi^2(47) = 149.89$, $p < .001$, GFI = .95, AGFI = .92, RMSEA = .07, NFI = .90, TLI = .90, CFI = .93).

Job stressors are evaluated via 12 specific items divided into four sub-scales (1) troubled interaction (4 items, $\alpha = .72$), which evaluates troubled and difficult relations with doctors, patients, and relatives (e.g. 'The doctors talk to me in an authoritarian way'); (2) work overload (4 items, $\alpha = .73$) (e.g. 'I have to care for too many patients'); (3) contact with pain and death (4 items, α = .74) (e.g. 'It affects me when I apply painful treatments'); and (4) role ambiguity (4 items, α = .78), which establishes nurses' perceived clearness of information about their work and their organizational role (e.g. 'The orders I receive are vague and ambiguous').

The burnout consequences measure consists of 16 items separated into four sub-scales that measure (1) psychological (4 items, α = .71) (e.g. 'I feel lifeless, as if I had no strength to do anything'); (2) organizational (4 items, α = .83) (e.g. 'I often have the desire to change my profession'); (3) social (4 items, α = .82) (e.g. 'My profession is negatively affecting my relations outside of work'); and (4) physical consequences (4 items, α = .73) (e.g. 'My work is affecting my physical health').

The NBS-SF is a 4-point Likert-type scale, ranging from 1 (*I totally disagree*) to 4 (*I totally agree*) and has been found to be reliable and valid (Garrosa et al., 2008; Tang et al., 2007). Besides the assessment of hardiness, burnout, stressors, and strains, the NBS-SF asks for socio-demographic and professional information such as gender, age, job status (employment terms), weekly hours worked, and the number of patients attended per day.

2.3. Analytical Strategy

The analytical approach we used in this study included the following three steps:

1. Analysis of the theoretical model (Figure 1) using: (a) a concatenated ANN, and (b) a multiple linear regression analysis (MLR), including a comparison of both methods (R^2 and t-test). For the analysis, we used 85% of the sample.
2. Validation of the theoretical model of the in the first step generated concatenated ANN and the MLR model, including a comparison of both methods (R^2 and t-test). For the validation step, we used the remaining 15% of the sample.
3. Evaluation of the concatenated ANN. This last step includes sensitivity analysis and visual analysis.

2.4. Statistical Analysis

As described in the introduction section, we employed an MLP for the burnout model approximation. Concretely, we concatenated two MLPs, each of them consisting of an input-layer, a hidden-layer, and an output-layer. The output-layer of the first network was connected to the input-layer of the second network. Consequently, the overall network was composed of 6 layers. Besides the number of layers, another important architecture-related issue is the number of neurons that each of these layers comprises. In the case of the input- and output-layers, this issue is straightforward. For each input and output variable, the network needs one neuron in the input- and output-layer. The same rule applies for the output-layer. The decision of how many neurons should be employed in the hidden-layer is more complicated and has a great influence on the network's predictive capacity. The required information to make this decision emerges during the trial-and-error phase of the network training. Two important aspects have to be taken into consideration. First, the more complex the model is that has to be estimated, especially with regard to its nonlinearity, the more neurons have to be integrated into the hidden-layer in order to achieve good prediction results. However, and this is the second aspect, too many neurons in the hidden-layer worsen the generalization capacity of the estimated model. To overcome this dilemma, the number of hidden neurons was reduced stepwise from 70 to 10 during the trial-and-error phase of the network training. Best results with respect to prediction accuracy and generalization capacity were achieved with 25 neurons in the hidden-layer of the first sub-network and 30 neurons in the hidden-layer of the second sub-network. An illustration of the final network is depicted in Figure 1, in which x_i are the network inputs, $w_{i,j}$ the weights between the different network layers, and a_i are the network outputs

For the training of the network, a training algorithm, as well as a transfer function and a performance function have to be chosen (Hagan et al., 2002; Negnevitsky, 2005). We tested four training algorithms: the classical gradient descent back-propagation (Rumelhart, Hinton, & Williams, 1986), the Levenberg-Marquardt algorithm (Hagan & Menhaj, 1994), Bayesian regulation back-propagation (Foresee & Hagan, 1997), and resilient back-propagation (Riedmiller & Braun, 1993). We achieved the best results, in terms of model fit, with the Levenberg-Marquardt algorithm, which was consequently chosen as the preferred training algorithm for the burnout model approximation.

For the actual training process, examples of proper network behaviour are required, that is, network inputs **x** (x_1,..., x_7 in the present study) and target outputs **t** (t_1,..., t_7). The network inputs are the data of the independent variables of the sample (e.g., troubled interaction, workload) and the network outputs are the data of the dependent variables of the sample (e.g., psychological consequences). Throughout training, the weight matrices $\mathbf{W}^i$ of the network are repeatedly adjusted to minimize the network error, which is calculated with a so-called performance function. The most commonly utilized performance function for feed-forward networks is mean square error (mse), the average squared error between the network outputs **a** (a_1, …, a_7) and the target outputs **t** (t_1,…, t_7). In order to improve the generalization capacity of the ANN, the more advanced mean squared error with regularization performance function was utilized, which measures network performance as the weight sum of two elements: the mean squared error (MSE) and the mean squared weight values. The minimization of the weights forces the ANN to implement the burnout model as smoothly as possible, making it more likely to generalize well. To further improve the generalization capacity of the network, the network training was performed applying a method called early stopping. This technique required the sample to be divided into three subsets. The first subset, the training set, comprised 70% of the sample, and was used to estimate the model (i.e., to calculate the gradient and to update the network weights and biases). The second subset (15% of the sample), the test set, was used to monitor the error during the training process. The test set error typically decreases during the early period of training, as does the training set error. However, when the network begins to overfit the data (i.e., the generalization capacity of the network decreases), the test set error typically begins to rise. When the test error increases for a specified number of iterations, the training of the network stops, and the weights and biases which were achieved at the minimum of the test error are saved. These weights and biases are the elements that define the estimated model. The validation set is used to validate the model generated and to compare different models. Analyses were conducted with the Neural Network Toolbox™ of Matlab® for Windows.

To estimate the main effect of the input variables on the output variables in the generated ANN burnout model, we used SA. The pseudorandom numbers sample was generated with r-LHS, as the input and output variables were correlated. To induce a correlation structure in the sample design, the Iman and Conover method was used (Iman & Conover, 1982) because it permits the generation of large sample sizes, which is better because the 7- and 10-dimensional input hyperspaces of the two concatenated networks can be divided into smaller fractions. For the r-LHS design, we selected a base sample of size $N = 100$ with $r = 50$ replicates. Hence, the total cost of estimating all the first-order effects S_i of the input variables is $N \times r = 5000$. Sample generation and analyses were performed with Simlab 2.2 (Simlab, 2011).

ANN results were examined in relation to those from MLR models (Palocsay & White, 2004; Somers, 2001). Specifically, hierarchical regressions were performed to predict each burnout dimension and each burnout consequence. In the first block, all burnout antecedents were included in the regression model and in the second block, the hardiness dimensions were added. Since we performed a cross-validation in the ANN analysis, we used the same approach in the MLR analysis, using 85% of the sample for the MLR analysis and 15% for the cross-validation. For the actual comparison of the ANN and the MLR analysis determination coefficients R^2 as well as t-tests between predicted and observed values for validation and training data were used. Analyses were conducted with the Statistics Toolbox™ of Matlab® for Windows.

3. Results

Correlations, means, standard deviations, and Cronbach's alpha of all study variables are shown in Table 1.

Table 1 Correlations, means, standard deviations, and internal consistencies (Cronbach's alpha) of all variables.

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
	Hardiness														
1.	Commitment	-													
2.	Challenge	.322**	-												
3.	Control	.169**	-.005	-											
	Burnout														
4.	Emotional exhaustion	-.224**	.174**	-.351**	-										
5.	Depersonalization	-.266**	-.040	-.471**	.570**	-									
6.	Lack of personal accomplishment	-.469**	-.029	-.442**	.573**	.470**	-								
	Antecedents														
7.	Role ambiguity	.006	.125**	-.492**	.339**	.413**	.232**	-							
8.	Troubled interaction	-.145**	.056	-.326**	.421**	.357**	.399**	.223**	-						
9.	Work overload	-.042	.148**	-.336**	.623**	.397**	.356**	.393**	.405**	-					
10.	Contact with death	.100*	.135**	.107*	.156**	.007	-.015	-.013	.189**	.235**	-				
	Consequences														
11.	Psychological	-.226**	.123**	-.335**	.568**	.388**	.486**	.292**	.299**	.405**	.039	-			
12.	Organizational	-.362**	.183**	-.237**	.516**	.339**	.490**	.193**	.362**	.364**	.158**	.542**	-		
13.	Physical	-.220**	.103*	-.260**	.510**	.293**	.431**	.261**	.361**	.439**	.074	.543**	.541**	-	
14.	Social-family	-.332**	.019	-.293**	.602**	.416**	.472**	.296**	.463**	.487**	.137**	.567**	.611**	.583**	-
	M	2.74	2.91	2.75	2.62	2.20	2.17	2.46	2.55	2.87	2.89	2.25	2.75	2.72	2.59
	SD	0.55	0.45	0.47	0.64	0.55	0.57	0.57	0.57	0.59	0.48	0.58	0.63	0.61	0.59
	α	.77	.69	.74	.82	.76	.75	.78	.69	.73	.74	.71	.83	.73	.82

$N = 465$. $^{*}p < .05$. $^{**}p < .01$.

3.1. Neural Network

After training, the concatenated ANN was simulated with the training data, and a linear regression was performed between the network outputs and the desired outputs from the training set for each of the burnout dimensions and the burnout consequences. The coefficients of determination for the three burnout sub-dimensions were R^2 =.450, R^2 =.410 and R^2 =.478, respectively, for emotional exhaustion, depersonalization and lack of personal accomplishment, and R^2 =.416, R^2 =.469, R^2 =.529, and R^2 =.428 for psychological, organizational, social and family, and physical consequences, respectively. To assess the generalizability (predictive capacity) of the burnout model, the trained network was subsequently simulated with validation data. All results including t statistics and their significance levels are summarized in Table 2. The t-test revealed no significant difference between the network outputs and the target outputs.

3.2. Multiple Linear Regressions

MLR results showed lower coefficients of determination than did the ANN, as indicated in Table 2. As a consequence of the mathematical equivalence of the t-test and the linear regression (DeMaris, 2004), the t-test shows for all variables a near zero mean difference ($t < .001$) and the significance is always $p > .999$ for the modelling data. However, for the validation data, results look quite different. The t-statistic, together with the p-value evince that the mean difference is significantly different from zero for the burnout sub-dimension

Table 2 Coefficients of determination (R^2) and t-test statistics (t, p) for the ANN and OLS regression analysis

		Artificial neural network data sets			OLS regression data sets	
		Training (n = 279)	Test (n = 93)	Validation (n = 93)	Modelling (n = 372)	Validation (n = 93)
Burnout						
Emotional exhaustion	R^2	.450	.415	.431	.394	.355
	t	0.035	0.220	0.544	<.001	-2.013
	p	.972	.826	.588	>.999	.047
Depersonalization	R^2	.410	.344	.401	.354	.316
	t	-0.027	-0.451	-1.257	<.001	-1.112
	p	.979	.653	.212	>.999	.269
Lack of personal accomplishment	R^2	.478	.439	.470	.432	.450
	t	0.030	-0.303	-0.116	<.001	-0.544
	p	.976	.763	.908	>.999	.588
Consequences						
Psychological consequences	R^2	.416	.341	.411	.348	.375
	t	-0.009	-0.562	-0.305	<.001	0.684
	p	.993	.575	.761	>.999	.496
Organizational consequences	R^2	.469	.380	.445	.381	.330
	t	0.004	-0.382	-0.408	<.001	2.152
	p	.997	.703	.685	>.999	.034
Social and family consequences	R^2	.529	.429	.479	.422	.373
	t	-0.009	-1.866	0.097	<.001	-0.447
	p	.993	.065	.923	>.999	.656
Physical consequences	R^2	.428	.375	.394	.308	.244
	t	-0.010	-1.194	0.256	<.001	1.268
	p	.992	.235	.799	>.999	.208

emotional exhaustion (t = -2.013, p =.047) and the organizational consequences (t = 2.152, p =.034).

3.3. Comparison of ANN and MLR Results

Regarding the coefficients of determination, two comparisons can be done with the results of the ANN and MLR analyses in Table 2. First, the results of the training data used in the ANN can be compared with the results of the modelling data of the MLR. Second, the results of the two methods using the validation data can be compared. Table 2 shows consistently higher coefficients of determination for ANN compared to the MLR results. For example, when using the ANN with the training/modelling data 45.0% of the variance was explained in emotional exhaustion (a sub-dimension of burnout), as compared to 39.4% of variance explained when MLR was used. In the case of the validation data the difference in explained variance was even larger (43.1% vs. 35.5%).

Regarding the t-test results, a comparison of the t-test statistics (t, p) of the validation data shows (see Table 2) smaller values of the t statistic in the case of the ANN as compared to MLR. Furthermore, in two instances there is a significant difference between the predicted outcomes and the actual outcomes in the case of the MLR. The results of these comparisons provide a strong indication of nonlinearity between/of the relationships involved in this study, particularly in the case of the relationships with emotional exhaustion and organizational consequences.

3.4. Sensitivity and Visual Analysis

SA was performed to calculate the importance indices, which supply the main effect of individual predictor variables. Interpretation is limited to a comparison of the importance indices. For instance, in the first row (Emotional exhaustion), control (0.51) has twice as much influence on emotional exhaustion as role ambiguity (0.25). Table 3 summarizes the importance indices (S_i) for all seven variables on all output variables. In sum, the hardiness sub-dimension control (S_{total}=1.43) had the highest first-order effect on the burnout construct, followed by work overload (S_{total}=1.22). Challenge (S_{total}=0.03) and contact with death and pain (S_{total}=0.03), on the other hand, had practically no effect on the development of burnout. For the consequences of burnout, the results showed that work overload (S_{total}=1.66) and troubled interaction (S_{total}=1.09) had the greatest influence, whereas challenge (S_{total}=0.25) and contact with death and pain (S_{total}=0.13) had the smallest influence on the burnout construct.

Table 3 Importance indices (First-order effects *S*)

	Burnout antecedents				Hardiness sub-dimensions		
	Role ambiguity	Work overload	Troubled interaction	Contact with death and pain	Commitment	Challenge	Control
Burnout sub dimensions							
Emotional exhaustion	0.25	0.55	0.33	0.01	0.07	0.01	0.51
Depersonalization	0.38	0.32	0.36	0.01	0.17	0.01	0.49
Lack of personal accomplishment	0.22	0.35	0.42	0.01	0.28	0.01	0.43
Total	0.85	1.22	1.11	0.03	0.52	0.03	1.43
Consequences							
Psychological	0.34	0.46	0.26	0.01	0.08	0.09	0.37
Organizational	0.12	0.26	0.26	0.08	0.26	0.07	0.11
Social and family	0.17	0.47	0.25	0.03	0.27	0.03	0.20
Physical	0.32	0.47	0.32	0.01	0.09	0.06	0.25
Total	0.95	1.66	1.09	0.13	0.7	0.25	0.93

Visual analyses portray patterns extracted from training data mapped by the ANN after training has finished. The 3D contour plots in Figure 3 represent relationships derived by the ANN with all other variables in the model kept constant at their mean values. The z-axis represents a predicted variable such as one of the burnout dimensions or one of the burnout consequences. The four 3D plots (of 84 possible combinations), selected according to the severity of the nonlinear relationships and presented in Figure 3, are indicative of substantial nonlinearity. The most pervasive pattern of nonlinearity includes work overload, control, and organizational consequences. However, nonlinearity is also evident in the relationships between troubled interaction, challenge and organizational consequences, as well as in the remaining two 3D plots.

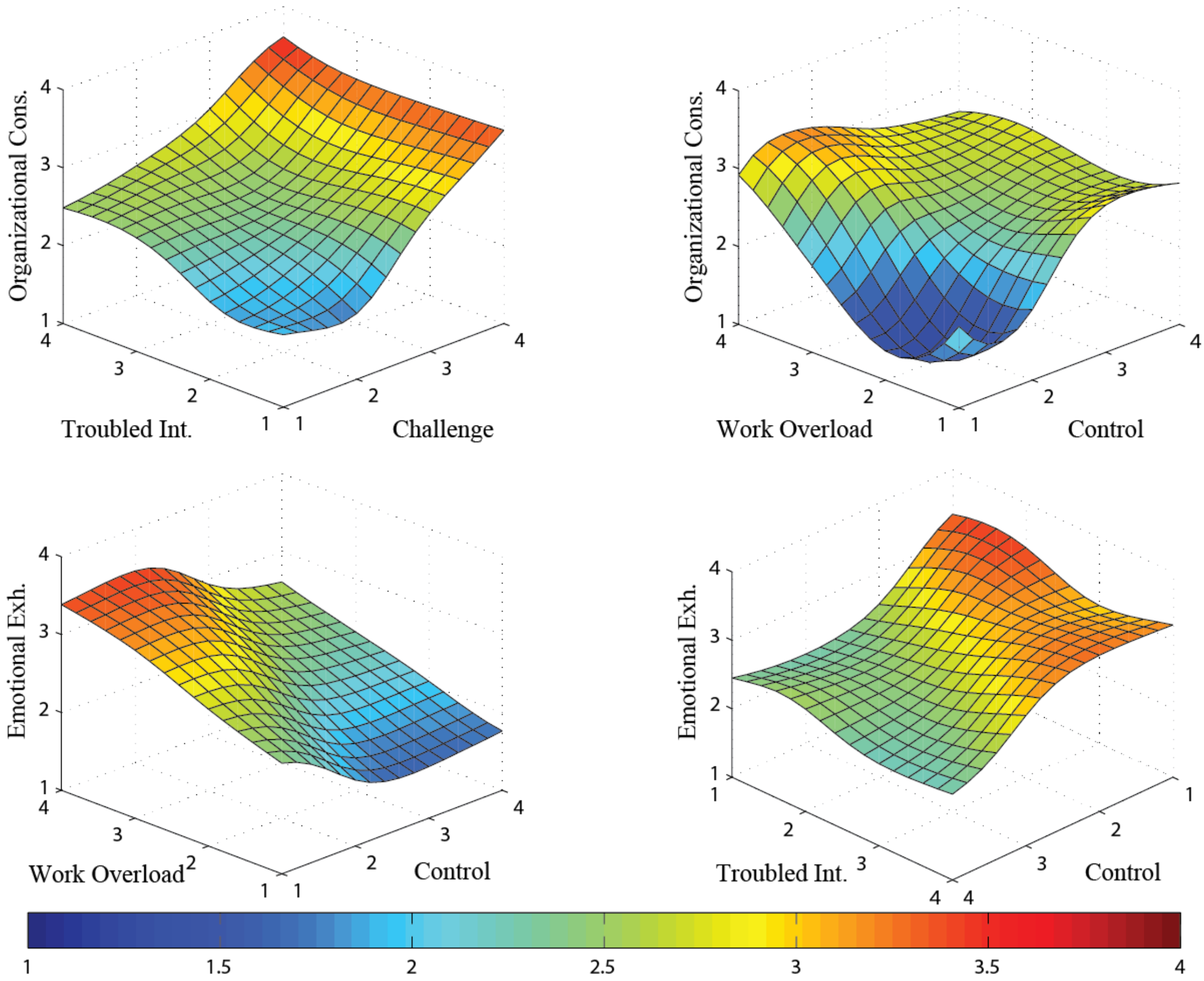

Figure 3. Nonlinear surface plots of selected input variables (troubled interaction, work overload, challenge and control) and output variables (organizational consequences and emotional exhaustion) extracted by the concatenated ANN.

4. Discussion

4.1. Theoretical Implications

The focus of the present study was threefold. First, to establish whether or not an ANN approach is feasible to model and analyse more complex processes such as the antecedents – burnout – consequences process, requiring a concatenated ANN architecture, rather than simple input - output problems, for which a single ANN is sufficient. Second, to confirm the existence of nonlinear relationships involved in the above-mentioned burnout process, which would manifest in better prediction results for the ANN methodology compared to MLR. Third, to determine whether SA is a suitable method to analyse the relative importance of the input variables utilized in the present study. The outcomes fulfilled these objectives, but before going into the details, the correlation results should be addressed. Among job stressors, burnout syndrome and consequences of burnout, the correlations of a sample of Chinese nurses confirm the results reported in the meta-analysis of Lee and Ashforth (1996) and in the reviews by Schaufeli and Enzmann (1998), Zapf, Seifert, Schmutte, Mertini, and Holz (2001), Maslach, Schaufeli, and Leiter (2001), and Crawford, LePine, and Rich (2010) for general samples. The sub-dimensions of hardiness also maintain the theoretical relations, showing negative correlations (Eschleman et al., 2010) except for challenge. A possible explanation for this deviation might be that in China, challenge is perceived to a greater degree as a threat and not as a source of personal development as in Western cultures. The current results further underscore the importance of studying these constructs in different cultures in order to understand the specific mechanisms (Wang et al., 2012). As mentioned before, we modelled the hardiness-modulated antecedents – burnout – consequences process with the concatenated ANN approach and the results suggest that the ANN's predictive accuracy outperforms MLR analysis. It has to be pointed out however, that perfect predictive accuracy is often neither achievable nor necessarily desirable, as it might indicate over-fitting of the model to the data which in turn would reduce the generalizability of the findings (Makridakis, Wheelwright, & Hyndman, 1998). Applying visual analysis, we could not only substantiate the existence of nonlinear relationships among various variables, but we could also illustrate the shape of the nonlinear relationships, which provides insight about how burnout and its consequences develop. Generally speaking, the four 3D plots show an S-shaped surface with a relatively flat bottom, subsequently a quite steep area which is followed by a more or less large—again, flat—ceiling). More specifically, a visual analysis of the relationship between work overload, control and emotional exhaustion (lower left 3D plot in Figure 3) suggests that high levels of control inhibit the development of emotional exhaustion even in the presence of severe work overload. However, the process of developing emotional exhaustion is not a linear one but one that includes a threshold which, once overstepped, results in a severe increase of emotional exhaustion. Results like these show that nonlinear methods such as ANNs are essential in theory development, as these methods identify areas of high sensitivity and challenge scientists to clarify these areas. In other words, once nonlinear relationships have been identified, it is crucial to explain the flat and steep regions and why crossing specific threshold values changes a relationship so radically. Thus, applying ANNs might lead to an adaptation of existing processes or to new theoretical frameworks.

This also suggests that using a linear approach to assess burnout may fail to adequately represent relationships between work characteristics and work-related health outcomes, and also among work characteristics as predictors of such outcomes, as they may be more complex than traditional linear approaches can accommodate. In other words, there is a tendency to find linear relationships with linear methods over finding nonlinear ones, and the linear relationships seem to be more significant even though that this is only due to the linear method applied. In this sense, it would be interesting to reinvestigate variables that have been discarded (due to applying a somewhat inadequate method) at an early stage of burnout research because, with this nonlinear method (ANN), some of those discarded variables might actually be important and should be included. Diagnosis of burnout and the development of specific programs to prevent burnout and its consequences in the workplace clearly depend on the accurate assessment of the syndrome and the involved variables and the analysis method (Hakanen & Schaufeli, 2012; Ladstätter et al., 2010; Somers & Casal, 2009).

Despite being known as a “black box” application, a mayor criticism which is aimed at the lack of capacity of ANNs to analyse the exact impact of a particular predictor variable on the output variable (Paruelo & Tomasel, 1997), light could be shed on the method using SA. With this MC-based approach, recommended by European and US regulations (EC, 2002; EPA, 1999; Saltelli et al., 2004) for policy analysis (to explore how the impacts of a model would change in response to variations in key variables and how they interact), the first-order effects of the variables in the burnout model were extracted from the concatenated ANN by SA (using r-LHS). Specific analysis showed that lack of personal accomplishment was the variable with the highest amount of explained variance (47%). The hardiness dimension control and role ambiguity, a variable linked to career development, were the best predictors of lack of personal accomplishment in accordance with other findings (Garrosa et al., 2008). Control was as well highly associated with protection from burnout regarding its sub-dimensions emotional exhaustion and depersonalization, corroborating existing findings (DePew, Gordon, Yoder, Goodwin, 1999; Hsieh, Hsieh, Chen, Hsiao, & Lee, 2004; Wang et al., 2010). However, commitment and especially challenge were not significant predictors of these two sub-dimensions, in contrast to existing outcomes. A possible explanation of this outcome might lie in the deep-rooted traditions and hierarchical thinking of Chinese people and a lack of openness to change or that these variables are still not included in the majority of career needs and career development interventions in China (Lee et al., 2011; Ng, Fong, & Wang, 2011).

Concerning the consequences of burnout, results showed that social and family consequences was the variable with the highest explained variance (48%) followed by organizational consequences (45%), and work overload and the hardiness dimension commitment were the most influential variables in predicting them.

4.2. Practical Implications

The present results corroborate the framework that points to job stressors, and personality factors as important predictors of burnout (Garrosa et al., 2011; Swider & Zimmerman, 2010). The findings suggest that personality factors are relevant in the explanation of burnout in Chinese nursing. Person-directed interventions, conducted individually or in a group setting, designed to reduce the risk of burnout would possibly be more effective if they included enhancing workers' hardiness. Nevertheless, it has to be pointed out that these person-directed interventions on their own may not have lasting effects, especially if the individual returns to the same stress inducing work environment. In other words, the root cause of their burnout may not have been addressed. Organization-directed interventions take into consideration the impact that work environment has on employees. The best way to target burnout is likely a combination of both types of intervention.

Even more important than the outcomes regarding hardiness, the results underscore the significance of understanding the interrelationships of the identified variables. Particularly the nonlinearly related variables, which show flat and steep areas with a noticeable threshold point between them. Such threshold points could assist healthcare organizations with decision-making strategies, for example in identifying the nurses who should be encouraged to attend specific person-directed intervention programs. The implication of these threshold points is consequently twofold: First, once these points are established, the intervention programs can be arranged specifically for nurses who are getting close to reaching such threshold points and do not have to be attended by everyone. Second, this more efficient approach to burnout interventions would help in reducing costs.

Additionally it is important to disseminate the results of this study in order to increase the awareness of the nonlinear nature of the burnout process within the healthcare sector. When nurses recognize that the relationship between specific stressors such as work overload and burnout is of nonlinear nature they are likely to appreciate the importance of an intervention program. Particularly when they realize that they may be close to one of the critical threshold points.

5. Limitations

This study has some limitations that need to be discussed. First, the present study relates to the use of self-report measures, meaning that the magnitudes of the outcomes we reported might have been contaminated by common method variance or the wish to answer consistently (Chang, van Witteloostuijn, & Eden, 2010). In order to avoid common method variance, future research on burnout and its consequences should also include non-self reports, such as peer ratings from colleagues or acquaintances. Second, the r-LHS employed in the SA only generated first-order effects. Future research should examine whether other sampling methods, such as FAST, Sobol, or Morris, which are capable of computing higher order and total effects but are limited when the input variables are correlated (Saltelli et al., 2004) generate more extensive and insightful results. The most important limitation, though, is the cross-sectional nature of our study, which excludes cause-effect relationships being revealed. We employed concatenated ANN analyses because it is an effective way to examine simultaneously a set of nonlinear relationships between various levels of variables. However, our analysis approach should not suggest that we examined causal relationships, meaning that the present results await further examinations in longitudinal and experimental studies.

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2.2 Study 2:

Deciphering Hardiness: Differential Relationships of Novelty Seeker, Rigid Control, and Hardy Profiles on Nurses' Burnout and Their Effects

Ladstätter, F., Garrosa, E., Cooper-Thomas, H. D., Moreno-Jiménez, B., Ponsoda, V., & Song, S. (2018). Deciphering hardiness: Differential relationships of novelty seekers, rigid control, and hardy profiles on nurses' burnout and their effects. *Nursing and Advanced Health Care, 2*(1), 8.

Abstract

Background: Nurses experience high levels of psychosocial stressors. Hardiness may help offset these and reduce burnout. Most research has used a variable-centered approach (e.g., regression, SEM) to address the additive and interactive effects of hardiness dimensions on stressors and strains.

Objective*:* To confirm the existence of different hardiness profiles in nurses using a person-centered approach and to assess their differential relationships between stressors and strains.

Methods*:* A cross-sectional survey was carried out among nurses in five Chinese hospitals. Hardiness was measured along with stressors as antecedents of burnout, burnout, and consequences of burnout. For the hardiness profile identification, data were analyzed by k-means cluster analysis and MANOVA.

Results: Three profiles were identified, consisting of individuals who scored: (1) average on commitment and control, and high on challenge, classified as the novelty seeker profile, (2) average on commitment and challenge, and high on control, labeled as the rigid control profile, and (3) high on all hardiness dimensions, classified as the hardy profile. Importantly, this result reveals that non-hardy nurses do not form a homogenous group.

Discussion: Nurses with a hardy profile showed the lowest levels of burnout and consequences; for the other two profiles, nurses with the novelty seeker profile were more likely to experience burnout than nurses with a rigid control profile.

Key words: Hardiness, Person-centered research, Burnout, Nursing

Nursing and health care system changes

Of all health professionals, nurses are exposed to especially high levels of workplace psychosocial stressors such as work overload, role ambiguity and contact with pain and death. This high exposure to workplace stressors is found among nurses internationally (Nantsupawat, Nantsupawat, Kunaviktikul, Turale, & Poghosyan, 2016; Pisanti, van der Doef, Maes, Lazzari, & Bertini, 2011; Xie, Wang, & Chen, 2011). Health care system changes that took place throughout the last decade were driven largely by scarceness of resources. These changes include increasing patient readmission, a persistent emphasis on clinical efficacy, and higher demands from patients with acute and chronic diseases (Hanrahan, Aiken, McClaine, & Hanlon, 2010; Lindberg, 2007; Sourdif, 2004). These result in increasing stressor levels negatively affecting nurses' job satisfaction (Hayes et al., 2015), and with the potential to decrease the quality of nursing care provided to patients (Lim, Bogossian, & Ahern, 2010; Tourangeau & Cranley, 2006).

While healthcare in general has changed rapidly across many countries, the transformation has been particularly marked in the Peoples' Republic of China. During the past three decades, China has experienced rapid growth in its economic output and important changes in its demographic structure which together have significantly increased the demands both for primary healthcare and for more health professionals, particularly for nurses. Since the late 1990s, the Chinese government has carried out several reforms on the primary health care (Q. Liu, Wang, Kong, & Cheng, 2011; Qin, Li, & Hsieh, 2013; Xu, Zhang, Wang, & Zhou, 2014). These reforms greatly improved healthcare – for example, the number of health care professionals has been increasing – but still left much to be desired, especially for the health workforces. The physician-nurse ratio generally showed a rising trend between 2008 (1:0.54) and 2012 (1:0.61), but was far below the international standard (1:2 ~ 4). Since the first health care reforms, there has also been a gradual shift from the traditional mode of disease-centered healthcare to a more holistic approach that encompasses biological, psychological and social aspects of the patients, resulting in nursing practice in China becoming increasingly demanding (Gao et al., 2012; Xu et al., 2014). As a consequence, Chinese nurses are confronted with increasing stressors and, consequently, higher levels of strain (Gao et al., 2012; Y.-E. Liu, While, Li, & Ye, 2015; Wang, Tao, Ellenbecker, & Liu, 2012).

Stressors, burnout and burnout consequences

Burnout is a specific work-related strain which, in nursing, is a consequence of stressors (burnout antecedents) stemming from the psychologically and emotionally challenging relationships among caregivers and their patients, team working, shift working, and the requirement for high skill levels (McVicar, 2003; Wilmar B. Schaufeli, Maassen, Bakker, & Sixma, 2011). Particularly negative stressors include: high workload, lack of clarity about tasks and goals (role ambiguity), contact with pain and death, and conflictual interactions with other nurses, physicians, patients, and their relatives (Garrosa et al., 2008; McGrath, Reid, & Boore, 2003). Burnout consists of three sub-dimensions: (1) emotional exhaustion, which is frequently considered the main symptom of burnout (Schirom, 2003); (2) depersonalization, specified as the development of negative, cynical attitudes toward patients; and (3) lack of personal accomplishment, defined as the tendency to believe that one is no longer effective in working with patients . Various consequences of burnout in healthcare have been studied. Among the psychological effects, depression has been considered to be strongly related to burnout (Hakanen, Schaufeli, & Ahola, 2008). An important physical consequence is musculoskeletal pain which was found to be related to burnout in the Health 2000 Study (Ahola & Hakanen, 2014; Honkonen et al., 2006). At the organizational level, intentions to leave the job is an important outcome of burnout (Christina Maslach & Leiter, 2016).

The role of hardiness in the burnout process

The availability of personal resources such as hardiness can mitigate burnout and its consequences (Dalal et al., 2015; Garrosa, Moreno-Jiménez, Rodriguez-Munoz, & Rodriguez-Carvajal, 2011; Schmidt & Diestel, 2013). Hardiness was proposed by Kobasa (1979) as a personality characteristic that provides a unique and active way of understanding a person’s goals, difficulties, and interactions with other individuals (Maddi et al., 2006; Merino-Tejedor, Hontangas-Beltrán, Boada-Grau, & Lucas-Mangas, 2015). More specifically, Kobasa proposed three dimensions of hardiness – commitment, control, and challenge – that affect relationships among stressors and strains.

Existing evidence confirms that hardy individuals perform better and stay healthier when confronted with stress (Abdollahi et al., 2014; Bartone, Eid, Helge Johnsen, Christian Laberg, & Snook, 2009; Coetzee & Harry, 2015; Eschleman et al., 2010; Hystad, Eid, Laberg, Johnsen, & Bartone, 2009; Moreno-Jiménez, Rodriguez-Munoz, Garrosa, & Manuel Blanco, 2014; Williams et al., 2015). In a recent study, researchers found that people with high levels of hardiness employ greater effort and, as a result, experience less work fatigue (Merino-Tejedor et al., 2015). Moreover, there is evidence that hardiness is negatively related to burnout in nurses (Abdollahi et al., 2014; Garrosa et al., 2010; Lambert, Lambert, Petrini, Li, & Zhang, 2007b; Rios Risquez, Godoy Fernandez, & Sanchez-Meca, 2011), although the magnitude of this effect varies across different burnout sub-dimensions (Ladstätter et al., 2010).

Two types of studies concerning hardiness are evident in the literature to date: examinations of the principal effect and of the moderating effect of hardiness on stressors and strains (Eschleman et al., 2010). Across both types of study, hardiness is either considered to have an overall score, or else the hardiness dimensions are examined separately. Both approaches are variable-centered because they emphasize identifying differences in relationships between variables using regression or structural equation modeling (J. P. Meyer, Stanley, & Vandenberg, 2013). Several authors have questioned and discussed both approaches (Carver, 1989; Hull, Van Treuren, & Virnelli, 1987). They point out that simple correlations between overall hardiness and other variables, or between separate dimensions of hardiness and other variables, cannot provide an accurate indication of the importance of individual differences in hardiness dimension levels, that is, the hardiness dimension profiles of distinct groups of persons. Little is known about the combined and potentially synergistic influence of dissimilar hardiness dimension levels. Asle M. Sandvik et al. (2013) compared individuals with roughly equal dimension levels to those with unequal dimension levels and found that being high in hardiness with a balanced profile is related to healthy immune and neuroendocrine responses to stress. An examination of the unbalanced individuals showed the greatest discrepancies between control and challenge, with challenge always being lower than control. This shows that for a more complete and realistic understanding of hardiness, the three dimensions need to be explored more systematically in combination.

A person-centered approach to the study of hardiness

Person-centered research includes two steps: (1) identifying subgroups of individuals (profiles) that share similar patterns of variable levels (internal cohesion) and (2) validating that the identified profiles are indeed unique. This is done by comparing the relationships that these profiles have with other related variables (external adhesion). Internal cohesion and external adhesion are two important defining features of profiles in person-centered research (J. P. Meyer et al., 2013; Sinclair, Tucker, Cullen, & Wright, 2005).

Identification of Hardiness Profiles

Researchers have adopted a person-centered approach in various fields (Sinclair et al., 2005; Van den Berghe et al., 2013; Wasti, 2005). Yet even though this approach has gained momentum in recent years, to date it has been used in only two hardiness studies: (1) Johnsen, Hystad, Bartone, Laberg, and Eid (2013) studied Norwegian soldiers and found four hardiness profiles: Hardy, non-hardy, sensation seeker (low on control and commitment but high on challenge), and rigid control (low on challenge but medium to high on control and commitment). (2) Ladstätter, Garrosa, and Dai (2014) studied whether, in accordance with hardiness theory, individuals would naturally form two subgroups, hardy and non-hardy, and confirmed this using cluster analysis. However, they pointed out that more profiles might exist that further research could uncover.

Using these aforementioned studies as a starting point and allowing hardiness profiles to have high, medium, and low levels, it would be possible to find $3^3 = 27$ hypothetical profiles. However, not all possible profiles may exist. Deriving from theoretical hardiness research, we should find individuals with profiles that are high (hardy), low (non-hardy), and medium (unresponsive) across dimension levels. Individuals high on all three dimensions see life as a constantly varying phenomenon that motivates them to learn and change (challenge), are convinced that through this developmental process, they exert power over changes and situations in a fashion that turns them into fulfilling experiences (control), and share this effort and learning in a valuable way with other individuals and organizations (commitment). Individuals with low levels on all dimensions are not interested in learning new skills but prefer routine (challenge), cannot imagine they could have a real influence on anything (control), and care little for others, things and events (commitment). In short, such people lack the existential courage and motivation to do the hard work of turning stresses to advantage (Abdollahi et al., 2014; Eschleman et al., 2010; Maddi, 2006, 2013).

Furthermore, Maddi (2013, p. 9-10) provides an excellent description of how individuals with heterogeneous hardiness dimensions levels would act. Considering these and other profiles that have been found in previous empirical studies (Bartone, Valdes, Spinosa, & Robb, 2011; Johnsen et al., 2013; Ladstätter et al., 2014; Asle M. Sandvik et al., 2013) we yield a list of twelve hardiness profiles that might be found, as shown in Table 1.

Table 1
Hardiness Dimension Level Profiles Found in Other Studies

Hardiness dimensions			Profile label	Described theoretically	Found empirically
Commitment	Challenge	Control			
High	High	High	Hardy	M	J*, L*
Medium	Medium	Medium	Unresponsive	M	
Low	Low	Low	Non-hardy	M	J*, L*
High	Low	Low		M	
Low	High	Low	Non persistent novelty seeker	M	
Low	Low	High		M	
Medium	Low	Medium			B/S

High	Medium	High		B/S
High	Low	High	Rigid control	B/S, J*
High	Low	Mediu m		B/S
Medium	Medium	High	Rigid control	B/S
Medium	High	Low	Sensation seeker	J*

Note. B/S – Bartone et al. (2011) and Sandvik et al. (2013), J – Johnsen et al. (2013), L – Ladstätter et al. (2014), M – Maddi (2013). * Person centered research approach

Validation of hardiness profiles

In step two, the identified profiles are compared to each other regarding the relationships they have with stressors and strains. Significant differences in the relationships across the identified profiles validate their uniqueness. Ladstätter et al. (2014) found that hardy individuals experience lower levels of stressors, burnout, and burnout consequences than non-hardy individuals. Johnsen et al. (2013) found a similar result regarding the hardy and non-hardy profiles although they focused on subjective health complaints, including psychological distress and reduced quality of life. Additionally, Johnsen et al. found that the rigid control profile had the highest symptom levels, whereas the sensation seeking profile had the lowest symptom levels.

The Study

Aims

The aim of this study is to enhance our understanding of hardiness through a person-centered method. Using a confirmatory approach, we will focus only on the profiles that have been found either in a person-centered study or in at least two variable-centered research studies including past theoretical hardiness research. Our hypotheses regarding the identification of hardiness profiles are as follows:

Hypothesis 1: There will be a hardy profile that is high in commitment, challenge, and control.

Hypothesis 2: There will be a non-hardy profile that is low in commitment, challenge, and control.

Hypothesis 3: There will be a rigid control profile with medium or high commitment levels, low or medium challenge, and high control levels.

Hypothesis 4: There will be a sensation seeker profile showing medium levels on commitment, high on challenge, and low on control.

Our hypotheses regarding the relationships of hardiness profiles with stressors, burnout, and burnout consequences are as follows:

Hypothesis 5: Hardy individuals will show the lowest perceived stressors, burnout, and burnout consequences.

Hypothesis 6: Non-hardy individuals will show highest perceived stressors, burnout, and burnout consequences.

Hypothesis 7: The rigid control profile will show higher perceived stressors, burnout and burnout consequences than hardy individuals.

Hypothesis 8: The sensation seeker profile will show low perceived stressors, burnout and burnout consequences.

Design

This survey was conducted in China in 2015 using a cross-sectional design.

Participants

Convenience sampling was used to recruit non-ICU nurses from five Chinese hospitals. The overall response rate was 84.2% which is similar to comparable research in Chinese nursing (Gao et al., 2012). After excluding individuals with missing data (n=17), the sample comprised 325 participants whose age ranged from 20 to 45 years (M = 26.5, SD = 4.6). Of the 325 participants, 316 were females and 9 males. Although there are no national statistics about the age and gender of nurses in China available (Kalisch & Liu, 2009), similar small numbers of male nurses were found in comparable studies (Gao et al., 2012; Ye & Du, 2006).

Data collection

We used the Chinese version of the Nursing Burnout Scale - Short Form (NBS-SF) (Garrosa et al., 2008; Moreno-Jiménez et al., 2000; Tang, Garrosa, Lei, & Liang, 2007). This questionnaire consists of 52 items and is organized into four scales measuring nursing-specific occupational elements relevant to the (1) hardiness, (2) stressors as antecedents of burnout, (3) burnout, and (4) consequences of burnout. Responses are on a 4-point Likert-type scale, ranging from 1 (*I totally disagree*) to 4 (*I totally agree*).

Hardiness

Hardiness was measured with 12-items, with 4 items each for commitment (e.g., 'My daily work satisfies me and makes me totally devoted to it') (α = .77), challenge (e.g., 'When it is possible I try to have new experiences in my daily work') (α = .73), and control (e.g., 'Though I try hard I do not obtain my work goals', reverse scored) (α = .74). A confirmatory factor analysis (CFA) revealed that the hypothesized three-factor structure of hardiness fits the data well, $\chi^2(47) = 203.47$, $p < .001$, goodness-of-fit index (GFI) = .94, adjusted goodness-of-fit index (AGFI) = .89, root mean square error of approximation (RMSEA) = .08, normed fit index (NFI) = .92, Tucker-Lewis index (TLI) = .90, comparative fit index (CFI) = .93).

Stressors

Stressors are evaluated via 16 specific items divided into the four subscales of: (a) conflictual interaction, which assesses troubled and difficult relations with doctors, patients, and relatives (e.g., 'The doctors talk to me in an authoritarian way') ($\alpha = .76$); (b) work overload, measuring the overload of quantitative and qualitative demands (e.g., 'I have to attend too many patients') ($\alpha = .73$); (c) experience with pain and death, evaluates the level to which nurses are sensitive to patients' pain (e.g., 'It affects me when I apply painful treatments') ($\alpha = .78$); and (d) role ambiguity, measures nurses' perceived clarity of information about their labor and their organizational role (e.g., 'The orders I receive are vague and ambiguous') ($\alpha = .81$).

Burnout

The burnout measure consists of 12 items and is subdivided into the three dimensions of emotional exhaustion (e.g., 'In my work, I often feel emotionally and physically exhausted') ($\alpha = .80$), depersonalization (e.g., 'With regard to my patients, I do not involve myself in their problems; it is as if they do not exist') ($\alpha = .77$), and personal accomplishment (e.g., 'Nobody considers me, I feel like "a maid for everything" ', reverse scored) ($\alpha = .72$) as proposed by Maslach and Jackson (1986). A CFA revealed that the hypothesized three-factor structure of burnout fits the data well, $\chi^2(47) = 199.71$, $p < .001$, GFI = .93, AGFI = .89, RMSEA = .08, NFI = .91, TLI = .90, CFI = .93).

Consequences of burnout

Consequences of burnout are measured with 12 items separated into three subscales that measure psychological (e.g., 'I feel lifeless like having no strength to do anything') (α = .75), physical (e.g., 'My work is affecting my physical health') (α = .78), and organizational consequences (e.g., 'Often, I desire to change profession') (α = .82).

Ethical considerations

The study was approved by the ethics committees of the Shandong College of Traditional Chinese Medicine and the study hospitals. Confidentiality was ensured and participants were informed that they could withdraw from the study at any point without adverse effects on their employment.

Data analysis

To ensure the reliability of the NBS-SF scale, we calculated Cronbach's alphas.

Identification of hardiness profiles

In the first step of the person-centered analysis, we used the k-means cluster analysis, which maximizes variability between clusters (i.e., profiles) and minimizes variability within clusters, thus satisfying the requirements of a good cluster solution (Hill & Lewicki, 2007). The k-means cluster technique produces distinct profiles that, in general, are clearly interpretable. We performed the cluster analysis on z-scores transformed from hardiness dimensions scores.

Validation of hardiness profiles

To confirm that the clusters extracted from the data were in fact distinct, we compared the identified profiles to each other to assess their relationships with stressors and strains using one-way MANOVA. All statistical procedures were performed using SPSS v.21.0.

Results

Reliability and descriptive statistics

Cronbach's alphas, means, standard deviations, and minimum and maximum values of all study variables are shown in Table 2.

Table 2
Descriptive Statistics and Cronbach Alphas for all Variables

Variables	*M*	*SD*	Min	Max	Alpha
Hardiness					
Total	2.81	0.36	1.00	4.00	.75
Commitment	2.68	0.50	1.25	4.00	.77
Challenge	2.86	0.49	1.00	4.00	.73
Control	2.91	0.44	1.25	4.00	.74
Stressors					
Role ambiguity	2.03	0.50	1.00	4.00	.81
Contact with death and pain	2.92	0.47	1.00	4.00	.78
Troubled interaction	2.48	0.56	1.00	4.00	.76
Work overload	2.74	0.55	1.00	4.00	.73
Burnout					
Emotional exhaustion	2.46	0.60	1.00	4.00	.80
Depersonalization	2.03	0.54	1.00	3.50	.77
Lack of personal accomplishment	2.14	0.55	1.00	4.00	.72
Consequences					
Psychological	2.13	0.52	1.00	4.00	.75
Organizational	2.70	0.60	1.25	4.00	.82
Physical	2.63	0.50	1.00	4.00	.78

Note. $N = 325$.

Associates of the hardiness dimensions

Pearson correlations between the hardiness dimensions and between these dimensions and associated variables appear in the upper part of Table 3 labeled as total sample.

Table 3
Pearson Correlations between the Hardiness Dimensions and their Associates for the Total Sample and for each Profile separately

		Hardiness		Stressors				Burnout			Consequences		
Profile	Hardiness dimensions	COM	CHA	ROL	CON	TRO	WOR	EMO	DEP	LAC	PSY	PHY	ORG
Total Sample *N*=325	Commitment			-.337**	.175**	-.199**	-.250**	-.386**	-.409**	-.548**	-.384**	-.354**	-.529**
	Challenge	.379**		-.297**	.159**	-.022	-.042	-.011	-.265**	-.197**	-.102	.004	-.025
	Control	.452**	.337**	-.368**	.135*	-.307**	-.280**	-.293**	-.425**	-.510**	-.242**	-.285**	-.243**
Hardy *n*=173	Commitment			-.200**	.152*	-.278**	-.243**	-.496**	-.452**	-.600**	-.398**	-.408**	-.493**
	Challenge	-.031		-.131	.174*	.143	.094	.209**	.018	.054	.026	.202**	.309**
	Control	.140	.285**	-.163*	.181*	-.282**	-.203**	-.161*	-.284**	-.211**	-.108	-.074	.018
Rigid control *n* = 87	Commitment			-.269*	.128	-.134	-.067	-.167	-.109	-.345**	-.116	-.088	-.364**
	Challenge	.119		-.444**	.068	-.357**	-.177	-.262*	-.398**	-.448**	-.010	-.248*	-.167
	Control	-.024	.442**	-.345**	-.130	-.602**	-.333**	-.522**	-.640**	-.548**	-.192	-.230*	-.104
Novelty seekers *n*=65	Commitment			.145	.056	-.138	-.169	-.279*	-.113	-.119	-.304*	-.317*	-.517**
	Challenge	-.055		.034	.140	-.040	.223	.145	-.279*	.199	.186	.287*	.315*
	Control	.292*	-.016	-.044	.033	-.233	-.047	-.203	-.256*	-.361**	-.079	-.301*	-.273*

Note. COM=Commitment, CHA=Challenge, ROL=Role ambiguity, CON=Contact with death and pain, TRO=Troubled interaction, WOR=Work overload, EMO=Emotional exhaustion, DEP=Depersonalization, LAC=Lack of personal accomplishment, PSY=Psychological consequences, PHY=Physical consequences, ORG=Organizational consequences.
**p* < .05 level (2-tailed). ***p* < .01 level (2-tailed).

Cluster analysis

We conducted k-means cluster analyses with three-, four-, five-, and six-clusters and decided the three-cluster (three-profile) solution to be the most appropriate because: (1) various repetitions of the cluster analysis always culminated in the same hardiness pattern in the case of the three-profile solution whereas for the other solutions the patterns changed. (2) The three-cluster solution was easy to interpret within existing theoretical frameworks. (3) The one-way ANOVAs revealed non-significant mean differences for stressors, burnout, and burnout consequences between some of the profiles within the four-, five-, and six-profile solutions.

Identified Hardiness Profiles

Table 4 shows the mean and the mean *z*-scores of each hardiness dimension by profile, the number of individuals, and the percentage of individuals in each profile. We used two methods to interpret our cluster. First, and in accordance with other researchers (Johnsen et al., 2013; Ladstätter et al., 2014; J. P. Meyer et al., 2013) we used z-scores for the interpretation of our results. We classified *z*-scores > 0.5 as "high" scores, *z*-scores < -0.5 as "low" scores, and *z*-scores between -0.5 and 0.5 as "average" scores. Using these cut-off points for classification, nurses in cluster 2 have high levels on all three hardiness dimensions. This configuration corresponds to the hardy profile and thus supports Hypothesis 1. Since we did not find a non-hardy profile, Hypothesis 2 was not supported. Cluster 1, comprising nurses who score low on the two hardiness dimensions commitment and challenge, and average on control, resembles partly the rigid control profile of Hypothesis 3. Similarly, cluster 3 consists of nurses with low scores on commitment and control, and average scores on challenge (sensation seekers), which partly supports Hypothesis 4.

For our second, more natural, interpretation approach we used 2.25 and 2.75 as cut-off points. For more information please see supplementary information file. In doing so, cluster 1 has average scores on commitment and challenge and high scores on control. Therefore we maintained rigid control as the label for cluster 1. In the case of cluster 3, this analysis revealed medium (rather than low) scores on commitment and control, and high (rather than average) scores on challenge, hence we changed the profile name from sensation seeker to novelty seeker. We believe that this subtle change better resembles the features of the individuals in our study who are nurses, rather than soldiers as in Johnsen et al. (2013) who coined this name.

Table 4
Cluster Analysis Results Showing Number of Participants per Cluster, Percentage of the Sample, Mean and Mean *z*-Scores for all Three Hardiness Dimensions

	Cluster (Profile)		
	1 – Rigid control	2 – Hardy	3 – Novelty seekers
N	87	173	65
% of total (N = 325)	26.8%	53.2%	20.0%
Hardiness dimensions Mean (*z*-score)			
Commitment	2.31 (-0.75)	2.98 (0.60)	2.38 (-0.60)
Challenge	2.31 (-1.12)	3.11 (0.51)	2.92 (0.13)
Control	2.81 (-0.23)	3.17 (0.58)	2.37 (-1.24)

Validation of hardiness profiles

The MANOVA indicated significant differences among the profiles on the multivariate combination of stressors, burnout, and burnout consequence measures: Pillai's trace = 1.129, $F(26, 622) = 31.042$, $p < .001$, $\eta^2 = .565$. Subsequent one-way ANOVAs showed significant differences across all three profiles (see Table 5), except for the stressors contact with death and pain and troubled interaction. Effect sizes showed small to moderate values which suggest that the profiles account for modest overall amounts of variance.

We then conducted post hoc pair-wise comparisons with Tukey's b. Results show that hardy nurses have significantly lower scores for role ambiguity, depersonalization, lack of personal accomplishment, psychological consequences, and organizational consequences, than nurses who have one of the other two profiles. This mainly supports Hypothesis 5. Hypothesis 6 could not be tested because we did not find a uniform non-hardy profile. The rigid control profile which we expected to have higher perceived stressors, burnout and burnout consequences than hardy individuals shows significantly higher means on role ambiguity, depersonalization, lack of personal accomplishment, as well as psychological and organizational consequences, thus partly supporting Hypothesis 7. Highest levels on stressors, burnout and consequences of burnout were found for the novelty seekers, an outcome that is totally opposite to Hypothesis 8.

Table 5
ANOVA Results Showing Means and Standard Deviations of all Variables for the Overall Sample and the Three Profiles

Variable	Overall Sample	Profile						$F(2,322)$	η^2
		Hardy		Rigid control		Novelty seekers			
	M	*M*	*SD*	*M*	*SD*	*M*	*SD*		
Stressors									
Role ambiguity	2.03	$(1.86)_a$	0.459	$(2.18)_b$	0.434	$(2.28)_c$	0.504	26.06***	.14
Contact with death and pain	2.92	$(2.97)_a$	0.484	$(2.86)_a$	0.441	$(2.84)_a$	0.470	2.46	.02
Troubled interaction	2.48	$(2.45)_a$	0.552	$(2.47)_a$	0.527	$(2.58)_a$	0.580	1.45	.01
Work overload	2.74	$(2.64)_a$	0.561	$(2.79)_b$	0.541	$(2.91)_{b.c}$	0.483	6.37**	.04
Burnout									
Emotional exhaustion	2.46	$(2.37)_a$	0.625	$(2.52)_{a.b}$	0.526	$(2.62)_b$	0.601	4.90**	.03
Depersonalization	2.03	$(1.89)_a$	0.502	$(2.20)_b$	0.479	$(2.19)_b$	0.521	15.28***	.09
Lack of personal accomplishment	2.14	$(1.93)_a$	0.474	$(2.27)_b$	0.483	$(2.51)_c$	0.563	36.35***	.18
Consequences									
Psychological	2.13	$(2.01)_a$	0.523	$(2.26)_b$	0.530	$(2.28)_b$	0.435	10.38***	.06
Physical	2.63	$(2.53)_{a.b}$	0.482	$(2.66)_a$	0.477	$(2.85)_c$	0.528	10.24***	.06
Organizational	2.70	$(2.53)_a$	0.601	$(2.86)_b$	0.549	$(2.93)_b$	0.524	16.04***	.09

Note. Means in the same row that have different subscripts are significantly different at $p < .05$ in the Tukey's b pairwise comparisons.
$^{**}p < .01$. $^{***}p < .001$

To assess how the hardiness dimensions are related to each other and to stressors, burnout, and consequences of burnout within a particular profile, additional bivariate correlations were calculated for each profile separately and are shown in Table 3. When comparing the overall sample correlations with those of the profiles, interesting changes of the correlation coefficients' magnitude and even their direction appear. Whereas for the overall sample the three hardiness dimensions are correlated with each other, the profiles show just one significant relationship between the three dimensions. Moving on to the relationships between hardiness dimensions and other variables, we found that challenge is negatively correlated to emotional exhaustion for the rigid control profile (r =-.262, $p < .05$) whereas for hardy nurses the relationship is positive (r =.209, $p < .01$). In the overall sample however, the relationship does not exist (r =-.011, p = ns). Several similar examples exist and overall the results of these additional analyses further support the distinctiveness of the three profiles.

Discussion

Our discovery of the three-profile solution is interesting for several reasons. First, the profiles found in this study partially replicate profiles found in other person-centered studies (Johnsen et al., 2013; Ladstätter et al., 2014). Therefore, our study confirms naturally occurring subgroups within this population, although these vary both between and within occupations. This also shows that the hardiness construct is not as homogenous as previously thought across the nursing population. Second, the extraction of qualitatively different profiles (different levels on dimensions) and not just quantitatively different ones (equally high, medium or low on all dimensions), reinforces the person-centered analysis as an important tool in organizational research (J. P. Meyer et al., 2013). This does not mean that the variable-centered methods should be substituted by this person-centered approach. To the contrary, the two strategies should be viewed as complementary, providing different insights into the phenomenon of interest. Third, regarding the overall sample, the three hardiness dimensions correlate positively with each other and correlations between the hardiness dimensions and other variables (stressors, burnout, and burnout consequences) match well against past empirical research and theory (Eschleman et al., 2010). This supports the assumption that the hardiness theory applies equally to Chinese nurses. Fourth, the three profiles show different mean scores on stressors, burnout, and consequences. Furthermore, the profiles not only have different interrelationships among hardiness dimensions, but also have different correlations between hardiness dimensions and stressors, burnout, and consequences. This further supports the person-centered approach because it indicates that the homogeneity assumption underlying all variable-centered analyses does not hold.

The nature of the hardiness profiles

The profile we most expected to find was the hardy profile. Hardy individuals (high on commitment, challenge, and control) have scores below average on stressors, on the burnout dimensions and on all three types of consequences. This result is consistent with existing variable-centered research in the field (Abdollahi et al., 2014; Eschleman et al., 2010; Garrosa et al., 2008). More surprising is that challenge is positively related with emotional exhaustion for hardy individuals, which suggests that within this group, the normally null or negative relationship inverts. A possible explanation would be that those with especially high challenge scores, and who therefore constantly seek new experiences, are over estimating their own personal capabilities. This constellation eventually leads to a state of emotional exhaustion . A similar explanation fits the positive relationships between challenge and both organizational and physical consequences which we found only for the hardy and novelty seeker profiles.

Another interesting result of the profile approach is the discovery that the negative relationships between challenge and both depersonalization and lack of personal accomplishment disappears in the hardy profile. Similar to the explanation given before, this might be due to having reached very high levels of challenge where an increase or decrease in challenge has no additional consequences. A similar effect takes place with regard to the relationship of control and all burnout consequences. The negative correlations found in the overall sample disappear for the hardy profile. Following the aforementioned idea of having reached a high level of, in this case control, an increase or decrease of control may no longer have consequences. This outcome indicates the potential existence of non-linear relationships between variables (Ladstätter et al., 2016).

Another profile that we expected to find based on strong theoretical foundations and on two prior person-centered studies (Johnsen et al., 2013; Ladstätter et al., 2014) – the non-hardy profile – could not be extracted from our data with our three profile solution. This could be due to particular ethical values involved in nursing, including among others privacy, justice, autonomy in decision making, precision and accuracy in caring, and individual and professional competency. These values suggest that some minimal level of hardiness traits are required, and non-hardy nurses may not exist. While Johnsen et al. identified a non-hardy profile, they based their identification and interpretation on z-scores. If they had cross-checked their interpretation, as done here, using the original scale ranging from 0 to 15, their low-hardy profile would rather be labeled a medium-hardy profile (with all three dimensions having a score of approximately 8) which would also make more sense because their study participants were Norwegian infantry soldiers and combat engineers deployed on a six-month mission to Kosovo who, generally speaking, should be more hardy than other non-military groups of individuals.

The rigid control profile (high on control, low/average on commitment and challenge) does not fit with the current, primarily variable-centered approach to hardiness theory. It was hypothesized to exist due to previous empirical work using a person-centered approach. Indeed, the rigid control profile found here overlaps considerably with the rigid control profile found in Johnsen et al. (2013). Again we draw attention to the very different populations from which the samples were drawn (nurses vs. soldiers) and that Johnsen et al. used z-scores for their interpretation which does not coincide with the original scale interpretation. Besides the different profession, other variables might be the reason for the profile differences found between nurses and soldiers. For instance, it could be that gender has an effect on the differences. The Norwegian soldiers were mainly men (96.4%) whereas the Chinese nurses were almost entirely women. Rigid control individuals show values above the mean on role ambiguity and workload, on the three burnout dimensions and on the three types of consequences. Contrary to hardy individuals, rigid control individuals show a negative correlation between challenge and emotional exhaustion, which is consistent with existing theory. Interestingly, the negative correlations between commitment and both depersonalization and lack of personal accomplishment found in the overall sample weakened significantly in the rigid control profile.

Nurses with the novelty seeker profile (high on challenge and average on commitment and control) show the highest scores on stressors, burnout and burnout consequences. This outcome is contrary to our hypothesis and to the results found by Johnsen et al. (2013). The reason for the different functioning of the profile we found could be that novelty seeking involves being open to and pursuing stimulating activities. However, in order to achieve objectives, this attitude needs to be accompanied by persistence in activities (commitment).

Furthermore, an impulsive behavior would be also associated with lack of premeditation which involves acting in the moment without regard to consequences and lack of perseverance is characterized by the inability to remain focused on boring or difficult tasks. It is therefore possible that individuals with the novelty seeker profile attitudes seek stimulating situations yet are less able to handle the concomitant stressors, and therefore have more burnout and other negative consequences.

Study implications

The outcomes of this study could help to develop intervention programs targeted at the specific needs of nurses having different profiles. This would be especially important for nurses having either the rigid control or the novelty seeker profile. Novelty seekers, for instance, are most affected by burnout, however, they are probably more susceptible to intervention due to their high level of challenge which might help to start a self-recovery process after it is initiated by, for example, counselling sessions focusing on the importance of the control dimension. More generally, healthy practices implemented at the organization level may stimulate motivation, autonomy and adaptive self-regulation strategies Regarding the person-centered method applied in this study, we found that using the original scale for the interpretation instead of the z-score scale provides a more natural view of profiles and helps to avoid redundant profiles. Thus we recommend future person-centered approaches analyze their data using both original and z-score scales for a comprehensive understanding and interpretation.

Study limitations and suggestions for further research

First, this study is limited by its cross-sectional design. Future research should examine (1) how the hardiness profiles evolve over time to address issues of causal relationships, and (2) how profile-specific intervention programs affect the burnout process. Second, our study relied exclusively on self-report measures. Less subjective measures, such as peer reports, behavioral indicators and physiological concomitants, are needed. Third, in order to keep our results comparable to those of Johnsen et al.'s (2013) study of soldiers, we replicated the k-means cluster analysis. However, other analyses such as latent class analysis could have been used to test for different hardiness profiles.

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2.3 Study 3:

Deciphering Hardiness: Differential Relationships of Novelty Seeker, Rigid Control, and Hardy Profiles on Nurses' Burnout and Their Effects. Part 2: An Artificial Neural Network Analysis

Abstract

Background: A lot of attention is paid to research on the effects of the three-dimensional hardiness construct (commitment, control, challenge) on work-related stressors and burnout. So far, the main focus has been on the investigation of different levels of the whole hardiness construct such as high or low on all dimensions. This type of research is also known as variable-centered research. Person-centered research, on the other hand, investigates the effect of combining different levels across the dimensions (i.e., profiles) such as a high level of commitment and challenge and a low level of control.

Objective: To improve our understanding of the mitigating effect of hardiness on stressors, such as role ambiguity or workload and burnout as a consequence, by studying the hardiness profiles.

Design: The study was a cross-sectional questionnaire study.

Methods: The three hardiness profiles (novelty seeker, rigid control, and hardy profile) found in a previous cluster analysis of 325 nurses from five Chinese hospitals were examined employing an artificial neural network and OLS regression analysis for their different effects on stressors and burnout.

Results: The relationships between stressors and burnout worked differently for the three profiles. Nursing staff with the novelty-seeker profile had the highest probability of burnout. Hardy nurses, conversely and as expected, were least affected by burnout. Furthermore, some of these relationships were nonlinear and therefore not statistically significant when analyzed with regression analysis.

However, the very same relationships were detected as important by the artificial neural network.

Conclusion: Person-centered research alone or in combination with artificial neural networks is a useful method to find additional information about the effects of hardiness on burnout, which would not be possible with traditional variable-centered methods. If the relationships between the variables are (sufficiently) nonlinear, they do not show statistically significant when using regression analysis. With artificial neural networks, however, they are still recognized as important relationships.

Keywords: artificial neural networks; burnout; hardiness; nonlinear relationship; nursing; person-centered research.

What is already known about the topic?

- Nurses are considered to be highly vulnerable to burnout which develops as a consequence of psychosocial stress and is associated with individual and organizational problems such as absenteeism, lower patient safety, job turn-over, and abandonment of the nursing profession, anxiety, depression, and alcohol and drug abuse.
- The 3-dimensional hardiness construct (commitment, control, and challenge) has been found to mitigate the burnout process.
- Person-centered hardiness research found three hardiness profiles in Chinese nurses with each having distinct hardiness dimension configurations: (1) the hardy profile (high levels on all three dimensions), (2) the novelty seeker profile (high on challenge, average on commitment and control), (3) the rigid control profile (high on control, average on commitment and challenge).

What this paper adds

- The novelty seeker profile is associated with the highest burnout levels.
- The relationships between the stressors, hardiness, and burnout dimensions are nonlinear to varying degrees and work differently with the hardy, rigid control, and novelty seeker profile.
- Artificial neural networks enable researchers to find important relationships even if they are nonlinear and not statistically significant in regression analysis.

1 Introduction

1.1 Hardiness and its effect on the burnout process in nurses

In the last three decades, more and more studies from many different countries have shown that nurses are exposed to very high levels of stress (Butterworth, Carson, Jeacock, White, & Clements, 1999; Jose Luis Gómez-Urquiza et al., 2017; Kelly, Baker, & Horton, 2017; Pisanti et al., 2011; Todaro-Franceschi, 2019; Xie et al., 2011). This stress arises from various sources such as emotionally challenging relationships between nurses and their patients, and/or relatives of their patients, teamwork, shift work and the demand for a high level of qualification (Gil-Monte & Moreno-Jiménez, 2007; Hunsaker, Chen, Maughan, & Heaston, 2015; C. Maslach & Jackson, 1986; McVicar, 2003; Wilmar B. Schaufeli et al., 2011; Woodhead, Northrop, & Edelstein, 2016). As a consequence, gradually, burnout, an occupational strain consisting of the three dimensions emotional exhaustion, depersonalization, and lack of personal accomplishment, sets in (Gil-Monte & Moreno-Jiménez, 2007; C. Maslach & Jackson, 1986; Wilmar B. Schaufeli et al., 2011; Woo, Ho, Tang, & Tam, 2020). Without intervention, the incipient burnout will gradually lead to more serious psychological (Iacovides, Fountoulakis, Moysidou, & Ierodiakonou, 1999; Weigl et al., 2016), and physical (Jaworek, Marek, Karwowski, Andrzejczak, & Genaidy, 2010) problems for the nurses, diminished care quality (Poghosyan, Clarke, Finlayson, & Aiken, 2010) and safety for patients (X. Liu et al., 2018).

Burnout can also lead to organizational problems for hospitals. Examples are increased sick leave rates or, in the worst case, the abandonment of the nursing profession, which in turn can lead to a shortage of staff (Hetzel-Riggin et al., 2019).

Some researchers addressed the option that personality characteristics have a decisive impact on the burnout process (Bakker, Demerouti, & Isabel Sanz-Vergel, 2014; Park, 2017). One of these personality characteristics is hardiness, a three-dimensional construct introduced by Kobasa (1979) consisting of commitment, control, and challenge (Bartone et al., 2009; Eschleman et al., 2010; Hystad et al., 2009; Maddi, 2013; Stein & Bartone, 2020). Committed individuals feel deeply involved in the activities of their lives. Individuals strong in control are certain that if they try hard enough, they may be able to influence the outcomes taking place around them, no matter how difficult this becomes. Individuals strong in challenge belief that stressful situations stimulate their personal development, and see them as exciting and inspiring rather than threatening (Maddi, 2006). There is a lot of evidence that people with high levels of hardiness are more resistant to the effects of extreme stress than people with low levels (Bartone, 1989; Eschleman et al., 2010; Stein & Bartone, 2020). King, King, Fairbank, Keane, and Adams (1998), and Thomassen, Hystad, Johnsen, Johnsen, and Bartone (2018) for example, demonstrated in their studies a direct negative association of hardiness with post-traumatic stress disorder (PTSD). The helpful impact of hardiness is, at least in part, due to the different adaptive coping strategies. People high in hardiness cope with stress in a problem-oriented, proactive way. (Maddi, 2006), have a better ability to regulate their emotions, and even grow under adverse circumstances.

Hardiness has also been studied in the health care sector and various researchers found that the construct is negatively related to burnout in nurses (Abdollahi et al., 2014; Bagley, Abubaker, & Sawyerr, 2018; Garrosa et al., 2008; Ladstätter et al., 2010; Park, 2017; Xanthopoulou et al., 2007). Recently, results have shown that there was a significant negative relationship between hardiness and burnout on nurses, which means that the higher the hardiness personality, the lower the burnout and vice versa, the lower the hardiness personality, the higher the burnout experienced by the nurse (Lucia & Asih, 2015; Aprilia & Yulianti, 2017).

However, it should be mentioned that researchers generally only distinguish between low and high hardiness. Other hardiness-profiles, which might be helpful to learn more about hardiness itself but especially about their effects on the burnout process, are overlooked.

1.2 Variable-centered vs. person-centered strategies in hardiness research

Most of the hardiness research to date has been conducted based on the variable-centered approach. The focus in variable-centered research is on identifying the relevant variables and examining the relationships among them. The objective is to explain as much variance as possible in a variable of interest (e.g., emotional exhaustion) from a set of predictors (e.g., workload, role ambiguity, contact with death and pain, hardiness) using methods such as regression or structural equation modeling (J. P. Meyer et al., 2013). Within this variable-centered approach, the effect of hardiness has been examined in two ways: as the principal effect and as the moderating effect on stressors and burnout. Within both groups of studies, hardiness is either considered to have an overall score, which can be somewhere between high and low or else the hardiness dimensions are examined separately (Eschleman et al., 2010). The variable-centered investigation has added much to our understanding of hardiness but it also has limitations such as problems to detect complex interactions or the assumption that the sample under investigation is homogeneous. Therefore the variable-centered approach alone may not be well suited to address some of the questions that are beginning to emerge. Person-centered analyses strive to identify distinct profiles of individuals and thus are not limited by the homogeneity assumption. The person-centered approach seems to be predestined for the analysis of higher-dimensional constructs including hardiness.

Ladstätter et al. (2018) took another approach, applying a cluster analysis on the three dimensions of hardiness and found three profiles: (1) individuals with high levels on all three hardiness dimensions as proposed by Kobasa (1979) labeled as the hardy profile, (2) individuals who score average on the two hardiness dimensions commitment and challenge, and high on control, classified as the rigid control profile and (3) individuals who score average on commitment and control, and high on the challenge dimension branded as the novelty seeker profile.

1.3 Artificial neural networks and nonlinear relationships

Artificial neural networks (ANNs), a branch of artificial intelligence, have been used successfully in many areas (Durodola, Li, Ramachandra, & Thite, 2017; Karanika-Murray & Cox, 2010; Muhammad et al., 2019; Samanta & Al-Balushi, 2003; Scarborough & Somers, 2006) and often have been found superior to regression analysis (Benbouras et al., 2018; Jamal & Nodehi, 2017; Ladstätter et al., 2016; Somers, 2001). ANNs are capable to deal with nonlinear relationships (Akdeniz et al., 2018), missing data (Cabeza et al., 2016), and outliers (Khamis et al., 2005; Liano, 1996). As data analysis and prediction tools, ANNs are especially well suited to study burnout and hardiness for two additional reasons: (1) both are not seen as single variables but as three-dimensional constructs. This is problematic because common statistical methods such as regression analysis have to analyze each of the three dimensions separately (when used as dependent variables). ANNs are capable of analyzing the variables of a construct simultaneously, generating results that are not exclusively based on the separate dimensions but that also take into account interdependencies between these dimensions. (2) whether the relationships between stressors and burnout dimensions and the effect of hardiness on these relationships are completely linear is questionable and so is the use of linear statistical methods (e.g., OLS regression analysis) to analyze those.

Despite their benefits, until now, occupational health researchers scarcely took advantage of ANNs in their studies (Karanika-Murray & Cox, 2010; Ladstätter et al., 2010; Shahid, Rappon, & Berta, 2019; Straton, Mukkamala, & Vatrapu, 2017).

This study verifies the following hypotheses:

Hypothesis 1: The relationships between the stressors, hardiness, and burnout dimensions are nonlinear to varying degrees.

Hypothesis 2: The relationships between the stressors and burnout dimensions work differently with the hardy, rigid control, and novelty seeker profile.

Hypothesis 3: Highly nonlinear relationships between stressors and burnout dimensions can be detected by ANNs, even if they are not statistically significant in OLS regression.

2 Method

2.1 Participants

Convenience sampling was used to recruit nurses from five Chinese hospitals. The sample comprised 325 participants whose ages ranged from 20 to 45 years (M = 26.5, SD = 4.6).

2.2 Measures

We utilized the Nursing Burnout Scale - Short Form (NBS-SF) (Garrosa et al., 2008; Moreno-Jiménez et al., 2000) to evaluate the process of burnout. The NBS-SF assesses specific nursing-related occupational stressors, burnout, consequences of burnout, and includes a hardiness measure.

The burnout measure has 12 items divided evenly among emotional exhaustion, depersonalization, and lack of personal accomplishment, the three classical dimensions in human services.

Stressors are evaluated via 16 specific items divided into the four subscales of conflictive interaction, work overload, experience with pain and death, and role ambiguity.

Hardiness is measured with 4 items each for the three dimensions commitment, challenge, and control.

The NBS-SF uses a 4-point Likert-type scale, stretching from 1 (*I totally disagree*) to 4 (*I totally agree*) and it has been found to be reliable and valid (Garrosa et al., 2008).

Besides the assessment of hardiness, stressors, and burnout, the survey asks for socio-demographic and professional information such as gender, age, job status (employment terms), weekly working hours, and the number of patients attended per day. More detailed information about participants and measures can be found in Ladstätter et al. (2018).

2.3 Data analysis

We conducted the ANN analyses on the data of the three different profiles we found in a previous study that employed K-means cluster analysis to classify participants based on their mean z-scores on each of the hardiness dimensions. Detailed results of the cluster analysis, MANOVA, one-way ANOVA, and Pearson correlations among all variables and for all profiles can be found in Ladstätter et al. (2018).

2.3.1 ANN analysis

For this study, SPSS Neural Networks Version 25 has been used which is based on the familiar SPSS interface and easy to use.

To efficiently and successfully train the ANN we standardized all predictor and criterion variables (Anysz, Zbiciak, & Ibadov, 2016; Scarborough & Somers, 2006).

The design of the ANN is primarily specified by the number of predictor and criterion variables. Specifically, the number of predictor variables defines the number of neurons in the input layer and the number of criterion variables defines the number of neurons in the output layer of the ANN. In this study, 7 predictor variables (4 stressors and 3 hardiness dimensions) and 3 criterion variables (3 burnout dimensions) defined the ANN. The number of neurons in the hidden layer is specified by the ANN itself and depends on the number of variables included and the complexity of the relationships between them. For our study, the ANN application chose 5 hidden layer neurons. An illustration of the ANN used for the data analysis is shown in Figure 1.

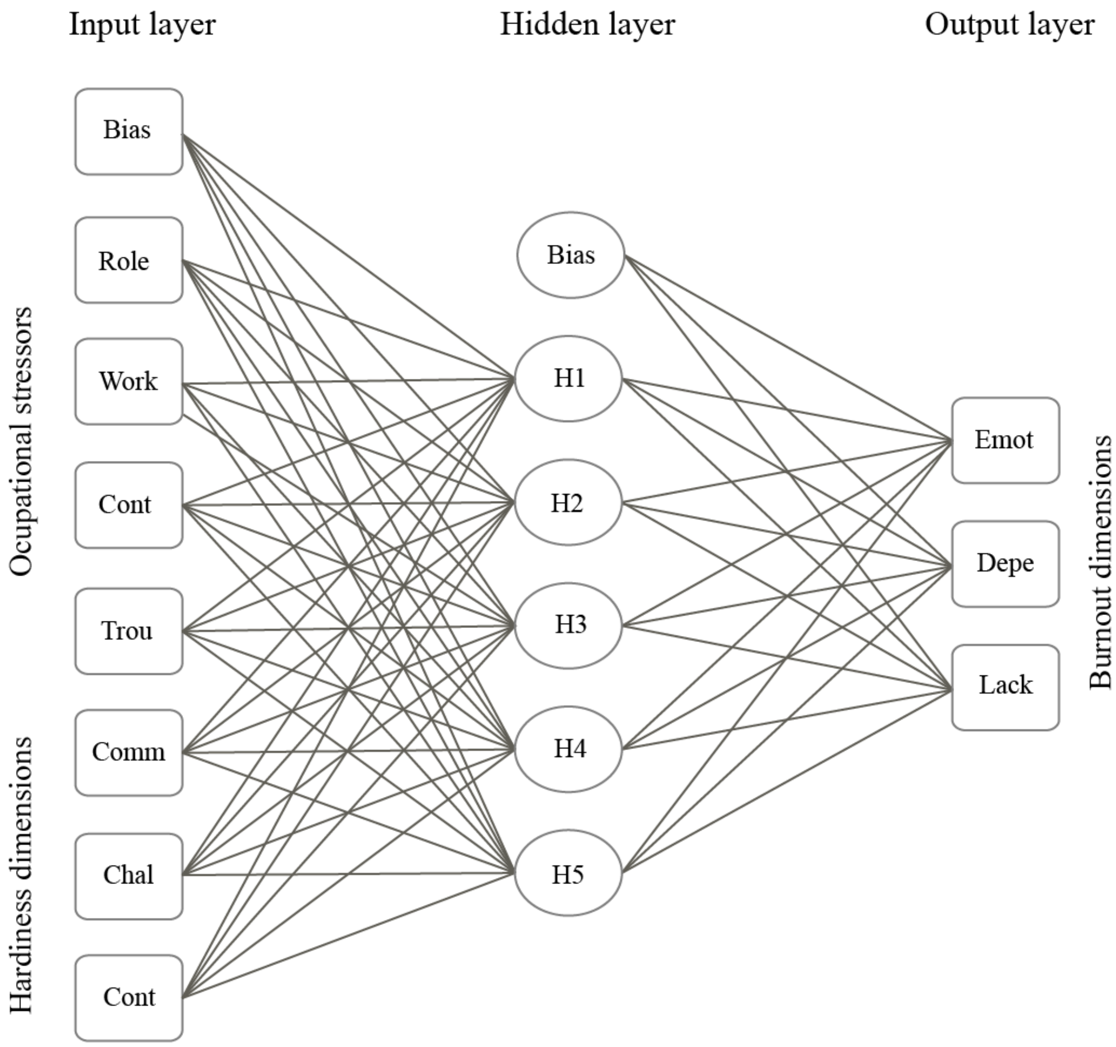

Figure 1 Artificial neural network architecture

The neurons labeled "Bias" are automatically included by the ANN to make the ANN more powerful in finding complex relationships (Negnevitsky, 2011).

The actual training process requires a set of examples of proper ANN behavior: inputs (predictor variables) and target outputs (criterion variables). During training, the weights and biases of the ANN are iteratively adjusted to minimize the performance function. The default performance function for the ANN is the sum of the squared errors (SSE), between the ANN outputs and the target outputs (Beale et al., 2014, p. 2.12).

To further improve the generalization capacity of the ANN, the training was performed applying a method called early stopping (Beale et al., 2014, p. 13.06). This technique required the sample to be divided into two partitions. The first partition (training partition,) comprised 70% of the sample and was used to estimate the model (i.e., to calculate the gradient and to update the weights and biases). The second partition (test partition,) consisted of 30% of the sample and was used to monitor the error during the training process. The test error normally decreases during the initial phase of training, as does the training set error. However, when the ANN begins to over-fit the data (i.e., the generalization capacity decreases), the test partition error typically begins to rise. When the test error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the test error are returned. These weights and biases are the elements that define the estimated model. All ANN parameters can be found in Table 1.

Table 1 ANN parameters

Input layer	Independent variables (IVs)	1	Role ambiguity
		2	Work overload
		3	Contact with death pain
		4	Troubled interaction
		5	Commitment
		6	Challenge
		7	Control
	Number of neurons		7
	Rescaling method for IVs		Standardized
Hidden layer(s)	Number of hidden layers		1
	Number of neurons		5
	Activation function		Hyperbolic tangent
Output layer	Dependent variables (DVs)	1	Emotional exhaustion
		2	Depersonalization
		3	Lack of personal accomplishment
	Number of neurons		3
	Rescaling Method for DVs		Standardized
	Activation function		Identity
	Error function		Sum of squares

2.3.2 Importance analysis

To measure the predictive capacity of the predictor variables IBM SPSS Neural Networks includes a technique called importance analysis which is essentially a sensitivity analysis that computes the first-order effects of the predictor variables on the burnout dimensions (Pentoś, 2016; Saltelli et al., 2008; Yeung, 2010). The importance analysis is based on the combined training and testing samples.

2.3.3 Visual analysis

As a final point, plots were produced to visualize: (1) the relationship between stressors and burnout and (2) the effect of the hardiness profiles on this relationship.

2.3.4 OLS regression

To have a benchmark to which the ANN results can be compared to, ordinary least square (OLS) regression analyses (using SPSS Version 25) were performed for each of the burnout dimensions separately.

Ethical approval

The study was approved by the Ethics Committee of Shandong College of Traditional Chinese Medicine.

3 Results

3.1 Coefficients of determination (R^2)

Coefficients of determination showed consistently higher values for the ANN analysis compared to OLS regression analysis for all hardiness profiles and all burnout dimensions. This indicates that the ANN has a better predictive capacity than the OLS regression. All results are summarized in Table 2.

Table 2 Coefficients of determination R^2

	Coefficient of determination R^2					
Burnout dimension	Emotional exhaustion		Depersonalization		Lack of personal accomplishment	
Hardiness profile	ANN	OLS regression	ANN	OLS regression	ANN	OLS regression
Hardy	.704	.603	.425	.358	.693	.559
Novelty seeker	.537	.429	.749	.410	.559	.556
Rigid control	.667	.555	.712	.476	.587	.527
Total	.568	.535	.451	.369	.575	.569

3.2 Importance indices and regression coefficients

Table 3 shows the importance indices of the ANN analysis compared to the standardized regression coefficients of the OLS regression analysis for all hardiness profiles, the combined profiles, and all burnout dimensions. In the present analysis, we considered importance indices larger than .143 to be good predictors as they explain more than an average predictor would predict (1 / 7 = .1429).

Table 3 ANN and OLS results

Profile	Antecedents	Emotional exhaustion ANN i	Emotional exhaustion OLS regression β	Depersonalization ANN i	Depersonalization OLS regression β	Lack of personal accomplishment ANN i	Lack of personal accomplishment OLS regression β
Hardy	Work overload	.365	.508	.224	.232	.138	.212
	Role ambiguity	.090	.005	.198	.139	.191	.174
	Contact with pain and death	.052	.022	.079	.023	.091	.052
	Troubled interaction	.039	.120	.050	.063	.151	.243
	Commitment	.243	-.337	.232	-.329	.225	-.437
	Challenge	.157	.134	.058	.038	.108	.019
	Control	.054	-.020	.159	-.166	.096	-.006
Novelty seeker	Work overload	.378	.520	.181	.370	.146	.259
	Role ambiguity	.150	.002	.082	.006	.074	.044
	Contact with pain and death	.146	.013	.112	.173	.087	.182
	Troubled interaction	.094	.133	.212	.305	.304	.504
	Commitment	.076	-.140	.070	.035	.049	.080
	Challenge	.048	.027	.185	-.326	.148	.186
	Control	.107	-.106	.158	-.177	.191	-.244
Rigid control	Work overload	.230	.504	.148	.020	.202	.267
	Role ambiguity	.158	.022	.105	.065	.161	.130
	Contact with pain and death	.071	.031	.111	.110	.061	.044
	Troubled interaction	.131	.099	.106	.173	.099	.002
	Commitment	.109	-.127	.109	-.083	.196	-.277
	Challenge	.108	.015	.119	-.105	.067	-.147
	Control	.193	-.293	.302	-.462	.215	-.362

3.3 Visual Analyses

The plots we produced show that the relationships between stressor variables, hardiness, and burnout, were not only nonlinear but also different for each of the hardiness profiles. Figure 2 exhibits three of the relationships. Explicitly, emotional exhaustion is shown as a function of role ambiguity for each of the three hardiness profiles.

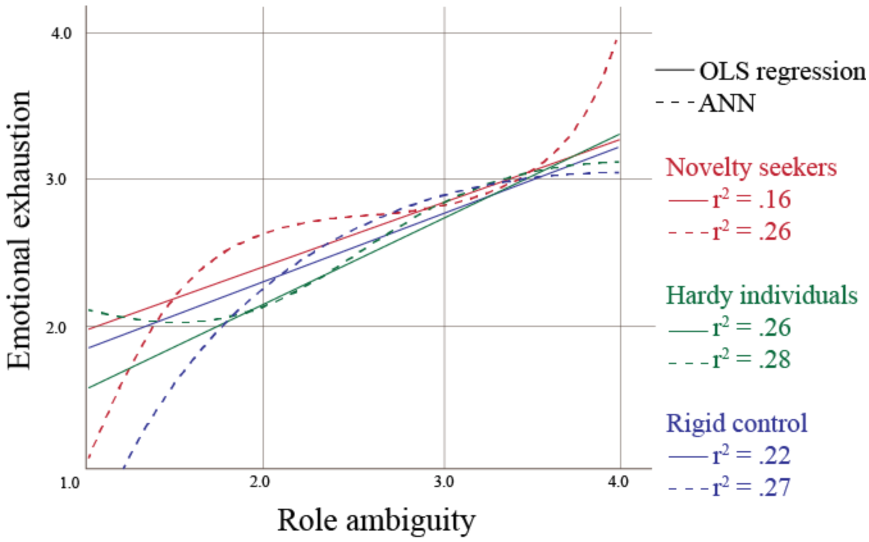

Figure 2 Visual analysis of all profiles for emotional exhaustion and role ambiguity

The figure illustrates that the stressor role ambiguity is not linearly related to emotional exhaustion because the best fitting line is not straight but curved. It also shows that the relationship works differently for the three hardiness profiles. Figure 3 displays the relationship of work overload and depersonalization for the rigid control profile (left) and control as a predictor of depersonalization for the novelty seeker profile (right).

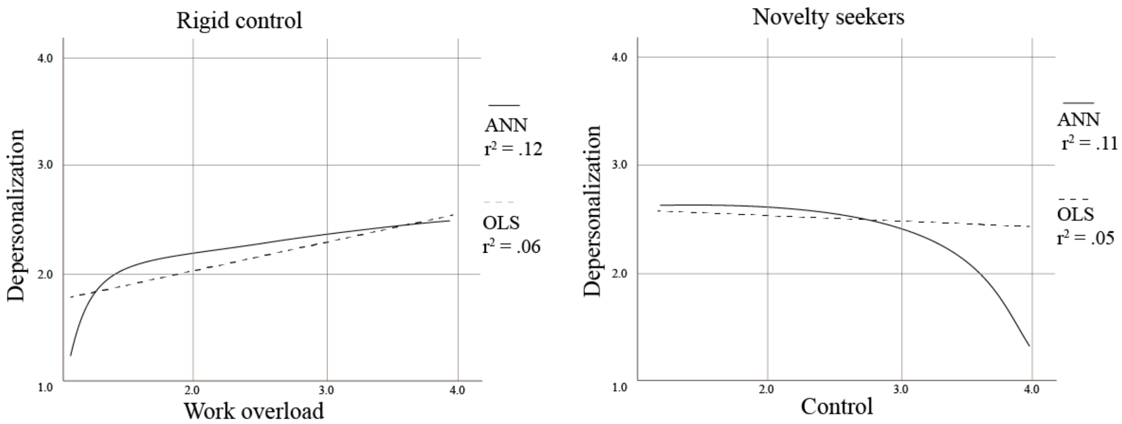

Figure 3 Visual analysis of the rigid control and the novelty seekers for depersonalization and work load

Again, it shows that the two variables are not linearly related. This nonlinearity is responsible for the weaker or even not significant standardized regression coefficients when analyzed with OLS regression. These outcomes confirm Hypotheses 1 and 2.

Regarding hypothesis 3, there are several relationships which support it: For the novelty seekers profile, when using OLS regression, role ambiguity was a not significant predictor of emotional exhaustion (β = .002, p = .987), however, the same predictor explained an important part of the variability in the data of emotional exhaustion when using ANN analysis (i = .15). The same pattern can be found for individuals with a rigid control profile (OLS regression: β = .022, p = .807, ANN: i = .158). Other examples are work overload as a predictor of depersonalization for the rigid control profile (OLS regression: β = .020, p = .827, ANN: i = .148) and control as a predictor of depersonalization in novelty seekers (OLS regression: β = -.177, p = .110, ANN: i = .158).

4 Discussion

Although much progress has been made in recent decades in the study of hardiness, it seems necessary to further deepen our knowledge of hardiness through additional intelligent data analysis techniques. Most research on hardiness has focused on gaining a better understanding of how hardiness directly affects burnout and its consequences, using a variable-centered approach. Some researchers have expressed an interest in using new analytical techniques to improve the understanding of hardiness. Specifically, this involves the application of methods that also find nonlinear relationships between variables (if any), thus bringing us closer to the complexity of reality where variables also interact in a nonlinear way (Ladstätter et al., 2016).

Following the universal idea that the exploration and application of innovative methods is a fruitful path for any research, we followed a different approach than all previous empirical work on the topic of hardy personality. Specifically, we used a person-centered approach to find naturally occurring hardiness profiles, which were then analyzed by an ANN to show that some of the relationships between stressors and burnout are nonlinear.

The obvious starting point for interpreting the results of the ANN analysis is the revealed nonlinear relationships between stressors and burnout. Examination of the graphical representations of the relationships between predictors and criterion variables shown in Figures 2 and 3 reveals a fairly consistent pattern that varies in magnitude primarily as a function of the hardiness profile: The best-fitting lines are curved and not straight, a clear sign of the nonlinearity between the variables. This result, which supports Hypothesis 1, may be surprising since many researchers always use linear statistical techniques to analyze relationships between variables, which in turn always leads to straight fitting lines. But why do we automatically assume that relationships between variables are straight (i.e., linear), especially in the social sciences? This linear analytical approach has been criticized and the need to move forward with proposals that better reflect reality has been mentioned (Baxt, 1994; Karanika-Murray & Cox, 2010; Kilifarska, 2011).

As a result of this finding, the interpretation of the relationships between stressors and burnout, which are nonlinear, needs to be revised: Linear relationships have a straight best-fit line and can have different slopes, but these slopes are constant over the whole range of values of the predictor variables, which makes their interpretation easy. In nonlinear relationships, within the same relationship, there may be flat areas (an increase in the level of the predictor variable has no effect on the criterion) and steep areas (an increase/decrease in the level of the predictor variable has an effect on the criterion) that must be interpreted separately. Figure 2 shows that in all three profiles role ambiguity is positively related to emotional exhaustion. However, the relationship is (1) nonlinear, since the better fitting line is always a curved line and (2) these curved lines have a different curvature: The emotional exhaustion of novelty seekers (red dotted line) rises steeply to values above the mean when the degree of role ambiguity increases from 1 to 2. Between values of 2 to 3 for role ambiguity, emotional exhaustion stagnates at a level of about 2.7 but rises steeply again to the highest values (near 4) when the degree of role ambiguity rises above the threshold value of 3.5. An explanation for this behavior could be, that the novelty seekers, who like new and stimulating tasks but have little control and commitment, quickly become emotionally exhausted if their role is not clear. From this point of view, it is more difficult for novelty seekers to apply coping strategies such as problem-solving because they feel they have little control, which in turn leads to burnout and disengagement (Biggs, Brough, & Drummond, 2017; Folkman & Lazarus, 1984).

As expected, hardy people (green dotted line) are the least affected group of people. They show a low to medium degree of emotional exhaustion when role ambiguity is low (1 to 2). Then, when the role ambiguity increases from 2 to 3, the emotional exhaustion also increases. However, a further increase in role ambiguity beyond the level of 3 does not further increase emotional exhaustion, but it remains practically at a level of about 3. A reason for this might be that hardy individuals cope with role ambiguity using a problem-focused style. Problem-focused coping refers to doing something to solve the problem causing the distress, generating alternative solutions, and following a plan of action. A meta-analytical study by Shin et al. (2014) found that the problem-focused coping style correlated negatively with all three burnout dimensions.

People with a rigid control profile (blue dotted line) behave similarly to novelty seekers when confronted with a low to medium degree of role ambiguity: The degree of emotional exhaustion increases considerably, while the degree of role ambiguity rises from a low to a medium level. However, in contrast to novelty seekers, emotional exhaustion does not increase even at the highest level of role ambiguity. People who belong to the rigid control profile have a low level of commitment and challenge but a high level of control. This high degree of control appears to be responsible for the less severe consequences of emotional exhaustion, even when faced with the highest level of role ambiguity. These results show that rigid controllers find role ambiguity more manageable compared to novelty seekers because they feel less exhausted. It, therefore, seems important to include both problem-oriented coping training and an improved perception of the controllability of the situation in the prevention of burnout among nurses (Wilski, Chmielewski, & Tomczak, 2015).

This demonstrates that the three profiles show different relationships between some of the stressors and burnout dimensions, and therefore support hypothesis 2.

The last, but no less important question that needs to be discussed is the consequences of using linear methods such as OLS regression as a generic tool to analyze an existing relationship without questioning whether the relationship is truly linear. If a relationship is nonlinear but a linear statistical method is used to analyze it, the result is at best less significant than it actually is. This, however, would not be the worst case, since the predictor variable in question could still be considered a significant predictor, published as such, and then included in an intervention program. In the worst case, the relationship would not prove to be statistically significant. Then, the researcher would be irritated at first, since the variables are usually included in an analysis on a theoretical basis and are therefore likely to prove to be significant predictors. But finally, this not significant predictor is not mentioned in the report or, what is worse, it is mentioned that it has no significant impact on the criterion variable. This, in turn, would lead other researchers not to use this variable in similar studies.

4.1 Study limitations and suggestions for further research

First, this study is limited by its cross-sectional design. Second, other personality variables were unknown. Higher self-esteem or optimism may lead to stronger negative relationships between hardiness and burnout. Future research should, therefore, monitor additional personality variables. Third, several other questions that should be further researched concern the replication of the hardiness pattern found in this study to see if the results turn out to be a consistent finding or an artifact of the present sample. These questions are: Do the hardiness profiles found in this study replicate in (a) similar populations as in the present study, (b) in other professions or work environments, (c) in cultures other than Chinese, and if not, which aspects of culture influence the hardiness profiles of its members?

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Conflict of interest

The authors declare no conflict of interest.

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Chapter 3
Discussion

1. Major Findings and Theoretical Implications

The main objective of this work was to see if ANNs in their simple and concatenated form are useful instruments to analyze the burnout process and the effect of hardiness on it. The goal of the first study was to analyze the whole burnout process which consists of the three linked elements antecedents → burnout → consequences. To model and analyze this entire process simultaneously, it was necessary to combine two ANNS. The second and third studies aimed to confirm hardiness profiles discovered in an empirical study (Johnsen et al., 2013) in a different population (soldiers) and to find out more about the effect of these different hardiness profiles on the antecedents → burnout relationship. For this analysis a simple ANN was sufficient. In all studies, OLS regression analysis was used as a benchmark to see how well the ANNs would perform.
The results of all studies suggest that the ANN's predictive accuracy outperforms OLS analysis.

1.1 Advantages of Using ANNs Together with OLS Regression

At the beginning of this work, the only reason to use OLS regression in the analysis of the different data sets was to have a benchmark against which the ANN result could be compared. This was important because without this benchmark it would have been difficult to argue that ANNs are an effective method for analyzing burnout data. However, during the phase of analyzing the results of ANN and OLS regression, it became increasingly clear that using OLS regression not only as a benchmark but together with ANNs was advantageous because what could not be achieved with one method could be achieved with the other. ANNs are known to be very good function approximators, able to detect nonlinear relationships between variables. A disadvantage of ANNs is that they are "black boxes", and the main criticism aims at the lack of ability of ANNs to analyze the exact effect of a given predictor variable on the output variable. However, sensitivity analysis has been able to shed some light on the "black box" (Paruelo & Tomasel, 1997; Shwartz-Ziv & Tishby, 2017; Tzeng & Ma, 2005). Using this approach, the first-order effects of the variables in the burnout model were extracted from the concatenated and simple ANN. However, there is still the limitation that the statistical significance of the prediction variables is not known, even though efforts have been made to overcome this limitation (Horel & Giesecke, 2019). OLS regression, on the other hand, can distinguish significant from non-significant predictors. The disadvantage of OLS regression is that it is not able to find nonlinear relationships (the more nonlinear, the lower the statistical significance). The advantage of using both methods together is therefore that the two methods complement each other.

1.2 ANNs Give Better Results in Burnout Prediction

One important finding of this work is that the ANNs used in the studies always either gave similar or better prediction results in terms of coefficients of determination R^2. The same predictor variables explained therefore more variance in the criterion variable when an ANN was used to analyze the data compared to OLS regression. The reason for this consistent finding is most likely the existence of nonlinear relationships between some of the predictor criterion variable pairs. If nonlinear relationships exist, OLS regression will explain a smaller amount of variance because it only can fit a straight line through the data points. An ANN on the contrary can fit a curved line through the data points and therefore can explain a larger amount of variance. The results showed that the lack of personal accomplishment was the variable with the highest amount of explained variance (47%). In line with other results (Garrosa et al., 2008), the dimension control of resilience and role ambiguity were the best predictors of lack of personal accomplishment. Control was also highly associated with protection from burnout in relation to the subdimensions emotional exhaustion and depersonalization, confirming existing findings (DePew et al., 1999; Hsieh & Chao, 2004). However, in contrast to existing findings, commitment and above all challenge were not significant predictors for these two subdimensions. A possible explanation for this result could be the deep-rooted traditions and hierarchical thinking of the Chinese people and their lack of openness to change (J. Lee, Lim, Yang, & Lee, 2011; Ng, Fong, & Wang, 2011). These results also support the need to understand burnout in relation to cultural aspects and the specific context where it occurs (Wilmar B. Schaufeli, 2017).

1.3 Nonlinear Relationships Between Variables of the Burnout Process

Through the application of visual analysis, it was not only possible to show the existence of non-linear relationships between different variables, but also to illustrate the form of these non-linear relationships, which provides information on how burnout and its consequences arise. In general, both the 3D and 2D graphs show an S-shaped surface or line with flat areas interrupted by steep areas. Especially pronounced nonlinear relationships were found in those relationships where the difference in coefficient of determination R^2 between ANN and regression was particularly large. Such a strong nonlinear relationship was found between work overload, control, and emotional exhaustion, suggesting that a high degree of control limits the development of emotional exhaustion even in severe work overload. However, the process of developing emotional exhaustion is not linear but contains a threshold, the crossing of which leads to a sharp increase in emotional exhaustion.

1.4 Implications of Using ANNs in Occupational Health Research

Results like these show that nonlinear methods such as ANNs are essential in theory development, as these methods identify areas of high sensitivity and challenge scientists to clarify these areas. In other words, once nonlinear relationships have been identified, it is crucial to explain the flat and steep regions and why crossing specific threshold values changes a relationship so radically. Thus, applying ANNs might lead to an adaptation of existing processes or new theoretical frameworks.

This also suggests that using a linear approach to assess burnout may fail to adequately represent relationships between work characteristics and work-related health outcomes, and also among work characteristics as predictors of such outcomes, as they may be more complex than traditional linear approaches can accommodate. In other words, there is a tendency to find linear relationships with linear methods over finding nonlinear ones, and the linear relationships seem to be more significant even though that this is only due to the linear method applied. In this sense, it would be interesting to reinvestigate variables that have been discarded (due to applying a somewhat inadequate method) at an early stage of burnout research because, with this nonlinear method (ANN), some of those discarded variables might actually be important and should be included. Diagnosis of burnout and the development of specific programs to prevent burnout and its consequences in the workplace clearly depend on the accurate assessment of the syndrome and the involved variables and the analysis method.

1.5 Hardiness Profiles

To date and apart from this work only two studies exist in which the person-centered method was used to find hardiness profiles (Johnsen et al., 2013; Ladstätter et al., 2014). The profiles found in this work (hardy profile, rigid control, and novelty seeker profile) partially replicate profiles found in the above-mentioned studies which confirm naturally occurring subgroups within the nurse population. This also shows that the hardiness construct is not as homogenous as previously thought across the nursing population. The extraction of qualitatively different profiles (different levels on dimensions within a profile) compared to a single hardy profile with either high, medium, or low levels on all dimensions, reinforces the person-centered analysis as an important tool in organizational research (J. P. Meyer et al., 2013). This does not mean that the variable-centered methods should be substituted by this person-centered approach. On the contrary, the two strategies should be viewed as complementary, providing different insights into the phenomenon of interest.

1.5.1 Hardy Profile

The most expected profile was the hardy profile (high commitment, challenge, and control). Hardy nurses have below-average scores for stressors, for the burnout dimensions, and the psychological, physical, and organizational consequences of burnout. This finding is consistent with existing variable-centered research in this area (Abdollahi et al., 2014; Eschleman et al., 2010; Garrosa et al., 2008). More surprisingly, within the hardy profile, challenge is positively associated with emotional exhaustion, suggesting that the normally zero or negative relationship is reversed. One possible explanation would be that those with particularly high levels of challenge, who therefore constantly seek new experiences, overestimate their own personal abilities (Heppner, Witty, & Dixon, 2004; Larson & Heppner, 1989). The results of their work would then not meet their expectations, which in turn would lead to a state of emotional exhaustion. A similar explanation fits the positive relationship between challenge and both organizational and physical consequences that we have found only for the Hardy and novelty-seeker profiles.

Another interesting result of the profile approach is the discovery that the negative relationships between challenge, and both depersonalization, and lack of personal accomplishment disappear in the Hardy profile. Similar to the explanation given above, this could be because a very high level of challenge has been reached where an increase or decrease in challenge has no additional consequences. A similar effect occurs with regard to the relationship between control and all three burnout dimensions. The negative correlations found in the overall sample disappear for the hardy profile. Following the above-mentioned idea of having achieved a high level of control, an increase or decrease in control can no longer have any consequences.

1.5.2 Rigid Control Profile

The rigid control profile (high control, low/average commitment, and challenge) does not fit with the current, primarily variable-centered approach of hardiness theory. However, it overlaps considerably with the rigid control profile found by Johnsen et al. (2013) in their study, in which they also used a person-centered approach. However, it must be mentioned that the populations from which the samples were drawn were very different (nurses vs. soldiers) and that Johnsen et al. used z-scores for their interpretation that did not match the original scale. In addition to the different professions, other variables could also be responsible for the profile differences found. For example, it could be that gender influences the differences. The Norwegian soldiers were mainly men, while the Chinese nurses were almost exclusively women. Regarding the characteristics that persons with rigid control show, it is worth mentioning that they have values above the average for role ambiguity and workload, for the three burnout dimensions and the three types of consequences. In contrast to hardy individuals, rigid control individuals show a negative correlation between challenge and emotional exhaustion, which is consistent with the existing theory. Interestingly, the negative correlations found in the overall sample between engagement and both depersonalization and lack of personal accomplishment weakened significantly in the profile of rigid control.

1.5.3 Novelty Seeker Profile

Nurses with the profile of novelty seekers (high challenge and average commitment and control) have the highest scores for stressors, burnout, and burnout consequences. A reason why the profile we have found, works like this could be that the pursuit of novelty is related to be open and engage in stimulating activities. However, to achieve the goals, this attitude must be accompanied by perseverance in the activities (commitment). Besides, impulsive behavior would also be associated with a lack of planning, which means acting without consideration of consequences at the moment, and lack of perseverance is characterized by an inability to concentrate on boring or difficult tasks. It is, therefore, possible that people with the novelty-seeking profile are looking for stimulating situations, but are less able to deal with the accompanying stressors and therefore have more burnout and other negative consequences.

2. Strengths, Limitations, and Future Research

The studies presented in this paper have several strengths but also limitations that should be taken into account for future investigations.

2.1 Strengths of the Studies

The study presented in Chapter 2.1 is the first in which a concatenated ANN was used to analyze occupational health data. In this way, the study paves the way for further investigations using this analytical approach. The application is not limited to the analysis of burnout but can be used in many different research areas. Moreover, the concatenation of ANNs could be further developed to the non-linear equivalent of structural equation modeling (SEM). Even though not as novel as the point mentioned before, the study could show again that at least some of the variables of the burnout process are to different degrees nonlinearly related to each other which is important for two reasons. Firstly, the interpretation of a relation between two variables is not as simple as in a direct or indirect linear relation. This in turn means that more specific and precise intervention programs can and should be developed for people who are in danger of burning out. Secondly, the discovery of nonlinear relationships shows that in previous occupational health research, nonlinear relationships between variables may have been declared statistically not significant because linear methods were used to analyze the data. When linear methods are used to analyze data, the result is that linear rather than nonlinear relationships are found. The linear relationships appear to be more significant, even if this is only due to the linear method used.

In the case of the study presented in Chapter 2.2, this was the first research to identify naturally occurring hardiness profiles in nurses using the person-centered methodology. This way, some of the hardiness profiles discussed theoretically (Maddi, 2013) and found in another empirical study about soldiers (Johnsen et al., 2013) could be confirmed. It also showed that the 3-dimensional hardiness construct (commitment, challenge, and control) is not as homogenous as the mainly variable centered research has led us to believe. Furthermore, the extraction of qualitatively different profiles (with different levels on hardiness dimensions) and not just quantitatively different ones (with equally high, medium or low levels on all dimensions), reinforces the person-centered analysis as an important tool in organizational research.

In the last study (Chapter 2.3) the three hardiness profiles (hardy, rigid control, and novelty seeker) found in the previous study were taken up again and analyzed separately with ANNs. This approach made it possible to identify the influence that the different profiles have on the burnout process and that several relationships between the variables of this process were nonlinear. The profile of the novelty seeker is associated with the highest burnout values and the hardy profile with the lowest burnout values. Nurses with the rigid control profile are probably better protected from burnout than novelty seekers because they control, or at least have the impression that they control what is going on around them.

Another important result, which gradually emerged during the work on this doctoral thesis, concerns the methodology applied. Namely, that the joint use of ANNs and OLS regression to analyze the data combines the advantages of both and removes their individual limitations.

2.2 Limitations of the Studies and Suggestions for Improvement

Despite the strengths and contributions that this work makes to the scientific literature, the studies presented have significant limitations that need to be mentioned with the aim of proposing future research that can achieve the same results by improving these aspects. Although these limitations have been made explicit in the various scientific publications, they are explained in more detail below.

2.2.1 Self-Report Measures

A limitation of this work is that all studies used self-reports to measure constructs, and variables which implies some response bias and that the common method variance may affect the results (Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). Despite this, questionnaires are frequently used to measure one's perception of working conditions, burnout, burnout consequences, and hardiness. However, given that burnout, but especially the burnout consequences as well as occupational stress such as workload could be at least partly reflected in objective terms, studies need to be developed that analyze these constructs using this type of measure.

2.2.2 Design

The studies of this thesis are limited by their cross-sectional nature. Even if the words prediction of burnout or burnout process is used, causal relationships between the variables cannot be established due to the lack of temporal distance. Even in the case of the two concatenated ANNs in the first study, which is even more suggestive of causal relationships between the three layers of variables (stressors, burnout, burnout consequences), it must be stressed that there is no causal relationship between these variables. This limitation suggests the need for future studies in which the variables predictor, mediator, and criteria are separated over time. Similarly, experimental studies could be initiated to investigate the relationship between the variables studied.

2.2.3 Sample

Convenience sampling was used to recruit nurses from Chinese hospitals due to its extremely speedy, easy, and cost-effective application. However, this form of sampling also has disadvantages. Especially, the generalization of the results of convenience sampling to the target population is problematic. The reason for this lies in the possible under-representation of subgroups in the sample compared to the target population. Therefore, conclusions based on convenience sampling should only be drawn about the sample itself. Furthermore, convenience sampling is characterized by its insufficient power to detect differences between population subgroups. (Bornstein, Jager, & Putnick, 2013).

The sample size of 465 in the first study, but especially the 325 in the second study, may be too small for use with ANNs. In more technical areas ANNs are trained with thousands of input-output data pairs. However, this is not possible for data collection by questionnaire. In the case of the second study, the sample size was additionally reduced by the cluster analysis, so that for the ANN analysis of the three profiles a sample size of 87 was available for the profile of the rigid control, 173 for the hardy profile, and 65 for the novelty seeker profile. These sample sizes are too small even for OLS regression (Bujang, Sa'at, & Bakar, 2017; Green, 1991; Kotrlik & Higgins, 2001). Furthermore, the different sample sizes across the profiles make it difficult to compare the results. Therefore, it would be interesting to repeat the person-centered study with a larger overall sample size and the same sample size of the three profiles (random samples from the subsamples) and see if the ANN and regression results are repeated under these circumstances.

Another weakness of this work concerns the high proportion of women in the sample. However, it is known that the female gender is predominant in the nursing profession and the health sector in general (Sun et al., 2017). Perhaps the results of this research would not be the same in a more balanced sample, given that men perceive emotional demands differently than women, that they are often perceived as instrumental rather than emotional, and that they express their emotional distress differently (Cottingham, 2013; Gratz & Roemer, 2004). Future research should, therefore, address these issues by including a larger population of male nurses.

2.2.4 Future Research

This section intends to propose future research that not only repeats the proposals to improve previous limitations but goes beyond that in order to stimulate research on the topic of this work.

Regarding the hardiness profiles found with the person-centered approach, it would be interesting to see if these profiles found here replicate in similar studies. Specifically, and to eliminate one of the limitations mentioned before, the person-centered study should be repeated with a larger overall sample of Chinese nurses. Besides that, it would also be interesting if the profiles found with Chinese nurses replicate in other countries. Regarding the statistical method that was used to find the profiles, it needs to be pointed out that we used the k-means cluster analysis mainly to keep our results comparable to those of the study by Johnsen et al. (2013) on soldiers who also used this method. However, other techniques such as latent class analysis could have been used to test for different hardiness profiles. The results of simulation studies indicate that latent class analysis substantially outperforms the K-means cluster analysis (Magidson & Vermunt, 2002).

Future studies should investigate how burnout develops over time with regard to the different hardiness profiles to clarify questions of causal relationships.

Additionally, profile-specific intervention programs could be tested to see their influence on the burnout process. As mentioned in the limitation section, the study was based solely on self-reporting measurements. Less subjective measures, such as peer reporting, behavioral indicators, and physiological concomitants, are needed.

Regarding the sensitivity analysis used to quantify the effect of the predictor variables on the criterion variables, the r-LHS employed only generated first-order (main) effects. Future research should examine whether other sampling methods, such as FAST, Sobol, or Morris, which are capable of computing higher-order interaction effects provide additional and maybe even more revealing results (Saltelli, Tarantola, Campolongo, & Ratto, 2004).

3. Conclusions and Practical Implications

The three profiles found in the person-centered study could contribute to the development of intervention programs that address the specific needs of nurses with different profiles. This would be particularly important for nurses who have either the rigid control or novelty seeker profile. Novelty seekers, for example, are most affected by burnout, but because of their high degree of challenge, they are likely to be more receptive to intervention, which could help to initiate a self-healing process after it has been initiated, for example through counseling sessions focusing on the importance of the control dimension. More generally, healthy practices implemented at the organizational level can stimulate motivation, autonomy, and adaptive self-regulation strategies.

Concerning the ANN analysis and the non-linear relationships found, it must be emphasized that with the discovery of specific threshold points through visual analysis, burnout intervention programs can now be applied more specifically to nurses. This reduces expenses for the organization, as the usually cost-intensive intervention programs are only used where they are needed. It is in an organization's own interest to regularly monitor the psychosocial factors at the workplace and the well-being of employees so that timely and targeted burnout prevention measures can be taken. Since organizations are legally obliged to monitor psychosocial risk factors, it is a mistake to use unsuitable data analysis and its results as a basis for implementing prevention measures. From this point of view, the present work makes an important contribution by applying a method for the analysis of non-linear and linear relationships and by taking into account the hardiness profiles of nurses.

A practical implication concerning ANN analysis is that it is beneficial to use the ANN technique together with regression because it combines the advantages of both techniques and removes their individual limitations.

Concerning the person-centered approach, it seems that using the original scale for interpretation instead of the z-score scale allows a more natural view of the profiles and helps to avoid redundant profiles. Therefore, the data should be analyzed using both the original and z-Score scales for full understanding and interpretation.

Conclusiones e Implicaciones Prácticas

Los tres perfiles encontrados en el estudio centrado en la persona podrían contribuir al desarrollo de programas de intervención que aborden las necesidades específicas de las enfermeras con diferentes perfiles. Esto sería particularmente importante para las enfermeras que tienen el perfil de control rígido o de buscador de novedades. Los buscadores de novedades, por ejemplo, son los más afectados por el agotamiento, pero debido a su alto grado de desafío, es probable que sean más receptivos a la intervención, lo que podría ayudar a iniciar un proceso de auto curación después de que se haya iniciado, por ejemplo, mediante sesiones de asesoramiento centradas en la importancia de la dimensión de control. En términos más generales, las prácticas saludables aplicadas a nivel organizativo pueden estimular la motivación, la autonomía y las estrategias de autorregulación adaptativa.

En lo que respecta al análisis de las RNA y a las relaciones no lineales encontradas, hay que subrayar que con el descubrimiento de puntos de umbral específicos a través del análisis visual, los programas de intervención para el agotamiento pueden aplicarse ahora de forma más específica a las enfermeras. Esto reduce los gastos de la organización, ya que los programas de intervención, que suelen ser muy costosos, sólo se utilizan cuando son necesarios. A la organización le interesa vigilar regularmente los factores psicosociales en el lugar de trabajo y el bienestar de los empleados para poder adoptar medidas oportunas y específicas de prevención del agotamiento. Dado que las organizaciones están legalmente obligadas a vigilar los factores de riesgo psicosocial, es un error utilizar análisis de datos inadecuados y sus resultados como base para aplicar medidas de prevención. Desde este punto de vista, la presente tesis hace una importante contribución al aplicar un método de análisis de las relaciones no lineales y lineales y al tener en cuenta los perfiles de resistencia de las enfermeras.

Una implicación práctica en lo que respecta al análisis de las RNA es que resulta beneficioso utilizar la técnica de las RNA junto con la regresión porque combina las ventajas de ambas técnicas y elimina sus limitaciones individuales.

En lo que respecta al enfoque centrado en la persona, parece que la utilización de la escala original para la interpretación en lugar de la escala de puntuación z permite una visión más natural de los perfiles y ayuda a evitar perfiles redundantes. Por lo tanto, los datos deberían analizarse utilizando tanto la escala original como la escala de puntuación z para su plena comprensión e interpretación.

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