ENHANCING INFORMATION AXIOM AND DEVELOPING AN AXIOMATIC DESIGN BASED MACROERGONOMICS FRAMEWORK FOR MANUFACTURING COMPANIES

by

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ABSTRACT

ENHANCING INFORMATION AXIOM AND DEVELOPING AN AXIOMATIC DESIGN BASED MACROERGONOMICS FRAMEWORK FOR MANUFACTURING COMPANIES

This study has three main goals: first, to redefine the “information axiom”, so it is applicable to ergonomic designs; second, to examine the information axiom on the cost associated with design and decision-making; and third, to develop an axiomatic design based macroergonomic framework for manufacturing companies to improve employee performance, health, safety, and overall company performance. For the stated objectives, in the light of existing literature, the “information axiom” was subjected to a rigorous evaluation. Information axiom proved to be inadequate for ergonomic designs and the existing formula was put into a new form to overcome this shortcoming. Going further, it has also been proven that information axiom does not minimize the cost associated with designs, and it has been reformulated to address this shortcoming. For the macroergonomic framework development, a Macroergonomic Evaluation Questionnaire (MEQ) was first created using the literature and expert opinions. As a result, a framework has been created for the manufacturing sector that can assist in decision-making. The usability of the formula was demonstrated in this way with a case study. In summary, this study makes two main contributions to the “information axiom”, one of the two axioms of axiomatic design: (1) The information axiom was reformulated to be applicable to ergonomic designs; and (2) the information axiom is reformulated to minimize potential costs in design and decision making. Finally, the information axiom formula reconstructed in the second phase has been successfully used to create a macroergonomic program framework for companies.

ÖZET

BİLGİ AKSİYOMUNUN GELİŞTİRİLMESİ VE İMALAT ŞİRKETLERİ İÇİN AKSİYOMATİK TASARIM TABANLI MAKROERGONOMİK ÇERÇEVE TANIMLANMASI

Bu çalışmasının üç ana amacı var: ilki, ergonomik tasarımlara uygulamada yetersiz kalan bilgi aksiyomunu ergonomik tasarımlara uygulanabilir hale getirmek; ikincisi, bilgi aksiyomunu, tasarım ve karar vermelerle ilgili maliyet konusunda mercek altına almak; ve üçüncü olarak da imalat şirketleri için aksiyomatik tasarıma dayalı bir makroergonomik çerçeve oluşturarak çalışan performansını, sağlık ve güvenliği ve şirket performansını iyileştirmek. Belirtilen hedeflere yönelik olarak, "bilgi aksiyomu", literatürden de faydalanılarak, titiz bir değerlendirmeye tabi tutuldu, ergonomik tasarımlarda yetersiz olduğu ispat edildi ve bu eksikliği gidermek üzere mevcut formül yeni bir forma sokuldu. Daha ileri gidilerek, mevcut bilgi aksiyomunun tasarımlarla ilgili maliyeti en aza indirmediği de ispat edildi ve bu eksikliği gidermek üzere yeniden biçimlendirildi. Makroergonomik çerçeveyi oluşturmak için literatürden ve uzman görüşlerinden yararlanarak önce bir Macroergonomik Değerlendirme Anketi (MDA) hazırlandı. Sonuçta, imalat sektörü için, makroergonomik konularda karar vermede yardımcı olabilecek, bir çerçeve oluşturuldu. Formülün kullanılabilirliği de bu şekilde bir vaka çalışmasıyla gösterilmiş oldu. Özetle, bu çalışma, aksiyomatik tasarımının iki aksiyomundan biri olan "bilgi aksiyomu" ile ilgili iki temel katkı sunmaktadır: (1) Bilgi aksiyomu, ergonomik tasarımlara uygulanabilecek şekilde formüle edildi; ve (2) bilgi aksiyomu, tasarım ve karar vermelerde olası maliyetleri en aza indirecek şekilde formüle edildi. Son olarak da, ikinci aşamada yeniden oluşturulan bilgi aksiyomu formülü, şirketler için makroergonomik program çerçevesi oluşturmada başarıyla kullanıldı.

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LIST OF SYMBOLS

A	Absolute difference between the lower bounds of DR and SR
A_i	Given design parameter of i^{th} component
B	Absolute difference between the upper bounds of DR and SR
C	Common range
C_i	Compatibility index
d^2	Squared rank differences
I_i	Information value of i^{th} component
P_e	Expected agreement between the raters by chance
p_i	Probability of satisfying the i^{th} FR
P_o	Observed agreement between the two raters
$\|R\|$	Determinant of the observed correlation matrix
r_{ij}	Partial correlation between variables i and j
R_i	Maximum exposure value
S^2	Sample variance
x	Extent to which SR corresponds with DR
x_i	Each data point in the dataset
$\bar{X}$	The sample mean
y	Deviation between nominal value and system midpoint
z	Variability of the system
Z_{ij}	Standardized value of variable
δ_{ij}	Pairwise correlation between variables i and j
κ	Degree of agreement
ρ	Spearman's rank correlation coefficient
σ_i^2	Variance of the i^th item

LIST OF ACRONYMS/ABBREVIATIONS

AD	Axiomatic Design
AHP	Analytic Hierarchy Process
AMT	Advanced Manufacturing Technologies
ANOVA	Analysis of Variance
ANP	Analytic Network Process
CA	Cronbach's Alpha
CDF	Cumulative Distribution Function
CE	Cognitive Ergonomics
CIS	Computer and Information Security
CR	Common Range
CSF	Critical Success Factor
CSR	Corporate Social Responsibility
CVI	Content Validity Index
DM	Design Midpoint
DP	Design Parameter
DR	Design Range
EAP	Employee Assistance Program
EDF	Empirical Distribution Function
FMEA	Failure Modes and Effects Analysis
FR	Functional Requirement
HAI	Healthcare Associated Infection
HCI	Human Computer Interaction
HFE	Human Factors and Ergonomics
HR	Human Resources
ICC	Intra-class Correlation Coefficient
IEA	International Ergonomics Association
IT	Information Technology
KMO	Kaiser Meyer Olkin

LS	Likert Scale
MAS	Macroergonomic Analysis of Structure
MCI	Macroergonomic Compatibility Index
MCQ	Macroergonomic Compatibility Questionnaire
MCS	Macroergonomic Compatibility Survey
MEAD	Macroergonomic Analysis and Design
MEQ	Macroergonomic Evaluation Questionnaire
MIT	Massachusetts Institute of Technology
MP	Macroergonomic Practice
MSB	Mean Square Between Subjects
MSD	Musculoskeletal Disorder
MSW	Mean Square Within Subjects
OSHA	Occupational Safety and Health Administration
PAF	Principal Axis Factoring
PCA	Principal Component Analysis
PDA	Personal Digital Assistant
SC	Spearman's Correlation
SEIPS	Systems Engineering Initiative for Patient Safety
SM	System Midpoint
SR	System Range
STS	Sociotechnical System
WRMD	Work-related Musculoskeletal Disorder

1. INTRODUCTION

This study aims to examine the universality of the information axiom of axiomatic design (AD), especially from the perspective of its applicability to ergonomic designs. Secondly, the study aims to propose an enhanced information axiom which considers the minimization of cost involved in design or decision-making. Both objectives are illustrated by examples. The third goal is to develop a new axiomatic design-based macroergonomic framework for manufacturing companies. The purpose of developing such framework is to help manufacturing companies construct their organizational structure on macroergonomics. It allows companies to obtain the most efficient and most suitable organizational structure for the performance and well-being of employees in the light of macroergonomics.

Axiomatic design (AD), developed by MIT professor Suh [2], stands as a comprehensive methodology for the design of products and systems. AD employs matrix algebra as a fundamental tool to translate customer requirements into functional requirements, design parameters, and subsequently, into process variables. This structured approach is further guided by a set of design principles, often referred to as design axioms, to steer the analysis and decision-making processes in the pursuit of creating high-quality product and system designs [2,3]. The AD consists of two axioms, namely, the independence axiom and the information axiom. The Independence Axiom underscores the importance of preserving the independence of functional requirements, while the Information Axiom emphasizes the need to minimize the information content within the design process (indeed, it is a probability value associated with a specific design parameter that will satisfy functional performance: functional performance risk). If these two are achieved the design is optimal from the perspective of AD [2,3]. Among the alternatives, the design with minimal information content (i.e., lower functional performance risk) should be preferred.

Human Factors and Ergonomics (HFE) seeks to improve performance and well-being through system/product design. HFE approach/principles can be applied to all stages of planning, design, implementation, evaluation, maintenance, redesign, and continuous improvement of systems. Macroergonomics, a subdiscipline of HFE, is "a top-down socio-technical systems approach to work system design [4]. It is a proactive and holistic approach to contribute to the performance of a work system (i.e., productivity, quality, cost reduction) and ensure the well-being of the workforce (i.e., preventing work-related health and safety issues, increasing morale and motivation and comfort).

At the first part of the first phase of this study, the applicability of information axiom of AD in ergonomics and beyond is examined: As a result, shortcoming of information axiom for the purpose of ergonomic product designs is identified and a new approach is proposed. In the second part of the first phase, not only for ergonomics but also for other design applications, a more precise formula, which integrates the information axiom and Taguchi Loss Function, is developed. In the second phase of the study, macroergonomics critical success factors (CSFs) are determined.

Based on these identified (CSFs) a macroergonomic framework for manufacturing companies is developed using the Enhanced AD approach. This framework is a decision-making tool to structure, organize, and manage the company´s macroergonomics activities.

2. LITERATURE REVIEW

2.1. Axiomatic Design

Axiomatic design (AD) is a universal design framework that aims to help designers find an efficient way of designing and selecting the best design alternative in a systematic way [2]. AD is established on four main domains (customer domain, functional domain, physical domain, and process domain) [5]. The customer domain contains the information of what customers need, the functional domain contains the requirements (FRs) derived from customer needs, design parameters (DPs) determined for satisfying functional requirements are in the physical domain and lastly, a process is defined to achieve a product that satisfies design parameters in process domain [5]. According to AD, there are mappings between customer domain and functional domain, functional domain and physical domain, physical domain, and process domain. Designers hierarchically decompose each domain to better specify related requirements. The whole process is called zigzagging [5]. The mapping process can be seen in Figure 2.1.

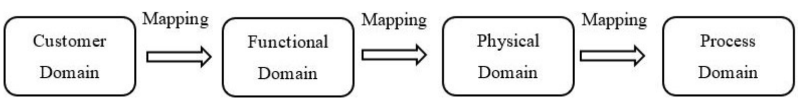

Figure 2.1. Mapping process in axiomatic design.

The domain on the left (relatively) defines "what we want to succeed" and the domain on the right (relatively) defines "how we will do it" [6]. We can see a sample zigzagging process in Figure 2.2.

The complex relationships between the different aspects of a design can be mathematically captured through axiomatic design domains. This mapping is expressed as a matrix that relates two vectors to each other, providing a structured way to analyze how changes in one domain influence another [6] as follows

$$\mathbf{FR} = [A]\mathbf{DP}, \tag{2.1}$$

where FR represents the vector of functional requirements, DP stands for the vector of design parameters and A is the matrix showing the relationships between FRs and DPs in the above equation [6].

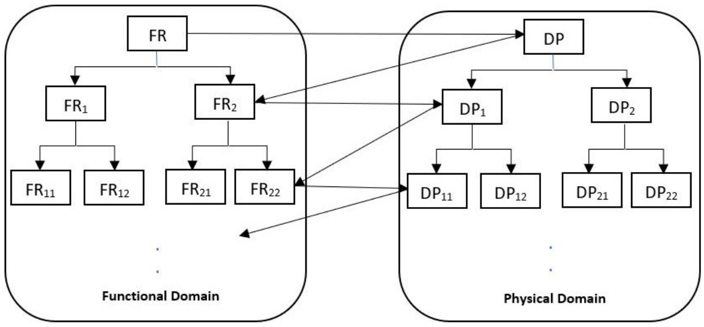

Figure 2.2. Zigzagging process in axiomatic design.

There are two axioms in axiomatic design. Namely, the independence axiom and information axiom.

2.1.1. Independence Axiom

It says we must ensure independence between functional requirements. Designs that violate this axiom can cause problems at any stage of our product lifecycle. Suh defines three types of design regarding the independence axiom in AD (uncoupled, decoupled and coupled). We can determine "which type of design we get" by examining the relationship matrix A [2].

Uncoupled design is the most desired design and it shows definite independence between FRs. If we get an A matrix in the form of a diagonal such as;

$$A = \begin{bmatrix} X & 0 & 0 \\ 0 & X & 0 \\ 0 & 0 & X \end{bmatrix}, \tag{2.2}$$

it says we have an uncoupled design. Decoupled design is the design that shows we have some dependence between FRs but we can overcome these dependencies by following a certain sequence of implementation. An A matrix in the form of a triangular,

$$A = \begin{bmatrix} X & 0 & 0 \\ X & X & 0 \\ X & X & X \end{bmatrix}, \tag{2.3}$$

indicates we have a decoupled design. Finally, coupled design is a design that has dependencies but has no obvious pattern so implementing it can cause some problems at any stage of the product lifecycle. We should not choose this type of design unless we have to. We may try to redesign our product to eliminate the complicated dependencies between FRs. If we have any A matrix other than diagonal and triangular (upper or lower), such as;

$$A = \begin{bmatrix} X & 0 & X \\ X & X & 0 \\ X & X & X \end{bmatrix}, \tag{2.4}$$

it indicates a coupled design [7].

2.1.2. Information Axiom

The information axiom helps us to select the best design among the alternatives which satisfy the independence axiom. This axiom uses a parameter called "information content" to decide the best alternative. The alternative that has the smallest information content value is the best design. Information content tells us that smaller information values require less information during the implementation of the design. In other words, while the satisfaction probability of FRs increases, information content value decreases. Suh [2] proposed an equation to calculate this value,

$$I_i = log_2 \frac{1}{p_i} \quad \text{i=1,2,3,...} \tag{2.5}$$

and

$$p_i = \frac{\text{common range}}{\text{system range}}, \tag{2.6}$$

where p_i represents the probability of satisfying the i^{th} FR. After calculating all I_i's, we should simply sum them up to get the information content value of the entire design alternative.

In every design, we can show the probability of success in terms of what FR requires with tolerances (desired range) and what the proposed alternative supplies (system range). These probabilities follow some probability distributions and we can show the probability areas of desired range, system range and common range by using the probability distribution function of the system Figure 2.3.

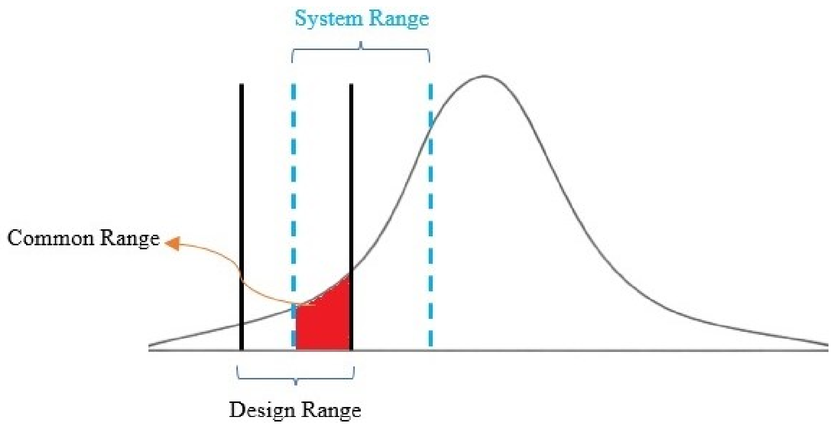

Figure 2.3. Common range, system range, design range and density function of a FR.

2.1.3. Studies on Axiomatic Design

Some of the well-known hybrid evaluation researches in the area of ergonomics and axiomatic design are listed below (Table 2.1). The details of the studies can be found in Table 2.2.

Table 2.1. Some well-known evaluation studies on ergonomics and axiomatic design.

Evaluation (Ergonomics and AD)
Büyüközkan et al. [8]
Çebi [7]
Yücel and Aktaş [9]
Guo et al. [10]
Liang and Lin [11]
Taha et al. [12]

Table 2.2. Some well-known evaluation studies on AD and ergonomics.

Author(s)	**Scope**	**Method(s)**	**Objective(s)**	**Result(s)**
Büyüközkan et al. [8]	E-learning Web Sites	Axiomatic Design Decision Making	Evaluate the quality of e-learning sites.	The proposed philosophy consolidates practical requirements into the ranking and selection process, and this proactive approach not only prioritizes options that demonstrably meet these necessities, but also effectively filters out choices that fall short.
Çebi [7]	General	Axiomatic Design Decision Making	To improve both axioms of AD. To develop a decision support system. To apply the proposed approach for the seat and display design of passenger cars	The full potential of the proposed algorithm can be unlocked by leveraging the insights about relative importance of various design parameters. This allows for the targeted optimization of design measurements, ultimately leading to the creation of superior and more efficient designs.

Table 2.2. Some well-known evaluation studies on AD and ergonomics. (cont.)

Liang and Lin [11]	Graphical User Interface	Axiomatic Design Statistics	Identifying potential design concerns related to the recognition of a set of biometric icons for a fingerprint capture device.	Results indicated that implementing improvements to system's iconography, either through a complete redesign of the icons themselves or by providing additional guidance within the system, could lead to a significant increase in the rate at which users are able to recognize and understand the icons' intended functions.
Yücel and Aktaş [9]	Electronic Consumer Products	Axiomatic Design Decision Making	Develop an evaluation methodology for electronic mobile products on ergonomic design	The proposed model can be applied to competing mobile electronic products in the consumer market. Likewise, the options of models can be assessed during the development process. In addition, measurements of ergonomic cell phones can help create ergonomic cell phones.

Table 2.2. Some well-known evaluation studies on AD and ergonomics. (cont.)

Guo et al. [10]	Consumer Electronics	Axiomatic Design Usability Engineering	Embrace a range of design challenges and create a design that meets perceived needs	More usability issues with the PDA were found by the axiomatic evaluation technique than by other methods. Over each of the three products, axiomatic evaluation technique was better in discovering issues of client requirements.
Taha et al. [12]	Virtual Environment	Axiomatic design	Investigate ergonomic design parameters within the virtual environment with the goal of reducing adverse effects through the implementation of axiomatic design principles	Results of their model shows that the ergonomic design parameters of virtual climate recognized have fulfilled the independence functional requirement and wanted visual comfort for clients.

AD has been used in various areas by researchers. Such as, product design [13–23], human-computer interaction [8–12], [24–28], ergonomics [5–7], [9], [12], [29, 30], management [31–37], decision making [16], [38–40] and so on.

2.1.3.1. Critics of Axiomatic Design Studies. The shortcomings of AD can be stated as follows;

(i) As we can see from reviewed studies, AD is very suitable to use in very different areas. However, we are interested in the studies on ergonomics. The studies on human-computer interaction are mostly about the evaluation of websites/electronics/virtual environments [8–10], [12], some others are about analyzing human-computer interaction principles with respect to AD [24]. However, none of them is in the scope of interest of the current study.

(ii) None of the available studies is about developing a generic macroergonomics framework. For instance, Helander and Lin [5] and Karwowski [6] analyzed the compatibility of axiomatic design with ergonomics, Taha et al. [12] used AD in analyzing the ergonomic design parameters of a virtual environment, Çebi [7] combined AD with fuzzy logic and illustrated its use on the ergonomic design of car cockpit. Again, none of the studies is directly involved in developing a macroergonomics framework for manufacturing companies.

(iii) Additionally, the studies in the area of management were about project planning [31], lean management [32], requirement management [33], and knowledge management [34].

2.2. Ergonomics

International Ergonomics Association (IEA) defines ergonomics as "Ergonomics, alternatively referred to as human factors, is the scientific discipline that focuses on understanding how humans interact with various components within a system. It is also a professional practice that applies theories, principles, data, and techniques to design with the goal of improving human well-being and overall system performance." [41].

The field of ergonomics is a multi-disciplinary field that includes, psychology, cognitive science biomechanics, engineering, physiology, anthropometry, interaction design, and so on.

Ergonomics is utilized to satisfy the objectives of occupational health, safety and efficiency. It is important in the design of such notions as secure furnishings and easy-to-use interfaces to machines and tools. Recurrent strain injuries and other musculoskeletal disorders, which can occur over time and result in long-term incapacity, require proper ergonomic design. Ergonomics is concerned about the "fit" between the people, hardware, and environment or "fitting a task to an individual". It depicts a person's ability and limitations in ensuring that tasks, data, functions, and the environment are appropriate for that individual. To evaluate the fit between an individual and the used technology, ergonomics professionals or ergonomists think about the task being done and the demands on the person; the tool utilized (its size, shape, and how proper it is for the task), and the data used (how it is introduced, accessed, and manipulated). Ergonomics incorporates anthropometry, biomechanics, mechanical and industrial engineering, information design, kinesiology, physiology, cognitive psychology, and spatial psychology into the study of persons and their settings [42].

Ergonomics has three fundamental sub-domains: physical, cognitive, and macro-ergonomics.

2.2.1. Physical Ergonomics

Physical ergonomics focuses on the fit between human physical characteristics and the design of work and products. Physical ergonomics aims to optimize performance and reduce job-related disorders by diminishing the mechanisms behind acute and chronic musculoskeletal disorders (MSDs). Risk factors, leading to MSDs, include excessive forces and repetition, awkward postures, inadequate rest, vibration, and stress. Main MSDs include disc herniation, tendinitis, and carpal tunnel syndrome among others. Ergonomics attempts to minimize the mentioned risk factors to reduce the occurrence of MSDs [42].

Work-related musculoskeletal disorders (WRMDs) bring about relentless pain, loss of capacity and work inability. Every year, 1.8 million U.S. laborers experience WRMDs and almost 600,000 of the cases are critical enough to make laborers suffer and miss work. The Occupational Safety and Health Administration (OSHA, USA) has discovered significant proof that ergonomics projects can reduce laborers' compensation expenses, increment efficiency and diminish worker turnover [42].

2.2.2. Cognitive Ergonomics

Cognitive Ergonomics (CE), as defined by the International Ergonomics Association [43], pertains to the management of mental processes such as perception, memory, reasoning, and motor responses, in relation to their impact on interactions among individuals and various components within a system. Key areas of focus encompass mental workload, decision-making, performance, human-computer interaction (HCI), human reliability, occupational stress, and training, as they relate to the design of human-system interfaces. CE delves into the study of cognitive aspects in task-oriented and operational environments, aiming to enhance the working conditions and overall effectiveness of human performance. Positioned as a subdiscipline within the broader field of ergonomics, CE emerges with a distinct emphasis on investigating the cognitive demands placed on individuals in the context of modern technologies. Theoretical frameworks encompass diagnosis, workload assessment, situational awareness, and forecasting. CE is geared towards enhancing the efficiency of cognitive functions through various interventions, including user-centric design of human-machine communication and human-computer interaction interfaces; formulation of information technologies that facilitate cognitive tasks (e.g., cognitive tools); refinement of training protocols; restructuring of job roles to manage cognitive workload and bolster human reliability [43].

2.2.3. Macroergonomics

In the last part of the 1970s, the Human Factors Society authorized a "Futures Study" [44]. This council recognized a few patterns anticipated to impact ergonomics over the accompanying 20 years. These patterns included: expanded innovation; expanded assorted variety of socioeconomics; more lenient qualities changes; expanded world rivalry; and a failure of microergonomics to accomplish significant and adequate outcomes [44]. While this examination officially prompted the formation of the supposed "macroergonomics" development in the US, there has been some other research around the world [45, 46].

Macroergonomics is a sub-discipline of ergonomics that essentially proposes to fit the association to the individual or people inside that association rather than fitting the job to the person [47].

Macroergonomics focuses on examining the broader organizational system and context in which work activities take place. This includes a thorough consideration of elements such as organizational culture, communication, leadership, and the integration of technology to ensure the effective functioning of the entire system and the promotion of worker well-being [47].

Macroergonomics contrasts with microergonomics, which focuses on the individual and his or her immediate work environment. By adopting a macroergonomic perspective, organizations can identify and address systemic challenges that could have a broader impact on productivity, safety, and employee satisfaction.

The main motivation behind Macroergonomics is to guarantee that work frameworks are completely blended and compatible with their sociotechnical attributes, giving synergistic enhancements on some criteria of organizational performance, for example, well-being, security, comfort, and efficiency [48–50]. Macroergonomics has been applied in various businesses, for example, nuclear, petrochemical, production, military, clinical, and aviation [51, 52].

The concept of a "macroergonomics framework" often prompts the question of its nature and purpose. In essence, a macroergonomics framework is a system that outlines how certain activities should be directed in order to achieve the goals of macroergonomics. These goals consist of achieving worker health, safety, comfort and enhancing company effectiveness. The activities include regulations, policies, rules, roles, and responsibilities.

The proposed framework is built upon foundational macroergonomics elements, including personnel, organization, tasks, technologies, and environment. Embracing this macroergonomics framework empowers companies to curtail employee turnover rates, minimize work-hour losses, prevent injuries and accidents, reduce production costs, and elevate the overall well-being of their workforce. In parallel, this approach augments productivity and enhances competitive prowess. Subsequent sections will delve into a comprehensive exploration of the benefits bestowed by macroergonomics.

2.2.3.1. Sociotechnical Systems Theory. Macroergonomics uses a certain and well-established hypothetical structure: Sociotechnical systems (STS) theory. Sociotechnical systems can go from a solitary individual utilizing a hand device to a global association, however, a work framework, as a rule, comprises at least two individuals connecting with some type of: 1- job design, 2- software and equipment, 3- inward climate, 4- outer climate, and additionally 5- organizational design [47]. Job design comprises work modules, information, assignments, skill needs, chance of social association, and furthermore factors from Hackman and Oldham [53] job characteristics model (for example self-sufficiency, input, and seriousness got from skill assortment, task character, and significance). In the macroergonomics approach, "software" refers to the management-related components such as strategies, rules, methodologies, and manuals, while "hardware" encompasses tools, equipment, machinery, workspaces, and structures [54]. The inward climate can be considered as psychosocial factors (e.g., cognitive complexity) and physical components (i.e., sound, temperature, air quality, moistness, light, and vibration). An association's culture is additionally included as a component of the inward climate [55]. The outer climate comprises components that can penetrate an association and to which an association must be responsive so as to be effective [47]. The level of dependability or change of social, financial, and political elements is especially significant for an association. Finally, organizational design contains a hierarchical structure and processes [47].

The aim of STS is to comprehend and depict the 'collaborative enhancement of both the social and technical systems,' which includes various subsystems or distinct components within the system. The concept of joint improvement encompasses interactions between different components within the system and between the system and its external environment in the context of macroergonomics [4]. In this framework, workers not only adapt to the sociotechnical system, but also play a role in shaping and modifying the sociotechnical system itself [56]. Communication occupies a central position in science, technology, and society (STS) theory, especially when examining the interactions between the sociotechnical system and its external environment. This perspective is consistent with the notion of the system as an "open system" [57] which emphasizes the importance of considering these external interactions.

Systems Theory emerged in the 1930s and 1940s as a response to the limitations of the classical analytical method known as "analytic reduction" in which a system is broken down into discrete components for the purpose of analysis. The development of systems theory was driven by the need to deal with the increasingly complex systems that were emerging at the time [56]. Wiener [58] applied this approach to control and communications engineering, while Ludwig von Bertalanffy [59] developed similar concepts for biological systems.

In traditional scientific and engineering approaches, systems are divided into specific parts that can be analyzed independently to gain an understanding of the overall system behavior. System components are decomposed into individual physical elements, and system behavior is broken down into discrete functions. This decomposition assumes that separation is both theoretically and practically feasible, that each component or subsystem operates independently, and that systematic results are not compromised when the components are studied separately.

However, this assumption falls short when dealing with complex socio-technical systems, where interactions between components and functions can be indirect and exhibit diverse structures, giving rise to the systems theory concept of emergent properties. These properties manifest only when components interact and are not evident in the behavior of individual components, as discussed in [56].

There are several models defined by various researchers, which define critical success factors in macro-ergonomics.

(i) Carayon's model: Carayon et al. [60] proposed a model called "Systems Engineering Initiative for Patient Safety (SEIPS 2.0)", in which, the researchers defined five success factors; 1- Person, 2- Organizational conditions, 3- Tasks, 4- Technologies and 5- Tools.

The first model (SEIPS) integrates ergonomics discipline into healthcare systems. In SEIPS 2.0, three innovative concepts are integrated into the original model: configuration, engagement, and adaptation. The concept of configuration encompasses the dynamic, evolving, and intelligent characteristics of socio-technical systems, allowing us to represent how health-related performance is shaped at a given moment. Engagement emphasizes the idea that different individuals and groups can engage in health-related activities both individually and collaboratively. Connected with people regularly incorporate patients, family parental figures, and other non-experts. Adaptation is presented as a criticism component that clarifies how powerful frameworks advance in arranged and unarranged manners [1].

(ii) Hyer's model: Hyer et al. [61] claimed that there was a lack about a well-developed and broadly focused theory of working cell design and its consequences on workers. Hence, they developed an extensive model of working cell structure design that thinks about both technical and social dimensions. The model considered macro-ergonomic success factors, for example; 1- Worker abilities, 2- Collaboration, 3- Communication and management styles, 4- Execution assessment, and 5- Worker prizes. With respect to the undertaking factors, Hyer et al. [61] suggested considering macro-ergonomic components, for example, task assortment, utilization of aptitudes, and worker inclusion in decision-making.

(iii) Other studies on success factors: Clegg [62] portrays the sociotechnical standards for work framework plan. Despite the fact that macro-ergonomic components are expressly excluded in these standards, they are verifiably included. 1- People (HR), 2- Organization, 3- Technology and tools, and 4- Tasks

As indicated by Karwowski [63], to address the ergonomic system design and evaluation problems, organizations must consider the significance of macro-ergonomic factors for example; 1- Human resources, 2- Organizational viewpoints, and 3-

The environment.

According to Kleiner [44], the macroergonomics assessment of a work framework must incorporate factors, for example; 1- Personnel, 2- Organizational, 3- Technical, and 5- Environmental (internal and external).

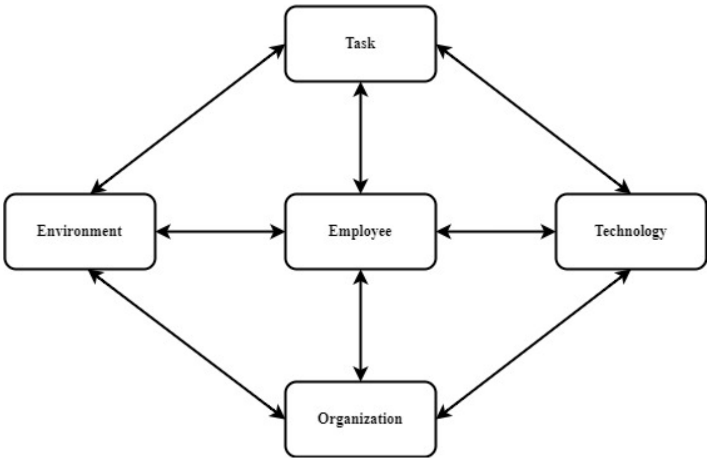

Figure 2.4. Interrelationship between critical success factors.

As we can easily notice there are common critical success factors in the literature Figure 2.4. Now, we can explain these factors in detail.

(i) People: Carayon and Smith [64] described "people" as a factor which has physiological and psychological components like character, health, skills and capacity, physical form, anthropometrics, prior experiences and learning, thinking processes, objectives and necessities. On the other hand, Erensal and Albayrak [65] define "people" in terms of "human performance capability" and "attitude in human performance"

(ii) Organization: Carayon and Smith [64] claim that organizational context has considerations that affect human performance, stress, and motivation. For instance; adapting to new technologies and some other changes, training, time to adapt (which are related to stress and performance), the chance of career development, potential job loss, shift work and overtime. According to Erensal and Albayrak (2004), organizational factors are related to "Leadership", "Company Culture" and "Participation and Involvement"

(iii) Technology: Technology misuse can cause issues, for example, motivation loss, stress, and bad performance, though the right utilization of the technology can bring more desirable outcomes at individual and authoritative levels. On the other hand, fear of losing a job due to changing technology increases stress and diminishes motivation while appropriate technology adaptation may increase ability utilization and job content. Finally, the anthropometric specifications of the tools and technology can cause physiological loads on the worker [64].

(iv) Task: Another factor in applying macroergonomics discipline in manufacturing systems is “task”. Components like; job demands (quantitative workload, work pressure, cognitive demands), job content (e.g., challenge, repetitiveness), working speed and job control can be placed in “Task” factor. To handle these issues, Carayon and Smith [64] recommend preventing repetitive tasks, both physical and mental, by taking part in a variety of tasks that challenge laborers and help them to utilize and improve their capacities and abilities.

(v) Environment: Carayon and Smith [64] include noise, lighting, temperature, air quality, and workplace design into “Environmental” factors. Noise can cause increases in arousal, blood pressure, and negative psychological mood while, air quality and housekeeping can affect energy consumption, heat exchange, stress responses, and sensory disruption.

Hence, all the above factors must be considered in the macroergonomic program development and assessment of macroergonomic frameworks.

Table 2.3. Studies on macroergonomics success factors (2000-2020).

Author	**People**	**Technology**	**Task**	**Organization**	**Environment**
Kleiner [44]	x	x	x	x	x
Carayon et al. [60]	x	x	x	x	x
Karwowski [63]	x			x	x
Clegg [62]	x	x	x	x	

Table 2.3. Studies on macroergonomics success factors (2000-2020). (cont.)

Realyvásquez and Maldonado-Macias [1]	x	x	x	x	x
Carayon and Smith [64]	x	x	x	x	x
Erensal and Albayrak [65]	x			x	x
Carayon et al. [66]	x	x	x	x	x
Molleman and Broekhuis [67]	x		x	x	
Baines et al. [68]	x			x	x
Sluga et al. [69]		x	x	x	
Kogi [70]		x	x	x	x
Karsh et al. [71]	x		x	x	x
Mumford [72]	x	x	x	x	x
Reiman and Oedewald [73]			x	x	
Robertson et al. [74]			x	x	x
Govindaraj [75]	x	x		x	

Table 2.3. Studies on macroergonomics success factors (2000-2020). (cont.)

Holden et al. [76]	x	x	x	x	x
Dencker et al. [77]	x	x	x		
Sittig and Singh [78]	x	x		x	
Mejías and Huaccho [79]	x	x	x	x	x
Armutlulu and Noyan [80]	x			x	
Koyuncu et al. [81]	x		x	x	x
Baxter and Sommerville [82]		x	x	x	x
Lawler et al. [83]	x	x	x	x	x
Chui et al. [84]	x	x	x	x	x
Drews [85]	x	x		x	x
Marras and Hancock [86]	x	x	x	x	x
Karsh et al. [87]	x		x	x	x
Sherehiy and Karwowski [88]	x		x	x	x
Zink [89]	x		x		x
Carayon et al. [90]	x	x	x	x	x

Table 2.3. Studies on macroergonomics success factors (2000-2020). (cont.)

Maguire [91]	x	x	x	x	
Steege and Dykstra [92]	x	x	x	x	x
Holden et al. [93]	x	x	x		
Larsen [94]	x	x		x	x
Realyvásquez et al. [95]	x	x	x	x	x

Table 2.3 provides comprehensive details regarding studies that pertain to success factors in macroergonomics (partially adapted from [96]).

2.2.3.2. Advantages of Macroergonomics in Companies. Competitiveness these days has caused organizations to embrace new strategies and procedures to survive in the market. Organizations can improve workers' aptitudes, capacities, human well-being, and performance by implementing ergonomic principles at the micro and macroergonomics levels [97, 98]. From one viewpoint, microergonomics principles are applied at an individual level to break down a particular job/task. Macroergonomics approach, on the other hand, is used at the organizational level to improve the work systems. As a result, Macroergonomics hopes to help the entire company increase its competitiveness in the global market [48], [65].

Hendrick and Kleiner [49] express that the improvement of human-systems interfaces by methods for the design of sociotechnical frameworks has been going on since the conventional initiation of Ergonomics in late 1940. Macroergonomics, distinguished by its unique dual approach, stands as a cornerstone of scientific inquiry within the realm of work system design. Its essence lies in the skillful integration of both top-down and bottom-up socio-technical perspectives. This comprehensive framework encompasses not only the intricate organizational structures, but also delves into the strategic considerations and operational processes that are fundamental to crafting an effective work system. Ultimately, its focus extends beyond individual components, embracing the crucial interfaces between people and the various facets of their work environment, including machines, software, and the surrounding physical space. [48], [99], [4].

This characterization implies that the improvement of structures and processes within the overall work system can be achieved through two complementary methods:

(i) analyzing and designing the structures and processes of the entire work system and then delving into the subsystems and components, or
(ii) examining the components first and then systematically building up to the overall system structure. [49, 50].

2.2.3.3. Studies on Macroergonomics. Given the expansive nature of the macroergonomics field and the voluminous body of research it encompasses, undertaking a comprehensive review of every single investigation would fall outside the purview of this thesis. Consequently, the scope of this work is deliberately narrowed to focus specifically on studies that delve into the realm of macroergonomics frameworks and their evaluation. These meticulously chosen studies will be meticulously reviewed and subsequently presented, offering valuable insights into this crucial aspect of the field.

Table 2.4. Some well-known studies on macroergonomics framework and evaluation.

Macroergonomics Frameworks	**Macroergonomics Evaluations**
Hendrick and Kleiner [4]	Realyvásquez-Vargas et al. [1]
Haro and Kleiner [55]	Erensal and Albayrak [65]
Carayon et al. [60]	Ho and Duffy [100]
Smith and Carayon-Sainfort [101]	Maldonado et al. [102]
Davis and Moro [103]	
Kraemer and Carayon [104]	
Murphy et al. [105]	
Weidman et al. [106]	

Table 2.5 gives the detailed information (scope, objective(s), and result(s)) about the studies listed in Table 2.4.

Table 2.5. Some well-known evaluation studies on ergonomics and AD.

Author(s)	**Type**	**Scope**	**Method(s)**	**Objective(s)**	**Result(s)**
Hendrick and Kleiner [4]	Framework	General	Sociotechnical System components / Macroergonomics	Help distinguishing disparities when compared to the work system of a current organization or applying to the design of another organization	While one of the proposed frameworks, MEAD, may be comprehensive, proposed frameworks in general are versatile and can be applied across various domains and fields.
Haro and Kleiner [55]	Framework	Construction	MacroErgonomic / Analysis and Design (MEAD) / Macroergonomic Analysis of Structure (MAS)	Formalizing the principles and strategies for sociotechnical systems theory and offering the organizational support required for the design and execution of a successful work system	MAS and MEAD, when considered together, not only signify the formalization of fundamental techniques within the domain of macroergonomics but also serve as valuable tools for organizing existing methodologies.

Table 2.5. Some well-known evaluation studies on ergonomics and AD. (cont.)

Carayon et al. [60]	Framework	Health Care	Macro-ergonomics	Propose an integrated model that harmonizes macroergonomic work systems framework with the structure-process-outcome model	In the realm of macroergonomic research, the SEIPS model can serve as a comprehensive framework to guide the collection of data on various factors within the work system.
Erensal and Albayrak [65]	Evaluation	Management Styles	AHP / Macroergonomics	Measure and compare the performance of different management styles	Research suggests that, when considering factors like organizational culture, support structures, human capabilities, and employee mindsets, Management by Values emerges as the most effective administrative style for fostering the widespread adoption of macroergonomics principles.

Table 2.5. Some well-known evaluation studies on ergonomics and AD. (cont.)

Holden et al. [76]	Evaluation	Change management	Macro-ergonomics	Determining useful principles for change management	They have exemplified some of the numerous approaches through which standards for effective organizational-level change can be implemented. They encourage other field scientists to build up their own rule-based research practices.
Murphy et al. [105]	Framework	General	Macro-ergonomics/ Safety climate/ Sociotechnical systems theory/ Mesoergonomics	Illustrating the conceptual intersections between macroergonomics and safety climate to formulate a conceptual model that harmonizes these domains within the framework of mesoergonomics	As a result, they discussed how this model can serve as a structure to control analysis and design of work systems and resulting organizational intercessions.

Table 2.5. Some well-known evaluation studies on ergonomics and AD. (cont.)

Ho and Duffy [100]	Evaluation	Manufacturing Companies	Structural Equation Modelling / Macroergonomics	Model and examine the contextual effects of some key organizational factors on the functioning and utility of work practices	Results show that continuous-learning culture may advance the execution of process management rehearses and that groundbreaking leaders will in general encourage cultural changes towards continuous-learning.
Acosta and Morales [107]	Framework	Food distribution	Macro-ergonomics	Support organization processes and ensure that knowledge is being moved within the organization	Their work upgraded the organization's processes and guarantee that information moves inside the organization.
Weidman et al. [106]	Framework	Systems, tools	Macro-ergonomics	Developing a framework to deal with occupational risks which includes risk disposal at the design phase of systems, tools, and materials.	They concluded that their conceptual model can be used in practice.

Table 2.5. Some well-known evaluation studies on ergonomics and AD. (cont.)

Maldonado et al. [102]	Evaluation	Advanced Manufacturing Technology	Fuzzy logic / Axiomatic Design / Macroergonomics	The assessment of ergonomics compatibility of Advanced Manufacturing Technology (AMT)	An ergonomic compatibility questionnaire was introduced for data collection, accompanied by a novel method for assessing Advanced Manufacturing Technologies (AMT).
Davis and Moro [103]	Framework	Client interaction centers	Macro-ergonomics	The design of client communication work systems and identify factors known to influence health and performance in customer services.	They developed an analytical framework, which outlines five critical elements of well-balanced work systems: the employee, the task, the technology, the organization, and the environment.
Realyvásquez-Vargas et al. [1]	Evaluation	Manufacturing Systems	Macro-ergonomic Compatibility Questionnaire	Develop a macro-ergonomic compatibility index.	The outcomes show that the Macroergonomic Compatibility Index (MCI) is a compelling instrument.

Table 2.5. Some well-known evaluation studies on ergonomics and AD. (cont.)

Kraemer and Carayon [104]	Framework	Computer and information security	Macro-ergonomics	To develop a macroergonomic framework for computer and information security (CIS).	They have formulated a framework for computer and information security, and the central focus of their structure provides a holistic understanding of CIS systems.
Steege and Dykstra [92]		Healthcare	SEIPS / Macroergonomics	To investigate the components which contribute or prevent fatigue, and boundaries and facilitators to individual nurse	They discovered that their study give direction on what nurses see as contributing to fatigue and factors that are useful or harmful to dealing with fatigue within their work environment.

Now that we have a summary of these studies, it is time for an in-depth discussion:

(i) Erensal and Albayrak [65] proposed a methodology which enable us to measure and compare the performance of different management styles (Management by instruction, Management by objectives, Management by value) based on macroergonomics criteria. They used the analytic hierarchy process (AHP) in order to make comparisons. As a conclusion, they found "management by value" is the best alternative in improving the adoption of macroergonomics.

(ii) Holden et al. [76] briefly reviewed the literature, determining 30 principles of fruitful change management, covering topics, for example, political awareness, assembling the change group, producing buy-in, and the management uphold. For every principle, relating proposals for macroergonomics field research practice are introduced.

(iii) Murphy et al. [105] portrayed the conceptual overlaps of macroergonomics and safety climate so as to introduce a theoretical model that incorporates these areas utilizing the structure of mesoergonomics. As a result, they discussed how this model can serve as a structure to control analysis and design of work systems.

(iv) Ho and Duffy [100] proposed a systematic macro-ergonomic approach to model and examine the contextual effects of some key organizational factors (leadership, organizational culture, and quality management practice) on the functioning and utility of work practices. They conducted a survey in 35 manufacturing companies in Hong Kong and used "Structural Equation Modelling (LISREL 8.14)" in order to estimate the effects of these organizational factors.

(v) Acosta and Morales [107] focussed on the work system configuration to be used by a Colombian food organization for distributing items. It considered as the idea of participative ergonomics, where individuals from the business, logistics, operation, occupational wellbeing areas related with the industrial designers, ergonomists who methodologically drove the project. They inferred that their study helped the organization's processes and guarantee that knowledge would be moved within it.

(vi) Maldonado et al. [102] presented a brand-new strategy for the assessment of ergonomic compatibility of Advanced Manufacturing Technology (AMT). This strategy might be considered as a choice guide; subsequently, experts may play out their obligations in a more complete way considering ergonomics traits. Their research contributes with a useful application for ergonomic compatibility assessment for AMT. They brought up the significant ergonomic attributes of AMT. At that point, those traits were initially organized after a multi-attribute axiomatic design approach for AMT ergonomics assessment under a fuzzy domain. Besides, they proposed new ergonomic compatibility questionnaire for information assortment and a unique system was produced for AMT assessment. Their discoveries were promising that the instrument is reasonable for the estimation of the proposed construct.

(vii) Weidman et al. [106] depicted a brand-new macroergonomics way to deal with occupational risks "Prevention through Design" which includes risk disposal at the design phase of systems, tools, and materials. Their model was based upon three well-established, hypothetical frameworks: The Health Belief Model, the Diffusion of Innovation Model, and the Technology Acceptance Model. They concluded that their conceptual model can be used in practice.

(viii) Davis and Moro [103] build up an analytical framework based on Carayon and Smith's Balance Theory, which distinguishes five components of balanced work systems: the environment, the task, the technology, the organization, and the individual. They surveyed the proof concerning the design of client communication work systems in the light of these five components and identified factors known to influence wellbeing and performance in exchange oriented and relationship situated client interaction centers.

(ix) Realyvásquez-Vargas et al. [1] claimed that no scientific study has developed a macro-ergonomic compatibility index. They suggest a macroergonomic compatibility index (MCI) to eliminate this deficiency. The information was gathered through the macro-ergonomic compatibility survey (MCS), and such data was enhanced with the assessment of ergonomics specialists to acquire the ideal weightings of the macro-ergonomic practices investigated in the variables. To exhibit the ability of their model, researchers utilized the MCI to quantify the macro-ergonomic compatibility of assembling organizations situated in Chihuahua, Mexico. The outcomes show that the MCI is a suitable instrument for estimating MC.

(x) Kraemer and Carayon [104] portrayed a macroergonomics framework for computer and information security (CIS). Moving endlessly from the current accentuation of technology centered ways to deal with CIS, their framework moves to a multi-dimensional assessment of CIS. This assessment incorporates four subsystems of a CIS: the technical, social, organizational, and external environment subsystems. Their framework underlines that the cooperations within and among these subsystems make technical computer and information security deficiencies. The commitment of this framework is a whole perspective on the complex and multivarious nature of CIS frameworks. They claimed that this view is significant for understanding the etiology of CIS vulnerabilities. With this understanding, people can construct secure computer and information systems to remediate CIS penetrates and assaults.

(xi) Steege and Dykstra [92] aimed to investigate the components contributing or forestalling fatigue, and boundaries and facilitators to individual nurse coping in medical clinic work systems. Interviews were made and analysed utilizing a directed qualitative content analysis approach guided by the Systems Engineering Initiative for Patient Safety (SEIPS) model. Topics identified as a source of fatigue within each of the five essential parts of the SEIPS work framework were identified, alongside barriers and facilitators to medical caretakers' encounters and strategies for dealing with fatigue. They discovered that their study give direction on what nurses see as contributing to fatigue and factors that are useful and harmful to dealing with fatigue within their work environment.

After discussing these studies in detail, we should also discuss the main structures in the field of macroergonomics.

(i) Macroergonomics analysis and design (MEAD): As depicted in detail in Hendrick and Kleiner [4], macroergonomics analysis and design (MEAD) is both a strategy and a framework for macroergonomics. It formalizes the principles and strategies for sociotechnical systems theory and offers the organizational support required for the design and execution of a successful work system [108]. This 10-stage methodology additionally produces training and other support framework assistance; however, it is the organizational viewpoints that differs this methodology from others.

- Scanning the environmental and organizational design subsystem
- Defining the production system type and performance expectations
- Defining unit operations and work process
- Identifying variances

- Creating the variance matrix
- Creating the key variance control table and role network
- Performing function allocation and joint design
- Understanding roles and responsibilities perceptions
- Designing/redesigning support systems and interfaces
- Implementing, iterating, and improving [109]

MEAD is a comprehensive and precise methodology that is aligned with the principles of macroergonomics and offers a wide range of benefits. It combines organizational analysis with ergonomic investigation, and differs from microergonomics approaches by addressing broader environmental and organizational considerations. However, like other macroergonomic methods, MEAD has certain drawbacks. Because of its comprehensiveness, it can be challenging to implement. Ideally, individuals should complete a macroergonomics training course or workshop prior to applying MEAD [110]. Although MEAD can be administered manually, some aspects may require software applications. Finally, researchers may opt for a qualitative assessment or choose to apply statistical analyses.

(ii) Macroergonomics analysis of structure (MAS): The MAS technique consolidates experimentally created analytical models of the impacts of three major sociotechnical system components, the technological subsystem, personnel subsystem and relevant external environment, on the fourth major component, the structure of the organization's work framework [49].

The MAS investigation results can help distinguish disparities when compared to the work system of a current organization or can be applied to the design of another organization. Within the organization, three crucial sociotechnical system components are interwoven: (1) the technological subsystem, (2) the personnel subsystem, and (3) the relevant external environment [111]. Exact models have been built up that review each of the sociotechnical system components according with the impacts upon the three organizational design measurements of complexity, formalization, and centralization [49]. Hendrick [49] characterized the center measurements that give a stage to MAS as follows:

Complexity—level of separation and coordination that exists inside a work system's structure. Formalization—the degree to which jobs inside the work system are normalized. Centralization—where formal decision-making is formed inside the work system.

The MAS uses scientific empirical models for the sociotechnical elements analysis. Joined with a rating framework of 1=low, 3=intermediate and 5=high, the elements distinguished by the models are assessed and a table is made. The empirical models used to incorporate the following [49]:

Technological Subsystem Analysis—model by Charles Perrow [112] for the technology-work-system structure relationship utilizing an information-based arrangement scheme. Two dimensions: (1) task variability—the quantity of exemptions in one's work and (2) task analyzability—sort of search methodology accessible for responding to task exceptions. A network yields four information-based technologies: routine, nonroutine, engineering and craft [55]. Employee Subsystem Analysis—incorporates three significant characteristics: professionalism, (2) cultural factors, and (3) psychosocial factors, which incorporates cognitive complexity [55]. Relevant External Environment—five sorts of outer environments were recognized by Negandhi and Reimann [113] that sway organizations: (1) financial, (2) educational, (3) political, (4) social, and (5) legitimate. Moreover, ecological uncertainly is viewed as utilizing the elements of change, the degree to which a given explicit task environment is dynamic or stays steady and predictable over time, and complexity, the quantity of segments that establishes an organization's certain assignment environment [55].

(iii) Systems engineering initiative for patient safety (SEIPS): The SEIPS (Systems Engineering Initiative for Patient Safety) model of work system and patient wellbeing [60] coordinates the macroergonomics work system model of Smith and Carayon [64], [101] and the Structure-Process-Outcome model of Donabedian [114]. As indicated by the SEIPS model (Figure 2.5), patient safety and, in general, medical services quality are impacted by work systems and processes. For example, HAIs (Healthcare associated infections) are impacted by different processes, for example, hand cleanliness, patient room cleaning, and other disease control rules. The design of work systems impacts the efficiency of processes that are known to avoid or reduce HAIs [115]. As indicated by Donabedian [116], a care process is "what is actually done in giving and receiving care" and is, thusly, impacted by all work system components. The SEIPS model grows Donabedian's model by including care processes as well as different processes (e.g., housekeeping, buying) that can impact results. Another significant part of the SEIPS model is the connection between patient results (e.g., patient safety) and worker and organizational results (e.g., clinician level of working life). For example, a medical attendant who is encountering back pain might not have the entirety of the physical (quality) and intellectual (consideration) capacities expected to lift a patient up; this circumstance may build the danger for patient falls. The SEIPS model likewise characterizes feedback loops among results and the work system furthermore, among results and the work system. These feedback loops speak to triggers for work system redesign: Data on process inadequacies and results may assist with recognizing requirements for changes in the work system. Regarding macroergonomics research, the SEIPS model (see Figure 2.5) can also be utilized as a general structure to direct data collection on the different work system factors that impact a specific care process or a particular medical care quality or patient wellbeing issue.

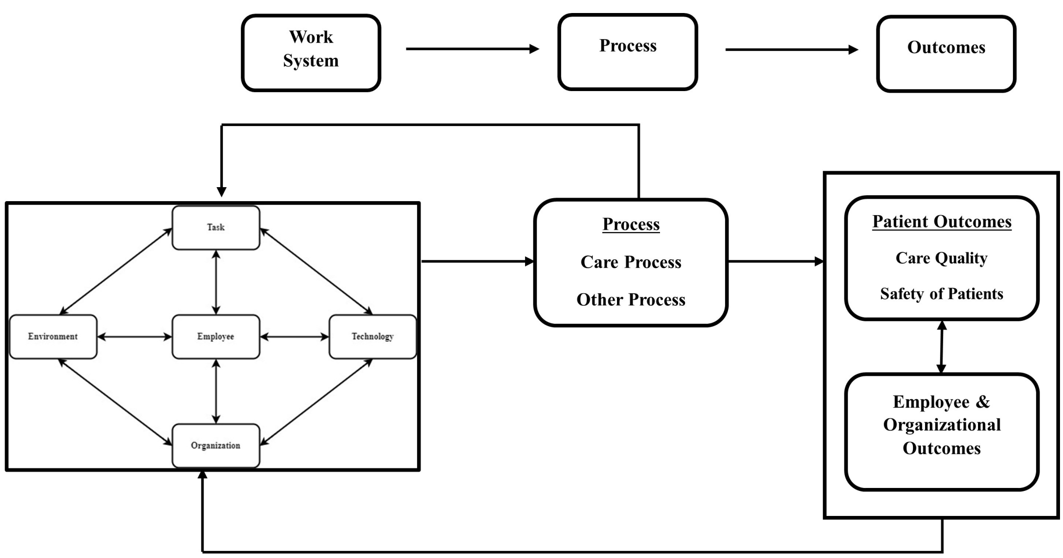

Figure 2.5. SEIPS model.

The examination of reviewed studies indicates the followings:

(i) The studies are far from offering a generic framework for macroergonomics. Moreover, they are not established on objectively described mathematical models. In this study, we plan to address this issue.

(ii) The study by Maldonado et al. [102] is the one similar to our study. However, it does not offer a framework (it just calculates a compatibility index). On the other hand, the study of Realyvásquez-Vargas et al. [1] has some similarities with respect to its scope. But it does not propose a macroergonomics framework and does not use AD as a base.

(iii) As a result; although there are some studies that offer a macroergonomics framework, they are neither about manufacturing companies nor utilize AD in their studies.

2.3. Critics of Macroergonomics Framework from the Perspective of Axiomatic Design

The literature review performed shows that there are some studies proposing a macroergonomics framework. Some of these are general while some are aiming at a specific area like construction or healthcare. Almost, all of them are established on Balance Theory and Sociotechnical Systems Theory while using some specific factors in macroergonomics (i.e. people, tasks, environment, technology and tools, and organization). However, none of them uses a well-established mathematical framework that is specialized in design. Focusing solely on a single perspective, such as macroergonomics in our context, can result in overlooking conventional design concerns, such as determining the required information levels or effectively handling inter-dependencies between various factors.

3. RATIONALE AND OBJECTIVES OF THE STUDY

3.1. Rationale

Before stating the objectives of the study, let´s summarize the logic and need behind this study. As it is known, Suh proposed a mathematical formula to calculate information value in AD. However, this information axiom does not consider the ergonomics perspective and thus it is not applicable to some ergonomic design cases. Some researchers such as Helander and Lin [5] and Karwowski [6] noticed this issue and proposed two different approaches to deal with this problem. However, their proposed modifications of information axiom, indeed are very limited and do not satisfy ergonomic and universal design requirements in every possible case. In summary:

(i) Applicability of information axiom of AD in ergonomic designs is problematic. Suh´s information axiom needs to be reformulated to solve this issue.

(ii) We have also this question that needs to be answered: Does Suh´s original information axiom select the least cost alternative?

(iii) Macroergonomics is a sub-discipline of ergonomics which have been applied in various areas over decades [55], [105], [117,118] and there have been some studies on developing a macroergonomics framework for different domains, such as office productivity [119], business transformation [120], risk reduction [106], computer and information security [104], education [121], etc. Yet, there is no study for AD-based macroergonomics framework on manufacturing companies. Without such a useful decision aid, the companies will face difficulties (such as productivity and safety issues (e.g.; higher level of accidents, injuries, turnover rate, loss of work time, low productivity and quality, and so on)) in developing their successful macroergonomics programs.

A macroergonomics framework is a system that outlines how certain activities should be directed in order to achieve the goals of macroergonomics. These goals are consisting of the performance of the workforce and system, workers´ well-being (health, safety, comfort, morale, and motivation) and overall enhancing company effectiveness. The mentioned activities can include regulations, policies, rules, roles, and responsibilities. By following the macroergonomics framework companies can reduce;

- employee turnover rate,
- loss of work hours,
- injuries,
- accidents,
- production cost

They can also improve;

- overall well-being of workers,
- productivity and quality,
- competitiveness,
- Quality of life.

While various decision-related techniques are applied in the field of macroergonomics, including AHP [65], [122], ANP [81], [123], and FMEA [124], Axiomatic Design (AD) offers its own set of advantages, such as:

- choices are formalized using a well-understood path.
- it reduces the information need necessary for the production phase.
- it is applicable to all designs: products, processes, systems, software, organizations, materials, business plans and so on which makes it a generic methodology [125].

Hence, AD has very promising characteristics to combine with macroergonomics in order to enhance the effects of macroergonomics in manufacturing companies. Since there is no study in the literature that uses AD to develop a macroergonomics framework for manufacturing companies, this study is an attempt to develop such a framework.

3.2. Objectives

Based on the stated rationale above, the objectives of this study are set as follows:

(i) Reformulating the information axiom, so that it is applicable to ergonomic design.

(ii) Reformulating the information axiom so that it takes cost minimization into account and thus it is more precise and universal.

(iii) Developing an axiomatic design-based macroergonomics framework for manufacturing companies to improve the performance and well-being of employees. The framework will serve as a decision aid for macroergonomics program development and management of the program.

4. CRITICAL EXAMINATION OF INFORMATION AXIOM FROM ERGONOMIC AND COST PERSPECTIVES AND PROPOSED REFORMULATIONS OF INFORMATION AXIOM

4.1. Axiomatic Design

The methodology employed in this study is based on Axiomatic Design, a well-established approach in the field of engineering and product/system design. Developed by Professor Nam Pyo Suh at the Massachusetts Institute of Technology (MIT), Axiomatic Design provides a structured framework for designing complex systems and products while meeting specific functional requirements and minimizing functional performance risk [2, 3]. The Axiomatic Design process is guided by two fundamental principles, known as axioms (Independence Axiom and Information Axiom). The Axiomatic Design process involves transforming customer needs (domain requirements) into functional requirements, followed by design parameters and process variables. Matrix algebra is often used to relate these different aspects of the design [2,3]. Axiomatic Design has found widespread applications in various industries, including manufacturing, engineering, and product development. Its systematic approach facilitates effective decision-making, ensuring the resulting designs align with the desired goals and requirements.

(i) Independence axiom: The independence axiom is a fundamental principle in Axiomatic Design, a methodology in engineering and product/system design. It emphasizes the importance of maintaining independence between functional requirements during design. In other words, changes made to one functional requirement should not negatively impact or constrain other requirements.

(ii) Information axiom: The Information Axiom in Axiomatic Design plays a significant role in the design process by guiding the minimization of information content associated with design parameters, thereby reducing functional performance risk [2, 3]. The axiom represents the probability value linked to a specific design parameter that will satisfy the desired functional performance. By minimizing information content, designers can enhance the efficiency and effectiveness of the resulting designs.

For the purpose of this study, the Information Axiom is a focal point of investigation, particularly from the perspective of its applicability in ergonomic designs and other relevant design applications. The limitations and potentials of the Information Axiom are extended in different contexts, contributing to a comprehensive understanding of its implications in practical design scenarios.

In the context of this study, the universality of the information axiom, particularly concerning its applicability in ergonomic designs, is examined.

4.2. Ergonomic Design Concerns about Suh's Information Formula

Suh's Axiomatic Design (AD) [2] is a well-established and widely accepted systematic design guideline that provides valuable support to decision-makers in selecting the optimal alternative among various options. Central to AD are two fundamental axioms: the independence axiom and the information axiom. The independence axiom emphasizes the importance of ensuring independence between requirements and design parameters.

On the other hand, the information axiom plays a crucial role in guiding the selection of the best alternative by utilizing a formula where "I" represents the information value

$$I = log_2 \frac{\text{system range}}{\text{common range}}. \tag{4.1}$$

Although the axiomatic design and its axioms developed by Suh [2] are well established, some experts in the area of ergonomics criticized their suitability for ergonomic designs.

They proposed a modified information axiom formula and new approaches as solutions to the shortcomings of the information axiom. For example, Helander and Lin [5] highlighted a crucial aspect of ergonomic design, which emphasizes the importance of the "human user". They argue that, based on the information axiom, when a specific design option is selected, it is assumed that any user who conforms to the distribution within the Design Range would be able to use it. However, this approach may not always be ergonomically suitable. According to Helander and Lin [5], this inherent challenge stems from the definitions of design range and system range. To address this issue effectively, it becomes essential to reevaluate and redefine these ranges with thoughtful consideration of human users. Additionally, Suh [29] acknowledged Helander as a pioneer in the application of Axiomatic Design (AD) within the field of ergonomic design due to the findings of his studies.

Furthermore, Karwowski [6] stated that to better address the ergonomic design concerns, the domains of AD should be redefined as Human capabilities and limitations (Functional Domain), Design of Compatibility (Physical Domain), and Management of Compatibility (Process Domain). Furthermore, the information axiom should be defined as “The Human Incompatibility Axiom”. Consequently, these scholars have proposed revisions and modifications to the information value formula to better align it with the ergonomics design.

4.3. Alternative Formulations of Information Axiom for Ergonomic Designs and Their Shortcomings

Please note that the examples in Section 4.3 and Section 4.4 are related to "design for adjustability" and "design for extremes".

Design for adjustability: Design for adjustability is an approach in product design and engineering that emphasizes the creation of products, systems, or environments that can be readily customized or adapted to meet individual needs or changing requirements. The objective is to increase usability, comfort, and functionality by enabling users to personalize or modify specific aspects of a design [126].

Design for extremes: Design for extremes in ergonomics refers to designing products, systems, or environments to accommodate users who fall outside the typical range of physical capabilities. The goal is to create designs that work for everyone, regardless of their physical abilities or limitations. This requires thoughtful consideration of the user's needs, such as designing wider doorways and hallways to accommodate wheelchairs, or adjusting the height and placement of controls and displays for individuals with limited mobility. This approach ensures that designs are inclusive and functional for a broader range of individuals, including those with physical disabilities or unique requirements [127].

4.3.1. Helander and Lin [5] Modification for Information Value Formula

Helander and Lin [5] claim that in some cases the original information axiom can mislead the decision-maker from the perspective of ergonomics.

An example [5]:

> "Imagine that we conducted a user survey to determine preferred adjustable table heights. Based on the survey results, we determined that the ideal height range was between 20 and 30 inches, resulting in a design range (DR) of 10 inches. We then evaluated two tables from different manufacturers. Table A had an adjustable height range of 20 to 25 inches, so its System Range (SR) A was 5 inches. In addition, the part of this range that met the user's preference was also 5 inches, called Common Range (CR) A. Meanwhile, Table B offered an adjustable height range of 20 to 35 inches, resulting in a System Range B of 15 inches. Within this range, the segment that overlapped with user preferences was 10 inches, referred to as Common Range B."

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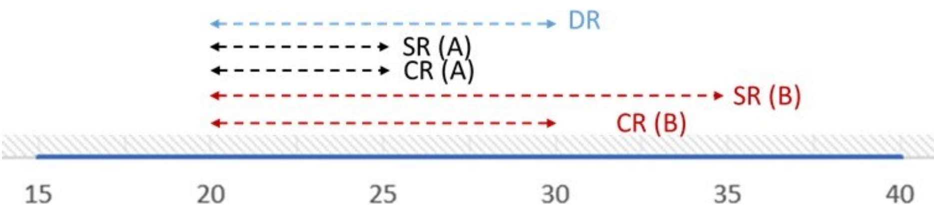


Figure 4.1. Example for Helander and Lin.

According to obtained Suh's information results

$$I_A = log_2 \frac{\text{system range A}}{\text{common range A}} = log_2 = \frac{5}{5} = 0 \qquad (4.2)$$

$$I_B = log_2 \frac{\text{system range B}}{\text{common range B}} = log_2 = \frac{15}{10} = 0.585, \tag{4.3}$$

Table A would have been selected because it has less information content than table B. However, table B will clearly satisfy the user group's full range while table A covers only half of them, and the correct choice would actually be table B.

Helander and Lin [5] proposed a modification to fix this ergonomics design issue

$$I = log_2 \frac{\text{desired range}}{\text{common range}}, \tag{4.4}$$

where desired range refers to the ergonomic design range. As can be seen from the obtained information values

$$I_A = log_2 \frac{\text{desired range A}}{\text{common range A}} = log_2 = \frac{10}{5} = 1 \tag{4.5}$$

$$I_B = log_2 \frac{\text{desired range B}}{\text{common range B}} = log_2 = \frac{10}{10} = 0, \tag{4.6}$$

Helander and Lin's formula chooses the correct alternative. However, their formula will not work in every possible case. Since they ignore the "cost" aspect of designing. Let's explain it with a counter-example.

Counter example for Helander and Lin [5] (adapted from [5]): Suppose we surveyed a user group and found that the preferred height range for an adjustable table was 10 to 15 centimeters, resulting in a design range of 5 centimeters. We then evaluated two tables from different manufacturers: Table A had an adjustable height range of 10 to 15 centimeters, so its System A range was 5 centimeters. The segment of this range that corresponded to the users' preferences was also 5 centimeters, known as Common Range A. Table B, on the other hand, offered an adjustable height range of 10 to 25 centimeters, resulting in a System Range B of 15 centimeters. However, the portion of this range that met the user's preference was 5 centimeters, referred to as Common Range B (Figure 4.2).

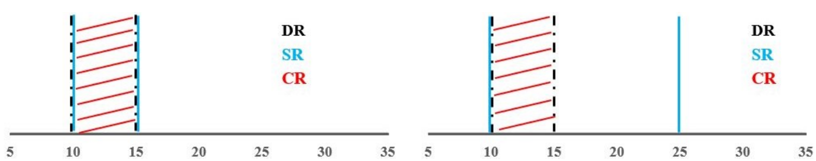


Figure 4.2. Demonstration of given values on distribution functions.

As can be seen from the obtained Helander's information equation results

$$I_A = log_2 \frac{\text{desired range A}}{\text{common range A}} = log_2 = \frac{5}{5} = 0, \tag{4.7}$$

$$I_B = log_2 \frac{\text{desired range B}}{\text{common range B}} = log_2 = \frac{5}{5} = 0, \tag{4.8}$$

both alternatives are equally selectable. However, it is obvious that choosing Table A is the correct action. However, Helander and Lin's [5] formula says both alternatives have equal information values. Because they solely focus on the covered design range and ignore the unnecessary range in Table B.

4.3.2. Karwowski [6] Modification for Information Value Formula

Karwowski [6] describes information axiom as "The Human Incompatibility Axiom" and he modifies the original formula as,

$$I_i = log_2(\frac{1}{C_i}) = -log_2 C_i, \tag{4.9}$$

where "I" denotes the incompatibility content of a design. C_i= Compatibility index.

Karwowski [6] describes C_i according to the purpose of decision maker. We can either minimize exposure to the negative effect of a given design parameter or maximize the positive effect of a desirable design parameter for minimizing system-human incompatibility.

If we intend to minimize exposure, we should use

$$C_i = \frac{R_i}{A_i}, \tag{4.10}$$

where R_i is the maximum exposure value (Exposure value can be related to any type of effect on person (e.g. weight, pressure, heat, sound, etc.)) and A_i is the given design parameter.

This formula is valid when we have $A_i > R_i$, $(A_i > 0, R_i > 0)$. Then, we can calculate incompatibility content of a given design parameter as

$$I_i = -log_2 C_i = -log_2 \frac{R_i}{A_i} = log_2 \frac{A_i}{R_i}. \tag{4.11}$$

If we get $A_i < R_i$ $(A_i > 0, R_i > 0)$, C can be set to "1". So that we will have $I = 0$. Apparently, Karwowski [6] didn't consider the case for equality $(A_i = R_i)$ or the case with more than one design alternative which satisfy $A_i < R_i$. Let's assume that we need a box with maximum 10 kg allowed carrying weight and we have two alternatives with 8 kg and 9 kg allowed carrying weights, relatively. Obviously, selecting the second alternative (9 kg) is better. However, his formula will fail to select the optimum alternative in those cases. Because alternatives which satisfy $(A_i \leq R_i)$ condition will all have $I = 0$ and there is no determined way to select one of them.

If we intend to maximize adaptability, we should use

$$C_i = \frac{A_i}{R_i}. \tag{4.12}$$

This formula is valid when we have $A_i < R_i$. Then, we can calculate incompatibility content of a given design parameter as

$$I_i = -log_2 C_i = -log_2 \frac{A_i}{R_i} = log_2 \frac{R_i}{A_i}. \tag{4.13}$$

If we get $A_i > R_i$, C can be set to "1". So that we will have $I = 0$. Again, Karwowski [6] didn't consider the case for equality $(A_i = R_i)$ or the case with more than one design alternative which satisfy $A_i > R_i$. His formula will fail to select the optimum alternative in those cases. Because alternatives which satisfy $(A_i \geq R_i)$ condition will all have $I = 0$ and there is no determined way to select one of them.

Karwowski's [6] formula is not suitable for alternatives which use a range of values. It is simply because, his formula only considers single values for both ergonomic standard (R) and design parameter (A). However, designers use some ranges (within upper and lower specification limits) while defining requirements and design parameters and there is no simple way of using Karwowski's formula with tolerance values. Moreover, his formula has a possibility of encountering with negative values. While Karwowski [6] suggests replacing obtained negative values with "1" to potentially simplify calculations, this recommendation can introduce errors in practical application. Furthermore, the potential for misinterpretation and misuse of the formula in our specific area of focus renders it an unsuitable choice for our purposes.

Counter example for Karwowski [6]: Let's assume we are designing a door according to 95%-man height which should be 185 cms [128] and we have the following alternatives. The details are given in Table 4.1.

Table 4.1. Example of design for extremes.

	Door A	**Door B**	**Door C**
Design Range	185 cm	185 cm	185 cm
System Range	184 cm	187 cm	185 cm
	Alternative A	**Alternative B**	**Alternative C**
Karwowski [6] $I = log_2 \frac{R_i}{A_i}$	$I = log_2 \frac{185}{184} = 0.008$	$I = log_2 \frac{185}{187} = 0$	$I = log_2 \frac{185}{185} = 0$
Suh [2] $I = log_2 \frac{SR}{CR}$	$I = log_2 \frac{184}{184} = 0$	$I = log_2 \frac{187}{185} = 0.015$	$I = log_2 \frac{185}{185} = 0$
Helander and Lin [5] $I = log_2 \frac{DR}{CR}$	$I = log_2 \frac{185}{184} = 0.008$	$I = log_2 \frac{185}{185} = 0$	$I = log_2 \frac{185}{185} = 0$

In the provided example, it is evident that Door C meets the ergonomic standard perfectly, making it the preferred choice. Unlike Door A, which falls short of covering the entire range, and Door B, which exceeds the required height, potentially leading to unnecessary costs (the difference between 187cm and 185cm is 2cm). As we can see, Karwowski [6] and Helander and Lin [5] formulas give a result where Door C and Door B are equally ergonomic. Suh [2] formula says Door C and Door A are equally ergonomic. As a result, all three formulas fail to select optimal alternative precisely which may mislead the decision makers.

4.3.3. Aydoğan et al. [129] Modification for Information Value Formula

Although we were not aware of the study of Aydoğan et al. [129] before this study was initiated and proposed its ergonomic information axiom formula, it is worth mentioning the alternative formula for ergonomic information axiom by Aydoğan et al. [129]. Aydoğan et al. [129] implies that Suh's formula only penalizes the alternative when the system range exceeds the design range (over design solutions). If a designer intends to penalize under-design solutions where the system range lies within the design range but does not meet the requirement exactly, Suh's formula cannot help. Hence, Aydoğan et al. [129] has modified Suh's formula as

$$I_i = log_2 \frac{\text{system range}}{\text{common range}} + log_2 \frac{\text{design range}}{\text{common range}}. \tag{4.14}$$

Their suggested formula works well but if we examine the given formula mathematically, we will see this formula can be simplified. Please note that above equations derived based on Figure 4.3. Figure is important because when using Aydoğan et al. [129] formula, the position of SR and DR relative to each other influences the information value it produces. The produced information value is affected by the position of SR and DR relative to each other while the formula we will propose is not affected. We will demonstrate this issue by using two different examples (Figure 4.3 and Figure 4.4)

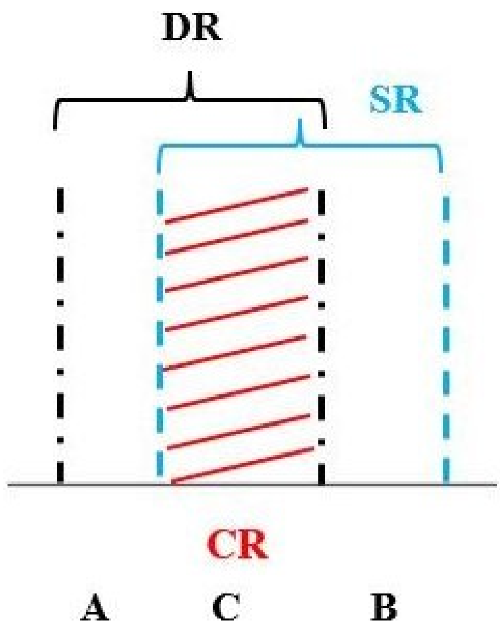


Figure 4.3. Example system and design ranges-I.

A: Absolute value of difference between lower bounds of design range and system range, B: Absolute value of difference between upper bounds of design range and system range and C: Common range (intersection of the SR and DR ($SR \cap DR$)).

The result of their formulas mathematical examination is

$$\begin{aligned} I_A &= log_2\frac{\text{system range}}{\text{common range}} + log_2\frac{\text{design range}}{\text{common range}} \\ &= log_2(\frac{\text{system range}}{\text{common range}} * \frac{\text{design range}}{\text{common range}}) \\ &= log_2(\frac{B+C}{C} * \frac{A+C}{C}) = log_2(\frac{B*A+B*C+A*C+C^2}{C^2}) \\ &= log_2(1+\frac{B*A}{C^2}+\frac{B+A}{C}), \end{aligned} \tag{4.15}$$

where the $\frac{B*A}{C^2}$ part of their formula adds no value to the decision-making process. Moreover, it gives unnecessarily larger information values. It can be seen in the following example that without $\frac{B*A}{C^2}$ part, their formula still works.

In the second example (Figure 4.4) let us have the following design and system ranges.

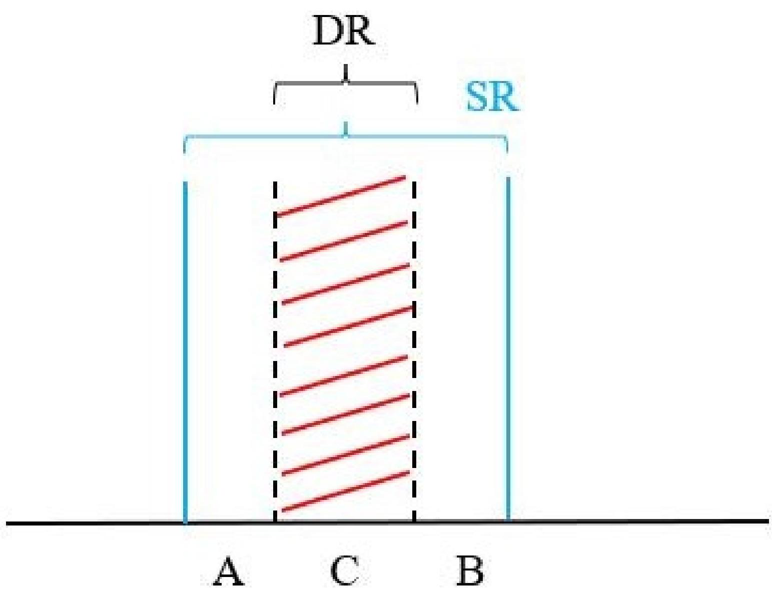


Figure 4.4. Example system and design ranges-II.

Now, we will calculate Aydoğan et al. [129] formula

$$\begin{aligned} I_A &= log_2\frac{\text{system range}}{\text{common range}} + log_2\frac{\text{design range}}{\text{common range}} \\ &= log_2(\frac{\text{system range}}{\text{common range}} * \frac{\text{design range}}{\text{common range}}) \\ &= log_2(\frac{A+B+C}{C} * \frac{C}{C}) = log_2(\frac{A+B+C}{C}). \end{aligned} \tag{4.16}$$

Obviously, $log_2(1 + \frac{B*A}{C^2} + \frac{B+A}{C}) \neq log_2(\frac{A+B+C}{C})$. Since their formula works on the ranges (SR and DR), variations in the positions of these ranges between different cases affect the mathematical equivalence of their formula. Hence, their formula behaves differently under different cases while our proposed formula, which is presented next, does not.

4.4. The Proposed Information Axiom Formula for Ergonomic Designs (Formula 1)

To overcome the insufficiencies in the formerly proposed formulas, through this study a simpler and more robust formula is developed as

$$log_2(\frac{A+B+C}{C}). \tag{4.17}$$

The developed formula works in a more effective and robust way. Hence, it is obviously better to use this proposed formula in AD.

4.4.1. Application Examples for Proposed Formula

We will examine the proposed formula starting with Table 4.2 which gives the details about the first example.

Table 4.2. Examples for testing proposed formula-I.

	Alternative A	**Alternative B**
Design Range	20 cm - 30 cm	20 cm - 30 cm
System Range	20 cm - 25 cm	20 cm - 35 cm

Although, alternative A does not cause any waste resources, it will not wholly satisfy our focused customer population. Since it covers all the necessary area, "Alternative B" is favorable in an engineering perspective. We can visualize the above example to make the given boundaries clear as in Figure 4.5.

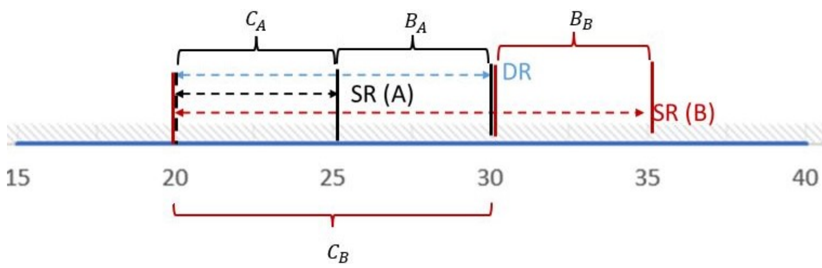


Figure 4.5. Demonstration of testing example -I for formula-1.

As can be seen in Figure 4.5, $A_A = 0$, $B_A = 5$, $C_A = 5$, $A_B = 0$, $B_B = 5$, and $C_B = 10$.

While upper limits for SR(A), SR(B) and DR are different, we have equal lower limits in the given example. The following Table 4.3 gives us the results of four different formula suggested for information value calculation.

Table 4.3. Solutions for given example-I.

	Alternative A	**Alternative B**
Suh [2] $I = log_2\frac{SR}{CR}$	$I = log_2\frac{C_A}{C_A} = log_2\frac{5}{5} = 0$	$I = log_2\frac{B_B+C_B}{C_B} = log_2\frac{15}{10} = 0.585$
Helander and Lin [5] $I = log_2\frac{DR}{CR}$	$I = log_2\frac{B_A+C_A}{C_A} = log_2\frac{10}{5} = 1$	$I = log_2\frac{C_B}{C_B} = log_2\frac{10}{10} = 0$
Aydoğan et al. [129] $I = log_2\frac{SR}{CR} + log_2\frac{DR}{CR}$	$I = log_2\frac{C_A}{C_A} + log_2\frac{B_A+C_A}{C_A} = log_2\frac{5}{5} + log_2\frac{10}{5} = 1$	$I = log_2\frac{B_B+C_B}{C_B} + log_2\frac{C_B}{C_B} = log_2\frac{15}{10} + log_2\frac{10}{10} = 0.585$
Proposed Formula $I = log_2\frac{A+B+C}{C}$	$I = log_2\frac{A_A+B_A+C_A}{C_A} = log_2\frac{0+5+5}{5} = 1$	$I = log_2\frac{A_B+B_B+C_B}{C_B} = log_2\frac{0+5+10}{10} = 0.585$

While Suh's formula didn't lead the decision maker to the correct alternative, other three formulas give the correct result. However, it can be observed from the table that the equivalences of each formula differ for each alternative in terms of A, B, and C, except for our proposed formula. This is because all other formulas consider the relative positions of SRs and DRs, whereas our proposed formula considers the absolute margins in the upper and lower boundaries, making our formula more robust.

Moreover, formula of Aydoğan et al. [129] and our suggested formula give the exact same result. Let's mathematically investigate the reason of getting exact same result with two formulas.

We simplify Aydoğan et al. [129] formula in the previous section as

$$I_A = log_2(1 + \frac{B * A}{C^2} + \frac{B + A}{C}), \tag{4.18}$$

where A: the absolute value of difference between lower bounds of design range and system range, B: absolute value of difference between upper bounds of design range and system range and C: common range.

If we have same values for lower and/or upper boundaries for design range and system ranges of alternatives, it means the values for A and/or B equals to zero. Since the lower boundaries for the above example is same, value A equals to zero which makes Aydoğan et al. [129] formula

$$\begin{aligned} I_A &= log_2(1 + \cancelto{0}{\frac{B * A}{C^2}} + \frac{B + A}{C}) \\ &= log_2(1 + \frac{B + A}{C}) = log_2(\frac{A + B + C}{C}), \end{aligned} \tag{4.19}$$

which equals to our formula. The details about the second example can be seen in Table 4.4.

Table 4.4. Example-II for testing proposed formula-I.

	Alternative A	**Alternative B**
Design Range	12 cm - 15 cm	12 cm - 15 cm
System Range	10 cm - 15 cm	10 cm - 25 cm

Although we have the same lower boundary for two alternatives, it is different from the lower boundary of DR. Both alternatives have an extra range in the lower boundary. Alternative A almost covering the intended DR without any waste. However, Alternative B has an extra range in the upper boundary which means using unnecessary resources. Hence, we should be in favor of Alternative A. Visualization of the example-2 is as in Figure 4.6.

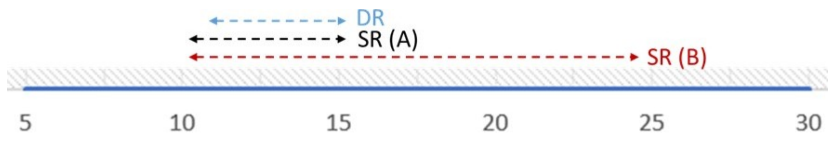


Figure 4.6. Demonstration of testing example-II for formula-1.

It can be easily calculated from Figure 4.6 that $A_A = 2$, $B_A = 0$, $C_A = 3$, $A_B = 2$, $B_B = 3$, and $C_B = 10$.

Table 4.5. Solutions for given example-II.

	Alternative A	**Alternative B**
Suh [2] $I = log_2 \frac{SR}{CR}$	$I = log_2 \frac{A_A+C_A}{C_A} = log_2 \frac{5}{3} = 0.74$	$I = log_2 \frac{A_B+B_B+C_B}{C_B} = log_2 \frac{15}{3} = 2.32$
Helander and Lin [5] $I = log_2 \frac{DR}{CR}$	$I = log_2 \frac{C_A}{C_A} = log_2 \frac{3}{3} = 0$	$I = log_2 \frac{C_B}{C_B} = log_2 \frac{3}{3} = 0$
Aydoğan et al. [129] $I = log_2 \frac{SR}{CR} + log_2 \frac{DR}{CR}$	$I = log_2 \frac{A_A+C_A}{C_A} + log_2 \frac{C_A}{C_A} = log_2 \frac{5}{3} + log_2 \frac{3}{3} = 0.74$	$I = log_2 \frac{A_B+B_B+C_B}{C_B} + log_2 \frac{C_B}{C_B} = log_2 \frac{15}{3} + log_2 \frac{3}{3} = 2.32$
Proposed Formula $I = log_2 \frac{A+B+C}{C}$	$I = log_2 \frac{A_A+B_A+C_A}{C_A} = log_2 \frac{2+0+3}{3} = 0.74$	$I = log_2 \frac{A_B+B_B+C_B}{C_B} = log_2 \frac{2+10+3}{3} = 2.32$

Only Helander and Lin [5] formula leads to the wrong result in this example (Table 4.5). Other three formula work fine. The details of the third example are as in Table 4.6.

Table 4.6. Example-III for testing proposed formula-I.

	Alternative A	**Alternative B**
Design Range	10 cm - 15 cm	10 cm - 15 cm
System Range	12 cm - 18 cm	9 cm - 12 cm

Although there is an uncovered place in the lower boundary of Alternative A. It certainly covers more of the design area. Hence, it should be favorable. Visualization of the example can be seen in Figure 4.7.

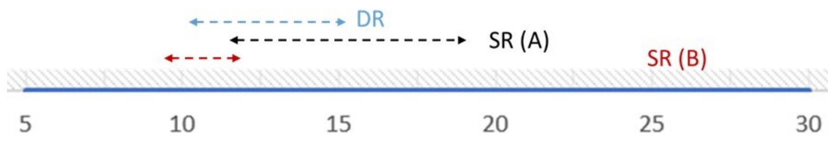


Figure 4.7. Demonstration of testing example-III for formula-1.

Table 4.7. Solutions for given example-III.

	Alternative A	**Alternative B**
Suh [2] $I = log_2 \frac{SR}{CR}$	$I = log_2 \frac{B_A + C_A}{C_A} = log_2 \frac{6}{3} = 1$	$I = log_2 \frac{A_B + C_B}{C_B} = log_2 \frac{3}{2} = 0.585$
Helander and Lin [5] $I = log_2 \frac{DR}{CR}$	$I = log_2 \frac{A_A + C_A}{C_A} = log_2 \frac{5}{3} = 0.74$	$I = log_2 \frac{B_B + C_B}{C_B} = log_2 \frac{5}{2} = 1.32$
Aydoğan et al. [129] $I = log_2 \frac{SR}{CR} + log_2 \frac{DR}{CR}$	$I = log_2 \frac{B_A + C_A}{C_A} + log_2 \frac{A_A + C_A}{C_A} = log_2 \frac{6}{3} + log_2 \frac{5}{3} = 1.74$	$I = log_2 \frac{A_B + C_B}{C_B} + log_2 \frac{B_B + C_B}{C_B} = log_2 \frac{3}{2} + log_2 \frac{5}{2} = 1.91$
Proposed Formula $I = log_2 \frac{A+B+C}{C}$	$I = log_2 \frac{A_A + B_A + C_A}{C_A} = log_2 \frac{2+3+3}{3} = 1.42$	$I = log_2 \frac{A_B + B_B + C_B}{C_B} = log_2 \frac{1+3+2}{2} = 1.585$

As we can see in Table 12, Suh [2] formula gave the wrong result but the other three formulas worked well. We should see that there is also a difference between Aydoğan et al. [129] formula and our formula. Their formula works well in every type of situation with a greater information value than our formula. This is because their formula includes non-value-added components by considering the relative positions of SR and DR, which we have eliminated.

Our formula is the most robust and simple one considering the above examples. Hence, we should use the formula while considering ergonomic design alternatives.

It is important to note that the proposed formula is reliable only for ergonomic designs, such as design for adjustability and design for extremes. This represents a significant contribution towards developing a formula that works for designs beyond ergonomics.

4.5. The Proposed General Information Axiom Formula with a Loss: Integrating Information Axiom with Taguchi Loss Function (Formula 2)

The proposed formula-2 is not related to the proposed formula-1 developed for ergonomics design. The aim of Formula-2 is to help designers with designs beyond ergonomics.

4.5.1. Overview of Information Axiom and Taguchi Loss Function

Suh's Axiomatic Design and its information axiom formula are widely accepted and used in literature. However, Suh's information axiom has some shortcomings, and Suh himself takes on these shortcomings [13]. Hence, our first and most important supporter is Suh himself while modifying his formula

$$I = log_2(\frac{\text{System Range}}{\text{Common Range}}). \tag{4.20}$$

Suh's formula is only concerned with the success probability of an alternative (system). From a universal design perspective, there are some other concerns like working in a tight range which allows robust design and working at the target (nominal) value on average. We should go into detail about these terms to explain the logic behind revising Suh's original formula.

Robust Design: The following Figure 4.8 explains the fact pointed out by Taguchi [130] about quality loss caused by deviation.

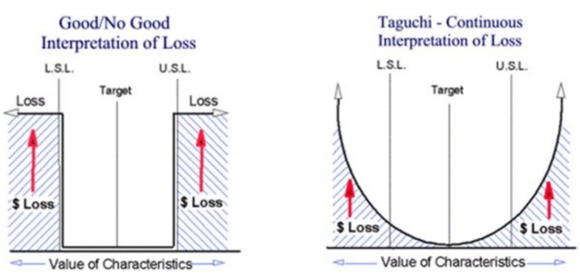


Figure 4.8. Interpretation of loss in classical and Taguchi approaches.

The consensus on specification limitations is that the customer is happy if the variance stays within the limits (Left Figure in Figure 4.8). If the variation exceeds the limits, the customer becomes unsatisfied right away. The specification limitations separate satisfaction and discontent.

However, according to Taguchi [130], any deviation from the nominal (target) performance will cause consumer dissatisfaction. As the variation increases, the customer will gradually (exponentially) become dissatisfied (Right Figure in Figure 4.8). Namely, getting away from the target value is a loss.

4.5.1.1. Taguchi's Loss Function. The loss function of Taguchi can be stated as

$$L = k(y - m)^2, \tag{4.21}$$

where L: quality loss, y: quality characteristic of a product, m: target value and k: quality loss coefficient.

Suh [13] accepted this deficiency in his article about quality in AD. He names it "bias". He says if we have a bias (a difference between the target value and what the system achieves), the system range can be shifted horizontally. However, it is only possible when we have an uncoupled design solution since shifting can cause other problems (i.e. causing a problem for another requirement) in a coupled design. In our opinion, trying to solve "the bias" issue after selecting an alternative can be time-consuming and ineffective. As a result, it is essential to incorporate the achievement of the target value by an alternative into the information formula. This guides us toward opting for a system alternative that exhibits minimal or no bias. Then, we can try to shift the system range horizontally if necessary. Hence, we've added the following part, which essentially is Taguchi Loss Function

$$log_2[(\frac{\text{System Range}}{\text{Common Range}})[1 + (SM - DM)^2]], \tag{4.22}$$

where SM is the system range mid-point and DM is the design range mid-point. The added part will penalize the difference between the target value and the alternative system's midpoint and will cause a greater information value which is not favourable.

Additionally, operating in a tighter range must be promoted in alternative selection since smaller variance is always desired in engineering. Suh [13] is also aware of this reality that he defines a desired system range distribution as in the following Figure 4.9.

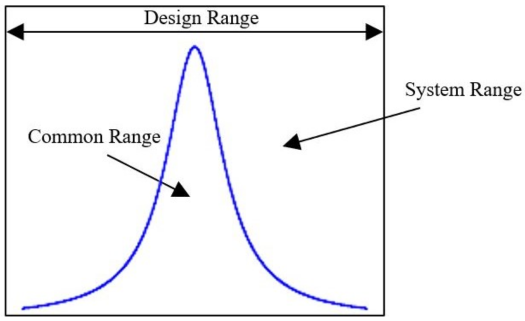


Figure 4.9. Suh's ideal system distribution (illustrative).

As can be seen in Figure 4.9, a desired system range distribution has a narrow shape. However, Suh's formula does not lead the decision-maker to choose the alternative with less variance. Hence, an extra part was added to our proposed formula

$$log_2[(\frac{\text{System Range}}{\text{Common Range}})[1+(SM-DM)^2](SR)], \quad (4.23)$$

where SR is the System Range.

The first part ($\frac{\text{System Range}}{\text{Common Range}}$) of the proposed formula considers the extent to which SR corresponds with DR, second part $[1+(SM-DM)^2]$ considers the bias (deviation between nominal value and system midpoint), and the third part (SR) considers the variability of the system.

Although Suh pointed out the issue [13], he didn't modify his formula which overcomes the mentioned problems. This is the main motivation of our current study: to bring a solution to the issue stated by Suh. Our final formula diminishes these two engineering concerns at the alternative selection phase of design. While Suh proposes to handle these concerns after selecting an alternative by using his formula, which is ineffective. Because selecting the appropriate alternative at first will reduce the time and resources needed for decision-making.

Counterexample for Suh's formula: Suppose that we must determine the suitable machine for producing a metal piece with design parameters of 30 ± 10, and there are 3 machines to evaluate. Machine 1 can produce 25 ± 5, Machine 2 can produce 30 ± 5 and Machine 3 can produce 31 ± 4.

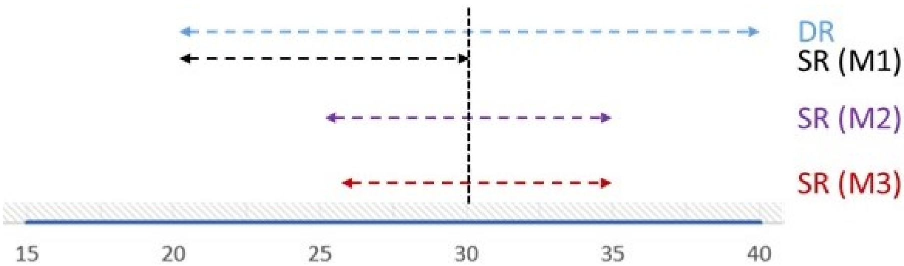


Figure 4.10. Counter example for Suh's formula.

We must select M2 to reduce costs and customer satisfaction (Figure 4.10). However, Suh [2] formula gives the following results.

Table 4.8. The results of Suh's formula for the counter-example.

Alternatives	**Results**
Machine 1	$I = log_2 \frac{10}{10} = 0$
Machine 2	$I = log_2 \frac{10}{10} = 0$
Machine 3	$I = log_2 \frac{8}{8} = 0$

As can be seen in Table 4.8, all three machines are equally selectable according to Suh [2]. Obviously, there is a weakness in the formula which may lead non-optimal selection. In reality, a formula must consider all the possible aspects for preventing possible misusage.

We must consider 3 aspects while calculating information value. Namely, shift in midpoints of DP and system specification, system range effect (tighter ranges are desirable), and finally design range coverage. Let's check if the proposed new formula works well (Table 4.9).

Table 4.9. The results of proposed formula for the counter-example.

Alternatives	**Results**
Machine 1	$I = log_2[(\frac{10}{10})[1 + (25 - 30)^2](10)] = log_2(260) = 8.02$
Machine 2	$I = log_2[(\frac{10}{10})[1 + (30 - 30)^2](10)] = log_2(10) = 3.32$
Machine 3	$I = log_2[(\frac{8}{8})[1 + (31 - 30)^2](8)] = log_2(16) = 4$

The outcomes presented in Table 4.9 demonstrate that our formula takes into account all essential elements that are vital during the design phase and produces precise results. Our formula is devised in such a way that it integrates all the crucial aspects of the design process. Additionally, we have ensured that our formula is versatile and applicable in all areas where Suh's formula is effective, as well as in areas where it may not work. By creating a comprehensive tool that considers all the necessary factors in design, we are confident that our formula will undoubtedly contribute to the advancement of the field of design.

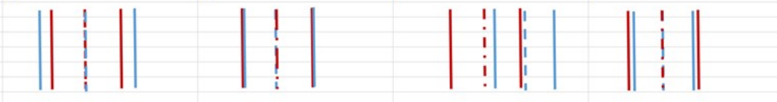
4.5.2. Robustness of the Proposed Formula for the Extreme Cases

The following examples are used to show the robustness of the proposed formula in extreme cases.

Case 1: The preferred ranking for the four machines is as follows, as depicted in Figure 4.11: $Machine4 > Machine2 > Machine1 > Machine3$. It's important to note that there are additional alternative formulas presented in Figure 4.11. These alternative formulas have been explored to determine if they can yield improved results compared to the proposed formula.

The findings obtained from the study indicate that Suh's formula falls short in determining the most suitable alternative with precision. However, formula-2, formula-4, formula-5, and the proposed formula have proven to be effective in accurately identifying the ranking. This implies that these formulas can be relied upon to make informed decisions when selecting the most appropriate option.

	Machine1	Machine2	Machine3	Machine4
Design Range	20-30	20-30	20-30	20-30
System Range	18-32	20-30	27-35	21-29
CR	10	10	3	8

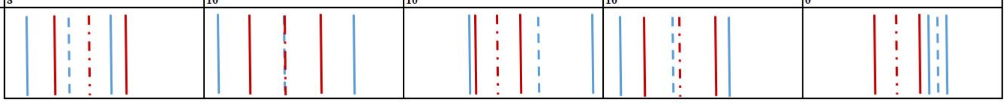


	Alternative A	Alternative B	Alternative C	
Suh (1990) $I = \log_2\left(\frac{SR}{CR}\right)$	$I = \log_2\frac{14}{10} = 0.49$	$I = \log_2\frac{10}{10} = 0$	$I = \log_2\frac{8}{3} = 1.415$	$I = \log_2\frac{8}{8} = 0$
$\log_2(1+(SM-DM)^2) + \log_2(SR)$	$\log_2(1+(25-25)^2) + \log_2(14) = 3.81$	$\log_2(1+(25-25)^2) + \log_2(10)$=3.32	$\log_2(1+(31-25)^2) + \log_2(8)$=8.21	$\log_2(1+(25-25)^2) + \log_2(8)$=3
$(SM-DM)^2 + SR^2$	$0 + 196 = 196$	$0 + 100 = 100$	$36 + 64 = 100$	$0 + 8 = 8$
$(SM-DM)^2 + S^2$	$0 + 5.43 = 5.43$	$0 + {5/3}^2 = 2.78$	$36 + 1.8 = 37.8$	$0 + {2/3}^2 = 1.8$
$\log_2(1+(SM-DM)^2) + \log_2(SR^2)$	$\log_2(1) + \log_2(196) = 7.62$	$\log_2(1) + \log_2(100) = 6.64$	$\log_2(37) + \log_2(64) = 11.21$	$\log_2(1) + \log_2(64) = 6$
$(SM-DM)^2$	$(25-25)^2 = 0$	$(25-25)^2 = 0$	$(31-25)^2 = 36$	$(25-25)^2 = 0$
$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR)$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 0.49 + 3.81 = 4.3$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 0 + 3.32 = 3.32$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 1.42 + 8.21 = 9.63$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 0 + 3 = 3$

Figure 4.11. Performance of the proposed formula in different cases-I.

Case 2: The accurate ranking in Figure 4.12 should be Machine-2, Machine-4, Machine-1, Machine-3, and Machine-5.

	Machine1	Machine2	Machine3	Machine4	Machine 5
Design Range	20-30	20-30	20-30	20-30	20-30
System Range	16-28	15-35	15-55	16-32	33-37
CR	8	10	10	10	0



Suh (1990) $I = \log_2\left(\frac{SR}{CR}\right)$	$I = \log_2\frac{12}{8} = 0.585$	$I = \log_2\frac{20}{10} = 1$	$I = \log_2\frac{40}{10} = 2$	$I = \log_2\frac{16}{10} = 0.68$	$I = \log_2\frac{4}{0} = \infty$
$\log_2(1+(SM-DM)^2) + \log_2(SR)$	$\log_2(1+(22-25)^2) + \log_2(12) = 6.91$	$\log_2(1+(25-25)^2) + \log_2(20)$=4.32	$\log_2(1+(35-25)^2) + \log_2(10)$=9.98	$\log_2(1+(24-25)^2) + \log_2(16)$=5	$\log_2(1+(35-25)^2) + \log_2(4)$=8.66
$(SM-DM)^2 + SR^2$	$9 + 144 = 153$	$0 + 400 = 400$	$100 + 100 = 200$	$1 + 256 = 257$	$100 + 16 = 116$
$(SM-DM)^2 + S^2$	$9 + 4 = 13$	$0 + {10/3}^2 = 11.1$	$100 + 2.8 = 102.8$	$1 + {8/3}^2 = 8.1$	$100 + 0.44 = 100.44$
$\log_2(1+(SM-DM)^2) + \log_2(SR^2)$	$\log_2(10) + \log_2(144) = 10.49$	$\log_2(1) + \log_2(64) = 6$	$\log_2(37) + \log_2(64) = 11.21$	$\log_2(2) + \log_2(16) = 5$	$\log_2(37) + \log_2(16) = 9.21$
$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR)$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 0.585 + 6.91 = 7.5$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 1 + 4.32 = 5.32$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 2 + 9.98 = 11.98$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = 0.68 + 5 = 5.68$	$\log_2\left(\frac{SR}{CR}\right) + \log_2(1+(SM-DM)^2) + \log_2(SR) = \infty + 8.66 = \infty$

Figure 4.12. Performance of the proposed formula in different cases-II.

Remarkably, only the proposed formula effectively identifies this correct ranking. These instances highlight that our proposed formula demonstrates robust performance not only in standard scenarios but also in challenging situations.

Nonetheless, Formula-2 is not suitable for application in the context of design for adjustability. This is because the suggested formula attempts to narrow down the system range without encompassing it entirely.

4.5.3. Monotonicity Assumption of Information Axiom

Suh utilizes the monotonicity property of his formula while summing up the values to obtain the total information value

$$I = \sum_i log_2 \frac{SR_i}{CR_i} = log_2 \prod_i \frac{SR_i}{CR_i}. \tag{4.24}$$

We should prove that our formula

$$I_i = log_2(\frac{\text{System Range}}{\text{Common Range}}) + log_2(1 + (SM - DM)^2) + log_2(SR) \tag{4.25}$$

also satisfies this assumption. To prove that our function is monotonically increasing, we will take the partial derivative of the developed formula. Let's assume that $x = \frac{SR}{CR}$ where SR and CR are measures of distance.

Hence, the values of SR, DR and CR cannot be less than 0 (zero). ($SR > 0$ & $CR \geq 0$) and $CR \leq SR$. Consequently, x strictly greater or equal to 1 ($x \geq 1$).

$$y = 1 + (SM - DM)^2 \tag{4.26}$$

where SM is the System midpoint and DM is the Design midpoint and $SM > 0$ & $DM > 0$. Consequently, y strictly greater than or equal to 1 ($y \geq 1$). $z = SR$ where $SR \geq 1$. Decision maker must convert the units to guarantee $SR \geq 1$ (e.g. $0.5cm \rightarrow 5mm$). Otherwise, $log_2(SR)$ will be negative. Our formula takes the form of

$$I_i = log_2(x) + log_2(y) + log_2(z). \tag{4.27}$$

Partial derivatives of a multivariate function can provide valuable insights into its behaviour, including potential monotonicity within a certain domain (for our case: $x, y, z \geq 1$) [131]. The partial derivative of x variable,

$$\frac{\partial}{\partial x}(I_i) = \frac{\partial}{\partial x}(log_2(x) + log_2(y) + log_2(z)) = 1/xln2, \tag{4.28}$$

is non-negative ($\frac{1}{xln2} \geq 0$) since $x \geq 1$, the partial derivative of y variable,

$$\frac{\partial}{\partial y}(I_i) = \frac{\partial}{\partial y}(log_2(x) + log_2(y) + log_2(z)) = 1/yln2, \tag{4.29}$$

is non-negative ($\frac{1}{yln2} \geq 0$) since $y \geq 1$, the partial derivative of z variable,

$$\frac{\partial}{\partial z}(I_i) = \frac{\partial}{\partial z}(log_2(x) + log_2(y) + log_2(z)) = 1/zln2, \tag{4.30}$$

is non-negative ($\frac{1}{zln2} \geq 0$) since $z \geq 1$.

The obtained partial derivatives provide compelling evidence to support the assertion that our proposed formula represents a monotonically increasing function [132]. As a crucial aspect of this study, the partial derivatives demonstrate that the information values (I_i) calculated from the formula are consistently non-negative ($I_i \geq 0$). This finding suggests that, regardless of the specific inputs or variables, the resulting information values will always exhibit a positive or neutral trend, reflecting the incremental nature of the formula's output. The following Figure 4.13 indicates the behavior of the ($log_2 x$) function which is strictly positive for $x \geq 1$.

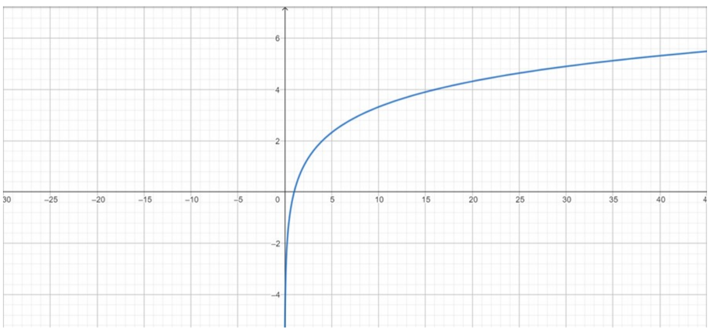


Figure 4.13. $Log_2(X)$ function.

The monotonic behaviour of our formula is of paramount importance in establishing the relationship between information values. In particular, when combining two individual information values (I_a and I_b) to form a composite information value ($I_c = I_a + I_b$), the obtained partial derivatives confirm that I_c will invariably be greater than or equal to both I_a and I_b ($I_c \geq I_a$ and $I_c \geq I_b$). This outcome reinforces the notion that our formula consistently preserves the hierarchical ordering of information values and ensures a logical progression of information accumulation.

Considering these salient characteristics of our formula, we can confidently assert that it is well-suited for analysing information in a monotonically increasing manner. As a result, the practice of aggregating individual information values to determine the total information value is not only legitimate but also a valid and insightful solution for the purpose of our research.

In summary, the rigorous examination of the partial derivatives and the monotonically increasing property of our formula substantiate its appropriateness for information analysis. By leveraging the additive nature of the formula and its ability to preserve the order of information values, we can utilize the approach of summing up individual values to obtain an understanding of the total information value.

Moreover, we are using logarithm function to obtain more comparable values (unitless). In some cases, it could be necessary to adjust the magnitude of the pieces ($log_2(\frac{SR}{CR})$, $log_2(1 + (SM - DM)^2)$ and $log_2(SR)$) of the developed formula.

Consequently, it is possible to write the developed formula as

$$I_i = a[log_2(\frac{SR}{CR})] + b[log_2(1 + (SM - DM)^2)] + c[log_2(SR)], \tag{4.31}$$

where $a, b, c \epsilon R^+$. In the scope of this study, taking $a = b = c = 1$ is suitable without sacrificing the nature of the formula. This will not affect the use of the formula in real cases.

5. DEVELOPING AN AXIOMATIC DESIGN BASED MACROERGONOMIC FRAMEWORK FOR MANUFACTURING COMPANIES

The aim of this section is to develop an AD-based macroergonomics framework for manufacturing companies, to achieve the third objective of the current study.

5.1. Data Collection Instrument

A research questionnaire serves as a research tool utilized to collect information from respondents during surveys or statistical studies. It comprises a series of questions or prompts designed to gather specific data. The questionnaire typically includes a combination of closed-ended questions, which provide predetermined response options, and open-ended questions that allow respondents to express their thoughts in greater detail [133]. Originally introduced by the Statistical Society of London in 1838, the research questionnaire has evolved over time to facilitate comprehensive data collection and analysis [134].

Advantages [135] can be listed as follows:

(i) Wide reach: Questionnaires can be distributed to many respondents, allowing researchers to collect data from a diverse range of individuals or groups.

(ii) Standardization: By utilizing the same set of questions for all respondents, questionnaires ensure consistency in data collection, enabling comparability and statistical analysis.

(iii) Anonymity: Respondents often have the option to remain anonymous when completing questionnaires, which can encourage honest and unbiased responses.

(iv) Cost-effective: Compared to other data collection methods, such as interviews or focus groups, questionnaires can be relatively inexpensive to administer, particularly when conducted online.

(v) Efficient data processing: Once completed, questionnaires yield structured data that can be easily quantified, analyzed, and interpreted, saving time and effort.

Disadvantages [136] can be stated as:

(i) Limited depth: Questionnaires often rely on closed-ended questions or pre-determined response options, which may restrict respondents' ability to provide nuanced or detailed answers.
(ii) Response bias: Depending on the wording and structure of the questions, respondents may be influenced to answer in a particular way, leading to response bias and potentially inaccurate data.
(iii) Non-response rate: Some individuals may choose not to participate in the questionnaire, leading to a non-response bias that may affect the representativeness of the collected data.
(iv) Interpretation challenges: Without the opportunity for clarifications or follow-up questions, researchers may face difficulties in fully understanding the respondents' perspectives or motivations.
(v) Design and implementation challenges: Designing effective questionnaires requires careful consideration of question wording, order, and response options. Poorly designed questionnaires can result in confusion, measurement errors, or low response rates.

It's important to note that these advantages and disadvantages can vary depending on the specific context and implementation of questionnaires in research studies.

5.1.1. Macroergonomic Evaluation Questionnaire (MEQ)

<u>5.1.1.1. Developing the MEQ.</u> To assess a manufacturing company and identify any macroergonomic shortcomings, a MEQ was developed, drawing inspiration from the Macroergonomic Compatibility Questionnaire (MCQ) [96], [137–139]. The MEQ was primarily designed to gather data on the implementation of macroergonomic factors within a manufacturing company and identify any deficiencies. Specifically tailored for

the manufacturing sector, the MEQ consists of two main sections:

(i) The initial part of the MEQ collects demographic data, encompassing details such as gender, age, seniority, company name, and years of work experience. This section comprises five questions utilized within this thesis to carry out a descriptive analysis of the participants.

(ii) The primary focus of the second section of MEQ is to gather data on the level of implementation of macroergonomic practices (MP) within manufacturing companies. In order to comprehensively analyze the macroergonomic practices, the MEQ incorporates all organizational elements associated with five macroergonomic factors: person, task, technology, organization, and environment. The entire list of MPs can be found in the Table 5.1 provided below. This section prompts participants to rate the extent to which these MPs are implemented in their companies. Initially, the MEQ's second section consisted of 114 potential questions, derived from a comprehensive literature review and various sources including forums, other questionnaires, and personal interviews. However, to enhance efficiency, encourage higher participation, and garner support from manufacturing companies, the potential questions and related macroergonomic factors and MPs are modified, merged or deleted by expert opinions to satisfy the study's needs (Table 5.2). The number of questions is reduced to 84. The questions were graded by using a five-point Likert scale. The entire list of the selected questions can be found in Appendix A.

Rensis Likert is credited with introducing the Likert scale in 1932. The Likert scale has gained widespread popularity as a method for evaluating psychometric data and is commonly employed in questionnaires [140]. It has been chosen to utilize the Likert scale due to its practicality, adaptability, and ease of use for respondents. A questionnaire that utilizes a Likert scale involves obtaining data by selecting responses from a set of predetermined categories, typically represented by integer numbers ranging from one to five. When developing a questionnaire, it is crucial to ensure that the designed Likert scale clearly communicates and employs appropriate wording for the scale points to capture the opinions, attitudes, or beliefs being measured.

Table 5.1. Macroergonomic factors and practices (before expert opinion) [1].

Employee	**Task**	**Technology**	**Organization**	**Environment**
Education, knowledge and skills	Task variety	Information technology	Teamwork	Layout
Physical characteristics	Job content, challenges and use of skills	Advanced manufacturing technologies	Organizational culture and safety culture	Noise
Psychological Characteristics	Autonomy, job control and participation	HR characteristics in technology and tools	Coordination, collaboration and communication	Lighting
Motivation and needs	Work demands		Work schedule	Temperature, humidity and air quality
			Social relationships	Workstation layout
			Supervision and management styles	
			Performance evaluation, rewards, incentives	

Table 5.2 represents the modified list of MPs, the modification and reduction are made by experts' opinions.

Table 5.2. Macroergonomic factors and practices (after expert opinion).

Employee	**Task**	**Technology**	**Organization**	**Work environment and occupational safety**
Education, knowledge and skills	The content, requirements, challenges, and skills of the job	Information technology	Teamwork	Facility layout and conditions
Physical characteristics	Autonomy, job control, and participation	Advanced manufacturing technologies	Organizational culture	Occupational health and safety
Psychological Characteristics		HR characteristics in technology and tools	Coordination, collaboration and communication	
Motivation and needs			Supervision and management styles	
Employee performance			Performance evaluation, rewards, incentives	
			Work schedule	

The MPs related questions can be found in Appendix A. Table 5.3 presents the questions from the initial section of the MEQ. In this section, participants were instructed to choose the most suitable option based on their knowledge and experience from a predefined set of multiple choices. The answer categories were derived from literature that aimed to capture the demographic information of the participants.

Table 5.3. Demographic survey questions.

Demographic Questions
Age
Gender
Which company are you currently working for?
How many years are you in your current workplace?
Are you in a managerial position?

Table 5.4 shows sample questions from the second part of MEQ, specifically focusing on the evaluation of the five macroergonomic factors. The left column of the table presents a sample of the questionnaire items, while the right column displays the rating scale used for responses.

The 5-point Likert scale rating is used in this study are represented as follows: (1) strongly disagree, (2) disagree, (3) undecided, (4) agree, and (5) strongly agree.

Table 5.4. Sample questions about employee factor of the MEQ.

Employee	**1**	**2**	**3**	**4**	**5**
Education, Knowledge and Skills					
Training activities are periodically updated and implemented.					
Organized trainings compensate for the lack of skills and knowledge of the employees.					
Managers know the training and information needs of employees.					
Employees do not have the necessary training and knowledge to be successful.					

Table 5.4. Sample questions of the MEQ. (cont.)

Employees are trained on legal regulations related to their work.					
Physical Characteristics					
Jobs based on physical strength are given to physically fit persons.					
The reasons for the work-related physical complaints of the employees are analyzed and tried to be resolved.					
Psychological Characteristics					
Whenever possible, the company analyzes and tries to resolve the causes of employees' psychological complaints.					
Employees have a high mental workload.					

5.1.1.2. Administering the MEQ. Implementation of the MEQ is planned in two phases (Initial (Pilot) and Actual Study). It is aimed to test the reliability and validity of the test in the Pretest Phase which is implemented with the help of 32 participants. After satisfying the reliability and validity of the survey, we have passed the second phase. The second phase of the survey was conducted in an infotainment system manufacturer company in the automotive sector. The primary aim of the second phase was to detect the macroergonomic deficiencies of the company and evaluate the alternative solutions by using the modified information formula. Alternative solution evaluation is conducted with the help of four experts. Their responses on the Likert scale were then used to construct the system range of the alternatives. The system range of an alternative solution is determined by selecting the minimum and maximum (1 to 5) values given by each expert. This system ranges then used as an input of information value calculation. An illustration of the logic employed can be found in Section 6.5.

5.2. Data Analysis Steps

The methodology for data analysis employed in this study is illustrated in Figure 5.1. The data analysis procedures outlined in this study have been diligently executed, adhering to each of these outlined steps.

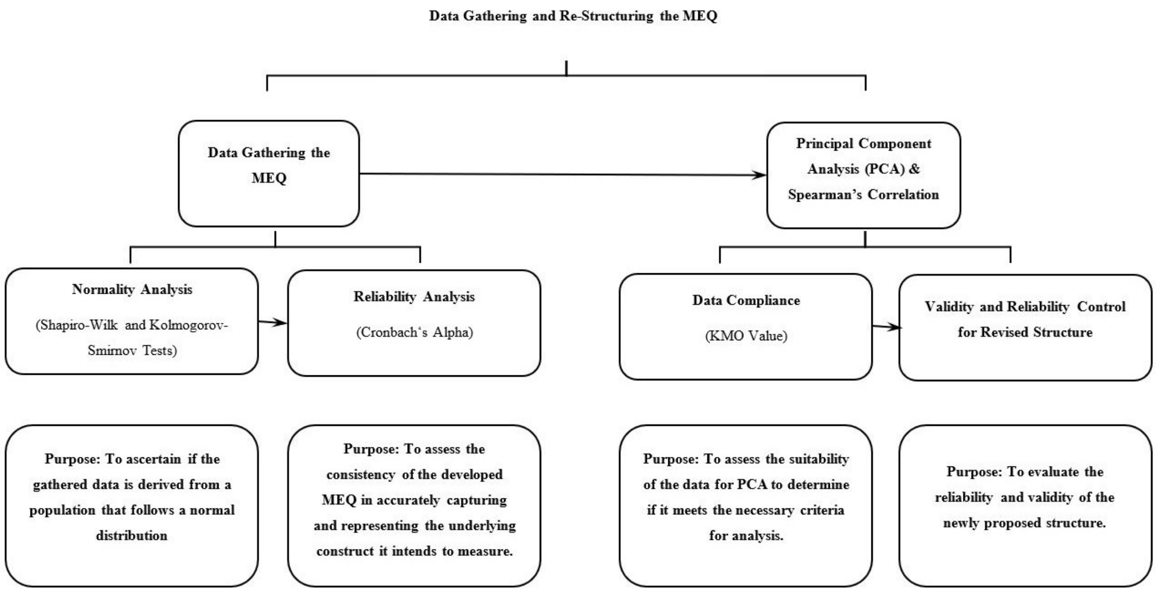


Figure 5.1. Data analysis methodology.

5.2.1. Normality Test

5.2.1.1. Shapiro-Wilk Test. The Shapiro-Wilk test is a widely utilized statistical test employed to determine if a dataset follows a normal distribution. Assessing normality is crucial as many statistical analyses and methods rely on the assumption of normality [141]. The Shapiro-Wilk test is a parametric statistical test that examines the null hypothesis that a given dataset conforms to a normal distribution. It operates under the assumption that if the data adheres to normality, the observed values should not significantly deviate from the expected distribution. The test employs a test statistic (W) to compare the observed data against the expected values under the null hypothesis [141].

The Shapiro-Wilk test generates a p-value, indicating the probability of observing the data if the null hypothesis of normality holds true. If the p-value exceeds a predetermined significance level (e.g., 0.05), the null hypothesis is not rejected, leading to the conclusion that the data exhibits a normal distribution. Conversely, if the p-value is below the significance level, the null hypothesis is rejected, suggesting that the data does not conform to a normal distribution.

The Shapiro-Wilk test finds applications in various disciplines such as social sciences, biology, finance, and engineering. It is commonly employed in statistical analyses, including hypothesis testing, regression analysis, and analysis of variance (ANOVA). Assessing normality is crucial as it ensures the validity and reliability of statistical tests and the accuracy of subsequent conclusions derived from the data.

5.2.1.2. Kolmogorov-Smirnov Test. The Kolmogorov-Smirnov test was developed for non-parametric data by Andrey Kolmogorov and Nikolai Smirnov in the 1930s (cited in [142]). Their seminal work, "Goodness of Fit Tests for the Normal Distribution," provides a comprehensive foundation for understanding the test's theory and application. The Kolmogorov-Smirnov test is a statistical test used to assess the goodness-of-fit between an observed dataset and a theoretical distribution. It helps researchers determine if the observed data follows a specific distribution or if it significantly deviates from it.

The Kolmogorov-Smirnov test measures the maximum discrepancy (D) between the empirical distribution function (EDF) of the observed data and the cumulative distribution function (CDF) of the theoretical distribution. The test compares the observed data against the expected distribution, evaluating the null hypothesis that the two distributions are identical.

The Kolmogorov-Smirnov test produces a p-value, which represents the probability of observing the data if the null hypothesis of goodness-of-fit is true. If the p-value exceeds a pre-specified significance level (e.g., 0.05), the null hypothesis is not rejected, indicating that the observed data fits the theoretical distribution. Conversely, if the p-value is below the significance level, the null hypothesis is rejected, suggesting a significant deviation between the observed and theoretical distributions.

The Kolmogorov-Smirnov test is widely used in various fields, including finance, biology, and social sciences. It is particularly valuable for model selection, comparing different theoretical distributions, and verifying assumptions in statistical analyses. Researchers rely on this test to assess the fit of their data to specific distributions, aiding in accurate modeling and inference [143, 144].

5.2.1.3. Skewness and Kurtosis. Skewness and Kurtosis are considered seperately in this section.

Skewness: Skewness and kurtosis are statistical metrics that offer insights into the characteristics of a dataset's shape and distribution. They serve to assess data asymmetry and peakedness.

Concerning skewness, it evaluates the extent of asymmetry in a probability distribution. If a dataset exhibits an elongated tail on the left side, it is termed negatively skewed, whereas a long tail on the right side indicates positive skewness [145]. Generally, a skewness value between -1 and +1 is considered close to symmetrical enough to be approximately normal. The value of skewness can be calculated as

$$Skewness = \frac{\frac{1}{n}\Sigma_1^n(x_i - \bar{X})^3}{(\frac{1}{n}\Sigma_1^n(x_i - \bar{X})^2)^(3/2)}, \tag{5.1}$$

where n is the number of data points, x_i is each data point in the dataset and $\bar{X}$ is the sample mean.

Kurtosis: Kurtosis is a statistical measure that assesses the level of peakedness or flatness of a probability distribution relative to the standard bell curve (normal distribution). A positive kurtosis suggests a more pronounced peak, while a negative kurtosis indicates a flatter distribution compared to the typical bell-shaped curve (cited in [146]. Excess kurtosis values between -2 and +2 are often considered within an acceptable range for normality. Kurtosis value can be calculated as

$$Kurtosis = \frac{\frac{1}{n}\Sigma_1^n(x_i - \bar{X})^4}{(\frac{1}{n}\Sigma_1^n(x_i - \bar{X})^2)^2} - 3, \tag{5.2}$$

where n is the number of data points, x_i is each data point in the dataset and $\bar{X}$ is the sample mean.

5.2.2. Reliability Test

Reliability testing is an essential aspect of research and measurement, focusing on evaluating the consistency and stability of measurement instruments and procedures [147]. Its primary goal is to ensure the dependability and reproducibility of obtained results.

Reliability testing examines the extent to which a measurement instrument or procedure produces consistent and reliable results across various conditions and over time. It enables researchers to assess the reliability of collected data and provides evidence of the instrument's consistency and stability.

5.2.2.1. Types of Reliability Testing. Reliability testing methods can be defined as follows:

(i) Test-retest reliability: Test-retest reliability assesses the consistency of measurements over time by administering the same instrument or procedure to the same group of participants on two separate occasions [148]. The correlation between the two sets of scores is calculated to determine the level of agreement. A high correlation indicates strong test-retest reliability, suggesting consistent results over time.

(ii) Parallel forms reliability: Parallel forms reliability evaluates consistency by employing two different but equivalent versions of the same instrument with the same group of participants [149]. The correlation between scores obtained from the two forms indicates the level of agreement. A high correlation indicates high parallel forms reliability, indicating consistent results across different forms.

(iii) Inter-rater reliability: Inter-rater reliability assesses the consistency of measurements when multiple raters or observers are involved. It examines the level of agreement among different raters in their ratings or observations. Measures like Cohen's kappa coefficient or intraclass correlation coefficient (ICC) are commonly used to calculate inter-rater reliability. High agreement among raters indicates strong inter-rater reliability.

The formula for Cohen's Kappa coefficient is as follows

$$\kappa = \frac{P_o - P_e}{1 - P_e}, \tag{5.3}$$

where P_o is the observed agreement between the two raters and P_e is the expected agreement between the raters by chance.

P_o is calculated by dividing the number of agreements by the total number of observations as

$$P_o = \frac{a + d}{N}, \tag{5.4}$$

where a is the number of agreements (cases where both raters agree), d is the number of disagreements (cases where raters do not agree) and N is the total number of observations.

P_e represents the agreement expected by chance and is calculated based on the marginal frequencies of the categories for both raters and it can be stated as

$$P_e = \frac{(a + b) \times (a + c) + (c + d) \times (b + d)}{N^2}, \tag{5.5}$$

where b is the number of cases where rater 1 selected one category and rater 2 selected another, c is the number of cases where rater 1 selected another category and rater 2 selected one and N is the total number of observations.

The resulting κ coefficient ranges from -1 to 1. A value of -1 indicates perfect disagreement, 0 indicates agreement expected by chance, and 1 indicates perfect agreement.

The formula for ICC is as follows

$$ICC(2,1) = \frac{(MSB - MSW)}{(MSB + (k-1) * MSW}), \tag{5.6}$$

where MSB is the mean square between subjects (variance between different subjects or items), MSW is the mean square within subjects (variance within the same subject or item) and k is the number of raters or measurements.

ICC values range between 0 and 1, where:

- 0 indicates no agreement beyond what would be expected by chance.
- 1 indicates perfect agreement.

(iv) Internal consistency reliability: Internal consistency reliability examines the extent to which different items or subscales within a single instrument consistently measure the same construct. Measures like Cronbach's alpha are often used to assess internal consistency. Cronbach's alpha calculates the interrelatedness or consistency among items. Higher Cronbach's alpha values indicate greater internal consistency reliability.

Among all types of reliability tests, Internal Consistency Reliability (Cronbach's Alpha) is used to test reliability in the scope of this study.

5.2.2.2. Cronbach's Alpha. Cronbach's alpha is a widely utilized measure of internal consistency reliability in research and measurement [150]. It examines the degree to which multiple items or subscales within a measurement instrument are interconnected and measures the same underlying construct. The range of Cronbach's alpha values is between 0 and 1, with higher values indicating greater internal consistency reliability.

The formula for Cronbach's alpha can be stated as

$$\alpha = \frac{k}{(k-1)}(1 - \frac{\Sigma\sigma_i^2}{\sigma^2}), \tag{5.7}$$

where k is the number of items in the scale or measurement instrument, σ_i^2 is the variance of the i-th item and σ^2 is the total variance of the scale.

Cronbach's alpha relies on a statistical analysis that examines the correlations between all the items within a scale. This process assesses how much each individual item's score tends to correspond with the scores of the other items. A higher alpha value suggests strong correlations among the items, indicating a reliable and internally consistent measurement. Conversely, a lower alpha value suggests weak correlations, implying that the scale may not consistently measure the intended construct.

Interpreting Cronbach's alpha values may vary depending on the field and context, but some general guidelines are commonly followed. An alpha value above 0.7 is generally considered acceptable for most research purposes, indicating satisfactory internal consistency [148]. A value of 0.8 or higher is often regarded as good, while values below 0.6 may indicate a need for further refinement of the scale or reconsideration of the measurement instrument [148].

It's important to note that Cronbach's alpha assumes a unidimensional construct measured by the items with equal weights or importance. Additionally, the number of items in the scale can influence the reliability estimate, as longer scales tend to yield higher alpha values.

Researchers employ Cronbach's alpha to assess and report the internal consistency reliability of their measurement instruments [149]. It helps determine the consistency and reliability of the items within a scale in measuring the construct of interest. By evaluating internal consistency, researchers can enhance confidence in the validity and reliability of their measurements, leading to more robust research outcomes.

5.2.3. Concept of Validity

Validity is an essential concept in research and measurement that focuses on the accuracy and appropriateness of drawing meaningful inferences from data. It ensures the trustworthiness of the conclusions made. Various types of validity offer different perspectives on the quality and appropriateness of measurement instruments and research designs.

5.2.3.1. Types of Validity. The four types of validity are explained as follows:

(i) Content validity examines whether a measurement instrument sufficiently represents the full range of the construct being measured. It assesses the extent to which the instrument's items or indicators are comprehensive and representative [151]. Content validity is often evaluated through expert judgment and examination of the relevance and representativeness of the instrument. If the proportion of the experts who find each item relevant to the concept,

$$CVI_i = \frac{(\text{\# of experts finds ith item relevant})}{(\text{total \# of experts})} \tag{5.8}$$

is greater than 0.7 (Content Validity Index - CVI), the content validity is satisfied [151].

(ii) Construct validity assesses how accurately a measurement instrument measures the underlying theoretical construct it intends to capture. It involves demonstrating that the instrument measures the construct as defined in the theory or conceptual framework [148]. Methods such as factor analysis, convergent and discriminant validity analyses, and hypothesis testing are commonly used to evaluate construct validity.

(iii) Criterion validity examines how well a measurement instrument or test correlates with an external criterion that represents the construct of interest. It assesses whether the instrument accurately predicts or relates to a specific outcome or behavior [149]. Criterion validity can be established through concurrent validity, where the instrument is compared to a criterion measure simultaneously, or through predictive validity, where the instrument predicts future outcomes.

(iv) Face validity refers to the superficial appearance or perceived relevance of a measurement instrument or research design. It assesses whether the instrument appears to measure what it claims to measure at face value [147]. Face validity is typically determined through subjective judgments by researchers or experts in the field.

5.2.3.2. Applications of Validity. Some of the application areas for validity are as follows.

(i) Psychological testing: Validity is of utmost importance in psychological testing to ensure accurate and meaningful measurement of constructs such as intelligence, personality traits, and mental health. Establishing validity enhances the reliability and usefulness of psychological assessments in various settings [152].

(ii) Educational research: Validity plays a critical role in educational research, particularly in the development and evaluation of tests, surveys, and educational interventions. Validity evidence helps ensure that assessments and interventions accurately measure desired educational outcomes [153].

(iii) Survey research: Validity is vital in survey research to ensure that survey instruments accurately measure the constructs under investigation. By establishing content, construct, and criterion validity, researchers can have confidence in the reliability and accuracy of survey data collected [133].

Validity is a fundamental aspect of research and measurement, providing assurance that the inferences drawn from data are accurate and meaningful. Content validity, construct validity, criterion validity, and face validity offer different perspectives in assessing the quality and appropriateness of measurement instruments and research designs. Understanding and establishing validity are crucial in various domains, including psychological testing, educational research, and survey research, ensuring the reliability and meaningfulness of research findings.

5.2.3.3. Factor Analysis. Factor analysis is a statistical technique utilized in data analysis to uncover hidden patterns among a set of observed variables [154]. It aims to simplify intricate datasets by identifying a smaller number of latent factors that can elucidate the correlations or covariances among the observed variables. These latent factors represent common underlying sources of variation in the data.

Factor analysis serves several purposes:

(i) Dimension reduction: It reduces data dimensionality by capturing crucial information while discarding redundant or less pertinent data.

(ii) Data summarization: Factor analysis efficiently summarizes extensive sets of correlated variables using a reduced number of latent factors.

(iii) Identifying underlying constructs: Particularly in fields like psychology, economics, or social sciences, factor analysis aids in uncovering latent constructs (e.g., intelligence, personality traits) that remain unobservable [155].

(iv) Variable grouping: Factor analysis facilitates the grouping of interconnected variables under coherent latent factors, simplifying the interpretation of intricate datasets.

Factor analysis presupposes that observed variables are influenced by concealed latent factors and random error. The fundamental objective is to estimate the relationships between these latent factors and the observed variables.

The process involves these steps:

(i) Data collection: Gather data on a collection of observed variables (also known as indicators or variables of interest) suspected of having correlations.
(ii) Correlation matrix: Calculate the correlation matrix or covariance matrix of the observed variables.
(iii) Factor extraction: Determine the most influential factors that explain data variance. Approaches such as Principal Component Analysis (PCA) or Principal Axis Factoring (PAF) are employed.
(iv) Factor rotation: Extracted factors might lack clarity. Factor rotation techniques such as Varimax, Promax, or Oblimin are employed to simplify and enhance interpretability.
(v) Interpretation: Interpret the rotated factor matrix to discern relationships between observed variables and latent factors. Variables with substantial factor loadings on a specific factor are directly impacted by that factor.
(vi) Evaluation: Assess model fitness using diverse fit indices and statistical tests.
(vii) Naming and reporting: Assign meaningful labels to identified factors based on interpretation. Communicate results and findings.

Factor analysis finds widespread application across fields like psychology, sociology, marketing, finance, etc., to unveil concealed relationships and patterns within data [156]. It empowers researchers to comprehend intricate datasets, construct theories, and make informed decisions grounded in underlying constructs.

5.2.3.4. Principal Component Analysis (PCA). Principal Component Analysis (PCA) is a widely utilized statistical technique with applications in diverse fields such as data analysis, pattern recognition, and dimensionality reduction. It offers an effective method for unveiling the underlying structure and relationships within datasets [157].

PCA, in its traditional form, assumes multivariate normality of the data. This means that the variables being analyzed are assumed to follow a multivariate normal distribution. However, the technique is also robust against non-normal distributions and can still be applied to non-normal data [158–160].

At its core, PCA aims to transform high-dimensional data into a lower-dimensional space while retaining relevant information, simplifying the data representation without sacrificing critical features. By identifying the principal components, which are linear combinations of the original variables, PCA provides a concise summary of the data's variability [158].

The fundamental concept of PCA involves determining a new set of orthogonal variables, known as principal components, that capture the maximum variance in the data. The first principal component represents the direction of greatest variation in the data space. Subsequent components are derived in a manner that ensures they are uncorrelated with the previous components while capturing the remaining variance. This step guarantees that each principal component is a unique combination of the original variables, offering distinct perspectives on the data [161].

Beyond dimensionality reduction, PCA serves as a valuable tool for data exploration and visualization. By plotting data points in the space defined by the first few principal components, patterns, clusters, and relationships become visually discernible. This aids in uncovering hidden associations, grouping similar observations, and identifying outliers.

Moreover, PCA plays a crucial role in feature selection and engineering. By assessing the contribution of variables to the variance in the principal components, one can identify the most influential features. This information guides subsequent analyses and model building, focusing on informative variables while discarding redundant ones [162].

Additionally, PCA facilitates data pre-processing and noise reduction. By discarding principal components with low variance, noise can be eliminated, and the most significant signal in the data can be preserved. This denoising step proves beneficial when noise and irrelevant variables impede accurate analysis or model performance.

While PCA offers valuable insights, it is important to consider certain considerations and limitations. One significant consideration is the interpretability of the principal components, as their physical or intuitive meanings may not always be apparent. Therefore, careful interpretation and context-specific analysis are necessary [158].

Furthermore, PCA assumes linearity in the data and is sensitive to outliers. In cases where nonlinear relationships exist or extreme outliers are present, alternative techniques or modifications of PCA, such as Kernel PCA or robust PCA, may be more suitable [163].

In conclusion, Principal Component Analysis is a powerful tool for data analysis, dimensionality reduction, and exploration. By identifying principal components and capturing maximum variance, PCA provides a concise representation of data while preserving critical information. Its applications span various domains, facilitating data visualization, feature selection, noise reduction, and more. Nevertheless, it is crucial to consider the assumptions and limitations of PCA to ensure accurate interpretation and analysis [164].

Steps of PCA can be listed as:

(i) Standardize the data: PCA begins by standardizing the data to ensure that all variables have zero mean and unit variance. This step is crucial for comparing variables with different scales. The formula for standardization is as follows

$$Z_{ij} = (x_{ij} - \bar{X}_j)/\sigma_j, \tag{5.9}$$

where Z_{ij} is the standardized value of variable, x_{ij} is the original value of variable x in the i-th observation, $\bar{X}_j$ is the mean of variable x and σ_j is the standard deviation of variable x.

(ii) Compute the covariance matrix: The covariance matrix is calculated based on the standardized data. It represents the relationships between pairs of variables in the dataset. The values in the covariance matrix indicate how the variables co-vary with each other.

(iii) Calculate the eigenvectors and eigenvalues: The next step involves finding the eigenvectors and eigenvalues of the covariance matrix. The eigenvectors represent the principal components, while the eigenvalues quantify the amount of variance explained by each principal component. The eigenvectors are perpendicular to each other, forming a new orthogonal basis for the dataset.

(iv) Select the principal components: The principal components are selected based on their corresponding eigenvalues. The components with higher eigenvalues explain more variance in the data. Typically, the principal components are arranged in descending order of explained variance.

(v) Project the data onto the new feature space: The original data is projected onto the new feature space defined by the selected principal components. This transformation results in a reduced-dimensional representation of the data while preserving the maximum amount of information.

(vi) Interpret the results: The transformed data can be visualized by plotting the observations in the reduced-dimensional space. Patterns, clusters, and relationships within the data can be identified based on the distribution of the observations along the principal components.

5.2.3.5. Kaiser-Meyer-Olkin (KMO) Test. The Kaiser-Meyer-Olkin (KMO) measure, developed by Kaiser [165] and further refined by Meyer and Olkin [166], is a statistical tool crucial for assessing the suitability of data for factor analysis.

The KMO measure evaluates the adequacy of a sample in reflecting the underlying population structure for factor analysis. It helps researchers identify if their data meets the necessary assumptions for meaningful factor extraction from observed variables.

To compute the KMO measure, the correlation matrix of observed variables is analyzed, taking into account partial correlations between them. The KMO value ranges from 0 to 1, with higher values indicating a more suitable sample for factor analysis.

The formula for calculating the KMO statistic is as follows

$$KMO = \frac{\Sigma\Sigma r_{\mathrm{ij}}^2}{\Sigma\Sigma r_{\mathrm{ij}}^2 + \Sigma\Sigma\delta_{\mathrm{ij}}^2}, \tag{5.10}$$

where r_{ij} is the partial correlation between variables i and j, controlling for all other variables and δ_{ij} is the pairwise correlation between variables i and j.

The numerator sums up the squared values of the partial correlations among all pairs of variables, indicating the strength of common variance shared between them. The denominator includes both the sum of squared partial correlations and the sum of squared pairwise correlations. The KMO statistic is essentially a ratio of these two sums, giving an indication of the proportion of common variance among the variables relative to the total variance.

KMO values are interpreted as follows:

- $KMO < 0.5$: The sample is inadequate for factor analysis.
- $0.5 \leq KMO < 0.6$: The sample is marginal, leading to potentially questionable results.
- $0.6 \leq KMO < 0.7$: The sample is mediocre, yielding moderately reliable outcomes.
- $0.7 \leq KMO < 0.8$: The sample is good, providing meaningful results.
- $KMO \geq 0.8$: The sample is excellent for reliable factor analysis.

The KMO measure holds vital significance in research. By evaluating sample adequacy, researchers can determine if their data is suitable for factor analysis. Conducting factor analysis without an adequate sample may lead to unreliable results and misinterpretation of findings. Therefore, the KMO measure aids researchers in refining their data collection process for more accurate outcomes.

5.2.3.6. Bartlett's Test of Sphericity. Bartlett's test of sphericity is another statistical tool commonly used in the context of factor analysis to assess whether the correlation matrix of observed variables is appropriate for conducting the analysis. It was proposed by Maurice Bartlett in 1950 (cited in [167]). The test evaluates the null hypothesis that the correlation matrix is an identity matrix, meaning that the variables are uncorrelated or orthogonal, which would not be suitable for factor analysis.

In factor analysis, the goal is to identify latent variables (factors) that explain the relationships among observed variables. For factor analysis to be meaningful, the observed variables should be correlated to some degree, indicating that they share variance and can be influenced by underlying factors.

The test of sphericity checks whether the correlations between variables are significantly different from zero. If the test yields a significant result, it suggests that the correlation matrix is not an identity matrix, indicating that the observed variables are related, and factor analysis may be appropriate.

Summary of the steps involved in Bartlett's test of sphericity consists of:

(i) State the null and alternative hypotheses:
Null hypothesis (H0): The correlation matrix is an identity matrix; the variables are uncorrelated, and factor analysis is not appropriate.
Alternative hypothesis (Ha): The correlation matrix is not an identity matrix; the variables are correlated, and factor analysis may be suitable.

(ii) Calculate the test statistic: The test statistic follows a chi-square distribution and is calculated based on the determinant of the correlation matrix and the sample size.

The formula for calculating the test statistic in Bartlett's test of sphericity is as follows

$$\chi^2 = \frac{(n - 1 - \frac{2p+5}{6}) * ln(|R|)}{1 - \frac{2}{9p}}, \tag{5.11}$$

where n is the number of observations (sample size), p is the number of variables and $|R|$ is the determinant of the observed correlation matrix among variables.

(iii) Determine the degrees of freedom: The degrees of freedom are determined by the number of observed variables in the correlation matrix. The formula to calculate the degrees of freedom is

$$\text{Degrees of Freedom} = \frac{p(p-1)}{2} - \frac{p(p+1)}{2}, \tag{5.12}$$

where p is the number of variables.

(iv) Compare the test statistic to the critical value: If the calculated test statistic is greater than the critical value from the chi-square distribution at a specified significance level (e.g., 0.05), then the null hypothesis is rejected, indicating that the correlation matrix is not an identity matrix, and factor analysis can be performed.

Bartlett's test of sphericity complements the Kaiser-Meyer-Olkin (KMO) measure. While the KMO measure assesses the adequacy of sampling, Bartlett's test evaluates the adequacy of correlations between variables for factor analysis.

It is important to note that Bartlett's test has its assumptions, such as the requirement of a large enough sample size and the assumption of multivariate normality. Additionally, when conducting factor analysis, researchers may also perform additional tests, such as parallel analysis or scree plots, to determine the number of factors to retain for interpretation.

5.2.3.7. Spearman's Correlation. In the realm of statistics, researchers often encounter data that do not meet the assumptions required for parametric correlation measures. Spearman's rank correlation, also known as Spearman's rho, emerges as a valuable alternative, particularly when dealing with ordinal or non-normally distributed data.

Spearman's correlation (SC) was introduced by Charles Spearman in his seminal paper "The Proof and Measurement of Association between Two Things" published in 1904 [168]. This non-parametric measure measures the monotonic relationship between two variables, meaning that it assesses how consistently the values of one variable change with respect to the values of the other, without assuming a linear association. It is suitable for a variety of research scenarios, especially when dealing with ranked or ordinal data.

To calculate SC, the following steps are taken:

(i) Rank the data: For each variable, rank the data from the smallest to the largest value. Ties (repeated values) are given an average rank.

(ii) Calculate the rank differences: Compute the differences between the ranks of each paired observation.

(iii) Square the rank differences: Square each rank difference.

(iv) Calculate the correlation coefficient: Use the formula of

$$\rho = 1 - (6 * \Sigma d^2/(n * (n^2 - 1))), \tag{5.13}$$

where ρ is Spearman's rank correlation coefficient, Σd^2 is the sum of the squared rank differences, and n is the number of data points.

Spearman's correlation finds application in a wide array of fields, including psychology, sociology, economics, and medicine. Its non-parametric nature makes it robust against deviations from normality and ideal for assessing relationships between variables when parametric assumptions are not met. Researchers often rely on Spearman's correlation to investigate the monotonic association between variables measured on ordinal scales or when dealing with non-normally distributed data.

Spearman's rank correlation, with its robustness and versatility, serves as a powerful tool for researchers working with non-parametric data. By offering insights into the monotonic association between variables, it enriches the understanding of relationships and patterns in various research domains. Understanding and utilizing Spearman's correlation expands the researcher's statistical toolkit, ensuring accurate and reliable analyses when assumptions of parametric methods cannot be met.

5.3. Pilot Study

5.3.1. Overview

Before conducting the main case study, an initial study was performed on MEQ to see whether any deficiency exist or not. For the purpose, a sample of 32 people has been reached for the pilot test. The obtained results are discussed in the following. All statistical data analysis is conducted on IBM SPSS Statistics v27 (64 bit) software.

5.3.2. Sample Information

The following Figure 5.2 represents the distribution of gender, age, position in the company, and total experience duration of 32 participants working in companies in the manufacturing sector.

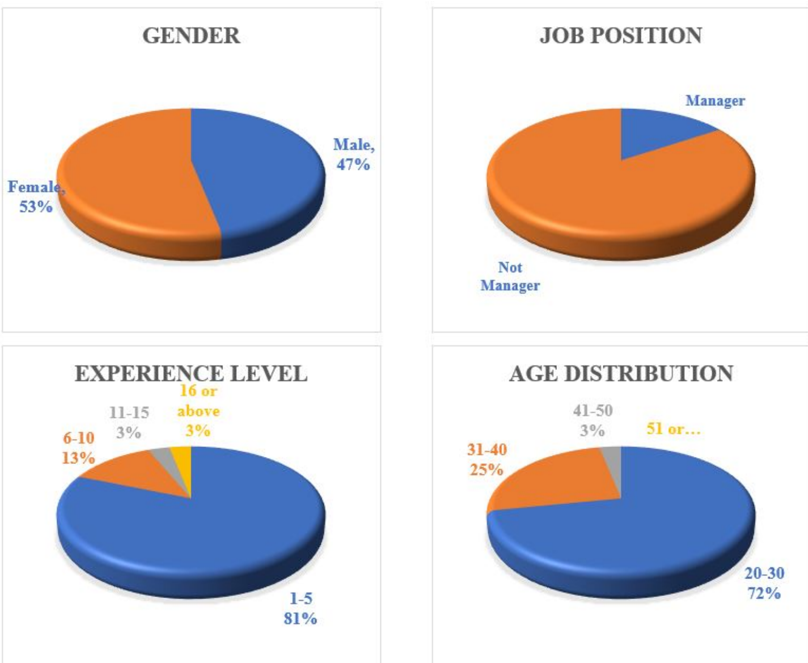


Figure 5.2. Summary on demographic information of the sample data.

5.3.3. Data Analysis

5.3.3.1. Normality. In this stage of the research, the normality of variables is assessed through statistical or graphical methods. The analysis is conducted using the SPSS statistical package. Two commonly used tests for normality are the Shapiro-Wilk test and the Kolmogorov-Smirnov test.

Regardless of the chosen test, to assume a normal distribution, the p-value should be greater than the significance value (in this study, set at 0.05). When the p-value is greater than 0.05, we can accept the null hypothesis (H0) for all groups, indicating that the data is approximately normally distributed at the specified confidence level.

Following results (in Figure 5.3) are shows normality test results of the macroergonomic factors.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Education, Knowledge and Skills	.161	32	.035	.950	32	.146
Physical Characteristics	.209	32	.001	.924	32	.026
Psychological Characteristics	.186	32	.006	.940	32	.076
Motivation and Needs	.088	32	.200*	.978	32	.737
Employee Performance	.151	32	.063	.953	32	.173
Content, Requirements, Challenges, and Skills	.107	32	.200*	.976	32	.672
Autonomy, Job Control, and Participation	.118	32	.200*	.971	32	.534
Information Technology	.187	32	.006	.896	32	.005
Advanced Manufacturing Technologies	.113	32	.200*	.957	32	.223
HR Characteristics in Technology and Tools	.175	32	.014	.943	32	.088
Team Work	.192	32	.004	.926	32	.031
Organizational Culture	.092	32	.200*	.988	32	.968
Coordination, Collaboration, and Communication	.138	32	.124	.961	32	.291
Supervision and Management Styles	.141	32	.104	.954	32	.187
Performance Evaluation, Rewards, Incentives	.124	32	.200*	.958	32	.241
Work Schedule	.145	32	.083	.873	32	.001
Facility Layout and Conditions	.169	32	.020	.902	32	.007
Occupational Health and Safety	.089	32	.200*	.988	32	.971

Figure 5.3. Normality test results of the factors.

As we can see from the above results, some of the factors satisfy the normality assumption and some not. Since we will use PCA for the construct validity (which is a robust technique for non-normal data [158–160]), violating normality assumption is not a problem for our study. However, Barttlet's test has a normality assumption, and we will not consider this test for controlling the suitability of the data for PCA. We will use KMO (Kasier-Meyer-Olkin) test for suitability control of the obtained data.

5.3.3.2. Reliability of the Pilot Study. Since reliability test (Cronbach's alpha) does not have strict normality assumption, we can rely on the obtained results in terms of the reliability test.

Reliability refers to the degree of consistency in the results obtained from an experiment, test, or any measurement procedure when it is repeated multiple times. It represents the reliability of the measurement method, suggesting that similar data would be obtained in repeated observations of the same phenomenon.

In our study, we opted for the most common method, which is internal consistency, to evaluate the survey's reliability. Internal consistency examines the extent to which different items within the survey measure the same construct or concept.

The following summary (in Table 5.5) Cronbach's Alpha values are obtained for each sub-factor of macroergonomics. The detailed information and interpretations can be found in Appendix B.

Table 5.5. Summary CA values for pilot study.

FACTOR	**Subfactor**	**Cronbach's Alpha**
EMPLOYEE	**Education, Knowledge and Skills**	0.819
	Physical Characteristics	0.631

Table 5.5. Summary CA values for pilot study. (cont.)

	Psychological Characteristics	0.593
	Motivation and Needs	0.826
	Employee Performance	0.705
TASK	**Content, Requirements, Challenges, and Skills**	0.821
	Autonomy, Job Control, and Participation	0.660
TECHNOLOGY	**Information Technology**	0.944
	Advanced Manufacturing Technologies	0.881
	HR Characteristics in Technology and Tools	0.848
ORGANIZATION	**Team Work**	0.708
	Organizational Culture	0.792
	Coordination, Collaboration, and Communication	0.907
	Supervision and Management Styles	0.912
	Performance Evaluation, Rewards, Incentives	0.779
	Work Schedule	0.635
WORK ENVIRONMENT AND OCCUPATIONAL SAFETY	**Facility Layout and Conditions**	0.912
	Occupational Health and Safety	0.887

The Cronbach's alpha values obtained for certain subfactors (Physical Characteristics, Psychological Characteristics, Autonomy, Job Control, and Participation, and

Work Schedule) are below 0.7, which is considered a threshold for good cases. It's important to approach values below 0.7 with caution. However, these results pertain to a preliminary pilot study involving a sample size of 32. Therefore, we can proceed with the main study as the discrepancy between the obtained values and the threshold of 0.7 is relatively modest and can be deemed acceptable.

5.3.3.3. Validity of the Pilot Study. The applications of four validity type are as follows:

(i) Face validity: Proactive measures are taken by engaging in iterative discussions and seeking expert guidance to establish face validity. The experts and predefined participants are asked whether the survey is relevant with the topic and the related questions are understandable/meaningful.

(ii) Content validity: In the present study, content validity is assessed through the evaluation of experts and pretest subjects, allowing for a thorough examination of the questionnaire's content validity. CVI values for each item in the questionnaire is calculated as 1 (total agreement).

(iii) Criterion validity: In the context of this study, the measures of activity areas are considered to have criterion-related validity if, collectively, they display a strong and positive correlation with the actual activities in the company. In other words, the activity areas covered in the questionnaire should comprehensively account for the ergonomic requirements and reflect the macroergonomic deficiencies of the company. To assess this dimension practically, a well-defined group of subjects is chosen, and their pre assessment results are compared with the questionnaire results. The similarity between results were determined by calculating the similarity percentage. Namely, counting the pre-assessment results and questionnaire results indicates a deficiency for the same variable and dividing it to the total number of variables. The obtained percentage of 75% indicates a powerful criterion validity.

(iv) Instrument validity: A reliable survey instrument demonstrates consistent measurement of a specific phenomenon. On the other hand, a valid instrument, such as scales or indexes, effectively measures the intended concepts accurately. Therefore, by definition, a valid measure is accurate and, in turn, must also be reliable. However, it is essential to note that a reliable instrument does not automatically imply validity. Researchers have identified various dimensions of validity, including face validity, content validity, criterion-related validity, and construct validity. In the context of the study's methodology, the most employed method for evaluating instrument validity is construct validity. Factor analysis is not recommended for sample sizes below 50 [155]. According to Hatcher [169] recommended that the sample size should be larger than five times the number of variables (p). Hence our pre-test sample size is not adequate for PCA. We will control the questionnaire structure in the main case study.

5.4. Actual Study

5.4.1. Overview

The purpose of this study is to develop an AD-based macroergonomics framework for manufacturing companies. This study will also serve as an application of the proposed information Formula 2 for macroergonomics decision-making. This case study is an attempt to find answers to the questions of how effectively the proposed macro ergonomic framework identified deficiencies in companies and how well the enhanced information value formula could evaluate alternative solutions to address these deficiencies. The case study was conducted at a prominent automotive electronics manufacturer specializing in infotainment systems. The company, established in 2002, has garnered a wealth of experience over the course of 21 years and currently boasts a workforce of over 160 employees. This extensive experience and a dedicated team contribute significantly to the company's success and its standing as a key player in the automotive electronics industry.

Headquartered in Istanbul, Türkiye, the company is a multinational company with an extensive presence across six countries. It operates technical centers, manufacturing sites, and customer support services in the following locations: Turkey, China, Uzbekistan, Italy, Brazil, France, and India. This international footprint allows the company to leverage global resources and cater to a diverse range of markets, contributing to its position as a prominent player in the automotive electronics industry.

5.4.2. Participants Information

The following Figure 5.4 represents the distribution of gender, age, position in the company, and total experience duration of 88 participants working in the company.

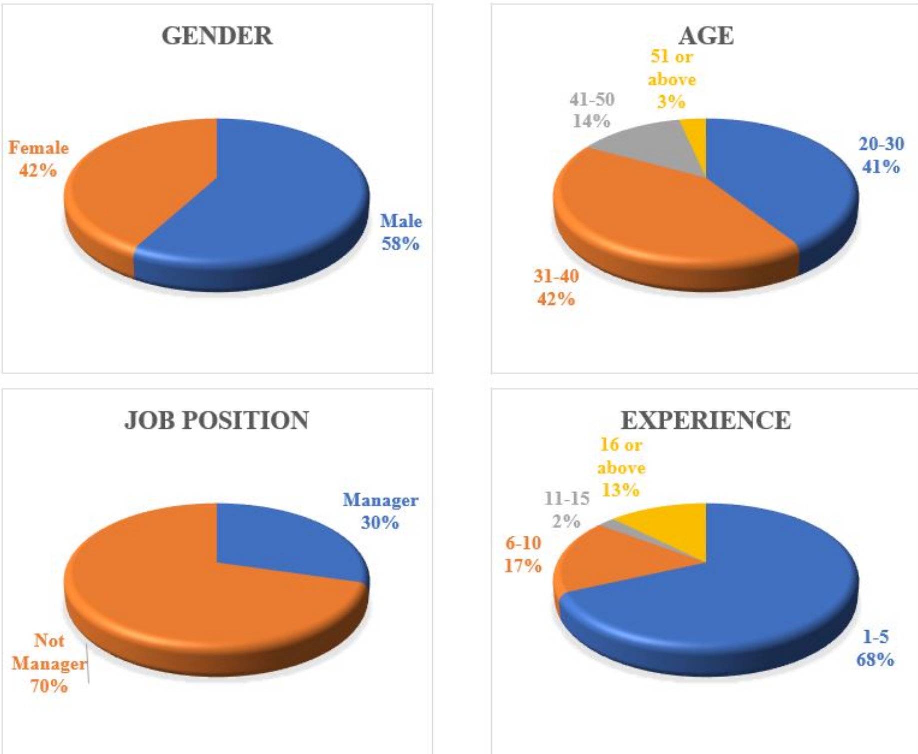


Figure 5.4. Summary information of the case study participants.

5.4.3. Normality Check for Case Study Survey Data

In accordance with the approach adopted in the pre-test section, both the Kolmogorov-Smirnov and Shapiro-Wilk tests will be employed to assess the normality of case study data. By subjecting the data to these two statistical tests, we aim to ascertain whether it adheres to a normal distribution or exhibits deviations from it. This will inform regarding the appropriate utilization of statistical methods.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
VAR00001	.209	88	<.001	.897	88	<.001
VAR00002	.228	88	<.001	.895	88	<.001
VAR00003	.256	88	<.001	.872	88	<.001
VAR00004	.238	88	<.001	.873	88	<.001
VAR00005	.301	88	<.001	.854	88	<.001
VAR00006	.197	88	<.001	.908	88	<.001
VAR00007	.233	88	<.001	.879	88	<.001
VAR00008	.330	88	<.001	.799	88	<.001
VAR00009	.301	88	<.001	.857	88	<.001
VAR00010	.199	88	<.001	.897	88	<.001
VAR00011	.172	88	<.001	.914	88	<.001
VAR00012	.193	88	<.001	.896	88	<.001
VAR00013	.286	88	<.001	.868	88	<.001
VAR00014	.189	88	<.001	.887	88	<.001
VAR00015	.257	88	<.001	.881	88	<.001
VAR00016	.270	88	<.001	.852	88	<.001
VAR00017	.201	88	<.001	.905	88	<.001
VAR00018	.250	88	<.001	.848	88	<.001
VAR00019	.290	88	<.001	.859	88	<.001
VAR00020	.219	88	<.001	.892	88	<.001
VAR00021	.213	88	<.001	.899	88	<.001
VAR00022	.206	88	<.001	.893	88	<.001
VAR00023	.231	88	<.001	.888	88	<.001
VAR00024	.312	88	<.001	.844	88	<.001
VAR00025	.301	88	<.001	.846	88	<.001
VAR00026	.281	88	<.001	.847	88	<.001
VAR00027	.281	88	<.001	.854	88	<.001
VAR00028	.320	88	<.001	.830	88	<.001
VAR00029	.336	88	<.001	.820	88	<.001
VAR00030	.277	88	<.001	.856	88	<.001
VAR00031	.212	88	<.001	.899	88	<.001
VAR00032	.175	88	<.001	.917	88	<.001
VAR00033	.314	88	<.001	.837	88	<.001
VAR00034	.210	88	<.001	.903	88	<.001
VAR00035	.274	88	<.001	.871	88	<.001
VAR00036	.236	88	<.001	.895	88	<.001
VAR00037	.221	88	<.001	.877	88	<.001
VAR00038	.320	88	<.001	.792	88	<.001
VAR00039	.329	88	<.001	.815	88	<.001
VAR00040	.229	88	<.001	.898	88	<.001
VAR00041	.167	88	<.001	.912	88	<.001
VAR00042	.217	88	<.001	.896	88	<.001
VAR00043	.205	88	<.001	.884	88	<.001
VAR00044	.245	88	<.001	.887	88	<.001
VAR00045	.225	88	<.001	.894	88	<.001
VAR00046	.268	88	<.001	.878	88	<.001
VAR00047	.244	88	<.001	.894	88	<.001
VAR00048	.198	88	<.001	.908	88	<.001
VAR00049	.227	88	<.001	.882	88	<.001
VAR00050	.288	88	<.001	.821	88	<.001
VAR00051	.232	88	<.001	.876	88	<.001
VAR00052	.231	88	<.001	.888	88	<.001
VAR00053	.209	88	<.001	.898	88	<.001
VAR00054	.208	88	<.001	.863	88	<.001
VAR00055	.325	88	<.001	.809	88	<.001
VAR00056	.275	88	<.001	.856	88	<.001
VAR00057	.244	88	<.001	.877	88	<.001
VAR00058	.307	88	<.001	.823	88	<.001
VAR00059	.281	88	<.001	.858	88	<.001
VAR00060	.233	88	<.001	.880	88	<.001
VAR00061	.249	88	<.001	.850	88	<.001
VAR00062	.219	88	<.001	.878	88	<.001
VAR00063	.193	88	<.001	.902	88	<.001
VAR00064	.293	88	<.001	.847	88	<.001
VAR00065	.276	88	<.001	.871	88	<.001
VAR00066	.251	88	<.001	.889	88	<.001
VAR00067	.183	88	<.001	.912	88	<.001
VAR00068	.239	88	<.001	.882	88	<.001
VAR00069	.256	88	<.001	.857	88	<.001
VAR00070	.301	88	<.001	.814	88	<.001
VAR00071	.282	88	<.001	.851	88	<.001
VAR00072	.224	88	<.001	.892	88	<.001
VAR00073	.274	88	<.001	.849	88	<.001
VAR00074	.225	88	<.001	.890	88	<.001
VAR00075	.242	88	<.001	.881	88	<.001
VAR00076	.252	88	<.001	.876	88	<.001

Figure 5.5. Normality results for the survey data.

Considering the data presented in the preceding table (in Figure 5.5), it becomes apparent that the survey data does not adhere to a normal distribution. Nevertheless, the deviation from normality is relatively modest (Table 5.6), allowing us to proceed with PCA, known for its robustness against non-normal data, particularly in the context of larger sample sizes (i.e. sample size of 100 or above) [158–160]. However, to maintain methodological coherence, we will abstain from employing Bartlett's Test of Sphericity in our analytical approach. Please refer to following Table 5.6 about Skewness and Kurtosis results of the data.

Table 5.6. The results of skewness and kurtosis.

FACTOR	**Subfactor**	**Variable**	**Skewness**	**Kurtosis**
EMPLOYEE	**Education, Knowledge and Skills**	Var1	0.018	-1.032
		Var2	-0.237	-0.865
		Var3	-0.349	-0.951
		Var4	-0.213	-1.12
	Physical Characteristics	Var1	-0.691	0.285
		Var2	-0.101	-0.735
	Psychological Characteristics	Var1	-0.306	-0.95
		Var2	-1.139	2.158
		Var3	-0.73	-0.033
	Motivation and Needs	Var1	-0.091	-0.784
		Var2	0.004	-0.777
		Var3	0.261	-0.783
		Var4	-0.686	-0.149
		Var5	-0.206	-0.899
		Var6	-0.476	-0.235
		Var7	-0.823	0.249
	Employee Performance	Var1	0.083	-0.851
		Var2	-0.409	-0.232
		Var3	-0.668	0.059
	Content, Reqs, Challenges, and	Var1	-0.223	-0.855
		Var2	0.088	-0.973
		Var3	0.056	-1.047

Table 5.6. The results of skewness and kurtosis. (cont.)

TASK	**Skills**	Var4	0.225	-0.698
	Autonomy, Job Control, and Part.	Var1	-0.852	0.504
		Var2	-0.798	0.026
TECHNOLOGY	**Information Technology**	Var1	-0.897	0.38
		Var2	-0.81	0.64
		Var3	-0.938	0.774
	Adv. Manufacturing Technologies	Var1	-0.968	0.39
		Var2	-0.842	0.093
	HR Characteristics in Tech. and Tools	Var1	-0.375	-0.147
		Var2	0.001	-0.712
ORGANIZATION	**Team Work**	Var1	-0.907	0.264
		Var2	-0.396	-0.572
	Organizational Culture	Var1	-0.632	0.194
		Var2	-0.349	-0.598
		Var3	-1.258	2.518
	Coordination, Collaboration, and Communication	Var1	-0.273	-0.866
		Var2	-0.029	-0.82
		Var3	0.069	-1.054
		Var4	-0.098	-0.974
		Var5	-0.527	-0.295
	Supervision and Management Styles	Var1	-0.132	-0.966
		Var2	-0.511	-0.618
		Var3	-0.396	-0.739
		Var4	-0.311	-0.519
		Var5	-0.596	-0.469
		Var6	-1.108	1.633
	Performance Ev., Rewards, Incentives	Var1	0.549	-0.376
		Var2	-0.255	-0.848
	Work Schedule	Var1	-0.138	-1.087
		Var2	-1.073	1.787

Table 5.6. The results of skewness and kurtosis. (cont.)

		Var3	-0.604	-0.528
Work Environment and Occupational Safety	**Facility Layout and Conditions**	Var1	-0.232	-0.978
		Var2	-1.02	1.563
		Var3	-0.827	0.5
		Var4	-0.629	0.027
	Occupational Safety Rules & Regulations	Var1	-0.828	0.663
		Var2	-0.452	0.153
		Var3	-1.167	1.618
		Var4	-0.733	1.026
	Occupational Safety Applications	Var1	-0.752	1.098
		Var2	-0.393	-0.315
	Employee Health Problems	Var1	-0.056	-0.554
		Var2	0.191	-0.343

As a general guideline, certain researchers view skewness values ranging from -1 to 1 as moderately acceptable, yet even if a distribution slightly deviates from this range, it may still be reasonably close to the normal distribution. Similarly, when considering kurtosis, it is commonly suggested that values between -2 and 2 are indicative of a normal distribution within a reasonable scope. However, akin to skewness, a distribution might be deemed approximately normal even if it modestly departs from this range [170].

Results in Table 5.6 indicates that only some of the obtained results are violates the stated intervals and although violating the normality, our survey data is still close to normality. Hence, using PCA becomes more reasonable.

5.4.4. Instrument Validity and Reliability of the Survey

Construct validity will be used to evaluate the instrument validity. Construct validity will be controlled by using PCA method for the factors with 3 or more variables in SPSS v27 (64 bit). The setting interfaces of the used tool can be found in Appendix C.

Conducting Principal Component Analysis (PCA) with only two variables is feasible, but its practical significance and interpretability may be restricted. While this approach can offer some insights, particularly in examining the relationship between the two variables, it might not yield substantial benefits in terms of reducing dimensionality or simplifying the data.

Therefore, in scenarios where we encounter factors comprising only two variables, we will opt for Spearman's Correlation. Spearman's Correlation, being a non-parametric measure, is suitable for assessing the monotonic relationship between ordinal or non-normally distributed variables. This choice ensures a robust analysis and allows for a meaningful exploration of the associations between the two variables in such cases.

5.4.4.1. PCA for Employee Factor. In this section, we present an investigation into the construct validity of the employee factor and its subfactors, aiming to assess the extent to which the measurement tool accurately captures the intended underlying construct of employee and its various dimensions. This will be achieved by implementing principal component analysis (PCA). It is important to note that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy will be calculated to assess the suitability of the data for factor analysis. This measure helps to determine whether the sampling method used is appropriate for this specific statistical technique, ensuring the results are reliable and generalizable. A KMO value above 0.5 is generally considered acceptable, indicating that the data set is suitable for further analysis. The results of this analysis will be used to determine the overall reliability and validity of the employee factor and its subfactors.

Education, knowledge, and skills subfactor: PCA results of education, knowledge and skills subfactor are as in Figure 5.6.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.772
Bartlett's Test of Sphericity	Approx. Chi-Square	99.676
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.694
VAR00002	1.000	.527
VAR00003	1.000	.672
VAR00004	1.000	.574

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.468	61.689	61.689	2.468	61.689	61.689
2	.663	16.570	78.259			
3	.450	11.257	89.516			
4	.419	10.484	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00001	.833
VAR00002	.726
VAR00003	.820
VAR00004	.758

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.6. PCA results for education, knowledge, and skills.

According to Kaiser's seminal work [165], a Kaiser-Meyer-Olkin (KMO) value of 0.70 is regarded as indicative of a satisfactory level of sampling adequacy. Consequently, the data obtained for the "Education, Knowledge, and Skills" subfactor is deemed suitable for conducting Principal Component Analysis (PCA). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. According to PCA results, we have only one component and it explains the %62[1] of the total variance. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor. The results provide

[1] An important factor evaluation criterion is that the explained variance should exceed 50% of the total variance. Because of the created factor structure explains less than half of the total variance, it would be wrong to talk about representation ability [171].

evidence that the survey accurately measures the intended construct, thus establishing the credibility and appropriateness of the survey for assessing the specific subfactor under investigation.

Psychological characteristics subfactor: PCA results of psychological characteristics subfactor are as in Figure 5.7.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.573
Bartlett's Test of Sphericity	Approx. Chi-Square	28.764
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.445
VAR00002	1.000	.695
VAR00003	1.000	.514

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.653	55.110	55.110	1.653	55.110	55.110
2	.821	27.379	82.489			
3	.525	17.511	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.667
VAR00002	.833
VAR00003	.717

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.7. PCA results for psychological char.

According to Kaiser's work [165], a Kaiser-Meyer-Olkin (KMO) value of 0.6 is classified as "mediocre" in terms of sampling adequacy. However, despite being categorized as mediocre, a KMO value of 0.6 is still considered an acceptable level of adequacy for conducting Principal Component Analysis (PCA). This means that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA, albeit with a moderate level of suitability. According to PCA results, we have only one component and it explains the %55 of the total variance. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor. The results provide evidence that the survey accurately measures the intended construct, thus establishing the credibility and appropriateness of the survey for assessing the specific subfactor under investigation.

Motivation and needs subfactor: PCA results of motivation and needs subfactor are as in Figure 5.8.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.834
Bartlett's Test of Sphericity	Approx. Chi-Square	211.970
	df	21
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.630
VAR00002	1.000	.615
VAR00003	1.000	.507
VAR00004	1.000	.433
VAR00005	1.000	.558
VAR00006	1.000	.515
VAR00007	1.000	.370

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.628	51.834	51.834	3.628	51.834	51.834
2	.884	12.624	64.458			
3	.708	10.108	74.566			
4	.558	7.970	82.536			
5	.490	6.997	89.534			
6	.441	6.294	95.827			
7	.292	4.173	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.794
VAR00002	.784
VAR00003	.712
VAR00004	.658
VAR00005	.747
VAR00006	.718
VAR00007	.609

Extraction Method: Principal Component Analysis.

Figure 5.8. PCA results for motivation and needs.

According to Kaiser's seminal work [165], a KMO value of 0.8 is regarded as indicative of a very good level of sampling adequacy. Consequently, the data obtained for the "Motivation and Needs" subfactor is deemed suitable for conducting Principal Component Analysis (PCA). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. The findings from analysis affirm the validity of our survey structure concerning the relevant subfactor. The results provide evidence that the survey accurately measures the intended construct, thus establishing the credibility and appropriateness of the survey for assessing the specific subfactor under investigation.

Employee performance subfactor: PCA results of employee performance subfactor are as in Figure 5.9.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.616
Bartlett's Test of Sphericity	Approx. Chi-Square	31.178
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.635
VAR00002	1.000	.434
VAR00003	1.000	.636

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.705	56.838	56.838	1.705	56.838	56.838
2	.759	25.305	82.143			
3	.536	17.857	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.797
VAR00002	.659
VAR00003	.798

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.9. PCA results for employee performance.

The obtained results indicate that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA, albeit with a moderate level of suitability. Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 57% of the total variance in the data. The results offer compelling evidence that the survey effectively measures the intended construct, thus reinforcing the credibility and appropriateness of the survey in assessing the specific subfactor.

This affirms the reliability and soundness of our research approach and contributes valuable insights to the study of the investigated subfactor.

5.4.4.2. SC for Employee Factor. To acquire more dependable information concerning the subfactors associated with the two variables (questions), Spearman's correlation will be employed in conjunction with PCA.

Physical characteristics subfactor: Spearman's Correlation and PCA results of physical characteristics subfactor are as in Figure 5.10.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.537**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00002	Correlation Coefficient	.537**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.10. Spearman's correlation results for physical characteristics.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.001 level) is observed between the two non-normal variables representing "Physical Characteristics." This significant correlation indicates that these two variables are well-suited to be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The significant correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey's measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.11 below depicts the outcomes of PCA. While it is essential to acknowledge that PCA results may be statistically uncertain in a scenario involving two variables, they still provide valuable insights into the relationship between these two variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	29.992
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.772
VAR00002	1.000	.772

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.544	77.197	77.197	1.544	77.197	77.197
2	.456	22.803	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.879
VAR00002	.879

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.11. PCA results for physical characteristics.

According to Kaiser's work [165], a KMO value of 0.5 is still considered an acceptable level of adequacy for conducting PCA. This means that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

5.4.4.3. PCA for Task Factor. The construct validity of task factor and its subfactors will be tested by using PCA in this section.

The content, requirements, challenges, and skills of the job subfactor: PCA results of "the content, requirements, challenges, and skills of the job" subfactor are as in Figure 5.12.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.748
Bartlett's Test of Sphericity	Approx. Chi-Square	78.337
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.541
VAR00002	1.000	.624
VAR00003	1.000	.596
VAR00004	1.000	.543

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.304	57.601	57.601	2.304	57.601	57.601
2	.707	17.670	75.271			
3	.522	13.039	88.310			
4	.468	11.690	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.735
VAR00002	.790
VAR00003	.772
VAR00004	.737

Extraction Method: Principal Component Analysis.

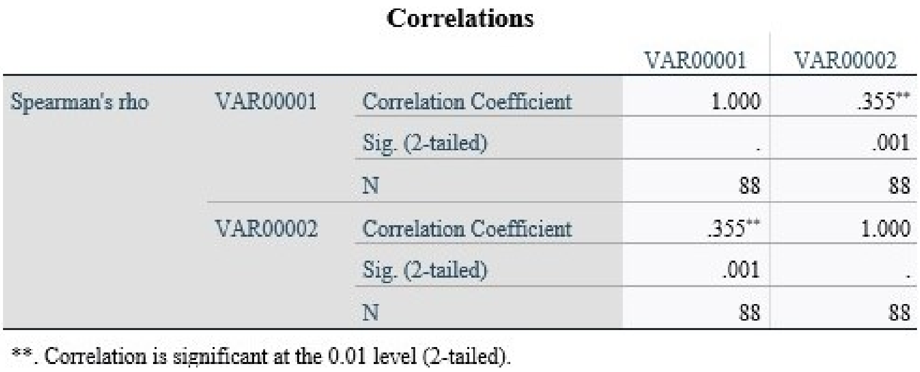
a. 1 components extracted.

Figure 5.12. PCA for content, requirements, challenges, and skills of the job.

The data obtained for the " The Content, Requirements, Challenges, and Skills of the Job " subfactor is deemed suitable for conducting Principal Component Analysis (PCA). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. According to PCA results, we have only one component and it explains the %58 of the total variance.

5.4.4.4. SC for Task Factor. To acquire more dependable information concerning the subfactors associated with the two variables, Spearman's correlation will be employed in conjunction with PCA.

Autonomy, job control, and participation subfactor: Spearman's Correlation and PCA results of "autonomy, job control, and participation" subfactor are as in Figure 5.13.



Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.355**
		Sig. (2-tailed)	.	.001
		N	88	88
	VAR00002	Correlation Coefficient	.355**	1.000
		Sig. (2-tailed)	.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.13. SC results for autonomy, job control, and participation.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing "Autonomy, Job Control, and Participation" This correlation indicates that these two variables can be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey's measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.14 below depicts the outcomes of PCA. While it is essential to acknowledge that PCA results may be statistically uncertain in a scenario involving two variables, they still provide valuable insights into the relationship between these two variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	19.571
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.726
VAR00002	1.000	.726

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.452	72.616	72.616	1.452	72.616	72.616
2	.548	27.384	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.852
VAR00002	.852

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.14. PCA results for autonomy, job control, and participation.

A Kaiser-Meyer-Olkin (KMO) value of 0.5 is still considered an acceptable level of adequacy for conducting Principal Component Analysis (PCA). This means that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA. Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 73% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

5.4.4.5. PCA for Technology Factor. The construct validity of technology factor and its subfactors will be tested by using PCA in this section.

Information technology subfactor: PCA results of information technology subfactor are as in Figure 5.15.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.702
Bartlett's Test of Sphericity	Approx. Chi-Square	117.155
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.692
VAR00002	1.000	.831
VAR00003	1.000	.785

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.308	76.921	76.921	2.308	76.921	76.921
2	.448	14.929	91.850			
3	.244	8.150	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.832
VAR00002	.911
VAR00003	.886

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.15. PCA results for information technology subfactor.

The data obtained for the " Information Technology" subfactor is deemed suitable for conducting Principal Component Analysis (PCA). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. According to PCA results, we have only one component and it explains the %77 of the total variance. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor.

5.4.4.6. SC for Technology Factor. To acquire more dependable information concerning the subfactors associated with the two variables, Spearman's correlation will be employed in conjunction with PCA.

Advanced manufacturing technologies subfactor: Spearman's Correlation and PCA results of "advanced manufacturing technologies" subfactor are as in Figure 5.16.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.690**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00002	Correlation Coefficient	.690**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.16. SC results for advanced manufacturing technologies.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing "Advanced Manufacturing Technologies". This significant correlation indicates that these two variables are well-suited to be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The significant correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey's measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor.

The Figure 5.17 below depicts the outcomes of PCA. While it is essential to acknowledge that PCA results may be statistically uncertain in a scenario involving two variables, they still provide valuable insights into the relationship between these two variables.

The obtained results mean that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA. Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 87% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	68.933
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.872
VAR00002	1.000	.872

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.744	87.197	87.197	1.744	87.197	87.197
2	.256	12.803	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00001	.934
VAR00002	.934

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.17. PCA results for advanced manufacturing technologies subfactor.

HR characteristics in technology and tools subfactor: Spearman's Correlation and PCA results of "HR characteristics in technology and tools" subfactor are as in Figure 5.18.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.402**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00002	Correlation Coefficient	.402**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.18. SC results for HR characteristics in technology and tools.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing ”HR in Technology and Tools” This correlation indicates that these two variables can be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey’s measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.19 below depicts the outcomes of PCA. While it is essential to know that PCA results may be statistically uncertain in a scenario involving two variables, they still provide valuable insights into the relationship between these two variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	19.468
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.726
VAR00002	1.000	.726

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.451	72.563	72.563	1.451	72.563	72.563
2	.549	27.437	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.852
VAR00002	.852

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.19. PCA results for HR in technology and tools subfactor.

Again, the obtained results mean that the dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA. Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 73% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

5.4.4.7. PCA for Organization Factor. The construct validity of organization factor and its subfactors will be tested by using PCA in this section.

Organizational culture subfactor: PCA results of organizational culture subfactor are as in Figure 5.20.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.696
Bartlett's Test of Sphericity	Approx. Chi-Square	58.698
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.606
VAR00002	1.000	.617
VAR00003	1.000	.349
VAR00004	1.000	.512

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.084	52.107	52.107	2.084	52.107	52.107
2	.851	21.278	73.386			
3	.566	14.148	87.534			
4	.499	12.466	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00001	.779
VAR00002	.786
VAR00003	
VAR00004	.715

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.20. PCA results for organizational culture-I.

Based on the information presented in the preceding table, it is evident that the third variable has no significant effect on the "Organizational Culture" subfactor. Consequently, we will proceed with the removal of the third variable from the analysis. By conducting the analysis again without the non-significant variable, we aim to refine and enhance the accuracy of our findings, focusing solely on the variables that contribute significantly to the "Organizational Culture" subfactor. This iterative approach ensures a more precise and meaningful assessment of the relationship between the selected variables and the subfactor of interest.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.673
Bartlett's Test of Sphericity	Approx. Chi-Square	43.839
	df	3
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.629
VAR00002	1.000	.614
VAR00004	1.000	.626

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.869	62.294	62.294	1.869	62.294	62.294
2	.575	19.172	81.466			
3	.556	18.534	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00001	.793
VAR00002	.784
VAR00004	.791

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.21. PCA results for organizational culture-II.

After removing the third variable, we obtained a KMO value of 0.673 (in Figure 5.21). Consequently, the data obtained for the "Organizational Culture" subfactor is deemed suitable for conducting Principal Component Analysis (PCA). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. According to PCA results, we have only one component and it explains the %62 of the total variance. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor. The results provide evidence that the survey accurately measures the intended construct, thus establishing the credibility and appropriateness of the survey for assessing the specific subfactor under investigation.

Coordination, collaboration, and communication subfactor: PCA results of "coordination, collaboration, and communication" subfactor are as in Figure 5.22.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.760
Bartlett's Test of Sphericity	Approx. Chi-Square	156.316
	df	15
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.342
VAR00002	1.000	.546
VAR00003	1.000	.542
VAR00004	1.000	.511
VAR00005	1.000	.526
VAR00006	1.000	.572

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.040	50.673	50.673	3.040	50.673	50.673
2	.982	16.362	67.035			
3	.631	10.513	77.548			
4	.561	9.357	86.905			
5	.474	7.906	94.811			
6	.311	5.189	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	
VAR00002	.739
VAR00003	.736
VAR00004	.715
VAR00005	.725
VAR00006	.756

Extraction Method: Principal Component Analysis.

Figure 5.22. PCA for coordination, collaboration, and communication-I.

Based on the information presented in the preceding table, it is evident that the first variable has no significant effect on the "Coordination, Collaboration, and Communication" subfactor. Hence, we will proceed with the removal of the first variable. By conducting the analysis again without the non-significant variable, we aim to refine and enhance the accuracy of our findings, focusing solely on the variables that contribute significantly to the " Coordination, Collaboration, and Communication" subfactor. This iterative approach ensures a more precise and meaningful assessment of the relationship between the selected variables and the subfactor of interest.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.825
Bartlett's Test of Sphericity	Approx. Chi-Square	118.500
	df	10
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00002	1.000	.490
VAR00003	1.000	.636
VAR00004	1.000	.525
VAR00005	1.000	.573
VAR00006	1.000	.564

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.786	55.728	55.728	2.786	55.728	55.728
2	.705	14.107	69.836			
3	.570	11.397	81.233			
4	.491	9.821	91.054			
5	.447	8.946	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00002	.700
VAR00003	.798
VAR00004	.724
VAR00005	.757
VAR00006	.751

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.23. PCA for coordination, collaboration, and communication-II.

The data obtained for the " Coordination, Collaboration, and Communication" subfactor is deemed suitable for conducting PCA. This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor. The results provide evidence that the survey accurately measures the intended construct, thus establishing the credibility and appropriateness of the survey for assessing the specific subfactor under investigation.

Supervision and management style subfactor: PCA results of "supervision and management style" subfactor are as in Figure 5.24.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.796
Bartlett's Test of Sphericity	Approx. Chi-Square	288.222
	df	21
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.722
VAR00002	1.000	.732
VAR00003	1.000	.778
VAR00004	1.000	.740
VAR00005	1.000	.574
VAR00006	1.000	.703
VAR00007	1.000	.620

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.839	54.846	54.846	3.839	54.846	54.846	2.805	40.077	40.077
2	1.030	14.707	69.554	1.030	14.707	69.554	2.063	29.477	69.554
3	.730	10.428	79.982						
4	.475	6.790	86.772						
5	.423	6.037	92.808						
6	.341	4.867	97.675						
7	.163	2.325	100.000						

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
VAR00001	.693	
VAR00002	.791	
VAR00003	.860	
VAR00004	.859	
VAR00005	.728	
VAR00006	.650	
VAR00007		

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Figure 5.24. PCA results for supervision and management style-I.

Based on the information presented in the preceding table, it is evident that the seventh variable has no significant effect on the ”Supervision and Management Style” subfactor. Consequently, we will proceed with the removal of the seventh variable from the analysis. By conducting the analysis again without the non-significant variable, we aim to refine and enhance the accuracy of our findings, focusing solely on the variables that contribute significantly to the ” Supervision and Management Style ” subfactor. This iterative approach ensures a more precise and meaningful assessment of the relationship between the selected variables and the subfactor of interest.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.784
Bartlett's Test of Sphericity	Approx. Chi-Square	260.343
	df	15
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.531
VAR00002	1.000	.645
VAR00003	1.000	.759
VAR00004	1.000	.727
VAR00005	1.000	.538
VAR00006	1.000	.395

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.596	59.930	59.930	3.596	59.930	59.930
2	.912	15.201	75.130			
3	.527	8.788	83.918			
4	.442	7.374	91.292			
5	.356	5.932	97.224			
6	.167	2.776	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.729
VAR00002	.803
VAR00003	.871
VAR00004	.853
VAR00005	.733
VAR00006	.629

Extraction Method: Principal Component Analysis.

Figure 5.25. PCA results for supervision and management style-II.

The data obtained for the " Supervision and Management Style" subfactor is deemed suitable for conducting Principal Component Analysis (PCA) (in Figure 5.25). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. According to PCA results, we have only one component and it explains the %60 of the total variance. The findings from our analysis affirm the validity of our survey structure concerning the relevant subfactor.

Work schedule subfactor: PCA results of "work schedule" subfactor are as in Figure 5.26.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.598
Bartlett's Test of Sphericity	Approx. Chi-Square	11.494
	df	3
	Sig.	.009

Communalities

	Initial	Extraction
VAR00001	1.000	.497
VAR00002	1.000	.457
VAR00003	1.000	.490

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.444	48.125	48.125	1.444	48.125	48.125
2	.795	26.492	74.618			
3	.761	25.382	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.705
VAR00002	.676
VAR00003	.700

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.26. PCA results for work schedule.

The dataset meets the basic requirements for factor analysis and can be used for exploring the underlying structure and relationships among variables through PCA, albeit with a moderate level of suitability. Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 48% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination. The results offer compelling evidence that the survey effectively measures the intended construct, thus reinforcing the credibility and appropriateness of the survey in assessing the specific subfactor.

5.4.4.8. SC for Organization Factor. To acquire more dependable information concerning the subfactors associated with the two variables, Spearman's correlation will be employed in conjunction with PCA.

Teamwork subfactor: Spearman's Correlation and PCA results of "teamwork" subfactor are as in Figure 5.27.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.469**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00002	Correlation Coefficient	.469**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.27. Spearman's correlation results for teamwork.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing "Teamwork". This correlation indicates that these two variables can be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey's measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.28 below depicts the outcomes of PCA. While it is essential to acknowledge that PCA results may be statistically uncertain in a scenario involving two variables, they still provide valuable insights into the relationship between these two variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	23.098
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.743
VAR00002	1.000	.743

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.487	74.328	74.328	1.487	74.328	74.328
2	.513	25.672	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.862
VAR00002	.862

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.28. PCA results for teamwork.

The Principal Component Analysis (PCA) results depicted in Figure 5.28 reveal a compelling finding. A single component emerges as dominant, capturing a substantial 74% of the total variance within the data. This outcome lends robust support to the validity of our survey structure, particularly about the specific subfactor under investigation. The dominance of this component suggests a high internal consistency within the items measuring this subfactor, indicating that they effectively tap into a single underlying construct. This finding strengthens the confidence in our data and paves the way for further analysis of the results related to this particular subfactor.

Based on the Principal Component Analysis (PCA) results (in Figure 5.28), it is evident that only one component is identified, explaining 74% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

Performance evaluation, rewards, incentives subfactor: Spearman's Correlation and PCA results of "performance evaluation, rewards, incentives" subfactor are as in Figure 5.29.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.458**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00002	Correlation Coefficient	.458**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.29. SC results for performance evaluation, rewards, incentives.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing "Performance Evaluation, Rewards, Incentives" This correlation indicates that these two variables can be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The correlation between these variables reinforces the notion that they share a meaningful relationship, thus reinforcing the integrity and reliability of the survey's measurement of the underlying construct. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.30 below depicts the outcomes of PCA. Though it is important to note that PCA results may not be statistically certain when only two variables are involved, PCA can still offer valuable insights into the connection between these two variables. These insights can aid in the detection of possible correlations or trends that may exist between the variables. Therefore, even if the results of PCA in a two-variable scenario may not be completely definitive, they can still be beneficial in understanding the relationship between the variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	23.705
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.746
VAR00002	1.000	.746

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.492	74.604	74.604	1.492	74.604	74.604
2	.508	25.396	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.864
VAR00002	.864

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.30. PCA results for performance evaluation, rewards, incentives.

Based on the Principal Component Analysis (PCA) results (in Figure 5.30), it is evident that only one component is identified, explaining 75% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

5.4.4.9. PCA for Work Environment and Occupational Safety. The construct validity of work environment and occupational safety factor and its subfactors will be tested by using PCA in this section.

Facility layout and conditions subfactor: PCA results of "facility layout and conditions" subfactor are as in Figure 5.31.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.569
Bartlett's Test of Sphericity	Approx. Chi-Square	86.506
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.385
VAR00002	1.000	.561
VAR00003	1.000	.619
VAR00004	1.000	.632

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.197	54.927	54.927	2.197	54.927	54.927
2	.886	22.144	77.072			
3	.616	15.412	92.484			
4	.301	7.516	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.621
VAR00002	.749
VAR00003	.787
VAR00004	.795

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.31. PCA results for facility layout and conditions.

Based on the Principal Component Analysis (PCA) results, it is evident that only one component is identified, explaining 55% of the total variance in the data. The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination. The results offer compelling evidence that the survey effectively measures the intended construct, thus reinforcing the credibility and appropriateness of the survey in assessing the specific subfactor.

Occupational health and safety subfactor: PCA results of "occupational health and safety" subfactor are as in Figure 5.32.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.797
Bartlett's Test of Sphericity	Approx. Chi-Square	570.241
	df	120
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.678
VAR00002	1.000	.632
VAR00003	1.000	.462
VAR00004	1.000	.592
VAR00005	1.000	.580
VAR00006	1.000	.615
VAR00007	1.000	.498
VAR00008	1.000	.699
VAR00009	1.000	.510
VAR00010	1.000	.641
VAR00011	1.000	.625
VAR00012	1.000	.687
VAR00013	1.000	.555
VAR00014	1.000	.440
VAR00015	1.000	.547
VAR00016	1.000	.522

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.250	32.812	32.812	5.250	32.812	32.812	4.103	25.645	25.645
2	2.486	15.536	48.347	2.486	15.536	48.347	2.929	18.306	43.951
3	1.547	9.669	58.017	1.547	9.669	58.017	2.251	14.066	58.017
4	.961	6.005	64.022						
5	.930	5.810	69.832						
6	.770	4.815	74.647						
7	.621	3.881	78.528						
8	.567	3.545	82.073						
9	.547	3.419	85.491						
10	.456	2.849	88.340						
11	.425	2.658	90.999						
12	.388	2.423	93.422						
13	.331	2.067	95.489						
14	.284	1.773	97.262						
15	.266	1.664	98.926						
16	.172	1.074	100.000						

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component		
	1	2	3
VAR00001	.663		
VAR00002	.748		
VAR00003			
VAR00004			
VAR00005			
VAR00006			
VAR00007		.669	
VAR00008			
VAR00009	.696		
VAR00010	.659		
VAR00011	.768		
VAR00012		.750	
VAR00013	.735		
VAR00014			
VAR00015	.617		
VAR00016	.660		

Figure 5.32. PCA results for occupational health and safety-I.

Despite obtaining a commendable Kaiser-Meyer-Olkin (KMO) value of 0.797, it is worth noting that some variables in our dataset are statistically insignificant. As a result, it is imperative to proceed by removing these non-significant variables before interpreting the results of our analysis. By eliminating these variables, we can ensure a more focused and accurate interpretation, emphasizing the meaningful and influential factors that contribute to the overall findings. This step ensures that our analysis remains robust and relevant, yielding more meaningful insights into the relationships among the retained variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.807
Bartlett's Test of Sphericity	Approx. Chi-Square	304.526
	df	36
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.595
VAR00002	1.000	.644
VAR00007	1.000	.654
VAR00009	1.000	.558
VAR00010	1.000	.674
VAR00011	1.000	.668
VAR00012	1.000	.555
VAR00013	1.000	.619
VAR00016	1.000	.531

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.934	43.715	43.715	3.934	43.715	43.715	3.909	43.432	43.432
2	1.565	17.390	61.105	1.565	17.390	61.105	1.591	17.673	61.105
3	.897	9.961	71.066						
4	.667	7.407	78.473						
5	.575	6.388	84.861						
6	.476	5.287	90.148						
7	.325	3.615	93.763						
8	.299	3.322	97.085						
9	.262	2.915	100.000						

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
VAR00001	.746	
VAR00002	.802	
VAR00007		.809
VAR00009	.720	
VAR00010	.735	
VAR00011	.813	
VAR00012		.725
VAR00013	.783	
VAR00016	.610	

Figure 5.33. PCA results for occupational health and safety-II.

According to Kaiser's seminal work in 1974, a KMO value of 0.8 is regarded as indicative of a very good level of sampling adequacy. Consequently, the data obtained for the Occupational Health and Safety subfactor is deemed suitable for conducting Principal Component Analysis (PCA) (in Figure 5.32). This suggests that the dataset meets the necessary criteria for exploring the underlying structure and relationships among the variables of interest, and thus, facilitates a robust application of PCA in this context. Based on the outcomes of Principal Component Analysis (PCA), we have identified two components that collectively account for 61% of the total variance. Consequently, we have decided to divide this subfactor into two distinct subfactors: Subfactor-1, comprising variables Var1, Var2, Var9, Var10, Var11, Var13, and Var16, and Subfactor-2, consisting of variables Var7 and Var12.

Now, we need to re-control the new subfactors with PCA and Spearman's Correlation.

Rotated Component Matrix[a]

	Component	
	1	2
VAR00001	.841	
VAR00002	.631	
VAR00003		
VAR00004	.866	
VAR00005	.693	
VAR00006		.780
VAR00007		.901

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 3 iterations.

Figure 5.34. PCA results for occupational health and safety-III.

Based on the updated results (in Figure 5.34), it appears that the third variable can now be extracted from the dataset. As a result, we will proceed with extracting the third variable and subsequently re-run the test. By including this newly extracted variable in the analysis, we aim to obtain a more comprehensive and accurate understanding of its contribution to the overall findings. This iterative approach allows us to continuously refine our analysis, ensuring that all relevant variables are considered and accounted for in the final results. The inclusion of the third variable may shed further light on the underlying relationships and enhance the overall robustness of our study.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.814
Bartlett's Test of Sphericity	Approx. Chi-Square	227.097
	df	15
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.735
VAR00002	1.000	.641
VAR00004	1.000	.768
VAR00005	1.000	.683
VAR00006	1.000	.789
VAR00007	1.000	.850

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.462	57.692	57.692	3.462	57.692	57.692	2.581	43.015	43.015
2	1.005	16.747	74.439	1.005	16.747	74.439	1.885	31.423	74.439
3	.540	9.004	83.443						
4	.370	6.162	89.605						
5	.330	5.504	95.110						
6	.293	4.890	100.000						

Extraction Method: Principal Component Analysis.

Rotated Component Matrix[a]

	Component 1	Component 2
VAR00001	.847	
VAR00002	.657	
VAR00004	.871	
VAR00005	.716	
VAR00006		.794
VAR00007		.920

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 3 iterations.

Figure 5.35. PCA results for occupational health and safety-IV.

After re-running the test (in Figure 5.35), our analysis has led us to identify two new subfactors, adding up to a total of three subfactors. The breakdown is as follows:

(i) Subfactor-1: This subfactor includes variables Var1, Var2, Var10, and Var11 from the initial dataset.

(ii) Subfactor-2: This subfactor consists of variables Var13 and Var16 from the initial dataset.

(iii) Subfactor-3: This subfactor comprises variables Var7 and Var12 from the initial dataset.

Through this re-analysis, we have effectively divided the original subfactor into three distinct and meaningful subfactors, each representing a specific set of variables with shared characteristics. This subdivision enhances our understanding of the underlying constructs and enables us to glean deeper insights into the interrelationships among the variables in the survey.

We will conduct a final check before re-naming the new subfactors.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.775
Bartlett's Test of Sphericity	Approx. Chi-Square	141.201
	df	6
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.679
VAR00002	1.000	.641
VAR00003	1.000	.696
VAR00004	1.000	.702

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.717	67.937	67.937	2.717	67.937	67.937
2	.601	15.032	82.970			
3	.354	8.840	91.809			
4	.328	8.191	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
VAR00001	.824
VAR00002	.801
VAR00003	.834
VAR00004	.838

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.36. PCA results for occupational health and safety-V.

Based on the results (in Figure 5.36) of the new subfactor-1 analysis, we achieved a commendable Kaiser-Meyer-Olkin (KMO) value of 0.775, indicating the high suitability and validity of the new subfactor structure for further considerations. The one-component nature of subfactor-1 reinforces its coherence and meaningfulness.

Upon a thorough examination of the variables (questions) constituting subfactor-1, we have opted to name it "Occupational Safety Rules & Regulations". The name aptly reflects the underlying construct that this subfactor represents, emphasizing the focus on ensuring a safe and secure work environment for employees.

Similarly, subfactor-2 is appropriately named "Occupational Safety Applications". This title reflects the subfactor's role in encompassing various practices, initiatives, and applications aimed at promoting health and safety in the workplace.

As for subfactor-3, it is aptly named "Employee Health Problems". This name accurately reflects the subfactor's focus on identifying and addressing health issues and challenges faced by employees within the work setting.

The detailed structure of the revised survey, encompassing the new subfactors and their constituent variables, can be found in Appendix A. This restructuring facilitates a more refined and comprehensive assessment of the underlying constructs and contributes to a deeper understanding of the relationships between the variables under investigation.

5.4.4.10. SC for Work Environment and Occupational Safety. To acquire more dependable information concerning the subfactors associated with the two variables, Spearman's correlation will be employed in conjunction with PCA.

Occupational safety applications subfactor: Spearman's Correlation and PCA results of "occupational safety applications" subfactor are as in Figure 5.37.

Correlations

			VAR00006	VAR00007
Spearman's rho	VAR00006	Correlation Coefficient	1.000	.612**
		Sig. (2-tailed)	.	<.001
		N	88	88
	VAR00007	Correlation Coefficient	.612**	1.000
		Sig. (2-tailed)	<.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.37. SC results for occupational safety applications.

Based on the data presented in the preceding table, a notable correlation (significant at the 0.01 level) is observed between the two non-normal variables representing "Occupational Safety Applications". This significant correlation indicates that these two variables are well-suited to be considered as part of the same subfactor. This finding serves as compelling evidence in support of the construct validity of the relevant section of our survey.

The observed strong, positive correlation between these variables bolsters the argument for a meaningful and substantive relationship between them. This finding not only strengthens the credibility and reliability of the survey's ability to capture the underlying construct but also validates the rationale behind including these variables within the same subfactor. This convergence of evidence suggests that the chosen subfactor effectively captures a coherent and unified concept, paving the way for confident analysis and interpretation of the data.

The figure below presents the outcomes of Principal Component Analysis (PCA). It's crucial to acknowledge that, while statistical uncertainty may arise when employing PCA with only two variables, the analysis can still offer valuable insights into the underlying relationship between these variables. This understanding can serve as a valuable starting point for further investigation or inform decision-making processes.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	44.472
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00006	1.000	.818
VAR00007	1.000	.818

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.637	81.842	81.842	1.637	81.842	81.842
2	.363	18.158	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00006	.905
VAR00007	.905

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.38. PCA results for occupational safety applications.

The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

Employee health problems subfactor: Spearman's Correlation and PCA results of the "employee health problems" subfactor are as in Figure 5.39.

Correlations

			VAR00001	VAR00002
Spearman's rho	VAR00001	Correlation Coefficient	1.000	.343**
		Sig. (2-tailed)	.	.001
		N	88	88
	VAR00002	Correlation Coefficient	.343**	1.000
		Sig. (2-tailed)	.001	.
		N	88	88

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5.39. Spearman's correlation results for employee health problems.

The result serves as compelling evidence supporting the construct validity of the relevant section of our survey. This outcome further validates the coherence and appropriateness of including these variables within the same subfactor for further analysis and interpretation.

The Figure 5.40 below depicts the outcomes of PCA which still provide valuable insights into the relationship between these two variables.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	12.605
	df	1
	Sig.	<.001

Communalities

	Initial	Extraction
VAR00001	1.000	.685
VAR00002	1.000	.685

Extraction Method: Principal Component Analysis.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.370	68.512	68.512	1.370	68.512	68.512
2	.630	31.488	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
VAR00001	.828
VAR00002	.828

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 5.40. PCA results for employee health problems.

The outcomes of this analysis support the validity of our survey structure, particularly regarding the relevant subfactor under examination.

5.4.5. Results of the Actual Actual Study

The subsequent Table 5.7 illustrates the condensed overview of all principal factors and subfactors concerning PCA, Spearman's Correlation, and Reliability.

Table 5.7. Validity and reliability results of the developed questionnaire.

FACTOR	Subfactor	Variable	KMO Value	Spearman's Correlation	p-Value	Cronbach's Alpha	Overall CA Value
EMPLOYEE	Education, Knowledge and Skills	Var1	0.772	-		0.792	0.953
		Var2					
		Var3					
		Var4					
	Physical Characteristics	Var1	-	0.537	<0.001	0.699	
		Var2					
	Psychological Characteristics	Var1	0.573	-		0.71	
		Var2					
		Var3					
	Motivation and Needs	Var1	0.834	-		0.843	
		Var2					
		Var3					
		Var4					
		Var5					
		Var6					
		Var7					
	Employee Performance	Var1	0.616	-		0.716	
		Var2					
		Var3					
TASK	Content, Requirements, Challenges, and Skills	Var1	0.748	-		0.754	
		Var2					
		Var3					
		Var4					
	Autonomy, Job Control, and Participation	Var1	-	0.355	0.001	0.702	
		Var2					
TECHNOLOGY	Information Technology	Var1	0.702	-		0.846	
		Var2					
		Var3					
	Advanced Manufacturing Technologies	Var1	-	0.69	<0.001	0.852	
		Var2					
	HR Characteristics in Technology and Tools	Var1	-	0.402	<0.001	0.716	
		Var2					
ORGANIZATION	Team Work	Var1	-	0.469	<0.001	0.745	
		Var2					
	Organizational Culture	Var1	0.673	-		0.694	
		Var2					
		Var3					
	Coordination, Collaboration, and Communication	Var1	0.825	-		0.799	
		Var2					
		Var3					
		Var4					
		Var5					
	Supervision and Management Styles	Var1	0.784	-		0.864	
		Var2					
		Var3					
		Var4					
		Var5					
		Var6					
	Performance Evaluation, Rewards, Incentives	Var1	-	0.458	<0.001	0.695	
		Var2					
	Work Schedule	Var1	0.598	-		0.759	
		Var2					
		Var3					
WORK ENVIRONMENT AND OCCUPATIONAL SAFETY	Facility Layout and Conditions	Var1	0.569	-		0.72	
		Var2					
		Var3					
		Var4					
	Occupational Safety Rules &Regulations	Var1	0.775	-		0.842	
		Var2					
		Var3					
		Var4					
	Occupational Safety Applications	Var1	-	0.612	<0.001	0.778	
		Var2					
	Employee Health Problems	Var1	-	0.343	0.001	0.737	
		Var2					

The outcomes presented in Table 5.7 reveal that all survey data utilized in PCA are suitable for analysis. As a result, the structural alterations made within the survey hold statistical validity and significance. Furthermore, the Spearman's correlation outcomes for subfactors involving two variables indicate a statistically significant correlation between these variables[2] , rendering the assumption that they represent the same subfactor reasonable. The PCA results obtained for the same factors also support this inference. Hence, both Spearman's correlation and PCA results collectively affirm the validity of the structure for these specific subfactors.

Ultimately, the CA (Component Analysis) results confirm the survey's reliability, meeting the threshold value of 0.7. Consequently, we can now place confidence in the findings of the case study, allowing for a macroergonomic perspective on the target company. Through the application of the proposed formula, we can explore improved alternatives.

5.4.6. Macroergonomic Evaluation of the Selected Manufacturing Company

The Table 5.8 presented here serves as a visual representation of the deficiencies identified within the surveyed organization in terms of macroergonomic factors and their corresponding subfactors. It summarizes data representing the average responses of all survey respondents to specific variables or questions under review. This holistic assessment sheds light on existing deficiencies within the company's macroergonomic framework and provides valuable insight into areas ripe for improvement or intervention.

In essence, this table provides a synthesized view of the company's macroergonomic performance. It distills insights from the collective input of all survey respondents, providing a clear and informative snapshot of the organization's strengths and weaknesses across a spectrum of macroergonomic factors.

[2]Each variable corresponds to a question in the survey.

Table 5.8. Average results for the target company.

Factor	**Subfactor**	**Questions**	**Mean Value for LS**
EMPLOYEE	**Education, Knowledge and Skills**	Training activities are periodically updated and implemented.	2.92
		Organized trainings compensate for the lack of skills and knowledge of the employees.	3.09
		Managers know the training and information needs of employees.	3.07
		Employees are trained on legal regulations related to their work.	2.93
	Physical Characteristics	Jobs based on physical strength are given to physically fit persons.	3.56
		The reasons for the work-related physical complaints of the employees are analyzed and tried to be resolved.	3.19
		Whenever possible, the company analyzes and tries to resolve the causes of employees' psychological complaints.	2.99

Table 5.8. Average results for the target company. (cont.)

	Psychological Characteristics	Employees have self-confidence in solving problems.	3.73
		Social relations between employees are good.	3.63
	Motivation and Needs	Employee morale and motivation are high.	3.01
		Working conditions and working environment increase the morale and motivation of the employees.	2.92
		Employees are satisfied with their wages.	2.44
		The work they do is professionally and personally developing the employees.	3.49
EMPLOYEE		Employees' achievements are rewarded.	2.81
		Employees are willing to take responsibility.	3.36
		My job is pretty monotonous and boring.	3.86
	Employee Performance	Leaving the job and absenteeism are very few.	2.93
		In job tasks, employee-related errors are rare.	3.28
		Employee performance is generally high.	3.44

Table 5.8. Average results for the target company. (cont.)

TASK	**Content, Requirements, Challenges, and Skills**	My job puts a lot of psychological pressure on me.	3.02
		My workload is too heavy (either physically or mentally).	2.78
		I am usually extremely tired after work.	2.67
		My job requires me to work very fast.	2.82
	Autonomy, Job Control, and Part.	Employees can make critical decisions regarding their jobs.	3.65
		The recommendations of the employees are taken into account by the managers.	3.42
TECHNOLOGY	**Information Technology**	Our company has a pretty good communication network (email, text, phone, etc.)	3.83
		Our company uses the software it needs.	3.82
		The software used in the company is up-to-date.	3.81
		Employees use advanced tools and equipment in their work.	3.61

Table 5.8. Average results for the target company. (cont.)

TECHNOLOGY	**Adv. Manufacturing Technologies**	Our company follows technology closely and is willing to implement new technologies.	3.66
	HR Characteristics in Tech. and Tools	Employees receive the necessary training and certificates for using technological devices and tools.	3.34
		The company conducts periodic controls to identify technology-based training needs.	2.95
ORGANIZATION	**Team Work**	The company encourages and supports teamwork.	3.57
		Teamwork has an important place in the performance evaluation system.	3.28
		Employees feel like family members in the company.	3.49
	Organizational Culture	Managers encourage employees to take risks and be open to extraordinary ideas.	3.23
		Employees can hold meetings to discuss any issue.	3.92

Table 5.8. Average results for the target company. (cont.)

ORGANIZATION	**Coordination, Collaboration, and Communication**	Employees are informed without delay on all matters concerning them.	3.14
		Employee cooperation is encouraged and rewarded.	2.86
		There is a system where employees can report the problems they encounter.	2.88
		The problems reported by the employees are responded to without delay.	2.89
		The participation and contribution of employees in the identification and solution of problems is encouraged.	3.31
	Supervision and Management Styles	Employees are observed and directed to improve their performance.	3.09
		Employee suggestions are welcomed by managers.	3.30
		Managers build teams suitable for the job and motivate them for success.	3.28

Table 5.8. Average results for the target company. (cont.)

ORGANIZATION	**Supervision and Management Styles**	Managers always provide support, direction and inspiration for the professional and personal development of employees.	3.20
		Managers do not discriminate among employees and act fairly.	3.55
		Managers treat their employees with respect.	3.85
	Performance Evaluation, Rewards, Incentives	The company gives incentive awards in order to increase the motivation and performance of the employees.	2.40
		Employees who are successful are more likely to be promoted or receive a higher pay raise.	3.01
	Work Schedule	In the company, there is no time pressure on the work schedules.	2.75
		Employees know their work schedule and upcoming tasks.	3.68
		Jobs usually do not require overtime.	3.20
		Facility layout is appropriate for interdepartmental workflow.	3.06

Table 5.8. Average results for the target company. (cont.)

Work Environment and Occupational Safety	**Facility Layout and Conditions**	The working environment is always kept neat and clean.	3.90
		After each tool and equipment is used in the working environment, it is put back in a ready-to-use form.	3.75
		The company implements planned maintenance to prevent breakdowns.	3.38
	Occupational Safety Rules & Regulations	The company has an occupational health and safety program.	3.92
		The company is fully prepared for emergencies.	3.69
		There is necessary personal protective equipment (such as earplugs, gloves, and glasses) in the work environment.	3.88
		Employees use personal protectors when necessary.	3.73
		Employees comply with occupational health and safety rules.	3.80

Table 5.8. Average results for the target company. (cont.)

Work Environment and Occupational Safety	**Occupational Safety Applications**	Employees contribute to solving occupational health and safety problems.	3.32
	Employee Health Problems	The dimensions of some workstations are not suitable for some employees.	3.18
		Among the employees, musculoskeletal disorders (disc herniation, neck hernia, tendinitis, carpal tunnel syndrome, etc.) are seen.	3.05

The values[3] under the threshold signal the areas in which the company should enhance its applications. The designated threshold value of 3.5 has been established in consultation with experts. During the computation of information values, questions scoring above 3.5 will not be included in the analysis. Our attention will solely be directed towards addressing the areas that present challenges. The survey results reveal that the company demonstrates strong performance in the realms of Information Technology. Advanced Manufacturing Technologies and Occupational Safety Rules & Regulations. Conversely, substantial challenges are evident within the domains of the Employee, Task, and Organization factors.

5.4.6.1. Information Value Calculation Approach. For each factor, we will propose two distinct alternatives to address the identified shortcomings. Subsequently, we will compute their respective information values to determine the more appropriate choice between the two. To compute the information values, it is essential to initially establish

[3]LS: Likert Scale

the design and system ranges. The subsequent example (in Table 5.9) elucidates the rationale employed in this study.

Example: Let's explain the calculation rationale behind the information value on "Training activities are periodically updated and implemented" variable.

Table 5.9. Rationale employed for information value.

	Desired Level		Alternative-1		Alternative-2	
QUESTIONS	**Lower**	**Upper**	**Lower**	**Upper**	**Lower**	**Upper**
Training activities are periodically updated and implemented.	40	50	35	45	30	45

With respect to AD, the term Desired Level represents the design range for the relevant variable. This range, determined through expert consultation, is set at 4-5 in our study. This signifies that while enhancing our processes and organizational structure, we aspire to achieve a level between 4 and 5 for each component.

Please be aware that the provided values have been adjusted to 40-50. This minor modification is aimed at rendering our formula applicable to this particular case study. Through multiple iterations, we have determined that to effectively employ our suggested formula within a Likert scale context, the resultant outcomes should be multiplied by a factor of 10.

The range pertains to the alternatives derived from input provided by 4 separate experts (three of them are senior managers, one of them is macroergonomist). These experts independently assessed the provided alternatives with regards to each component, without being privy to each other's evaluations. The system range for the proposed alternatives is established by utilizing the lowest and highest values provided by these experts.

The common ranges for the given example: Alternative-1: 45-40 (5 units) and Alternative-2: 45-40 (5 units).

With the adjustments and considerations in place, we are now prepared to apply our proposed formula

$$I_i = log_2(\frac{SR}{CR}) + log_2(1 + (SM - DM)^2) + log_2(SR) \quad (5.14)$$

to the case study.

Steps for the calculation approach are as follows:

(i) Identify the company's areas of weakness in the context of Macroergonomics by calculating the average of responses for each variable and identifying variables with an average score below 3.5.

(ii) Collaborate with experts to determine the design ranges (ranges that signify variable satisfaction in terms of macroergonomics). Two macroergonomists were consulted to establish a desired range for achieving satisfaction with macroergonomic factors.

(iii) Find alternative solutions (at least two) for each macroergonomic factor.

(iv) Establish the system ranges for each alternative by seeking input from experts on a scale of 10 to 50. Four experts were consulted to assess each alternative concerning each variable, and the system ranges were determined based on the minimum and maximum values provided by these experts.

(v) Calculate the information values for each variable by using the proposed formula and determined design and system ranges.

(vi) Calculate the cumulative information values for each alternative concerning each factor. Exclude the variables with an average score above 3.5, as defined in Step 1, and omit them from the information value calculation.

(vii) Identify the optimal alternatives by considering their cumulative information values.

5.4.7. Macroergonomic Alternatives Determined for the Case Study

The following topics are alternatives determined to satisfy the each macroergonomic factor for the case study company.

5.4.7.1. Alternatives for Employee Factor. In the context of this study, the following two alternatives related to employee factor are determined.

Talent Development-Oriented HR Style: The Talent Development-Oriented HR Style is an approach to human resource management that places a strong emphasis on developing the skills, knowledge, and potential of employees. This HR style recognizes that investing in talent development not only benefits individual employees but also contributes to the overall growth and success of the organization. The focus is on providing learning opportunities, fostering a culture of continuous improvement, and aligning individual development with the organization's strategic goals [172].

Key features of talent development-oriented HR style are as follows:

- Comprehensive Training and Development Programs: The HR department designs and implements a wide range of training and development programs to enhance employees' skills and knowledge in their respective roles.
- Individual Development Plans: HR collaborates with employees to create personalized development plans that align with their career aspirations.
- Performance-Based Learning: The HR style incorporates performance-based learning, where employees have the opportunity to apply newly acquired skills and knowledge in their day-to-day tasks.
- Learning Culture: The organization fosters a learning culture that encourages employees to actively seek continuous learning opportunities and share knowledge with colleagues.
- Leadership Development: Talent Development-Oriented HR focuses on developing leaders at all levels of the organization, providing leadership training and coaching to support career progression.
- Mentorship and Coaching: HR facilitates mentorship and coaching programs to provide guidance and support to employees in their career development journey.
- Recognition of Learning and Achievements: The HR style acknowledges and celebrates employees' learning achievements, reinforcing a sense of accomplishment and motivating further development.

Benefits of talent development-oriented HR style are as follows:

- Enhanced Employee Performance: By investing in talent development, employees acquire new skills and knowledge that contribute to improved performance and job competence.
- Increased Employee Engagement: A focus on talent development signals that the organization values employees' growth and development, leading to higher levels of engagement and commitment.
- Talent Retention: Employees are more likely to stay with an organization that invests in their development and provides opportunities for career advancement.
- Succession Planning: A talent development-oriented approach ensures a pipeline of skilled and capable employees ready to take on future leadership roles.
- Adaptability and Innovation: Employees with diverse skills and a strong learning mindset are better equipped to adapt to changing business environments and drive innovation.

Overall, the Talent Development-Oriented HR Style fosters a culture of continuous learning and growth, empowering employees to reach their full potential and contribute effectively to the organization's success. By aligning individual development with strategic goals, this HR style nurtures a skilled and engaged workforce, creating a competitive advantage for the organization in the long run [172].

Employee-Centric HR: Employee-Centric HR places employees at the center of HR practices and policies, recognizing that engaged and satisfied employees are more likely to contribute to the success of the organization [173]. This approach prioritizes the well-being and development of employees while also fostering a positive work culture.

Key aspects of employee-centric HR include:

- Employee Experience: Focusing on creating a positive employee experience by understanding employee needs, expectations, and pain points throughout their journey in the organization.

- Work-Life Balance: Promoting work-life balance through flexible work arrangements, paid time off, and employee wellness initiatives.
- Personal Development: Offering opportunities for professional and personal growth through training, mentoring, and career advancement programs.
- Recognition and Rewards: Implementing a robust recognition and rewards system to acknowledge and appreciate employee contributions.
- Employee Feedback: Encouraging regular feedback from employees to understand their concerns and suggestions, and acting upon this feedback to drive continuous improvement.

5.4.7.2. Alternatives for Task Factor. In the context of this study, the following two alternatives related to task factor are determined.

Kanban Task Management: Kanban is a task management approach that visualizes workflow and focuses on continuous delivery. It involves using a Kanban board to visualize tasks and their progress through various stages [174].

Some key elements of Kanban task management include:

- Visualizing Tasks: Representing tasks as cards on a Kanban board, with columns representing different stages of the workflow (e.g., To Do, In Progress, Done).
- Work in Progress (WIP) Limits: Setting limits on the number of tasks allowed in each column to prevent overloading team members and maintain a steady flow of work.
- Continuous Improvement: Regularly reviewing the workflow and identifying bottlenecks or areas for improvement to enhance efficiency.
- Pull System: Emphasizing a pull system, where team members pull tasks from the "To Do" column when they have capacity, rather than being assigned tasks.
- Visual Metrics: Using visual indicators or metrics (e.g., cycle time, lead time) to measure and monitor task progress and team performance.

Agile Task Management: Agile task management is an approach to managing and organizing tasks within a project using the principles of Agile methodology. Agile is a software development framework that emphasizes iterative development, flexibility, collaboration, and customer feedback. While initially designed for software development, Agile principles have found applications in various industries and project types beyond software development [175].

In the context of task management, Agile focuses on breaking down work into smaller, manageable tasks and completing them in short iterations called sprints or iterations. Agile task management promotes continuous improvement, adaptability, and transparency throughout the project lifecycle [175].

Here are some key aspects of agile task management:

- User Stories and Backlog: Instead of traditional detailed requirements, Agile task management often relies on user stories, which are brief, customer-centric descriptions of desired functionality. These user stories are organized in a backlog.
- Sprint Planning: At the beginning of each sprint (typically 1-4 weeks long), the team selects a set of tasks from the backlog to work on. The team collaboratively decides how many tasks they can complete during the sprint.
- Task Breakdown: During sprint planning or at the start of each sprint, the selected user stories are broken down into smaller tasks that can be completed within the sprint duration.
- Sprint Review and Retrospective: At the end of the sprint, the team holds a sprint review to demonstrate the completed tasks to stakeholders. Following the review, they conduct a sprint retrospective to discuss what went well and identify areas for improvement in the next sprint.
- Continuous Adaptation: Agile task management embraces change and encourages continuous adaptation to evolving requirements, customer feedback, and project realities.
- Visual Management: Many Agile teams use visual management tools like Kanban boards or task boards to visualize the progress of tasks throughout the project.

The benefits of Agile task management are as follows:

- Increased flexibility and responsiveness to changes.
- Enhanced collaboration among team members and stakeholders.
- Frequent delivery of tangible results and value to customers.
- Improved transparency and visibility into project progress.
- Opportunities for continuous improvement and learning.

Overall, agile task management helps teams deliver high-quality work in a collaborative, customer-focused, and adaptable manner. It promotes efficiency, empowers teams, and fosters a culture of open communication and learning [175].

5.4.7.3. Alternatives for Technology Factor. In the context of this study, the following two alternatives related to technology factor are determined.

Innovation-Driven Technology Management: Innovation-driven technology management emphasizes the strategic use of technology to foster innovation and drive competitive advantage for the company. This approach places a strong focus on leveraging technology to develop new products, services, and business processes [176].

Key elements of this style include:

- Research and Development (R & D) Investment: Allocating significant resources to research and development activities to continuously explore new technological opportunities and stay ahead of market trends.
- Open Innovation: Collaborating with external partners, startups, and research institutions to co-create and integrate cutting-edge technologies into the company's offerings.
- Agile Development: Adopting agile methodologies to quickly develop and iterate technology solutions, allowing for rapid prototyping and adaptation to customer feedback.

- Technology Scouting: Proactively scanning the technology landscape to identify emerging technologies that can be harnessed to drive innovation within the company.
- Cultivating an Innovation Culture: Encouraging a culture of creativity and risk-taking, where employees are empowered to experiment and propose innovative technology solutions.

Sustainable Technology Management: Sustainable technology management emphasizes the responsible and ethical use of technology to achieve long-term environmental, social, and economic sustainability. This approach focuses on adopting technology solutions that minimize environmental impact, enhance social well-being, and ensure economic viability [177].

Key aspects of this style include:

- Environmental Impact Assessment: Evaluating the environmental footprint of technology initiatives and striving to adopt energy-efficient, eco-friendly technologies.
- Corporate Social Responsibility (CSR): Aligning technology management practices with the company's CSR goals, such as promoting digital inclusion, diversity, and ethical supply chain management.
- Circular Economy Approach: Embracing a circular economy model by designing technology products for reuse, recycling, and extended product life cycles.
- Energy Conservation: Implementing energy-saving measures in data centers, IT infrastructure, and operational processes to reduce the company's carbon footprint.
- Socially Responsible Technology Deployment: Ensuring that technology is used responsibly, respecting user privacy, data security, and adhering to ethical AI and automation principles.

Sustainable technology management not only benefits the environment and society but also enhances the company's reputation and brand value, attracting environmentally conscious customers and investors. It demonstrates the company's commitment to making a positive impact on the world while leveraging technology for its business goals [177].

5.4.7.4. Alternatives for Organization Factor. In the context of this study, the following two alternatives related to organization factor are determined.

Team-Centered Management: Team-centered management is an approach to organizational management that places a strong emphasis on collaboration, empowerment, and shared decision-making within teams. This management style recognizes the value of teams as the driving force behind achieving organizational goals and fosters a culture of mutual support and accountability [178]. The focus is on creating an environment where teams have the autonomy to make decisions, innovate, and take ownership of their work.

Key features of team-centered management are as follows:

- Self-Managed Teams: The organization creates self-managed teams that have the authority to plan, execute, and evaluate their work independently, fostering a sense of ownership and responsibility.
- Participative Supervision: Team leaders act as facilitators and collaborators, encouraging team members to actively participate in decision-making and problem-solving processes.
- Transformational Leadership: Leaders adopt a transformational leadership style, inspiring and motivating teams to achieve their goals through a shared vision and values.
- Collaborative Performance Evaluation: Performance evaluations involve input from team members themselves, as well as peer feedback, to create a 360-degree view of team performance.
- Team-Based Rewards: Recognition and rewards are based on team achievements and contributions, reinforcing the value of collaboration and collective success.

- Flexibility and Adaptability: Team-Centered Management allows teams to be flexible and adaptive, making real-time adjustments to projects and priorities based on changing circumstances.
- Transparent Communication: Open and transparent communication channels are encouraged to promote sharing of ideas, feedback, and concerns among team members and with leadership.

Benefits of team-centered management are as follows:

- Increased Team Cohesion: The collaborative nature of this management style fosters stronger team cohesion and trust, leading to improved team dynamics and cooperation.
- Enhanced Innovation: Teams are empowered to innovate and bring fresh perspectives to problem-solving, leading to increased creativity and innovation within the organization.
- Higher Employee Engagement: Empowering employees through self-management and participation in decision-making enhances their sense of ownership and engagement.
- Faster Decision-Making: Teams can make faster decisions and take immediate action, reducing bureaucratic delays and improving overall organizational agility.
- Improved Problem-Solving: The diverse skills and perspectives within teams lead to more effective problem-solving and the ability to tackle complex challenges.
- Personal and Professional Growth: Team members have the opportunity to develop leadership and collaboration skills, contributing to their personal and professional growth.

Overall, team-centered management empowers teams to be the drivers of organizational success, fostering a culture of collaboration, innovation, and accountability. By nurturing a supportive and inclusive work environment, this management style unlocks the full potential of employees and drives organizational performance to new heights [178].

Servant Leadership Management: Servant leadership management is an approach to leadership and organizational management that prioritizes the well-being and development of employees. In this management style, leaders view themselves as servants to their teams, focusing on supporting and empowering employees to reach their full potential. The goal is to create a positive work environment that fosters collaboration, trust, and personal growth [179].

Key features of servant leadership management are follows:

- Empowering Leadership: Servant leaders empower employees by delegating authority and providing the necessary resources and support to excel in their roles.
- Coaching and Mentoring: Servant leaders offer coaching and mentoring to employees, guiding their professional growth and development.
- Transformational Supervision: Servant leaders adopt a transformational leadership style, inspiring and influencing employees to achieve their goals and embrace organizational values.
- Individual Performance Evaluation: Performance evaluations focus on employees' strengths and areas for development, encouraging a growth-oriented approach to performance management.
- Personalized Rewards: Rewards and recognition are tailored to individual employees' contributions and achievements, acknowledging their unique talents and efforts.
- Work-Life Integration: Servant Leadership Management recognizes the importance of work-life balance, promoting flexible work arrangements to support employees' well-being.
- Facilitative Coordination: Servant leaders use facilitative coordination to encourage open communication and collaboration among team members.
- Active Listening and Feedback: Servant leaders emphasize active listening and provide regular feedback to create a supportive and transparent communication culture.

Benefits of servant leadership management are as follows:

- Enhanced Employee Engagement: Employees feel valued and supported under servant leaders, leading to higher levels of engagement and commitment to the organization.
- Increased Job Satisfaction: The focus on employee well-being and personal growth contributes to higher job satisfaction and a positive work environment.
- Improved Team Collaboration: Servant leaders foster a collaborative work culture, where employees feel comfortable sharing ideas and working together toward common goals.
- Higher Employee Retention: The supportive and empowering nature of servant leadership enhances employee loyalty and reduces turnover rates.
- Fostered Creativity and Innovation: Servant leaders encourage employees to think creatively and take calculated risks, driving innovation and continuous improvement.
- Positive Organizational Culture: Servant Leadership Management cultivates a positive and inclusive organizational culture, strengthening the sense of belonging among employees.
- Employee Development: Employees benefit from the coaching and mentoring provided by servant leaders, leading to continuous personal and professional growth.

By fostering servant leadership management, organizations can cultivate a nurturing environment where employees feel valued, empowered, and intrinsically motivated to contribute their best efforts and full potential to the organization's success. By prioritizing employee well-being and personal growth, servant leaders cultivate a culture of trust, collaboration, and resilience, fostering a high-performing workforce [179].

5.4.7.5. Alternatives for Work Environment Factor. As part of this study, two distinct and promising alternatives have emerged for further investigation, offering the potential to positively impact both the work environment and occupational safety considerations.

Ergonomics-Driven Work Environment: Ergonomics-driven work environment is an approach that places a strong emphasis on designing workspaces, tools, and processes to optimize the well-being, comfort, and efficiency of employees. The goal is to reduce physical strain, prevent injuries, and enhance overall productivity and job satisfaction. This work environment is based on the principles of ergonomics, which involves the study of human capabilities and limitations about work tasks [180].

Key features of ergonomics-driven work environment are as follows:

- Facility Layout and Conditions: The workspace is carefully designed to promote good posture and reduce the risk of musculoskeletal disorders. Workstations, chairs, and equipment are adjustable to accommodate different body sizes and preferences.
- Task Analysis: Job tasks and processes are analyzed to identify potential ergonomic risks and inefficiencies. Modifications are made to ensure that tasks are comfortable and aligned with human capabilities.
- Employee Training: Employees receive training on proper ergonomics techniques and work practices to minimize the risk of injuries and discomfort. They are educated on how to adjust their workstations and use equipment correctly.
- Ergonomic Equipment: Ergonomically designed equipment and tools are provided to enhance comfort and support for employees during their tasks.
- Regular Assessments: Periodic assessments of workstations and job tasks are conducted to ensure that ergonomic standards are maintained and any necessary adjustments are made.

Benefits of ergonomics-driven work environment are as follows:

- Improved Employee Health: By reducing physical strain and promoting proper posture, ergonomic work environments can lower the risk of musculoskeletal disorders and related health issues.
- Increased Productivity: Comfortable and efficient workspaces can lead to higher productivity levels, as employees can work more comfortably and reduced fatigue.

- Enhanced Job Satisfaction: Employees appreciate a work environment that considers their well-being and comfort, leading to higher job satisfaction and morale.
- Lower Absenteeism and Turnover: A healthier and more comfortable work environment can result in reduced absenteeism and lower turnover rates.
- Reduced Workplace Injuries: Ergonomic adjustments can minimize the risk of workplace injuries, contributing to a safer work environment.

Overall, an ergonomics-driven work environment prioritizes employee health and well-being, leading to a more engaged and productive workforce. By creating workspaces that align with human capabilities, companies can foster a positive and supportive work environment while enhancing overall organizational performance [180].

Wellness-Centered Work Environment: A wellness-centered work environment is an approach to organizational management that prioritizes the health, well-being, and overall quality of life of employees. This management style recognizes that employee well-being directly impacts productivity, job satisfaction, and organizational success. The focus is on creating a supportive and positive work environment that promotes physical, mental, and emotional wellness [181].

Key features of wellness-centered work environment are as follows:

- Health and Wellness Programs: The organization offers a range of health and wellness programs, such as fitness classes and wellness workshops.
- Work-Life Balance: A Wellness-Centered Work Environment promotes work-life balance by offering flexible work arrangements, paid time off, and family-friendly policies.
- Stress Management Support: The organization provides resources and support for managing stress and maintaining emotional resilience, such as Employee Assistance Programs (EAPs) and counseling services.
- Healthy Workspaces: The physical work environment is designed to promote health and comfort, incorporating features like natural light, ergonomic furniture, and green spaces.

- Nutritional Support: The organization offers healthy food options, nutritional counseling, and wellness incentives to encourage healthy eating habits.
- Mental Health Initiatives: Wellness-Centered Work Environments prioritize mental health initiatives, reducing stigma, and providing resources for mental health support.
- Employee Engagement: The management style actively engages employees in wellness programs and encourages participation in wellness-related activities.

Benefits of wellness-centered work environment are as follows:

- Improved Employee Well-Being: Employees experience improved physical and mental well-being, leading to reduced absenteeism and higher productivity.
- Enhanced Job Satisfaction: A focus on wellness contributes to higher job satisfaction and a positive work culture.
- Increased Employee Retention: Employees are more likely to stay with an organization that prioritizes their well-being and offers comprehensive wellness programs.
- Healthier Lifestyle Choices: Employees are encouraged to adopt healthier lifestyle choices, leading to reduced health risks and healthcare costs.
- Greater Organizational Performance: A Wellness-Centered Work Environment leads to a more engaged and productive workforce, positively impacting overall organizational performance.
- Lower Workplace Stress: Stress management support and work-life balance initiatives help reduce workplace stress and burnout.
- Positive Employer Branding: Organizations that prioritize employee wellness gain a positive reputation as employers of choice, attracting top talent.

By cultivating and nurturing a wellness-centered work environment, organizations manifest their unwavering dedication to the welfare and health of their employees. In doing so, they establish a conducive and flourishing workspace that not only augments the well-being of their workforce but also significantly bolsters the overall health and prosperity of the organization as a whole. This approach to management extends its positive influence far beyond the individual, permeating throughout the organizational fabric to foster a culture of holistic health and success. [181].

Table 5.10 gives the detailed results for obtained information values of the conducted case study.

Table 5.10. Detailed information values for the alternative solutions.

				Desired Level		Talent Development-Oriented HR Style		Employee-Centric HR			
		QUESTIONS	Avg.	Lower	Upper	Lower	Upper	Lower	Upper	Information 1	Information 2
EMPLOYEE	Education, Knowledge and Skills	Training activities are periodically updated and implemented.	2.92	40	50	35	45	30	45	9.02	11.33
		Organized trainings compensate for the lack of skills and knowledge of the employees.	3.09	40	50	45	50	35	45	5.18	9.02
		Managers know the training and information needs of employees.	3.07	40	50	30	42	30	50	12.53	10.02
		Employees are trained on legal regulations related to their work.	2.93	40	50	40	45	30	45	5.18	11.33
	Physical Characteristics	The reasons for the work-related physical complaints of the employees are analyzed and tried to be resolved.	3.19	40	50	30	50	40	45	10.02	5.18
	Psychological Characteristics	Whenever possible, the company analyzes and tries to resolve the causes of employees' psychological complaints.	2.99	40	50	35	50	40	45	7.35	5.18
	Motivation and Needs	Employee morale and motivation are high.	3.01	40	50	35	43	45	50	9.62	5.18
		Working conditions and working environment increase the morale and motivation of the employees.	2.92	40	50	30	45	35	50	11.33	7.35
		Employees are satisfied with their wages.	2.44	40	50	30	45	30	45	11.33	11.33
		The work they do is professionally and personally developing the employees.	3.49	40	50	35	45	40	45	9.02	5.18
		Employees' achievements are rewarded.	2.81	40	50	40	50	30	45	3.32	11.33
		Employees are willing to take responsibility.	3.36	40	50	30	45	30	45	11.33	11.33
	Employee Performance	Leaving the job and absenteeism are very few.	2.93	40	50	25	41	30	50	15.18	10.02
		In job tasks, employee-related errors are rare.	3.28	40	50	35	45	30	42	9.02	12.53
		Employee performance is generally high.	3.44	40	50	40	45	30	45	5.18	11.33
				GRAND TOTAL of INFORMATION VALUE						134.63	137.65

Table 5.10. Detailed information values for the alternative solutions. (cont.)

				Desired Level		Agile Task Management		Kanban Task Management			
				Lower	Upper	Lower	Upper	Lower	Upper		
TASK	Content, Requirements, Challenges, and Skills	My job puts a lot of psychological pressure on me.	3.02	40	50	30	42	30	42	12.53	12.53
		My workload is too heavy (either physically or mentally).	2.78	40	50	30	41	30	45	13.43	11.33
		I am usually extremely tired after work.	2.67	40	50	30	45	30	45	11.33	11.33
		My job requires me to work very fast.	2.82	40	50	30	45	30	50	11.33	10.02
	Autonomy, Job Control, and Participation	The recommendations of the employees are taken into account by the managers.	3.42	40	50	40	45	25	45	5.18	12.98
				GRAND TOTAL of INFORMATION VALUE						53.8	58.19
				Desired Level		Innovation-Driven Technology Management		Sustainable Technology Management			
				Lower	Upper	Lower	Upper	Lower	Upper		
TECHNOLOGY	HR Characteristics in Technology and Tools	Employees receive the necessary training and certificates for using technological devices and tools.	3.34	40	50	40	50	35	42	3.32	10.05
		The company conducts periodic controls to identify technology-based training needs.	2.95	40	50	40	50	35	45	3.32	9.02
				GRAND TOTAL of INFORMATION VALUE						6.64	19.07
				Desired Level		Ergonomics-Driven Work Environment		Wellness-Centered Work Environment			
				Lower	Upper	Lower	Upper	Lower	Upper		
WORK ENVIRONMENT AND OCCUPATIONAL SAFETY	Facility Layout and Conditions	Facility layout is appropriate for interdepartmental workflow and traffic.	3.06	40	50	35	43	35	45	9.62	9.02
		The company implements planned maintenance to prevent breakdowns.	3.38	40	50	38	45	35	45	7.02	9.02
	Occupational Safety Applications	Employees contribute to solving occupational health and safety problems.	3.32	40	50	35	45	40	45	9.02	5.18
	Employee Health Problems	The dimensions of some workstations are not suitable for some employees.	3.18	40	50	38	50	35	45	4.85	9.02
		Among the employees, musculoskeletal disorders (disc herniation, neck hernia, tendinitis, carpal tunnel syndrome, etc.) are seen.	3.05	40	50	40	50	35	50	3.32	7.35
				GRAND TOTAL of INFORMATION VALUE						33.84	39.6

Table 5.10. Detailed information values for the alternative solutions. (cont.)

				Desired Level		Team-Centered Management		Servant Leadership Management			
				Lower	Upper	Lower	Upper	Lower	Upper		
ORGANIZATION	Team Work	Teamwork has an important place in the performance evaluation system.	3.28	40	50	45	50	40	45	5.18	5.18
	Organizational Culture	Employees feel like family members in the company.	3.49	40	50	35	45	35	45	9.02	9.02
		Managers encourage employees to take risks and be open to extraordinary ideas.	3.23	40	50	40	45	40	45	5.18	5.18
	Coordination, Collaboration, and Communication	Employees are informed without delay on all matters concerning them.	3.14	40	50	40	45	40	45	5.18	5.18
		Employee cooperation is encouraged and rewarded.	2.86	40	50	45	50	35	45	5.18	9.02
		There is a system where employees can report the problems they encounter.	2.88	40	50	35	45	35	45	9.02	9.02
		The problems reported by the employees are responded to without delay.	2.89	40	50	30	45	35	42	11.33	10.05
		The participation and contribution of employees in the identification and solution of problems is encouraged.	3.31	40	50	30	45	40	45	11.33	5.18
	Supervision and Management Styles	Employees are observed and directed to improve their performance.	3.09	40	50	40	45	35	45	5.18	9.02
		Employee suggestions are welcomed by managers.	3.3	40	50	35	45	40	45	9.02	5.18
		Managers build teams suitable for the job and motivate them for success.	3.28	40	50	35	45	35	45	9.02	9.02
		Managers always provide support, direction and inspiration for the professional and personal development of employees.	3.2	40	50	35	45	45	50	9.02	5.18
	Performance Evaluation, Rewards, Incentives	The company gives incentive awards in order to increase the motivation and performance of the employees.	2.4	40	50	40	43	40	45	5.31	5.18
		Employees who are successful are more likely to be promoted or receive a higher pay raise.	3.01	40	50	30	42	45	50	12.53	5.18
	Work Schedule	In the company, there is no time pressure on the work schedules.	2.75	40	50	40	45	35	45	5.18	9.02
		Jobs usually do not require overtime.	3.2	40	50	30	42	35	42	12.53	10.05
				GRAND TOTAL of INFORMATION VALUE						129.22	115.67

Table 5.11. Summary results for the information values.

	Talent Development-Oriented HR Style	**Employee-Centric HR**
Employee	**134.63**	137.65
	Agile Task Management	**Kanban Task Management**
Task	**53.80**	58.19
	Innovation-Driven Technology Management	**Sustainable Technology Management**
Technology	**6.64**	19.07
	Team-Centered Management	**Servant Leadership Management**
Organization	129.22	**115.67**
	Ergonomics-Driven Work Environment	**Wellness-Centered Work Environment**
Work Environment and Occupational Safety	**33.84**	39.60

Preceding the analysis of the study's findings, we will elucidate each alternative in detail.

5.4.8. Interpretations of the Results

As we can see in Table 5.11, Talent Development-Oriented Human Resource Style obtained a more desirable result (134.63) compared to Employee-Centric Human Resource Style. The closeness in the calculated information values indicates that both alternatives are good at satisfying Employee factor of Macroergonomics.

By taking a closer look at each macroergonomic component, it can be seen the proposed formula chooses the better alternative.

Table 5.12. Example of formula performance.

	Desired Level		Talent Development-Oriented HR Style		Employee-Centric HR			
QUESTIONS	Lower	Upper	Lower	Upper	Lower	Upper	Information 1	Information 2
Training activities are periodically updated and implemented.	40	50	35	45	30	45	9.02	11.33

For example, the following illustration shows the relative positions of SR, DR, and CR of the given example (Table 5.12)

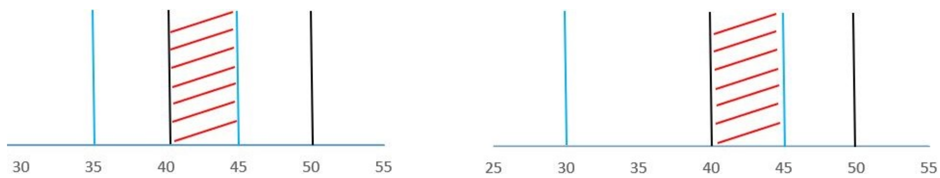


Figure 5.41. Illustration of the example.

As evident from the Figure 5.41 above, a notable alignment between SR and DR is observed for the first alternative, which our formula successfully identifies. This observation holds true for all components and the corresponding information value calculations. Additionally, it's important to note that the proposed formula has been assessed in extreme scenarios, as outlined in Section 4.5.2.

6. DISCUSSION

6.1. Proposed Reformulations of Axiomatic Design

As outlined by Suh [13], the initial information value formula presents certain shortcomings that hinder its intended functionality (refer to Section 4). The present study aimed to contribute to the field of axiomatic design by introducing a novel approach resulting reformulations of information axiom for both ergonomic and general designs.

The proposed first reformulation of information axioms brings solution to shortcoming of the application of original formula in ergonomics designs. The modified formula is tested and compared to the original formula as well as previously attempted reformulations.

The second formulation included the relative cost associated with non-optimal designs: Taguchi Loss function integrated with original information axiom worked better than the original formula for various cases.

It can be stated that the proposed formulas demonstrated their prowess by effectively addressing design and cost issues within a complex decision-making context.

The applicability of the proposed approach is also shown in the development of macroergonomic framework as a decision aid tool.

After comparing experts' judgments on the solution alternatives, the proposed formula is succeeded to reflect their opinions and helps the decision-making process in a methodological approach.

The results show that the Talent Development-oriented HR style (134.63) was slightly favorable than Employee-centric HR style (137.65). This is an expected result since, these two alternatives have capability of satisfying related variables, both ended with close results.

The results obtained for the Task factor alternatives indicate that Agile Task Management (53.8) is more favorable compared to Kanban Task Management (58.19). Despite both alternatives demonstrating proficiency in meeting the established variables, the deficiency of autonomy in Kanban Task Management renders Agile Task Management a superior choice.

Upon closer examination of the variables within the Technology factor, namely "Employees receive the necessary training and certificates for using technological devices and tools" and "The company conducts periodic controls to identify technology-based training needs," it becomes evident that Innovation-driven Technology Management holds a more potent advantage over Sustainable Technology Management. Since our focus is solely on the variables where the company exhibits weaknesses, opting for the first alternative becomes a logical choice. Consequently, Innovation-Driven Technology Management (6.64) gains a significant edge over Sustainable Technology Management (19.07).

As anticipated, the results align with the expectation that Servant Leadership Management surpasses Team-Centered Management in the domains of "Supervision and Management Styles" as well as "Performance Evaluation, Rewards, and Incentives."

The alternatives within the Work Environment and Occupational Safety factor exhibit both distinctions and shared attributes, resulting in closely aligned cumulative information values. While Ergonomics-Driven Work Environment (33.84) holds a slight edge over Wellness-Centered Work Environment (39.60).

The formula's adeptness in aligning System Range (SR) and Design Range (DR) was particularly noteworthy. This attribute was consistently observed across various components and their respective information value calculations, as evidenced by the findings in Section 4. Such alignment not only affirms the formula's ability to discern optimal alternatives accurately but also underscores its versatility and adaptability across diverse scenarios.

Furthermore, the proposed formula was tested in both conventional and extreme scenarios, as highlighted in Section 4. This rigorous evaluation affirms its robustness in not only normative conditions but also under the most challenging circumstances. This aspect of the formula is of paramount significance, as it reflects its practical utility in real-world decision-making scenarios that often involve uncertainties and complexities.

6.2. Developed Axiomatic Design based Macroergonomic Framework

In parallel to the proposed formula, the macroergonomic framework introduced in this study exhibited substantial promise. By incorporating multifaceted factors such as employee, task, technology, organization, and work environment, the framework extends beyond traditional paradigms of analysis. This holistic approach acknowledges the intricate interplay of these elements and recognizes that any comprehensive solution must consider their interconnectedness.

The framework, detailed in Section 5, is poised to drive improvements in various organizational domains. It guides the evaluation of macroergonomic factors, aiding organizations in identifying areas of strength and vulnerability. The holistic nature of the framework allows for a nuanced understanding of organizational dynamics, paving the way for targeted interventions that address deficiencies while leveraging strengths. As highlighted in the MEQ results, presented in Section 5.4.6, the framework aptly pinpointed the company's strong points in terms of Information Technology and Advanced Manufacturing Technologies, while also identifying critical shortcomings in Employee Engagement, Task Allocation, and Organizational Structure. This framework also enables companies to generate various alternatives and subsequently identify the most optimal choice among them.

In conclusion, the integration of the proposed formula and the macroergonomic framework presents a valuable contribution to the field of axiomatic design and macroergonomics. The formula's accuracy, adaptability, and resilience in the face of complexity elevate its potential for enhancing decision-making processes. Simultaneously, the macroergonomic framework's all-encompassing perspective highlights the interconnectedness of factors influencing organizational effectiveness. This study's findings underscore the potential for the proposed formula and macroergonomic framework to serve as valuable tools for practitioners, researchers, and decision-makers alike, promoting more informed and effective interventions within organizations.

7. CONCLUSION AND RECOMMENDATIONS

7.1. Conclusions

Based on the study objectives and the results, the following conclusions can be drawn:

(i) Suh´s information axiom formula is successfully reformulated so that it can be applied to ergonomic designs as well. This is an important contribution to ergonomic designs.
(ii) Information axiom formula is enhanced by considering the cost aspect of designs and decision-making. This is an important contribution to literature and axiomatic design.
(iii) By applying the enhanced information axiom formula, an axiomatic design based macroergonomic framework is developed for manufacturing companies. With this a new approach was successfully introduced in developing macroergonomic frameworks.

It is hoped that researchers and practitioners in the field of axiomatic design and design in general, ergonomists and decision-makers will benefit from the findings of this study.

7.2. Recommendations

Based on the insights derived from this study, several recommendations emerge that could further enhance the use of information axiom. These recommendations are intended to guide practitioners and researchers in being aware of the deficiencies of the current information axiom formula. Some key recommendations are:

(i) Although the proposed Formula-2 is more robust and reliable than Suh's formula, it is still not suitable for use in ergonomics domain. Instead, the proposed Formula-1 should be used for the ergonomic design evaluations.

(ii) For the purpose of this study, the Formula 2 is used for creating a macroergonomic framework for manufacturing companies. Indeed, the proposed Formula-2 can be used in many other areas and fields.

7.3. Limitations and Future Research

It is important to acknowledge the limitations of this study. Users of the enhanced information axiom (Formula 2) should be cautioned that; in some cases, the use of proposed Formula-2 requires data modifications to work. As shown in the case study, the Likert scale values multiplied by 10. Future study may address this limitation by a more robust formula in terms of data type/units.

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APPENDIX A: MACROERGONOMICS EVALUATION QUESTIONNAIRE

The following figures (Figure A.1-Figure A.21) show the structure of developed macroergonomic evaluation questionnaire (MEQ).

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

MacroErgonomics Evaluation Questionnaire (MEQ)

Dear Participant,

My name is Ömer Gündüz. I am a Ph.D. student at Boğaziçi University, Department of Industrial Engineering. Within the scope of my doctoral thesis, I would like to carry out this survey to determine the macroergonomics deficiencies (otherwise: organizational ergonomics) in enterprises with your contributions. I would appreciate it if you could help.

Macroergonomics helps company managers make critical decisions toward the company's strategic goals. For example, improving the performance of employees, correct and efficient use of technology and information, improving organizational structure and management style, company culture and company policies; creation of an efficient, healthy and safe work environment; customer satisfaction, etc.

This survey study is an important part of my doctoral thesis and I plan to make suggestions for the benefit of the industry as a result of the analysis and synthesis of the data to be obtained.

Please support this research with your participation. If you have any questions or concerns about this research, do not hesitate to contact me or my advisor. Survey results will be reported statistically.

I undertake in advance that I will comply with the law on the privacy and protection of personal data and that no personal information will be included in this regard. Also, if requested, I can share my updated CV for your reference.

Thanks in advance for your contribution.

Kind Regards,

Ömer GÜNDÜZ

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Figure A.1. Macroergonomic evaluation questionnaire-1.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

* Indicates required question

1. I have read the above statement and agree to participate in the research. *

   Mark only one oval.

   ◯ Yes, I accept.

   ◯ No, I do not accept.

General Instructions

Please read each item carefully. Answer the survey anonymously. For each jurisdiction, choose the option that best suits the company you work for.

The survey evaluation scale is as follows:

(1) I strongly disagree, (2) I do not agree, (3) I'm undecided, (4) I agree and (5)

I strongly agree.

· If you cannot participate in the survey on a computer, you can also participate on a personal or company phone (IOS or Android).

· A red asterisk (*) indicates mandatory response. If you do not answer the questions marked (*), you will receive an error message.

· This form consists of six parts: The first part of the form collects demographic and general employment information: *Gender, age, job position, seniority, and company name. Other sections collect information on the implementation of five critical macroergonomics factors (employee, task, technology, work environment-safety, and organization) in your company.

· At the end of the form, a privacy policy is shared for informational purposes. The estimated completion time of the form is **approximately 15 minutes**.

Demographic Information

2. Age

____

Figure A.2. Macroergonomic evaluation questionnaire-2.

3. Gender *

Mark only one oval.

- ◯ Male
- ◯ Female
- ◯ Prefer not to say
- ◯ Other: ____________

4. Which company are you currently working for? *

____

5. How many years are you in your current workplace? *

Mark only one oval.

- ◯ 1-5 years
- ◯ 6-10 years
- ◯ 11-15 years
- ◯ 16 or above

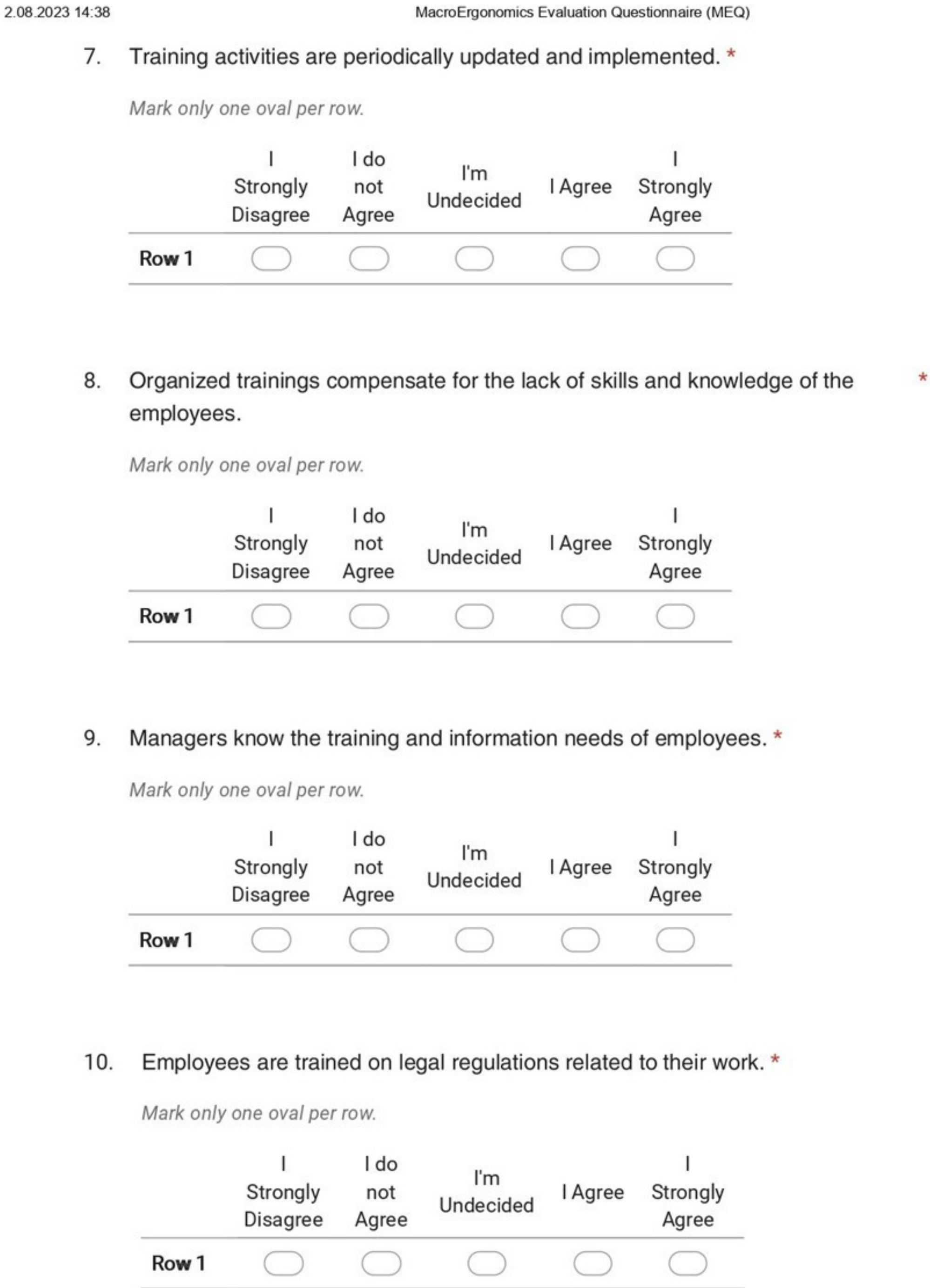
6. Are you in a managerial position? *

Mark only one oval.

- ◯ Yes
- ◯ No

EMPLOYEE

Figure A.3. Macroergonomic evaluation questionnaire-3.


2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

7. Training activities are periodically updated and implemented. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

8. Organized trainings compensate for the lack of skills and knowledge of the employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

9. Managers know the training and information needs of employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

10. Employees are trained on legal regulations related to their work. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.4. Macroergonomic evaluation questionnaire-4.

11. Jobs based on physical strength are given to physically fit persons. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

12. The reasons for the work-related physical complaints of the employees are analyzed and tried to be resolved. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

13. Whenever possible, the company analyzes and tries to resolve the causes of employees' psychological complaints. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

14. Employees have self-confidence in solving problems. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.5. Macroergonomic evaluation questionnaire-5.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

15. Social relations between employees are good. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

16. Employee morale and motivation are high. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

17. Working conditions and working environment increase the morale and motivation of the employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

18. Employees are satisfied with their wages. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

Figure A.6. Macroergonomic evaluation questionnaire-6.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

19. The work they do is professionally and personally developing the employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

20. Employees' achievements are rewarded. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

21. Employees are willing to take responsibility. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

22. My job is pretty monotonous and boring. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

Figure A.7. Macroergonomic evaluation questionnaire-7.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

23. Leaving the job and absenteeism are very few. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

24. In job tasks, employee-related errors are rare. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

25. Employee performance is generally high. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

TASK

26. My job puts a lot of psychological pressure on me. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

Figure A.8. Macroergonomic evaluation questionnaire-8.

27. My workload is too heavy (either physically or mentally). *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

28. I am usually extremely tired after work. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

29. My job requires me to work very fast. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

30. Employees can make critical decisions regarding their jobs. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

Figure A.9. Macroergonomic evaluation questionnaire-9.

31. The recommendations of the employees are taken into account by the managers. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

TECHNOLOGY

32. Our company has a pretty good communication network (email, text, phone, etc.) *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

33. Our company uses the software it needs. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

34. The software used in the company is up-to-date. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.10. Macroergonomic evaluation questionnaire-10.

35. Employees use advanced tools and equipment in their work. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

36. Our company follows technology closely and is willing to implement new technologies. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

37. Employees receive the necessary training and certificates for using technological devices and tools. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

38. The company conducts periodic controls to identify technology-based training needs. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

ORGANIZATIONAL

Figure A.11. Macroergonomic evaluation questionnaire-11.

39. The company encourages and supports teamwork. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

40. Teamwork has an important place in the performance evaluation system. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

41. Employees feel like family members in the company. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

42. Managers encourage employees to take risks and be open to extraordinary ideas. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.12. Macroergonomic evaluation questionnaire-12.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

43. Employees can hold meetings to discuss any issue. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

44. Employees are informed without delay on all matters concerning them. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

45. Employee cooperation is encouraged and rewarded. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

46. There is a system where employees can report the problems they encounter. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1					

Figure A.13. Macroergonomic evaluation questionnaire-13.

47. The problems reported by the employees are responded to without delay. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

48. The participation and contribution of employees in the identification and solution of problems is encouraged. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

49. Employees are observed and directed to improve their performance. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

50. Employee suggestions are welcomed by managers. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.14. Macroergonomic evaluation questionnaire-14.

51. Managers build teams suitable for the job and motivate them for success. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

52. Managers always provide support, direction and inspiration for the professional and personal development of employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

53. Managers do not discriminate among employees and act fairly. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

54. Managers treat their employees with respect. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

Figure A.15. Macroergonomic evaluation questionnaire-15.

55. The company gives incentive awards in order to increase the motivation and performance of the employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

56. Employees who are successful are more likely to be promoted or receive a higher pay raise. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

57. In the company, there is no time pressure on the work schedules. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

58. Employees know their work schedule and upcoming tasks. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	◯	◯	◯	◯	◯

Figure A.16. Macroergonomic evaluation questionnaire-16.

59. Jobs usually do not require overtime. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

WORK ENVIRONMENT and OCCUPATIONAL HEALTH AND SAFETY

60. Facility layout is appropriate for interdepartmental workflow and traffic. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

61. The working environment is always kept neat and clean. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

62. After each tool and equipment is used in the working environment, it is put back in a ready-to-use form. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.17. Macroergonomic evaluation questionnaire-17.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

63. The company implements planned maintenance to prevent breakdowns. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

64. The company has an occupational health and safety program. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

65. The company is fully prepared for emergencies. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

66. There is necessary personal protective equipment (such as earplugs, gloves, and glasses) in the work environment. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.18. Macroergonomic evaluation questionnaire-18.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

67. Employees use personal protectors when necessary. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

68. Employees comply with occupational health and safety rules. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

69. Employees contribute to solving occupational health and safety problems. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

70. The dimensions of some workstations are not suitable for some employees. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Figure A.19. Macroergonomic evaluation questionnaire-19.

71. Among the employees, musculoskeletal disorders (disc herniation, neck hernia, tendinitis, carpal tunnel syndrome, etc.) are seen. *

Mark only one oval per row.

	I Strongly Disagree	I do not Agree	I'm Undecided	I Agree	I Strongly Agree
Row 1	⬭	⬭	⬭	⬭	⬭

Privacy Policy Statement Form

Your privacy is important to us. The identity information of the survey participants is never shared. The information collected in this survey (including the company you work for) will be kept strictly confidential. No information will be given to your supervisor or company. This research is conducted for academic purposes only. Responses will never be used to identify you. These survey results will only be published in summary tables and reports. The information obtained will not be used for any purpose other than the purpose for which it was collected.
Your responses will be grouped with others' responses for reporting purposes. Reports will include aggregated results for all employees. You can request a copy of the results after the reporting is finished by entering your e-mail address.

72. E-mail:

____

73. I request a copy of the research results.

Mark only one oval.

⬭ Yes
⬭ No

74. I request your updated CV.

Mark only one oval.

⬭ Yes
⬭ No

Figure A.20. Macroergonomic evaluation questionnaire-20.

2.08.2023 14:38 MacroErgonomics Evaluation Questionnaire (MEQ)

75. Do you have anything to suggest for the development of the survey, as per our principle of continuous improvement and development?

Figure A.21. Macroergonomic evaluation questionnaire-21.

APPENDIX B: RELIABILITY RESULTS FOR PILOT STUDY

B.1. Employee Subfactor

B.1.1. Education, Knowledge and Skills

Although, the overall Cronbach's alpha value is adequate (0.74 > 0.70), extracting the fourth question will significantly increase the survey reliability. Hence, we exclude the fourth question (Employees do not have the necessary training and knowledge to be successful).

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.740	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00002	13.7500	9.032	.532	.684
VAR00003	13.7813	8.241	.537	.683
VAR00004	13.8125	7.835	.762	.592
VAR00005	13.3125	11.383	.125	.819
VAR00006	13.7188	8.660	.633	.648

Figure B.1. Reliability analysis for education, knowledge, and skills.

B.1.2. Physical Characteristics

Although, the CA value is slightly under the commonly accepted CA value of 0.70. It is still acceptable for a pilot study, and we can use this level of reliability in our study.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.631	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	3.0625	1.415	.465	.
VAR00002	3.5313	1.096	.465	.

Figure B.2. Reliability analysis for physical characteristics.

B.1.3. Psychological Characteristics

To reach an acceptable level of reliability, we must exclude the second question (Employees have a high mental workload.). In this pilot study, 0.593 is an acceptable level for a pilot study, and assuming that this section of the survey is reliable for the related factor is reasonable.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.278	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	9.7500	3.419	.252	.067
VAR00002	10.1250	5.532	-.199	.593
VAR00003	9.1875	3.641	.260	.073
VAR00004	9.1875	3.254	.353	-.067[a]

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Figure B.3. Reliability analysis for psychological characteristics.

B.1.4. Motivation and Needs

Although excluding the last question gives a better CA value (0.842), the difference is not worth excluding. We will continue with all the questions of "Motivation and Needs" subfactor in the PCA method. The value of 0.826 is favorable in terms of reliability.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.826	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	19.8438	18.394	.759	.773
VAR00002	19.8125	17.254	.759	.768
VAR00003	20.3438	19.652	.479	.820
VAR00004	19.6875	19.254	.569	.803
VAR00005	20.1250	19.339	.545	.808
VAR00006	19.6563	20.297	.629	.797
VAR00007	19.0938	22.152	.303	.842

Figure B.4. Reliability analysis for motivation and needs.

B.1.5. Employee Performance

While it is true that omitting the second question results in a slightly improved CA (Cronbach's Alpha) value, standing at 0.736, the marginal gain in doing so does not appear significant enough to warrant exclusion. Consequently, we have decided to proceed by retaining all the questions falling under the "Employee Performance" sub-factor during the PCA (Principal Component Analysis) process. The CA value of 0.705, which we obtained by including all the questions, is highly satisfactory and demonstrates a commendable level of reliability in our analysis. This decision aligns with our commitment to comprehensiveness and robustness in our research methodology.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.705	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	6.6563	2.491	.508	.651
VAR00002	6.0938	3.636	.414	.736
VAR00003	6.0625	2.448	.684	.395

Figure B.5. Reliability analysis for employee performance.

B.2. Task Subfactor

B.2.1. Content, Requirements, Challenges, and Skills of the Job

Excluding the second question (I have the necessary knowledge and skills for my job.) will significantly increase our CA value (0.458 $\rightarrow$ 0.629). Hence, we will exclude the second question of sub-factor "content, requirements, challenges, and skills of the job".

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.458	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	16.1563	11.620	-.078	.562
VAR00002	15.8750	12.629	-.213	.629
VAR00003	16.2188	8.241	.464	.277
VAR00004	16.2188	7.789	.481	.252
VAR00005	16.6875	7.899	.408	.293
VAR00006	16.5000	8.129	.461	.274

Figure B.6. Reliability analysis for content, requirements, challenges, and skills of the job-I.

Upon a meticulous examination of our data, it has come to our attention that the exclusion of the first question pertaining to job definition ("My job is well defined in terms of what I should do, how I should do it, and how long I should do it.") would result in a substantial enhancement of our CA (Cronbach's Alpha) value. This transition would elevate our CA from its current standing at 0.629 to an impressively heightened level of 0.821.

In light of this noteworthy improvement in the measure of internal consistency, we have made the considered decision to omit the first question within the sub-factor "content, requirements, challenges, and skills of the job."

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.629	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	12.5000	13.355	-.239	.821
VAR00003	12.5625	7.996	.585	.475
VAR00004	12.5625	7.286	.649	.427
VAR00005	13.0313	7.580	.529	.492
VAR00006	12.8438	7.943	.568	.481

Figure B.7. Reliability analysis for content, requirements, challenges, and skills of the job-II.

B.2.2. Autonomy, Job Control, and Participation

It is obvious that extracting the third question (The company does not allow employees to make individual decisions regarding their work.) will make this section of the pilot study acceptable in terms of Cronbach's Alpha (0.66).

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.386	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	6.7188	2.338	.276	.193
VAR00002	7.0625	1.609	.496	-.401[a]
VAR00003	6.7813	3.725	-.028	.660

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Figure B.8. Reliability analysis for autonomy, job control, and participation.

B.3. Technology Subfactor

B.3.1. Information Technology

We obtained a very high CA value (0.944) and no extraction activity is statistically significant. Hence, we will use the questions in the main study without any modification.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.944	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	7.7188	3.951	.838	.961
VAR00002	7.6250	4.177	.920	.892
VAR00003	7.7188	4.338	.905	.905

Figure B.9. Reliability analysis for information technology.

B.3.2. Advanced Manufacturing Technologies

It is obvious that extracting the third question (We experience manufacturing delays due to the use of outdated machinery, equipment, or other obsolete technology.) will make this section of the survey acceptable in terms of Cronbach's Alpha (0.881).

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.489	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	7.1875	2.738	.526	-.013[a]
VAR00002	7.1563	2.717	.537	-.033[a]
VAR00003	7.1563	4.588	-.012	.881

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Figure B.10. Reliability analysis for advanced manufacturing technologies.

B.3.3. HR Characteristics in Technology and Tools

We've obtained a very satisfying result in terms of reliability, and we will continue to PCA section with the current questions.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.848	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	2.8438	1.233	.736	.
VAR00002	3.2188	1.144	.736	.

Figure B.11. Reliability analysis for HR characteristics in technology and tools.

B.4. Organizational SubFactor

B.4.1. Team Work

As the obtained CA value (0.708) is adequate in terms of reliability, we will not modify or extract any questions.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.708	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	3.4688	.967	.553	.
VAR00002	3.5938	1.281	.553	.

Figure B.12. Reliability analysis for team work.

B.4.2. Organizational Culture

Evidently, it is apparent from our analysis that the necessity to achieve a favorable CA (Cronbach's Alpha) value of 0.617 obliges us to extract the third question, which asserts that "Employees are extremely goal-oriented, and managers are tough and demanding to meet the success criteria defined by the company." This meticulous decision aligns with our pursuit of ensuring a more robust and reliable measurement of internal consistency within our research framework.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.464	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	15.6250	7.597	.578	.238
VAR00002	15.9688	7.644	.438	.294
VAR00003	15.9063	11.572	-.172	.617
VAR00004	16.1875	9.254	.107	.495
VAR00005	16.0938	7.894	.335	.353
VAR00006	15.2188	9.015	.259	.406

Figure B.13. Reliability analysis for organizational culture-I.

As can be seen in the table above, we must extract the third question (The company has a hierarchical structure; Most of the activities and decisions are determined by existing methods rather than innovation and free thinking.) to obtain a favorable CA value (0.792).

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.617	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	12.5313	7.289	.668	.424
VAR00002	12.8750	7.081	.568	.455
VAR00004	13.0938	10.862	-.093	.792
VAR00005	13.0000	7.226	.470	.507
VAR00006	12.1250	8.113	.452	.527

Figure B.14. Reliability analysis for organizational culture-II.

B.4.3. Coordination, Collaboration and Communication

Since 0.907 is a very high value in terms of CA, we will not extract any question from this section of the survey for the main study.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.907	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	16.2188	20.951	.718	.894
VAR00002	16.6875	20.867	.648	.905
VAR00003	16.5625	20.641	.824	.881
VAR00004	16.8750	20.306	.644	.908
VAR00005	17.0313	20.225	.810	.881
VAR00006	16.4688	19.805	.862	.874

Figure B.15. Reliability for coordination, collaboration and communication.

B.4.4. Supervision and Management Styles

Since 0.912 is a very high value in terms of CA, we will not extract any questions from this section of the survey for the main study.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.912	7

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	20.1875	34.996	.594	.914
VAR00002	19.9375	33.802	.767	.896
VAR00003	20.0000	32.968	.818	.890
VAR00004	20.0625	32.577	.834	.888
VAR00005	20.0938	31.959	.764	.896
VAR00006	19.6875	34.028	.719	.901
VAR00007	20.4688	35.612	.658	.907

Figure B.16. Reliability analysis for supervision and management styles.

B.4.5. Performance Evaluation, Rewards, Incentives

We've obtained a favorable CA value (0.779) and will continue with the current question set in the main study.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.779	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	3.4688	1.096	.654	.
VAR00002	2.8750	1.726	.654	.

Figure B.17. Reliability for performance evaluation, rewards, incentives.

B.4.6. Work Schedule

Although the obtained value (0.635) is under the favorable CA value (0.7), it is still statistically acceptable. We will use the current question set in the main study.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.635	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	6.8438	2.781	.523	.420
VAR00002	6.0313	3.709	.378	.624
VAR00003	6.5000	2.710	.450	.537

Figure B.18. Reliability analysis for work schedule.

B.5. Work Environment and Occupational Safety SubFactor

B.5.1. Facility Layout and Conditions

Given the exceptionally high value of 0.912 obtained in terms of CA (Cronbach's Alpha), it is evident that there is no need to eliminate any questions from this section of the survey for the main study. This exceptionally high measure of internal consistency underscores the comprehensive and reliable nature of the data collected and confirms the soundness of our research approach.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.912	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	10.8438	10.588	.729	.909
VAR00002	10.4063	10.507	.768	.896
VAR00003	10.6250	9.274	.842	.870
VAR00004	10.6875	9.448	.863	.862

Figure B.19. Reliability analysis for facility layout and conditions.

B.5.2. Occupational Health and Safety

Although, excluding some of the questions from the set (Q7, Q12, etc.) results in a higher CA value, the difference is not statistically significant. Hence, we will not extract any question. However, if we have a problem with the detected questions in the PCA study. We can consider extracting some of the questions.

Case Processing Summary

		N	%
Cases	Valid	32	100.0
	Excluded[a]	0	.0
	Total	32	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.887	16

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
VAR00001	52.4688	83.225	.729	.873
VAR00002	52.5625	82.706	.825	.869
VAR00003	52.9063	89.120	.463	.884
VAR00004	52.3750	93.532	.211	.895
VAR00005	52.4063	86.184	.720	.874
VAR00006	52.4688	85.225	.665	.876
VAR00007	52.7813	95.854	.099	.900
VAR00008	52.3750	91.339	.364	.888
VAR00009	52.4688	84.451	.787	.871
VAR00010	52.4375	85.157	.695	.875
VAR00011	52.5000	85.097	.808	.871
VAR00012	52.9688	100.999	-.126	.903
VAR00013	52.5313	83.160	.859	.868
VAR00014	52.7813	91.015	.378	.887
VAR00015	52.6250	86.113	.709	.875
VAR00016	52.7500	86.645	.718	.875

Figure B.20. Reliability analysis for occupational health and safety.

APPENDIX C: SPSS SETTINGS FOR PCA

The following information shows the PCA setting used in the SPSS tool.

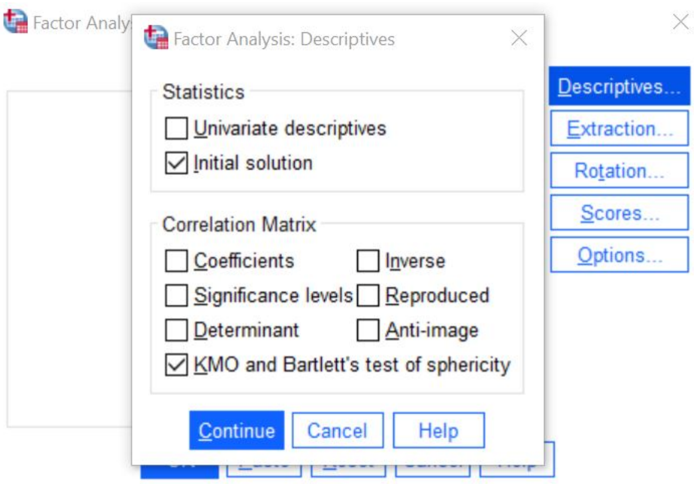


Figure C.1. Descriptives for PCA.

Kaiser-Meyer-Olkin test will be used for evaluating the suitability of the survey data for Principal Component Analysis. Since, we have a non-normal data Barttlet's Test of Sphericity will not be reliable and thus will not be used.

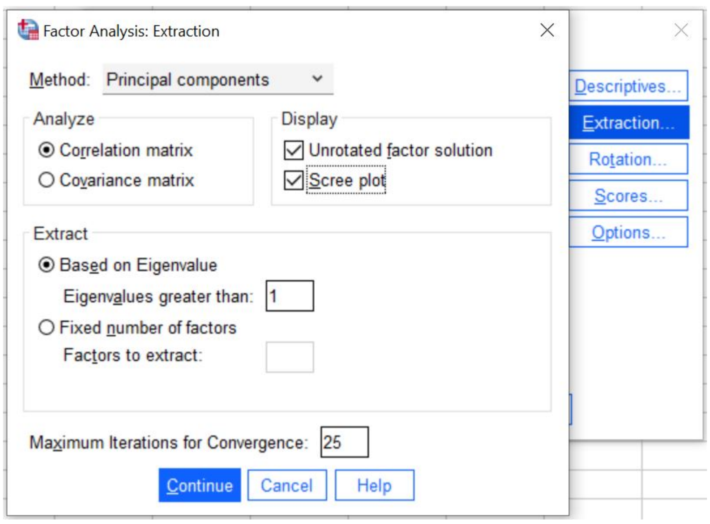


Figure C.2. Extraction method.

The Extraction based on Eigenvalue method defines a critical eigenvalue that a component must exhibit to be retained. An eigenvalue represents the variance accounted for by a specific component. In Principal Component Analysis (PCA), one commonly used criterion for determining the number of components is the eigenvalue criterion. According to this approach, components with eigenvalues greater than 1 are retained and interpreted.

The rationale behind this criterion is that each observed variable (Factor) contributes one unit of variance to the overall variance in the dataset. Consequently, any component displaying an eigenvalue greater than 1 accounts for more variance than a single variable contributes. Hence, such a component is deemed to account for a substantial amount of variance and is considered meaningful for retention.

Conversely, a component with an eigenvalue less than 1 accounts for less variance than a single variable contributes. As the primary goal of PCA is to reduce the number of observed variables into a smaller set of components, it is not effective to retain components that account for less variance than individual variables.

As a result, this study adopts an EIGEN VALUE = 1 criterion, meaning that components with eigenvalues less than 1 are not retained.

The Display Scree Plot Option is a graphical representation illustrating the size of the eigenvalues corresponding to each component. The scree test is employed to identify a distinctive break point between components with relatively large eigenvalues and those with smaller eigenvalues. Components that appear before this break point are considered meaningful and are retained for rotation. On the other hand, components that appear after the break point are regarded as unimportant and are not retained for further analysis. The scree plot aids researchers in making informed decisions about the appropriate number of components to retain for a more meaningful interpretation of the data.

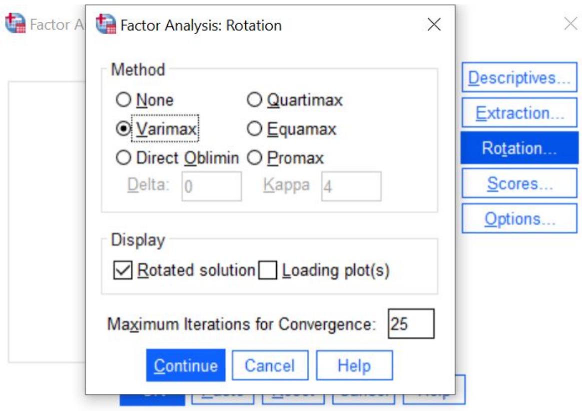


Figure C.3. Rotation method for PCA.

In this study, a rotation method is employed to facilitate the interpretation of the factor solution. Rotation involves a linear transformation applied to the factor solution, aiming to achieve better interpretability. The specific rotation technique utilized in this study is varimax rotation, known for its orthogonality, which leads to uncorrelated components. Furthermore, varimax rotation is favored for its ability to maximize variance, contributing to a more refined and informative factor solution.

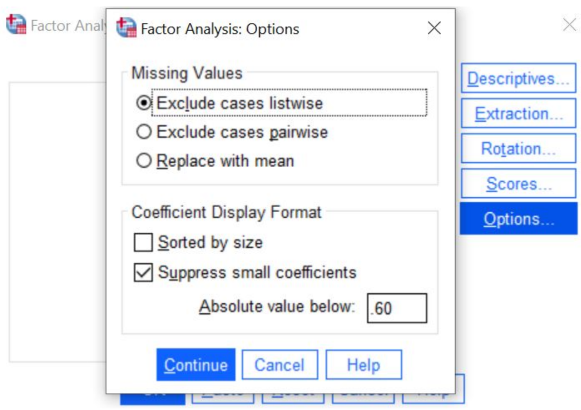


Figure C.4. Other options for PCA.

In the “Coefficient Display Format” section, we choose “Suppress small coefficients” below 0.60 loading which means SPSS will not display the variables that have a loading below 0.60. As per the research by Hair et al. [155], loadings of 0.6 or above are considered significant for a sample size of 85.

"Loading" pertains to the correlation between the original variables and the principal components obtained through Principal Component Analysis (PCA). It signifies the degree to which each original variable contributes to the creation of a specific principal component.

After conducting PCA, the dataset is transformed into a new set of uncorrelated variables, known as principal components. These principal components are linear combinations of the original variables, with the coefficients representing the loadings. The loadings indicate the weights attributed to each original variable in the construction of the corresponding principal component.

The magnitude and direction of the loading coefficients hold significant implications for interpreting the relationship between the original variables and the principal components. Larger positive or negative loadings suggest substantial influence of a specific original variable on the respective principal component, while loadings approaching zero indicate minimal impact of the variable on that particular component.