Development of a Method for the Characterization, Assessment and Control of Human Induced Uncertainty During Usage

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von
Marius Oberle M. Sc.
aus Dieburg

1. Prüfer: Prof. Dr.-Ing. Ralph Bruder
2. Prüfer: Prof. Dr.-Ing. Reiner Anderl

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I herewith declare that I wrote the presented thesis without any help besides the explicitly mentioned.

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Abstract

Prediction of a system's stress in succession to a human-machine interaction is difficult due to the variety and variability of the involved factors. Thereby, the human factor represents an important role, positive as well as negative, whereat the resulting uncertainty can be ascribed to the human performance variability. Current approaches for the investigation of the human influence onto system stress predominantly focus on human error and thus only on the negative aspects. In contrast, the concept of uncertainty recently attracts increased attention and allows for a holistic assessment of human induced uncertainty, but misses an applicable method. Assessment of the human influence onto the uncertainty during usage would lead to the reduction of safety measures and thus to a conservation of resources.

The present work addresses the development of a holistic approach for the characterization, assessment, quantification and control of the human influence onto the uncertainty during usage. Based on a literature review, a model for the description of human-machine interaction, focusing on human sub-processes, is developed and a total of 67 influencing factors are allocated to the model's elements. On this basis, the method of *Human Uncertainty Modes and Effects Analysis* (HUMEAn) is derived, which allows for a systemic assessment and quantification of human induced uncertainty.

The developed method of HUMEAn is subsequently applied within a laboratory study to investigate the uncertainty of the human sub-process *execution of action*. For this, 58 participants must fulfill the task to place a specific weight on top of a tripod. The interindividual human influence, represented by the strength and dexterity of the participants, as well as the influence of task variation in form of different placing weights and instructions, are assessed. As a first result, system stress seems to follow a lognormal distribution. Thereby, a significant negative influence of the placing weight as well as the strength of the participants onto the resulting system stress is found. In contrast, specific instructions as well as the dexterity of the participants show a significant positive impact onto uncertainty.

During a second study with 44 participants, the HUMEAn is applied for the investigation of the complex task of landing an airplane. Thereby, the human sub-process *choice of action* in conjunction with intraindividual influences are focused. The uncertainty of choice of action is quantified by means of a Markov model. Again, the resulting uncertainty is represented by a lognormal distribution. Further, pilots holding a commercial pilot license tend to less variation within their action sequence as other pilots. Overall, a significant positive influence of the factors qualification, simulator- and flight experience are found. Moreover, several predictors for the resulting system stress for specific states of the Markov model are identified.

A third study with 32 participants is conducted to investigate the applicability of appropriate interface design for the reduction of uncertainty. Therefore, participants must stack two identical weights consecutively on top of a tripod. The findings confirm the possibility to reduce uncertainty regarding the resulting system stress through the implementation of appropriate feedback.

Overall, the developed model and the derived methodological approach of the HUMEAn allow for a systematic and holistic characterization and quantification of human induced uncertainty. Based on the application of the method, implications for the control and reduction of human induced uncertainty can be realized, e.g. through selection or qualification of the operator as well as through appropriate interface design.

Zusammenfassung

Die Vorhersage von Systembelastung in Folge einer Mensch-Maschine-Interaktion ist herausfordernd, auf Grund der Vielzahl und Variabilität der involvierten Faktoren. Dabei spielt insbesondere der Faktor Mensch eine entschiedene Rolle, da er die resultierende Unsicherheit auf Grund der Leistungsvariabilität sowohl negativ als auch positive beeinflusst. Bisherige Ansätze basieren meist auf der Analyse von menschlichen Fehlern und prägen daher eine einseitige, negative Sicht auf den Faktor Mensch. Dagegen gewinnt das Konzept der Unsicherheit in den letzten Jahren an Bedeutung, welches eine umfassende Betrachtung sowohl der negativen als auch positiven Faktoren ermöglicht. Eine Erfassung des menschlichen Einflusses auf die Unsicherheit würde letztlich zur Reduzierung von Sicherheitsbeiwerten und somit zur Ressourcenschonung beitragen.

Die vorliegende Arbeit beschäftigt sich mit der Entwicklung eines ganzheitlichen Ansatzes zur Charakterisierung, Quantifizierung und Beherrschung des menschlichen Einflusses auf die Unsicherheit in der Nutzung. Basierend auf einer Literaturrecherche wird ein Modell zur Beschreibung der Mensch-Technik-Interaktion, mit Fokus auf potentielle Teilhandlungen des menschlichen Akteurs, entwickelt und um 67 Einflussfaktoren der beteiligten Elemente ergänzt. Folgend wird die Methode der *Human Uncertainty Modes and Effects Analysis* (HUMEAn) abgeleitet, die eine systematische Beschreibung und Quantifizierung des menschlichen Einflusses auf die Unsicherheit erlaubt.
Die abgeleitete Methode der HUMEAn wird zunächst für die Untersuchung der Handlungsausführung in einem Laborversuch angewendet. Im Rahmen einer Studie mit 58 Probanden wird mittels der Aufgabe ein Gewicht auf einem Dreibein abzustellen der interindividuelle Einfluss von Kraftvermögen und Geschicklichkeit sowie der Einfluss variierender Handlungsanweisungen und verschiedener Gewichte auf die resultierende Unsicherheit untersucht. Für die resultierende Beanspruchung ergibt sich eine Lognormalverteilung. Zudem kann ein signifikanter negativer Einfluss des Gewichtes sowie des Kraftvermögens der Probanden nachgewiesen werden. Geschicklichkeit sowie fokussierte Handlungsanweisungen wirken sich hingegen signifikant positiv aus.
In einer zweiten Studie mit 44 Probanden wird die HUMEAn auf die komplexe Aufgabe der Flugzeuglandung in einem Flugsimulator angewendet. Der Fokus liegt hierbei auf der Untersuchung des Einflusses der Handlungsauswahl. Mit Hilfe eines Markov-Modells wird die Variation hinsichtlich der Handlungssequenz quantifiziert. Erneut folgt die resultierende Beanspruchung einer Lognormalverteilung. Es zeigt sich, dass Piloten mit kommerziellen Pilotenlizenzen eine geringere Streuung hinsichtlich der Handlungssequenz aufweisen als andere Piloten. Insgesamt wird ein signifikanter positiver Einfluss von Qualifikation, Simulations- und Flugerfahrung festgestellt. Zudem werden für spezifische Markov-Zustände Prädiktoren für die resultierende Unsicherheit identifiziert.
In einem dritten Versuch mit 32 Probanden wurde letztlich der Einfluss eines ergänzenden, digitalen Belastungsfeedbacks auf die resultierende Unsicherheit untersucht. Die Probanden mussten hierzu zwei Gewichte nacheinander auf dem Dreibein stapeln. Durch die Verwendung eines geeigneten digitalen Belastungsfeedbacks konnte die resultierende Unsicherheit signifikant reduziert werden.

Der im Rahmen der Arbeit entwickelte Modellansatz und die daraus abgeleitete Methode der HUMEAn ermöglicht somit eine systematische Beschreibung und Quantifizierung des menschlichen Einflusses auf die Mensch-Technik Interaktion. Auf Basis der Methode lassen sich weiterhin Maßnahmen zur Beherrschung und Reduzierung von Unsicherheit ableiten.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

BBT	Box-and-Block-Test
CPL	Commercial Pilot License
CRC 805	Collaborative Research Center 805
FEM	Finite-Element-Method
FMEA	Failure Modes and Effects Analysis
FSX	Microsoft's Flight Simulator X
HMI	Human-Machine Interaction
HUMEAn	Human Uncertainty Modes and Effects Analysis
IQR	Inter Quartile Range
KSS	Karolinska Sleepiness Scale
M	Mean
P-P Plot	Probability-Probability Plot
PPL	Private Pilot License
SD	Standard Deviation
SRK	Skill, Rule, Knowledge
UMEA	Uncertainty Modes and Effects Analysis
VIF	Variance Inflation Factor

1 Introduction

1.1 Motivation

> "All knowledge resolves itself into probability. [...] In every judgment, which we can form concerning probability, as well as concerning knowledge, we ought always to correct the first judgment deriv'd from the nature of the object, by another judgment, deriv'd from the nature of the understanding."
>
> \- David Hume (*A treatise of Human Nature*, 1739)

Even though David Hume wrote these lines nearly 300 years ago, it still holds truth for the present and will hold truth prospectively. The prediction of things and events remains flawed as observations always represent the past and don't guarantee future validity. Causality thus is limited to probabilities regarding the recurrence of observations. This leads to the conclusion that nothing is certain.
In present days, the shortcoming of knowledge as addressed by David Hume remains crucial and manifests itself especially when applying knowledge to prevent danger and to protect people and things from harm. This is for example the case for the development and design of technical systems with which humans interact. Thereby, prediction of the resulting stress on a system in response to its utilization is vital, as it affects the initial design and the dimensioning of a system regarding forthcoming stress. However, such predictions are generally challenging and nearly impossible, beyond the described flaw of knowledge, due to the multitude and variability of the involved factors (Hanselka & Platz, 2010). Besides systemic influencing factors, like the natural variation of material properties, unexpected influencing factors or external disturbances affect system stress. Thereby, humans are frequently attributed a major role as an influencing factor onto resulting system stress in succession of an interaction.
In the field of aviation for example about 66% to 70% of all accidents are attributed to pilot or flight crew errors (e.g. Dismukes, 2010, p. 336; McMahon & Busby, 2005, p. 290; Nagel, 1988; Zhang & Xue, 2013, p. 134). For general aviation the numbers are even higher, though varying over time, where a range of about 79% (Krey, 2007) up to 90% (Nagel, 1988) of accidents are attributed to pilot errors. The human effect on accidents is not unique to aviation, but generally impacts on accidents and financial losses in almost every industry (Dismukes, 2010, pp. 336–337). About 80% of shipping accidents (McMahon & Busby, 2005, p. 290), 66% of accidents within aerospace operations (Giesa & Timpe, 2002), 52% to 70% of accounted incidents in the field of nuclear power plants (Giesa & Timpe, 2002; van Cott, 1994) and about 85% of all incidents concerning automobiles (van Cott, 1994) are attributed to human contribution. This mainly resolves into the view that humans impose a safety risk, which is also reflected within the widely accepted and used concept of human error. The concept of human error is generally applied for the attribution and cause study of failures. For this purpose, a variety of methods exist (e.g. Celik & Cebi, 2009; Deacon, Amyotte, & Khan, 2010; Dekker, 2002).

Nonetheless, the concept of human error is not without controversy. The modern scientific perspective on human error states that not professional and trained humans are the cause of accidents, but the inherent limitations and misconceptions of the overall sociotechnical system (Bogner, 1994; Dismukes, 2009, 2010; Reason, 1990). Even though tasks exist which can be perfectly performed by computers, human expertise is still needed when making decisions in novel situations or by relying on complex information and especially in the case of value judgements (Dismukes, 2010, p. 339). Thus, pure focus on errors represents only a small margin. Concentration on whole processes and the deviation of human performance in correspondence to influencing factors leads to insights concerning the promotion of positive human influences. Humans not only are cause for accidents or systemic strain but in contrast represent a possible regulation for unexpected events and external influences (Dekker, Hollnagel, Woods, & Cook, 2008; König, Oberle, & Hofmann, 2016) and thus play a vital role for the anticipation of possible risks and threats (cf. Badke-Schaub, Hofinger, & Lauche, 2008, p. 4). In comparison to technical systems, only the human possesses the ability to adapt to unexpected challenges (cf. Vidulich, Wickens, Tsang, & Flach, 2010, p. 176). As final critic on human error it can be noted that the valid prediction of failure probabilities of action sequences is near impossible in the case that the error probabilities itself are close to 0 (Sheridan, 2010, p. 58). Thus, the term and underlying concept of human error leads to the stigmatization of the human, denying him the role as a positive impact factor on human-machine interaction and ignoring the influence of the overall sociotechnical system. For a holistic investigation and prediction of system stress a new approach considering the overall sociotechnical system beyond error is needed.

In recent years, the concept of uncertainty gains more and more importance (e.g. Wiebel et al., 2013, p. 246), also in the field of human factors and ergonomics (Grote, 2014a). Thereby, a sole focus on technical system optimization neglects the human factor (Badke-Schaub et al., 2008), promoting an integrated approach for dealing with uncertainty. Thus, knowledge about the human influence on the uncertainty of human-machine interaction is of importance. Previous studies on uncertainty of human action were majorly conducted from a human reliability perspective (e.g. Bubb, 1992) and thus basically reflected upon human errors occurring during the execution of complex tasks (e.g. Hinckley, 1994). In contrast to human reliability, dealing with and reducing uncertainty not solely focuses on (human) error, but further investigates the overall human influence on a system. In relation to the control of complex systems the term of human performance variability is known, which affects systemic failure as well as the mastery of critical situations (cf. Wickens, Hollands, Banbury, & Parasuraman, 2012). Performance variability addresses the natural variation of human performance within and between people (cf. Smith, Henning, Wade, & Fisher, 2015), which subsequently leads to different outcomes regarding the result of human-machine interaction. Performance variability thus represents a possible source for the human influence on uncertainty, which further allows to focus on positive as well as on negative aspects by regarding the entire distribution of possible outcomes (Neufville & Weck, 2004). As until today the human contribution to system stress is predominantly associated with human error and discussed in terms of reliability, a holistic approach which also addresses the positive human impact on a system is omitted. The concept of uncertainty may represent the foundation for such an approach. The exact goal of the present work is described within the following chapter.

1.2 Objective

As the main objective of the present work the concept of uncertainty is applied for the investigation and prediction of system stress resulting from HMI (human-machine interaction). Thereby, the human impact on system stress is focused as previous research often neglects the human contribution, negative as well as positive, by solely focusing on technical optimization (cf. Badke-Schaub et al., 2008). For this purpose, existing methods for the assessment of uncertainty of technical systems and HMIs are reviewed and if appropriate adopted to consider the human influence on uncertainty. In this case, human-machine

interaction refers to the purposeful interaction with technical systems and products during the product life-cycle phase of usage.
Even though the human being is at the core of the present research, the goal is not to investigate how a system affects humans, leading to physical and mental strain and e.g. causing impairments – which is the focus of most research within the field of ergonomics and human factors. In contrast, the human impact onto the stress of a system is the focus of present work. Further, the term of uncertainty regarding human contribution does not refer to the discussion of “decisions under uncertainty” as investigated for example by Tversky and Kahneman (1974). Of course, decisions under uncertainty may affect the stress of a system, pointing out that topic as one possible source for uncertainty. However, further human actions are possibly involved and relevant for a holistic assessment of uncertainty. The personal uncertainty of humans towards technical systems is not focus of the present work.

Concluding, the present work represents a contribution to the understanding of the human part of HMIs and their impact on the uncertainty regarding the resulting system stress. Through the promotion of uncertainty and its intentional integration into organizational strategies and into product design, innovations and more flexible structures are supported. Dealing with uncertainty therefore represents an approach for the promotion of resilience. By controlling uncertainty, safety factors concerning the limits of system stress can be reduced, oversizing avoided, resources preserved and new areas of application explored, leading to an overall increase of economic and humanitarian profit (cf. Hanselka & Platz, 2010).

1.3 Structure

Within the first chapter the topic of the present work was introduced starting with an explanation of the motivation (chapter 1.1). Afterwards, the objective of this thesis was presented (chapter 1.2), followed now by the introduction of the structure for the present work.
Chapter two presents the theoretical foundations for this work. Initially, general definitions, concepts and terms needed for the understanding of the present work are given (chapter 2.1). Following, the term HMI is defined and discussed on the example of a model for its description (chapter 2.2), before a short overview over common models for the description of human information processing is given (chapter 2.3). The next section (chapter 2.4) focuses on various concepts of uncertainty and introduces the concept of human induced uncertainty as used throughout this work. Chapter 2.4 focuses on the elements involved in HMI by defining associated influencing factors. Concluding, an analysis of the existing literature concerning uncertainty of HMI is operated and research deficits are identified as guideline for the subsequent work (chapter 2.6).
Chapter three addresses the development of a model for the description of HMIs with focus on the human contribution. Within chapter 3.1 the model is developed, followed by the integration and allocation of the identified influencing factors (chapter 3.2). Based on the resulting model, the inherent uncertainty represented within the model is characterized (chapter 3.3). Within chapter 3.4 a holistic method, consisting of five steps, for the assessment and quantification of human induced uncertainty is derived of the model. Chapter 3.5 summarizes the hitherto work by relating it to the prior derived research deficit.
Chapter four focuses on a first study for the application of the developed methodological approach. After defining the study objectives and the observed task example (chapter 4.1) the five steps of the method are applied. First, the observed task is specified and operationalized (chapter 4.2), followed by the

specification of the subsystems of the investigated HMI (see chapter 4.3). Within step three of the method, the predominant sources for uncertainty are selected (see chapter 4.4). Afterwards, the experimental methods, experimental setup, procedure and the sample used for the investigation are explained (chapter 4.5). The results of the study are presented in form of descriptive statistics and a first quantification of the human impact on uncertainty is given (chapter 4.6). Next, a discussion of the findings regarding the uncertainty of the observed task and implications concerning the developed approach follows (chapter 4.7). With chapter 4.8, the results are summarized and the achieved progress regarding the derived research deficit is assessed.

Chapter five treats a second study for the evaluation of the developed methodological approach. After presentation of the application example for study two (see chapter 5.1), the five steps of the method are again processed one by one (see chapter 5.2 to chapter 5.6). Within chapter 5.7, the results of study two are discussed, especially regarding the applicability of the developed method. Concluding, the hitherto results regarding the research deficit are summarized (chapter 5.8).

Chapter six addresses a third study, which is conducted to investigate whether uncertainty can be reduced through appropriate interface design. Initially, the objective of study three as well as the main hypotheses are presented in chapter 6.1. Following, the experimental setup, procedure and the participants are described (chapter 6.2). Consecutively, the results of study three are presented in chapter 6.3 and discussed (chapter 6.4). Finally, the results of the third study are summed up in chapter 6.5 and compared to the remaining research deficit.

Chapter seven contains a general discussion and conclusion of the present work. The discussion is done separately for the applicability of the developed model and method regarding the findings of the three studies (chapter 7.1) and further for the identified limitations of the developed model (chapter 7.2). The chapter ends with a general conclusion of this work (chapter 7.3).

Chapter eight focuses on the implications for future work. First, implications for the application of the findings of the present work are discussed (chapter 8.1), followed second by the presentation of implications for future research (chapter 8.2), which finally concludes the present work.

2 State of the Art

This chapter first covers general definitions, concepts, terms and models used throughout the present work. After a brief presentation of general definitions and concepts, the concept of human-machine interaction is defined and a model for its description is presented. Afterwards, a review of models and concepts for the description of human action and human information processing is introduced. Fourth, theories and concepts regarding uncertainty are discussed and the term of human induced uncertainty is introduced. Fifth, influencing factors on HMI, subdivided into human, technical and environmental influencing factors, are covered. Lastly, a summary of the chapter as well as a deficit analysis concludes the chapter.

2.1 Definitions

Following, the terms and concepts of system, behavior, action, task and activity, error and human error, risk, reliability and human reliability as well as stress and strain are defined briefly as applied within the present work.

System

The term system describes a composition of single, interrelated elements forming a coherent unit, whereat the single elements can be real or abstract, interacting groups of activities as well as natural or man-made (Sheridan, 2010, p. 24). Therefore, each system is a combination of interrelated, dependent and dynamic elements and interacting dynamic relations (Masak, 2007, p. 305). Commonly, a system is defined by setting a boundary, defining what is included within the system and what is excluded from the system (Pritchett, 2010, p. 66). Based on its boundaries, a system's behavior is further described through transformation of input variables to causal related output variables (Sheridan, 2010). Further, a distinction between closed and open systems can be made, where the former is independent and the latter highly dependent on its environment and external variables.

Examples for different systems and system views could be the front wheel of an airplane's landing gear, the mechanical framework of a landing gear, a complete airplane, including or excluding passengers, crew and pilot or the total of an airport. The scaling of a system by means of defined boundaries, input and output variables thereby depends on the perspective of the observer and its intended goal (Masak, 2007, p. 305). For the investigation of the structural dynamics of a landing gear, a system including the complete airport seems inappropriate, whereas during analyzing the organizational aspects of arrival and departure at an airport, a single wheel is negligible. Generally, using a system approach always results into a simplification of the examined problem. Especially the system boundaries as well as the attributes of the defined system are artifacts of the model-building process and have to be regarded critically (Masak, 2007, p. 305; Sheridan, 2010, p. 26).

Behavior

Behavior describes the entirety of all possible utterances of life of living beings, like breathing or blinking, spontaneous and unwillingly reactions and reflexes, further including native as well as learned reflective and instinctive operations (cf. Heckhausen, H. & Heckhausen, J., 2010; Kleinbeck, 2010).

Action

Action describes a temporal and self-contained operation to achieve a certain goal (Kleinbeck, 2010, p. 7). Thus, action represents intentional behavior (cf. Schulz-Schaeffer, 2000).

Task and Activity

A task is defined as a part of work or a performed process which has to be done to achieve a certain goal (cf. Tavanti & Bourgois, 2006, p. 3; Chou, Madhavan, & Funk, 1996, p. 308). According to Chou et al. (1996) a task must only partly be done by a human, allowing it to describe an HMI. Further, a task represents the unit of human behavior often referred to by human factors and engineering psychology researchers.

The term activity is defined as a series of tasks, e.g. in form of a job description (Tavanti & Bourgois, 2006, p. 3). Activity therefore represents a broader concept and can itself be subdivided into single tasks.

Error and Human Error

Generally, an error occurs when an observed characteristic exceeds a predefined tolerance value (Reichart, 2001, p. 15). As per definition, an error therefore adheres to a binary characteristic, not distinguishing between different states below or above an observed tolerance and solely stating if or if not the tolerance is exceeded.

According to Rigby (1970), a "human error is any member of a set of human actions that exceeds some limit of acceptability", coming close to the general definition of error. The term human error is used whenever humans take part in the occurrence of an error, making it a concept used in almost every industry from aviation to general accidents (Dismukes, 2010, pp. 336–337). With regard to HMIs, human error often is a result of misunderstandings and miscommunications (Degani, 2004). As Reason (1990, p. 148) states, human errors represent a tradeoff for the ability to cope with difficult informational tasks. This further addresses criticism on the term of human error, as it gives the impression that errors only derive from human beings. Actually, human error often evolve due to a combination of several circumstances like organizational aspects or technical misconceptions and therefore represents a systemic issue (Sträter, 1997).

Reliability and Human Reliability

Technically, reliability is defined as the probability that a component fulfills its intended function over time (Dekker & Woods, 2010, p. 126). It is generally expressed through failure rates or failure probability over a certain period. According to Bubb (1992), human reliability is defined as the human ability to accomplish a task under predefined requirements for a certain period of time and within a specified margin. Quantitatively human reliability can be described as the probability of a successful task execution, whereas the quality of an executed task is measured by compliance between task assignment and task accomplishment (Reichart, 2001, p. 15). Therefore, determining the reliability of a human task relies on the prediction of possible error occurrence (Muckler, 1984, p. 14). The concept of reliability is thus connected to the concept of error, inheriting its binary limitation.

Risk

Risk is defined as the probability of failure occurrence and the severity of its consequences (cf. Sheridan, 2010, p. 57; Johnson, 2003, p. 64). A high risk would therefore result from high failure probability combined with severe consequences. The concept of risk is commonly used in economic sciences, but also in the field of engineering, for example within the Failure Modes and Effects Analysis (FMEA) (e.g. Stamatis, 2003), or when identifying critical tasks in the field of project management (e.g. Raftery, 2003).

In comparison to reliability, risk represents a broader concept, as it combines the probability of error occurrence (reliability) with the possible consequences of an error. Generally, the probability of error occurrence as well as the severity of an error's consequences, must be estimated. Application of the concept of risk is thus accompanied by uncertainty (Mackie, 1966).

Stress and Strain

Stress and strain are conceptually related, but still different within their implications. The general distinction derives from the field of mechanical engineering, where stress refers to the objective, non-individual amount of physical influence onto a system, like a certain force or torque (e.g. Groß, Hauger, Schröder, & Wall, 2010). In contrast, strain refers to the subjective and individual reaction of a system to the external stress, like mechanical tension.

The same principle is also applied within the field of human factors and ergonomics. Thereby, stress represents an objective measure, which may result into different amounts of strain depending on the specific individual (e.g. Rohmert, 1984). For example, even though a stone weighs 10 kg (objective, stress) the resulting strain is different if the stone is lifted by a child or by a body builder (subjective, strain) resulting to a probably higher strain for the child.

2.2 Human-Machine Interaction

The following chapter deals with the concept of human-machine interaction. Within the fields of engineering and computer science the term of interaction is used to designate the mutual influence between a user (human) and an interactive system or machine with the goal to solve tasks in consultation (e.g. Fischer & Hofer, 2011; Franz, 2014, p. 20; Weiß & Kilian, 2003). Additionally to the given definition, HMIs further involves the environment in which the interaction takes place – resulting in the trinity of human, machine and environment (e.g. Schneider, 2010, p. 23; Sheridan, 2010, p. 30). Thus, models for the investigation of HMIs generally consist of these three basic elements, which each act on and interact with each other (cf. Oberle & Bruder, 2015, p. 2).

For the present work, the model of HMIs as described by Bubb (2005, p. 355) is used for a further distinction and investigation of HMIs (see Figure 2-1). The model generally consists of the three above mentioned elements - human, machine and environment - but further includes several additional aspects important to HMIs, like an initial task, a result and feedback. At the beginning of an interaction stands the task, which defines the goal for a given interaction and further describes the intended result of the interaction. The human element is characterized by individual properties and abilities, which are not outlined further, and acts itself onto the machine. This action results into a direct reaction from the system to the human and lastly into a result, which is also looped back to the human as feedback. Thereby, the environment affects the human, the interaction between human and machine as well as the machine itself and is characterized by Bubb (2005, p. 354) as "external influences". In case of the environmental impact onto the human, this influence is addressed as strain. Strain impacts on the individual properties and abilities and in conjunction with task, interaction and feedback results into a specific workload onto the human operator.

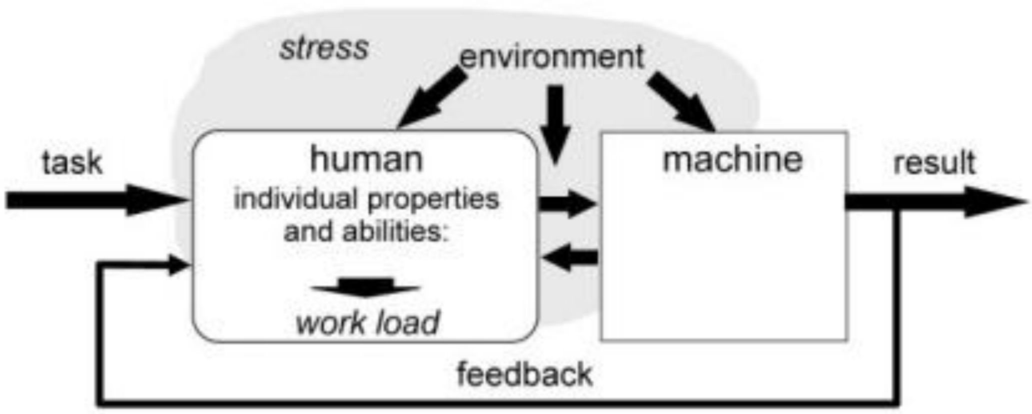

Figure 2-1. Structure of human work and related influences for a human-machine interaction (Bubb, 2005, p. 355).

Even though the presented model considers elements beside the sole mentioning of human, machine and environment and even describes their relation in detail, no immediate influencing factors are addressed. An approach for detailing of the human element is found in Sheridan (2010, p. 30), who divides the human element into the functions sensation, cognition and action. However, Sheridan states that further differentiation of the human subsystem is difficult due to the characteristics of the human body. Concluding on the human element, direct mention of specific influencing factors or specification of the above addressed "individual properties and abilities" and their relation is not found within the literature. Same applies for the other two elements machine and environment. Even though environment is commonly distinguished between social and physical environment (e.g. Bernotat, 2008, p. 6), a direct inclusion of influencing factors within the context of HMI is non-existent. Still, model-independent references of influencing factors on human performance and of the environment, like experience and individual goals or organizational aspects (e.g. Badke-Schaub et al., 2008, p. 51; Dismukes, 2010, p. 339), exist and are discussed in chapter 2.4. Beforehand, different models for the description of human information processing and action are discussed.

2.3 Models for the Description of Human Information Processing and Action

Within the following chapter, several models for the description of human information processing and human action are discussed and presented. A further distinction of human action is needed to investigate possible sources for human induced uncertainty in relation to human sub processes. Models already incorporating influencing factors onto human induced uncertainty are preferred for the above reason.

Generally, a multitude of models for the description of human behavior, human action, decision-making and human information processing exist throughout the literature. Thereby, the models strongly differ in structure, complexity, field of research and scope of application. Especially the field of psychology reasonably yields a high contribution to the investigation of human behavior and action. However, most psychological models are found to be inappropriate for the further classification of the human element of HMIs.

For instance, the models attributed to the field of activity theory, like the TOTE model by Miller (1960) or the VVR model by Hacker (1980), describe basic, sequential principles of human action. They are generally used within the field of work psychology to depict that actions are generally repeated until a desired or at least best possible result is achieved by an iterative variance analysis. But only little information is added to the in chapter 2.2 described model of HMI. On the other hand, theories from the field of cognition, like the PSI-theory by Dörner (1999) or the ACT-R theory by Anderson (1983), represent complex concepts. Thereby, they are intended for the simulation of cognition and are hardly descriptive. Also the Rubicon-model as proposed by Heckhausen and Gollwitzer (1987) is inappropriate for a further classification of human contribution to HMIs. The model yields some information on human decisions by stating that at some point of human action a motivation for an action irreversibly resolves into its execution (crossing the Rubicon). But the focus of the model remains on decision-making. Lastly, theories for the explanation of human behavior, like the theory of reasoned action (Fishbein & Ajzen, 1975) or the theory of planned behavior (Ajzen, 1991), are too complex for an application. Though both theories contain references to human influencing factors, or more precisely to categories of influencing factors, the focus onto behavior represents a broader concept and not only involves single, explicitly goal-driven actions.

Concluding, the above-mentioned models and theories from the field of psychology, though certainly contributing to the explanation of behavior and decision-making, are inadequate for the description of the human element within HMI. Henceforth, models for the description of human information processing and human performance are used, as they allow for a process oriented approach. According to Schlick, Bruder, and Luczak (2010, 286 ff.), distinction between phenomenological-empiric and mathematical-functional models can be made. The former category of models focuses on perceptional and cognitive processes and is further divided into sequential and capacity models. The latter focuses on the functional description of human information processing through equations with the goal to quantify certain elements of human performance. Models of the mathematical-functional category are inclined to concentrate on specific aspects of human information processing to allow for the derivation of equations. Thus, the models of the phenomenological-empiric category are preferred consecutively, as they represent a more holistic approach for the description of human information processing. Thereby, two models from the sequential subgroup and one model of the capacity subgroup are presented, followed by a last model which expands the approach of the first model and further allocates specific sub processes of human information processing to types of tasks. The outlined models were chosen as basic examples within their fields and in conjunction build the foundation for the present work.

2.3.1 Block Diagram of Sensory-Motor Performance (Welford, 1968)

The block-diagram of sensory-motor performance by Welford (1968) represents the basic principles of human information processing (see Figure 2-2) and represents a sequential approach. The model describes the processing of an external signal or cue through three central and sub-sequential mechanisms, which are the perceptual mechanism, the translation mechanism and the central effector mechanism. Thereby, a stimulus is first received by the sensory organs, which convert them into nerve impulses. Then, the nerve impulses are transmitted to the perceptual mechanisms, at which the information is identified. Within the translation mechanism a specific action is chosen in response to the identified information. Through the central effector mechanism, the chosen action is executed through the determination and coordination of effector organs, like hands or feet. Besides the sequential arrangement of the mechanisms, Welford (1968) argues that parallel processing of two mechanisms is possible, for example when still reacting to a previous signal, a new signal can already be perceived.

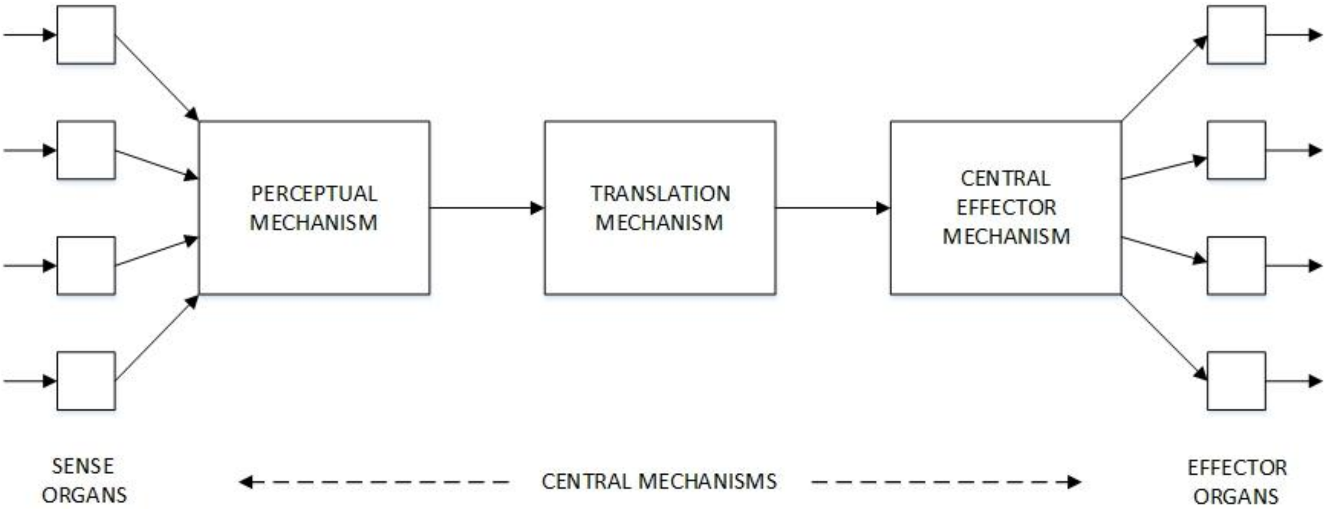

Figure 2-2. Block diagram of sensory-motor performance (according to Welford, 1968, p. 192).

The block diagram of sensory-motor performance represents a simple distinction of three human sub-processes occuring between the input and output of information in relation to sense and effector organs. Singer and Rieder (1985, p. 107) extended the above model by including a short-term memory between perceptual and translational mechanism to better represent the proposed parallel processing of information of two mechanisms. Also a long-term memory is added, which allows for the storage of made decisions and their relation to the perceptional mechanism for improved identification.

The inclusion of the memory represents an approach also conducted by the following model of human information processing.

2.3.2 Levels of Human Performance (Rasmussen, 1983)

The levels of performance as proposed by Rasmussen (1983) describe three different stages of decision-making and the related mode of mental information processing and are also a representative of the sequential subgroup. Thereby, the levels of skill-, rule- and knowledge-based performance are differed. Within the field of human factors the SRK (skill, rule, knowledge) model is well known and widely applied (Vicente, 1999), e.g. for the classification of different types of human error (Reason, 1990). Due to the connection to human error, the applicability of the SRK model for the investigation of uncertainty is examined.

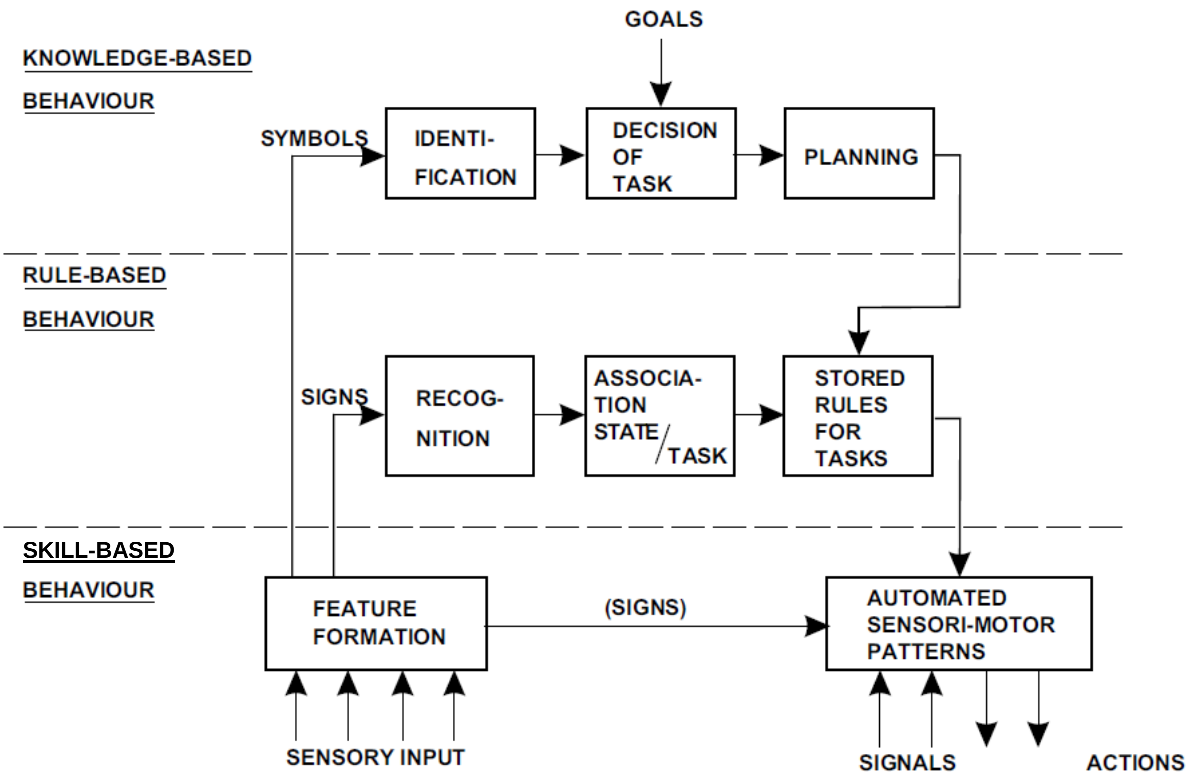

Figure 2-3. The three levels of human performance (Rasmussen, 1983, p. 258).

According to the SRK model as depicted in Figure 2-3 a sensory signal enters on the lower left side and is further processed on one of the three performance levels, depending on the operator's degree of expertise with the task and the given conditions. In case of highly trained operators, signal processing is done on the skill-based level without high demands on mental processing. Thus, an automatic reaction based on the sensory input is directly executed. In case an operator is generally accustomed to the task and the demands of the perceived information but lacks further training, processing is done on the rule-based level. This involves the recognition of the perceived information and its association to known tasks and reactions based on stored "if-then"-relations. Thereby, processing is done intuitively and needs more time than automatic, skill-based reactions. When confronted with unknown and/ or complex situations, a task is processed on the knowledge-based level. After identification of the perceived information a new reaction must be derived through the combination of existing knowledge according to the task-related goal. Due to the novelty of the perceived information and possibly the chosen reaction, the highest amount of time is needed for processing in relation to rule- and especially skill-based performances.
Even though the SRK model does not include direct mention of environmental or machine elements, similarities to the information processing, like the direct transformation of perceived information to an executed action, exist. Further, the model explains the differences between novices and experts and gives insights into sources for interindividual differences of humans regarding their performance.

2.3.3 Human Information Processing (Wickens, Hollands, Banbury & Parasuraman, 2012)

In contrast to Welford, the model of human information processing as proposed by Wickens et al. (2012, p. 4) relies on four process stages (see Figure 2-4)[1]. Thereby, the task of the sense organs is transferred

[1] All information of this chapter refers to Wickens, Hollands, Banbury, and Parasuraman (2012), except where stated differently.

into a new and initial state of sensory processing, which is followed by perception, response selection and response execution. Additionally, the model contains an element for working memory and cognition, an element for long-term memory and an element for attention resources.
Working memory and cognition is located between perception and response selection and further interacts with the long-term memory and thus is responsible for retrieving information from the long-term memory to compare them to the perceived signals for identification and response selection. Thereby, made decisions may further be added to the long-term memory for successive processes. Interestingly, a direct connection between perception and response selection exists additionally, allowing for a fast and intuitive processing in case of emergency. Besides interacting with working memory and cognition, the long-term memory is further connected to perception facilitating the intuitive comparison of perceived information.

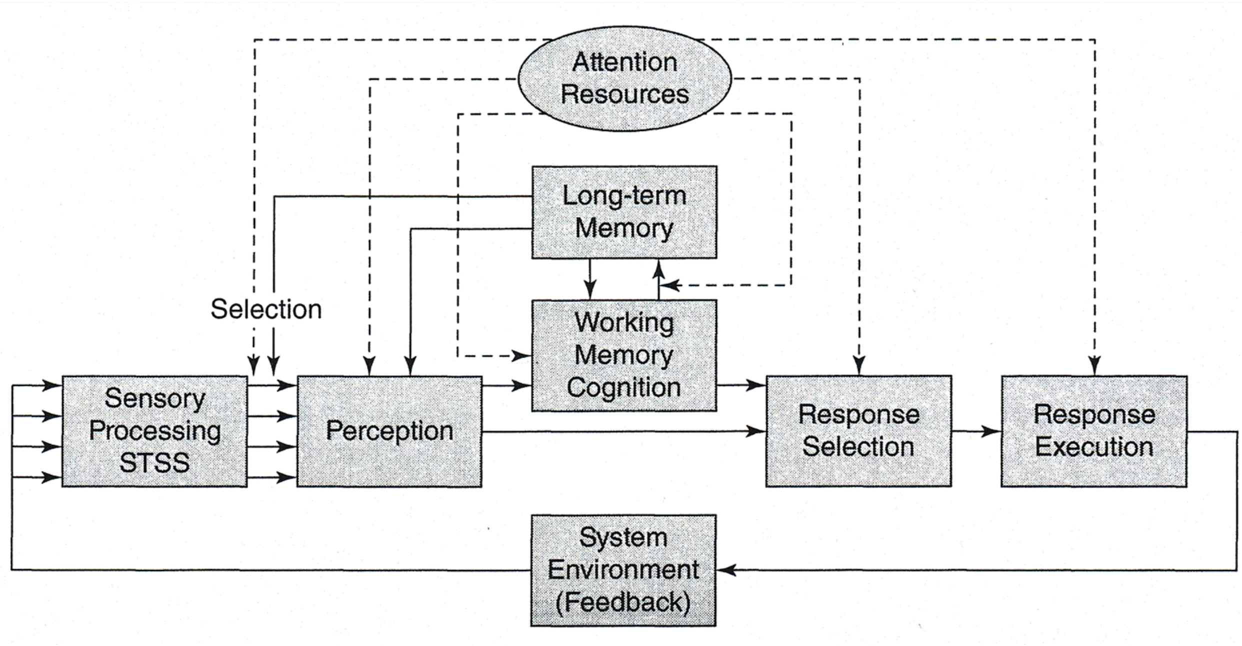

Figure 2-4. Model of human information processing stages (Wickens et al., 2012, p. 4).

Further, long-term memory affects the link between sensory processing and perception in combination with attention resources. Thereby, the latter affects all four stages of information processing as well as working memory and cognition and its link to the long-term memory. The element of attention resources represents the central element of the model and illustrates the effect, that information processing is directed by attention. If sufficient attention resources are unavailable for a new incoming signal, no processing is initiated, which explains why the model belongs to the group of capacity models. Therefore, the model allows for a specific explanation of the effect of possible multiple information processing as suggested by Welford (1968, p. 192) and further depicts the limits of information processing.
Finally, response execution results into a block also containing system, environment and feedback. Hence, a common foundation for a combination of the human information processing model and the model of HMI exists. Thereby, distinction of four basic stages of information processing as described above can be regarded as common ground and is found within various other models (e.g. Sanders, 1983, p. 79).

2.3.4 Classification of Mental Work Based on Human Information Processing (Luczak, 1975)

Based on the general distinction of work into physical and mental work (Rohmert, 1983), Luczak (1975) defined an approach for the further categorization of mental work, based on a model of sensory-motor performance, which is depicted in Figure 2-5.

Luczak (1975) structures the process of human information processing into the four steps of detect, recognize, decide and act. Within the first step of detection external cues and signals are processed with the help of the sensory modalities. This step generally states if and how external cues are processed. During the second step, the detected cues are compared to the stored information within memory to identify the received signals. Based on the identification of the external cues, an appropriate reaction is derived from memory or newly designed, if no adequate information is present. Thus, a decision how to react to the signal is made. Finally, the chosen action is executed through motoric movements of the muscles which can result into motion as well as speech.

Based on the process of information processing, which is almost equal to the model of Wickens and Hollands (2000), Luczak (1975) embedded a distinction of different types of mental work. Thereby, each step of information processing is associated with a specific type of mental work. To classify a specific activity, its highest demand on a corresponding step of information processing is identified. An activity focusing on the detection of external cues and signals is defined as sensory work. A typical example for sensory work would be the visual inspection of a product for manufacturing defects. An activity primarily based on the recognition is defined as discriminatory work, for which the activity of air traffic control is an example. The term combinational work is applied for activities with high demands on decision making, like managing tasks. Finally, the work of a traffic policeman could be primarily associated with the step of action, which is defined as signal-giving-motoric work. Since in terms of mental work a sole action is impossible without prior sensory work, a further type, the sensorimotor work, is defined. Sensorimotor activities generally rely on high precision and thus on the close relation of translating external cues into precise movements. According to Luczak (1975) a last type for activities exist, which is defined as creative work. Creative work represents the most complex activity and involves all four steps of information processing. An example would be product development.

Besides, physical work can be attributed with step four of human information processing, acting.

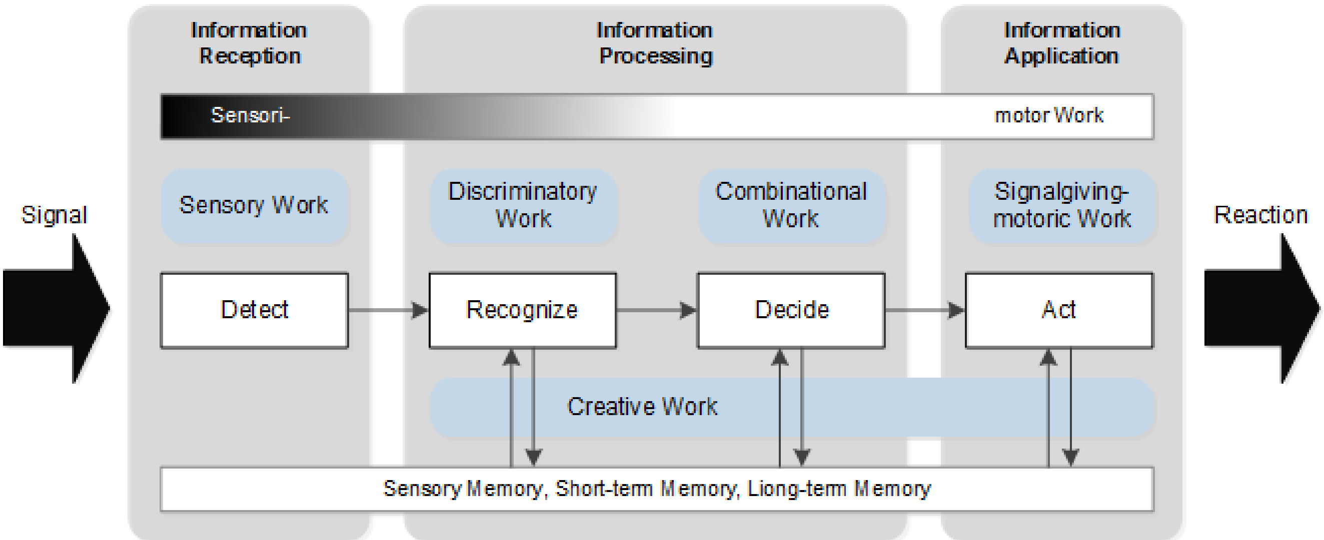

Figure 2-5. Classification of mental work types based on human information processing (adapted from Damböck (2013), based on Schlick et al. (2010) and Luczak (1975)).

The above described classification of mental work is of use for the investigation of human induced uncertainty. By characterizing a given task, a corresponding step of human information processing can be identified, as for specific tasks a different focus within the human sub-process is relevant. As an identified step embodies the highest demand for a given task, it represents the bottleneck of human processing and thus is likely to be a major source for uncertainty.

2.4 Uncertainty of Human-Machine Interaction

The following two subchapters focus on the definition and discussion of uncertainty and accompanying methods. First, different concepts of uncertainty are discussed and a definition for the present work is derived. Second, the term of human induced uncertainty is defined and specified for the description of uncertainty of HMIs.

2.4.1 Uncertainty Theories

As the initial quote of David Hume depicts, uncertainty has been subject to research for a long time. Thereby, almost every discipline, from physics, economics, philosophies to mechanical engineering, has created own definitions and concepts for the description and treatment of uncertainty. Following, some major concepts for different disciplines are presented.

One of the first direct annotations to uncertainty was given by Knight who discussed the difference between risk uncertainty from the view of economics. Knightian uncertainty is defined as occurring "when the probabilities of future states, or even the nature of possible future states [are] not known" as summarized by Soros (2013, p. 314). In contrast, Knight (1921, p. 20) designates risk as "measurable uncertainty", which means that possible states and the probabilities for the occurrence of each state are known and quantifiable. Uncertainty thus represents the absence of knowledge concerning the outcome or even the existence of an event.
The connection of knowledge and uncertainty is found in the field of social sciences, too. Hammond (1996, p. 15) states that in "the case someone would know every detail of a process and its outcome, no uncertainty would be at hand". He further distinguishes two forms of uncertainty, the *subjective* and *objective uncertainty*. The former represents a person's individual estimation of probability that a certain event occurs, whereas the latter stands for the real and objective probability of an event. This distinction clearly adheres to human decisions and judgements by focusing on an individual's interpretation of probability, based on his personal knowledge and information. A concept of uncertainty also focusing on human decision is proclaimed within the field of human factors and ergonomics, where uncertainty is designated as "not knowing for sure" (Grote, 2014b, p. 72) as cause of insufficient and misleading information. This definition is addressed to uncertainty of organizations and management. Thereby, Milliken (1987) distinguishes between *state uncertainty*, which addresses the probability of an event, *effect uncertainty*, which represents absent knowledge about the result of an event and *response uncertainty*, which lastly describes missing knowledge about response options. Both latter uncertainty concepts address the uncertainty of humans towards events, products, organizations or systems, which is not the direct focus of the present work (cf. chapter 1.2). Still, the definitions confirm again the relation of uncertainty to knowledge.
Within the field of civil engineering, uncertainty is considered from a data-driven perspective, attributed to inaccurate measures, models and information. Thereby, Reuter (2013, p. 179) distinguishes between

uncertainty deriving from variability and from fuzziness. Variability addresses the random changeability of elements of a specific sample or of a whole population, whereas fuzziness addresses the impossibility of the precise assessment of a single observation. Even though data uncertainty is of importance for measurements in general, this definition only addresses a specific application in comparison to the prior stated concepts. An example for the importance of data uncertainty for one and the narrowness of solely focusing on data uncertainty for another is demonstrated within the field of mathematics. Viertl and Yeganeh (2013, pp. 272–274) distinguish no less than seven different types of uncertainty: variability, data uncertainty, physical uncertainty, statistic uncertainty, model uncertainty, cause-effect uncertainty and uncertainty of hypotheses[2]. These types are strongly related to the world of numbers and measurements. And even though these types of uncertainty are relevant when dealing with measurements, they are not generally applicable to the field of mechanical engineering.

From the field of product design, uncertainty is reflected as both, the probability of incorrect assumptions and the existence of unknown facts germane for prospective conditions of a product and market success (Weck, Eckert, & Clarkson, 2007, p. 1). In comparison to the first stated Knightian uncertainty concept, former can be addressed as risk and the latter as uncertainty. Weck et al. further distinguish uncertainty dependent on its source. Thereby, uncertainty from within a system boundary is addressed as endogenous uncertainty in contrast to exogenous uncertainty, which derives from influences outside system boundaries. Additionally, Weck et al. (2007, p. 4) state that endogenous uncertainty is easier to handle in comparison to exogenous uncertainty.

In contrast to the initially stated Knightian uncertainty, concepts of uncertainty within the field of engineering tend to incorporate risk as one type of uncertainty and further define more types of uncertainty. This conceptual approach is confirmed by Hastings and McManus (2004, p. 2) from the field of mechanical engineering, who define uncertainty as “things that are not known, or known imprecisely”. Hastings and McManus (2004, pp. 3–5) further identify three different types of uncertainty: statistically characterized (random) variables/ phenomena, known unknowns and unknown unknowns. The first type is defined as facts that can be described statistically. The second type, known unknowns, represents the awareness towards unknown things which can at best be characterized through bounding conditions. The third and last, unknown unknowns, adheres to things totally unexpected and thus not regarded at all. The last type is somewhat contradictory in its interpretation, as things one did not expect, but which suddenly occur, directly transform into known unknowns. Thus, it best represents the Knightian definition of uncertainty. Another distinction of uncertainty is described by Hauptmanns and Werner (1991; cf. Knetsch, 2006, p. 3), who discern aleatoric uncertainty (random variation of influencing factors) from epistemic uncertainty (due to insufficient knowledge). Whereas the latter can be decreased through the acquisition of new knowledge, the former is an integral part of all systems and can at best be described statistically.

Stirling (2001, 2003) differentiates uncertainty by probability and significance each on a scale of known and unknown. In combination with the concept of aleatoric and epistemic uncertainty, a recent definition and model for uncertainty is given by Engelhardt et al. (2010). The model was developed within the Collaborative Research Center 805 (CRC 805) and is depicted in Figure 2-6.

[2] Due to reasons of brevity, the referenced literature is referred to for details.

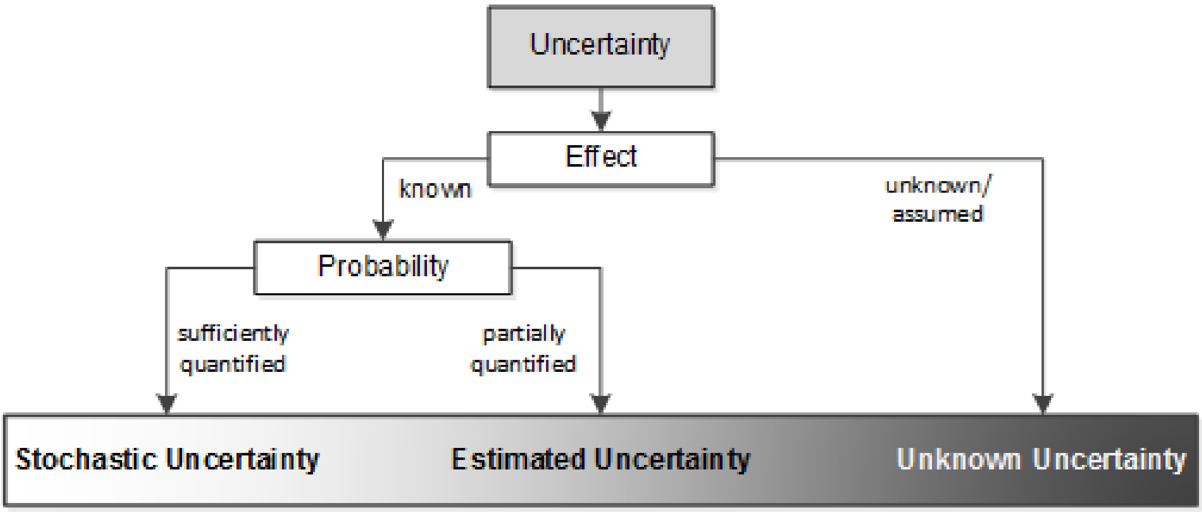

Figure 2-6. Model of uncertainty of the CRC 805 (adapted from Engelhardt et al., 2010, p. 58).

The uncertainty model was developed within the context of load bearing technical systems. According to the paradigm of the CRC 805 uncertainty occurs when process properties of a system cannot or only partially be determined (Hanselka & Platz, 2010, p. 57). Thereby, uncertainty is classified as unknown uncertainty, estimated uncertainty and statistical uncertainty. The type of unknown uncertainty occurs, if no knowledge about a process and the involved influencing factors exist. In case of estimated uncertainty, the influence of involved factors onto a process is partially known and can be represented through boundary values. Statistical uncertainty represents a state, where the impact of influencing factors onto a system's stress can be described through distribution functions. Thereby, the amount of uncertainty decreases throughout the three types and is least in case of statistical uncertainty, which allows for predictions concerning the resulting stress. Thus, obtaining further knowledge is the main goal to cope with uncertainty.

All definitions above coincide to the fact that uncertainty relates to knowledge. For the present work, uncertainty is thus generally defined as the "absence of knowledge". Concerning the multitude of different types of uncertainty, this thesis abides to the distinction according to the CRC 805, which classifies uncertainty into stochastic, estimated and unknown uncertainty.

2.4.2 Human Induced Uncertainty of Human-Machine Interaction

To prevent confusion between different aspects of uncertainty within this thesis, the term of "human induced uncertainty" is introduced. Human induced uncertainty is defined as a part of the uncertainty of HMI and addresses the human impact onto the resulting system stress. Human induced uncertainty is thus the part of uncertainty, which is attributed to the active human participation. Human induced uncertainty generally classifies as unknown uncertainty, as by today, no explicit knowledge about human impact on the stress of a system exists. Human induced uncertainty can be assessed by measuring the mean and standard deviation of the resulting system stress due to an interaction. Thereby, possible other sources for uncertainty, for example from within the system, must be eliminated or known in advance.
Further distinction of human induced uncertainty and possible sources within the human part of an interaction as well as the contribution of human influencing factors are content and aim of the following work. At this stage, no further explanation can be given.

2.5 Influencing Factors on Human Induced Uncertainty

Regarding HMIs, the literature coincides that the elements of human, machine and environment are involved and affecting each other (e.g. Bubb, 2005, p. 355; Schneider, 2010, p. 23). To understand the involvement of these elements, each element must be further described. Thereby, certain characteristics can be identified for each element. First, this helps to further discern a single entity of an element (e.g. discerning different humans through their characteristic height) and second the identified characteristics lastly impact on an HMI as influencing factors[3].

Thus, the following chapter identifies and defines influencing factors of each element of an HMI, starting with the human, proceeding with the technical subsystem and lastly focusing on the environment.

2.5.1 Human Influencing Factors

The following chapter represents an overview over various human influencing factors, which impact on human performance, on HMI and thus on human induced uncertainty. First, an approach for the categorization of the human influencing factors is derived, to cope with the high number of existing factors. Thereby, each identified factor is assigned to one category. Second, the identified factors are defined grouped by category. Finally, typical attributes of human influencing factors with regard to uncertainty are presented.

2.5.1.1 Categorization of Human Influencing Factors

Based on Badke-Schaub et al. (2008, p. 4), human influencing factors are all physical, mental and social characteristics of the human which impact on or are impacted by the interaction with socio-technical systems. With this definition, a categorization of influencing factors into physical, mental and social factors is given. A different, process oriented categorization is given by Johnson (2003, p. 65), who reports of "performance shaping factors" which impair on perceptual, cognitive and physiological resources during an action.

As the first definition originates from the field of psychology and the second from the field of ergonomics and human factors, both definitions address a different approach. First it can be noted, that each definition involves a unique category, social and perceptual. Second, the remaining four categories address different human aspects. Both statements correspond in bringing up the categories of mental/ cognitive and physical/ physiological factors. Due to the different fields of origin, both may use different words for the same categories. Anyway, both address a category centered on the human mind and a different category focusing on the physical aspects of the human body. Therefore, a category for the two mentioned aspects is adopted, resulting into a total of four categories: perceptual, mental, physical and social.

Table 2-1 shows all covered human influencing factors for the above-mentioned categories. The majority of the presented factors are gathered from the work of Johnson (2003), Muckler (1984), Durso and Alexander (2010) as well as Schlick et al. (2010). During the collection and definition of the human influencing factors some factors couldn't be allocated to only one specific group. For example, the factor fatigue can be applied to address physical and mental fatigue. For this reason, another column was added to the table to account for these ambiguous factors. It should be noted that the presented and

[3] Following, the term of influencing factors is used when referring to the characteristics of the HMI elements to emphasize their contribution to the result of an HMI.

defined factors within this thesis don't incorporate all possible and existing human influencing factors, but only represent a first collection based on the above-mentioned literature. Probably other factors exist and, more so, various covered factors can be subdivided into other factors. Still, the presented factors represent a core-collection, which are used within this work for a first investigation of human induced uncertainty.
As this chapter focuses on the individual and personal human influencing factors, the category of social factors is described within chapter 2.5.3 as part of the social environment.

Table 2-1. Human influencing factors grouped by category.

Perceptual Factors	Mental Factors	Physical Factors	Ambiguous Factors
Visual	Attitude	Anthropometry	Age
Auditory	Creativity	Dexterity	Attention
Tactile	Experience	Handedness	Ethnic Origin
Vestibular	Expertise	Strength	Emotion
Gustatory	Intelligence		Fatigue
Olfactory	Knowledge		Genetics
Kinetic/ Proprioceptive	Mental Model		Health
Thermal	Mode Awareness		Metabolism
Pain	Morality		Motivation
	Qualification/ Education		Personality
	Situation Awareness		Practice
			Rhythmology
			Sex
			Training

2.5.1.2 Definition of Human Influencing Factors

Perceptual Factors

The perceptual factors are necessary for the detection of external signals and are characterized by the sensory modalities of visual, auditory, tactile, vestibular, gustatory, olfactory, kinetic/ proprioceptive, thermal and pain perception (cf. Keidel, 1971; Schlick et al., 2010; Schönpflug & Schönpflug, 1997). These factors represent the initial phase of human information processing (e.g. Schlick et al., 2010, p. 313). Only if humans correctly detect the relevant environmental cues and signals, adequate actions can be chosen and exerted (Johnson, 2003, p. 66). The above mentioned sensory modalities are defined in Table 2-2.

Table 2-2. Definition and description of the perceptual influencing factors (sensory modalities).

Factor	Definition
Visual Perception	The visual system consists of the processing of visual cues and signals in combination with parts of the brain, especially the visual cortex. Important factors for visual processing are the detection of differences in brightness, color and motion as well as the size of the visual field, visual acuity and the impression of spatial depth (Schlick et al., 2010, pp. 317–337).

Auditory Perception	Auditory cues are perceived through the processing of sound waves within the ear. Important factors for auditory processing are the detection of different tone pitch, tone composition and volume as well as spatial perception (Schlick et al., 2010, pp. 338–344).
Tactile Perception	Tactile perception is the detection of haptic cues and signals based on force and pressure, which is generally achieved through receptors on the skin (Schlick et al., 2010, pp. 346–347).
Vestibular Perception	Vestibular perception is responsible for spatial orientation and achieved through the inner ear and thus connected to auditory perception (Schlick et al., 2010, p. 345).
Gustatory and Olfactory Perception	Gustatory and olfactory perception are responsible for the detection of scents and flavors though mouth and nose. Both sensors are needed for the detection of scents and flavors, but the olfactory perception (scents) is predominant (Schlick et al., 2010, pp. 351–354).
Kinetic/ Proprioceptive Perception	The kinetic or proprioceptive perception is responsible for the detection of limb- and body-positions as well as for motion. Appropriate sensors are located within joints, muscles, tendons, skin and the vestibular apparatus (Schlick et al., 2010, pp. 348–349).
Thermal Perception	Thermal perception is responsible for the detection of temperature, where at independent sensors for coldness and heat exist (Schlick et al., 2010, p. 350).
Pain Perception	Pain is directly detected by so called pain mediators within the tissues, which stimulate the nerve endings (Schlick et al., 2010, pp. 350–351).

Mental Factors

Following, the mental influencing factors are treated. A definition as well as additional literature for each factor is given in Table 2-3. As single factors fill whole volumes or even represent a distinct field of research the consecutive account of factors only represents a brief overview to help for a better understanding of each factor within the present work.

Table 2-3. Definition and description of the mental human influencing factors.

Factor	Definition	Additional Literature
Attitude	"Attitudes are the evaluative judgements that integrate and summarize […] cognitive/ affective reactions." (Crano & Prislin, 2006, p. 347).	Berger & Burgoon, 1995; Crano & Prislin, 2008.
Creativity	Creativity is the ability to apply knowledge and experiences of differing domains to create new ideas by overcoming solidified patterns of thought (Geschka & Reibnitz, 1990, p. 844).	Holm-Hadulla, 2000; Jez, 2005; Müller, 1990.
Experience	Experience represents single encountered events which were perceived as important in contrast to other events (Wehner & Dick, 2007).	Gruber, 1999.

Expertise	Expertise is domain specific and specialized knowledge, which is acquired through deliberate practice and generally provides a measurable performance advantage (Wickens et al., 2012, p. 208).	Cellier, Eyrolle, & Marine, 1997; Ericsson, 2007; Vidulich et al., 2010.
Intelligence	Intelligence is the ability to correctly solve problems and to handle new situations through the understanding, creation and interpretation of relationships (Schlick et al., 2010, pp. 134–135).	Jez, 2005; Sternberg, 1999.
Knowledge	Knowledge is "acquired information that can be activated in a timely fashion in order to generate an appropriate response" (Charness & Schultetus, 1999, p. 61).	Lewandowsky, Little, & Kalish, 2007.
Mental Model	"Mental models are dynamic [change over time], functional representations of 'reality'. Their reliability [inaccurate, incomplete, mostly wrong, poorly defined] increases with expert knowledge [differ between experts and novices]" (Märki, Maas, Kauer-Franz, & Oberle, 2016, p. 350).	Carroll & Olson, 1987; Moray, 1999; Schmidt, 2007; Völkel, 2005, p. 6; Wickens et al., 2012, p. 236.
Mode Awareness	Mode Awareness is the ability of a user to comprehend and predict the behavior of an automated system (Sarter & Woods, 1995).	
Morality	Morality is the code of conduct used for discerning good or wrong actions, which is shaped by the social environment and certain experiences (based on Gert & Gert, 2016).	Greene, 2013; Johnson, 1997; Stich, 1993.
Qualification/ Education	Qualification and education cover all certified knowledge, skills and abilities needed for the accomplishment of a specific task (Schlick et al., 2010).	Peters, 2007.
Situation Awareness	Situation awareness is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1995, p. 36).	Durso, Rawson, & Girotto, 2007; Vidulich et al., 2010, pp. 204–205.

Besides their definition, various connections and interdependencies between the mentioned factors can be identified. For example, the factors of mental model and knowledge are related, as mental models represent a process oriented combination of knowledge allowing to simulate actions before their execution (Moray, 1999). Further it can be noted that the definition of various factors remains highly controversial. This especially applies for factors originating from the field of psychology or social sciences, like intelligence, personality or morality (e.g. Guilford, 1974; Sternberg, 1999). In these cases,

definitions promoting a certain applicability are preferred to further endorse instruments and methods for their assessment. Lastly, only a general definition of the concept of each factor is given in favor of brevity. Therefore, factors like attention which can be further subdivided into selective, focused, divided and sustained attention (e.g. Wickens et al., 2012, p. 49) are not discussed in detail. The same applies for the factor knowledge, which can be subdivided into explicit, implicit and tacit knowledge (e.g. Wallace, Ahmed, & Bracewell, 2005, p. 331).
Concluding it can be noted that the above-mentioned factors are at best complex and the given information and definitions only reflect a small fragment of each factor's nature.

Physical Factors
Within Table 2-4 the physical influencing factors are defined and additional literature is referenced.

Table 2-4. Definition and description of the physical human influencing factors.

Factor	Definition	Additional Literature
Anthropometry	Anthropometry characterizes the physical build and dimensions of a human body in form of phenotypes and parameters like height and reach (based on Schlick et al., 2010).	DIN 33402-2, 2005
Dexterity	Dexterity is defined as the aptitude to perform precise movements. A distinction is made between fine motor skills (small, fast and precise movements with low force exertion, generally of fingers or hands) and gross motor skills (movements of larger muscle factions or whole body movements) (Singer & Rieder, 1985, pp. 18–19; Teipel, 1988).	Fleishman, 1972; Schmauder, 2007.
Handedness	Handedness defines the preferred hand (left or right) a person utilizes for the execution of tasks and actions. A distinction between hand preference and hand performance can be made, where the former represents the learned preference to operate a task with one hand and the latter represents the dominance of one hand over the other regarding performance (Schmauder, 1999, pp. 2–3).	Schmauder, 1996; Schmauder, 2007.
Strength	Strength describes the amount of possible force exertion through the muscles and can be distinguished between the maximum possible force exertion for a short time period and regular force exertion below the maximum but with increased duration and frequency (Rohmert, 1989).	Luczak, 1989; Mainzer, 1982; Rohmert, Rückert, & Schaub, 1992; Wakula et al., 2009.

The factor of body phenotypes, which characterizes certain body shapes into ectomorph, mesomorph and endomorph (cf. Sheldon, 1970), remains unconsidered. Anthropometry represents a more applicable concept in relation to phenotypes. Thereby, anthropometry directly allows for the assessment of descriptive data like a person's height or reach, which are important for the execution of actions.
In contrast to the mental factors, the physical factors seem to be less controversial and their definitions more practically oriented. This is because the factors represent well known concepts and are partly assessable through visual examination. Still, their impact on HMIs is not less substantial then that of the perceptual or mental factors.

Ambiguous Factors

As discussed initially, some factors cannot be categorized explicitly as perceptual, mental or physical factors. Thereby, the ambiguous factors represent basic principles and itself affect several other factors. For example, the factor age interferes with factors like experience, anthropometry and auditory perception. Thus, the ambiguous factors may not only impose a direct impact to performance but further interrelate with other factors. Table 2-5 presents definitions for the identified ambiguous factors.

Table 2-5. Definition and description of the ambiguous human influencing factors.

Factor	Definition	Additional Literature
Age	"The length of time a person has lived" (Oxford University Press, 2017b).	
Attention	Attention is a mental state of enhanced vigilance which directs the awareness – willingly or unwillingly - onto certain objects, operations and thoughts (Badke-Schaub et al., 2008, p. 64).	Davies, Matthews, Stammers, & Westerman, 2000; Kahneman, 1973; Strayer & Drews, 2007; Wickens et al., 2012, p. 49.
Ethnic Origin	Ethnic origin describes the affiliation to a cultural and regional population or tribe and is characterized by the idea of a corporate and collective identity (Hopfner & Naumann, 2009, p. 28).	
Emotion	Emotions are a complex patterns of processes that include motivations, arousal, cognitive processes and behavioral tendencies (Zimbardo, Gerrig, & Hoppe-Graff, 2003).	Badke-Schaub et al., 2008, p. 96.
Fatigue	Fatigue is commonly characterized as the need for sleep, is the result of ongoing stress or work, can be physical or mental, leads to a reduction of performance and is generally reversible through rest (Becker-Carus, Dorsch, Häcker, & Stapf, 2009; Greif, 1989; Mallis, Banks, & Dinges, 2010; Schlick et al., 2010; Schmidtke, 1965). Fatigue and monotony strongly relate, where at monotony is known to lead to an increase of fatigue (cf. Brown, 1994; Hacker, 1984; Schlick et al., 2010; Ulich, 2005).	Brown, 1994; Geißler, Hagenmeyer, Erdmann, & Muttray, 2007.

Genetics	"The genetic properties or features of an organism" (Oxford University Press, 2017a).	
Health	"Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO, 1946). Especially, mental health is "a state of well-being in which every individual realizes his or her own potential, can cope with the normal strains of life, can work productively and fruitfully, and is able to make a contribution to her or his community" (WHO, 2014).	WHO, 1986.
Metabolism	Metabolism covers all chemical processes of a body like food intake and conversion (Schlick et al., 2010, p. 266).	
Motivation	Motivation represents the current orientation on a specific action and its connected goal (Heckhausen, H. & Heckhausen, J., 2010).	Nerdinger, Blickle, & Schaper, 2008; Weinert, 1992. Zimbardo et al., 2003, p. 319.
Personality	Personality are an individual's characteristic, temporally enduring cognitive, emotional and behavioral patterns (Schlick et al., 2010, p. 112).	Guilford, 1974; Goldberg, 1993; Wiggins & Pincus, 1992.
Practice	Practice is the unwilling and automatic improvement of performance through repetition of an activity (Liebau & Landau, 2007).	Jeske, 2013; Schlick et al., 2010; Singer & Rieder, 1985; Ungerer, 1971.
Rhythmology	Rhythmology addresses the biology-driven periodic fluctuation of the body functions which impact on performance and for which the circadian rhythm is most prominent (Schlick et al., 2010, p. 167).	Nyhuis, Ullmann, & Potthast, 2012.
Sex	Represents the biological and genetical difference between male and female humans (Schlick et al., 2010, p. 89).	
Training	Training is the planned and systematic improvement of performance through repetition of an activity (Liebau & Landau, 2007).	Jeske, 2013; Schlick et al., 2010; Singer & Rieder, 1985; Ungerer, 1971.

The effects of stimulants like alcohol, caffeine or drugs are covered within the factor of metabolism. This is mentioned as the influence of external substances affects other factors, like fatigue (Johnson, 2003, p. 63), but is easily missed.

Following, specific attributes of the identified and presented human influencing factors especially regarding their impact on performance are discussed.

2.5.1.3 Attributes and Characteristics of Human Influencing Factors

As mentioned in chapter 1.1, one cause for uncertainty depends on human performance variability. Thus, the result of an interaction may differ between different people executing an action or between different times the same person executes an action. Both can be attributed to the above defined human influencing factors, which vary between different humans and further over time within humans entitled as intraindividual (within humans) and interindividual (between humans) performance variability (e.g. Rohmert, 1988, p. 16). As an example for intraindividual differences of human influencing factors, Figure 2-7 depicts the change of time to achieve a defined task of a single person. Through repetition a practicing effect can be seen which impacts on performance. Figure 2-8 depicts the distribution of body height of the world population and thus is an example for interindividual differences of an influencing factor.

Additional to intra- and interindividual differences between human influencing factors, each factor can be characterized by its variability over time. The factor sex for instance is generally fixed throughout life and thus represents a constant factor, whereas fatigue for example may vary throughout a single day. A categorization of human influencing factors regarding the aspect of temporal variability is given by Luczak (1989) as depicted in Figure 2-9. Luczak distinguishes four different categories for variability over time and entitles them as constitutional, dispositional, qualifying and educational and adaptable factors (based on Schlick et al., 2010, p. 88). As a simplification, the constitutional category refers to factors which are regarded as unchangeable over time, like sex or anthropometry. The dispositional category refers to factors which remain relatively constant, but still may be assumed as generally variable, like weight or age. Qualifying and educational factors are defined to be changeable through learning processes in the short, medium or long term, like experience or knowledge. Lastly, adaptable factors are changeable in the short term through systematic interventions resulting from the direct interaction and the environment.

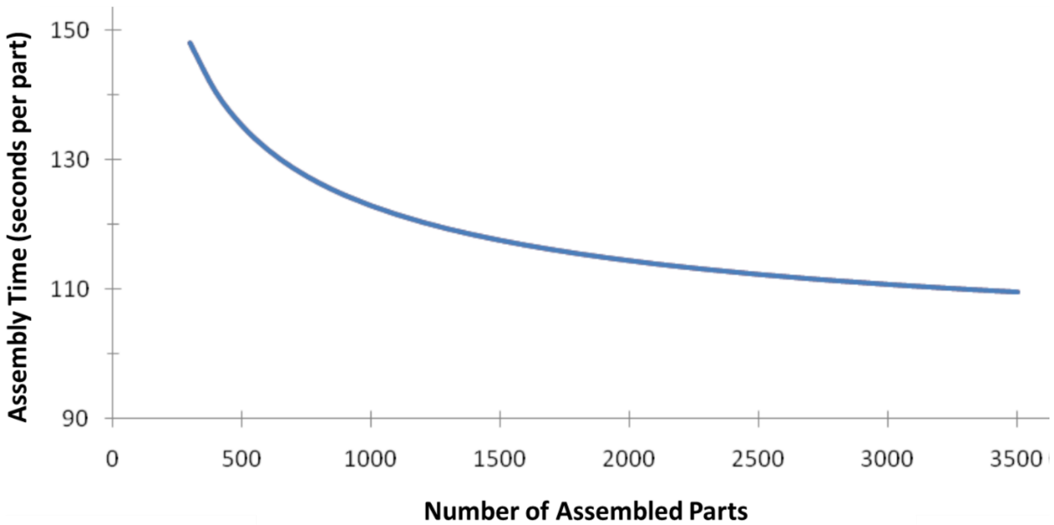

Figure 2-7. Learning curve effect for the assembly of a gasifier-fold-nozzle (according to Schlick et al. (2010, p. 176); based on Greiff, 2001).

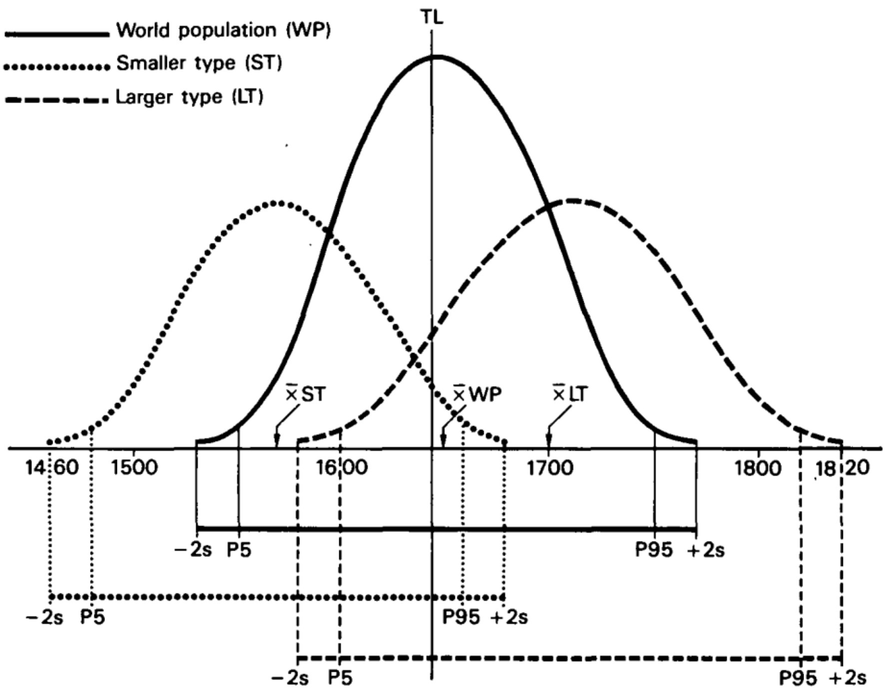

Figure 2-8. World population, smaller type and larger tvpe, with their mean values and extreme measurements (P5, P95, $\bar{x}$ + 2s), using stature as an example (Jürgens, 1990, p. 76).

Concomitantly with the characteristic of temporal variability, human influencing factors vary regarding their external suggestibility. Thereby, factors of the adaptable as well as qualifying and educational category are easier to manipulate, due to their general ability to change over comparably shorter time-periods than factors of the other two categories. Manipulation of the latter two groups are therefore easier to achieve on an interindividual scale through a change of the person interacting with a technical system instead of direct manipulation of an operator's influencing factors on an intraindividual scale.

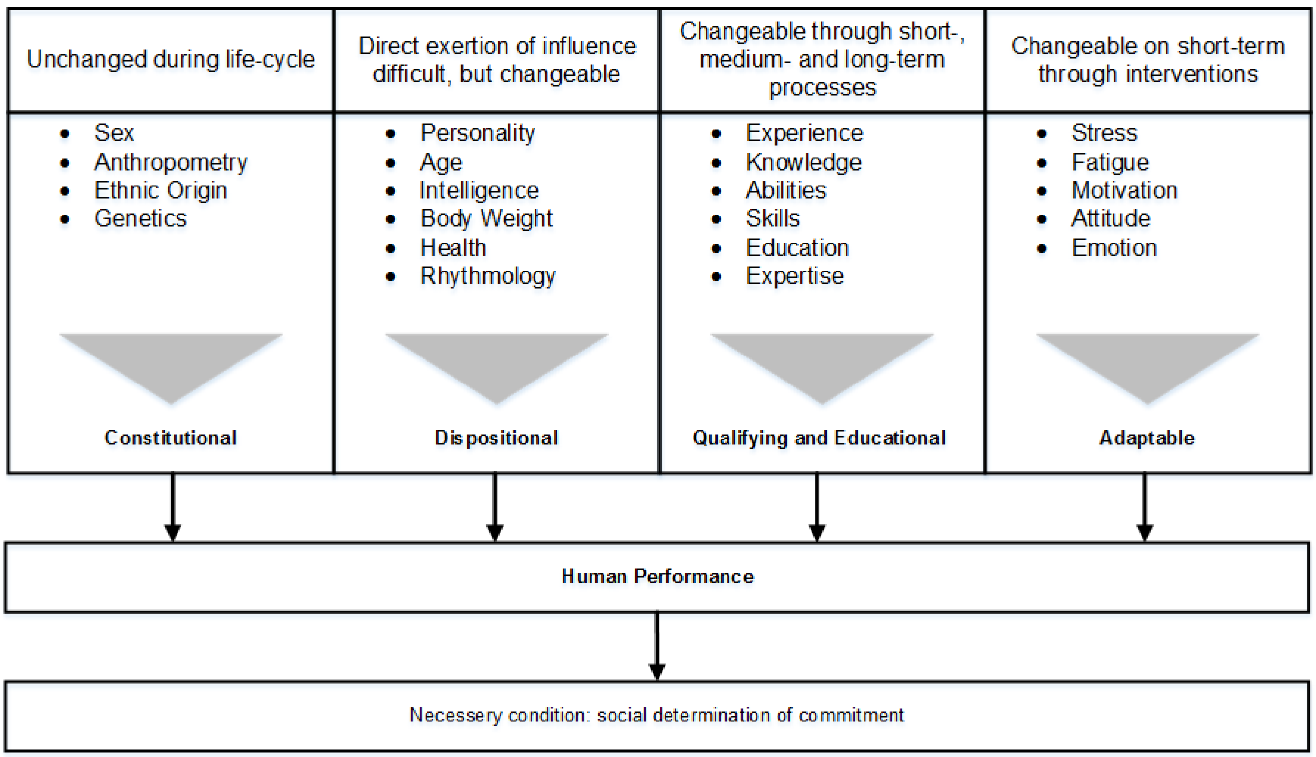

Figure 2-9. Individual parameters of human performance (adapted from Schlick et al. (2010, p. 88), based on Luczak (1989)).

Further, influencing factors can be characterized through their general measurability. Thereby, the measurability of a factor can be distinguished between the two dichotomous categories direct / indirect and subjective / objective. Direct / indirect describes whether a factor is measurable immediately or must be derived through the measurement of at least one ancillary factor. For example, the height of a person can be measured directly in centimeters, whereat fatigue must be derived e.g. from the eyelid blinking frequency. Subjective / objective refers to whether the factor is measurable through scientific observation (objective) or relies on personal opinions, assumptions or beliefs (subjective). In the above example both factors, height and fatigue, classify as objective measurements. In contrast, the factors fatigue could also be measured subjectively through a questionnaire, which would ask for the individual and personal assessment of one's own fatigue. The last example further depicts that the characterization of the measurability of a factor is closely related to the possible and known measurement methods for its assessment. Thus, the measurability cannot be determined generally for a specific factor, but only in conjunction with a specific measurement method.
Lastly, the influencing factors can further be characterized through their interdependencies and correlations with other influencing factors. For example, the factors age, sex and anthropometry all correlate within specific boundaries. Even though some interdependencies are known, a comprehensive and conclusive assessment of all possible interdependencies between the influencing factors seems impossible.

Concluding, the human influencing factors can be characterized by their variability over time, their suggestibility, their measurability and their interdependencies between other factors. Further, the value of a certain human influencing factor is subject to intra- and interindividual changes. Regarding uncertainty, the variability of influencing factors as well as the question whether to investigate intra- or interindividual differences seems of major importance when investigating human induced uncertainty.

2.5.2 Influencing Factors of the Technical Subsystem

As the technical influencing factors strongly depend on the observed technical system, no general list of technical influencing factors is given. Thus, the assessment of influencing factors of the technical subsystem must be done separately for every investigation. Nevertheless, certain methods for the assessment for influencing factors of and on a technical system exist.
Following, the process model of the CRC 805 for the description of the uncertainty of technical processes, as developed by Eifler et al. (2011), is presented (see Figure 2-10). The process model generally consists of a system, characterized through its system quantities and separated from its environment by system boundaries, a process, further characterized through a function and possible work appliances, and external influences in form of disturbances, information, resources and a user. Prior to a process the system quantities are determined and fixed with an initial state t_n. The process then transforms the initial system quantities into a subsequent state t_{n+1}, whereby the external influences impact on the process and thus on the resulting state of the system. Through the difference between the system quantities of the actual state t_{n+1} in comparison to the expected system quantities for a planned process the amount of uncertainty is assessed and can be related to the external influences or internal process uncertainty. Schmitt, Avemann, and Groche (2012) exemplarily applied the described model for the visualization and investigation of uncertainty of a manufacturing chain.

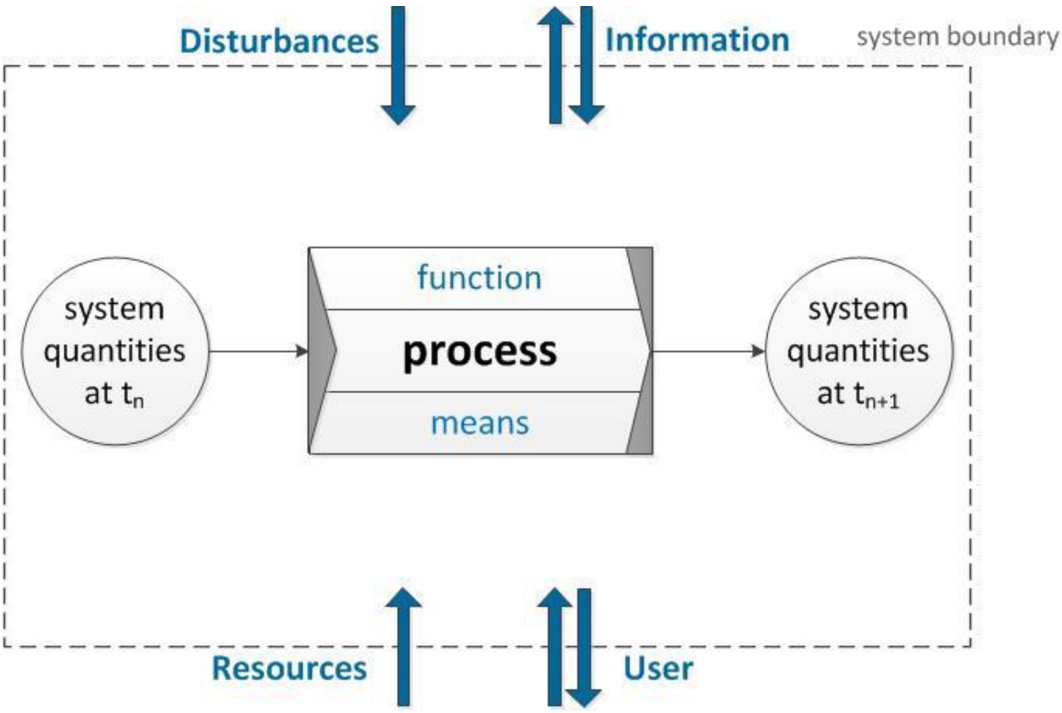

Figure 2-10. Process model of the CRC 805 to visualize the transition of system quantities through a process including external influences onto the process (based on Eifler et al., 2011).

The above described process model for the investigation of uncertainty of technical systems was recently extended to further include a detailed model for working appliances (Freund, Würtenberger, Calmano, Hesse, & Kloberdanz, 2014). As this adaptation does not directly interfere with the objective of this work, the former model is used onwards.

Within the CRC 805 a series of methods for the assessment and treatment of uncertainty throughout the product life cycle exist.

Within the phase of development, most methods concern the general identification of uncertainty and their possible sources, their estimation and lastly their visualization for construction. For example is Uncertainty Modes and Effects Analysis (UMEA) developed as a methodologic toolbox for the consideration of uncertainty (Engelhardt, Birkhofer, Kloberdanz, & Mathias, 2009). Also an approach for the consideration uncertainty within the process of product modelling is created by Würtenberger, Freund, Lotz, and Kloberdanz (2016). Additionally to modelling, various approaches for the statistical and mathematical estimation of product properties are derived (e.g. Enss, Kohler, Krzyzak, & Platz, 2016; Kohler, Krzyzak, & Walk, 2014). Finally, the digital assembly process is supported through methods for the visualization of uncertainty with CAD-systems (e.g. Heimrich & Anderl, 2016; Zocholl, Trinkel, & Anderl, 2014).

Methods for the product phase of manufacturing focus on modeling, simulation and smart structures. Thus, a statistical analysis of a model based product property control for sheet bending is conducted (Groche, Calmano, Felber, & Schmitt, 2015). New manufacturing methods for the incorporation of smart structures and sensor elements within product parts is investigated by Krech and Groche (2016).

Methods for the treatment of uncertainty within the phase of product usage focus on the measurement of current system strain and the application of passive and active methods for their treatment. Thus, the transmission behavior of a sensory rod is assessed (Melzer et al., 2015) and the application of piezo actuators for the implementation of active control of stress through shunting (Götz, Platz, & Melz, 2017).

2.5.3 Influencing Factors of the Environment

The environment always impacts on a human as well as a technical system. Thereby, the environmental influencing factors are generally distinguished between social and physical factors (cf. Badke-Schaub et al., 2008; Bubb, 1992; Schlick et al., 2010).

The physical environmental influencing factors are generally agreed upon and involve illumination, noise, mechanical vibrations, climate, harmful substances and radiation (Badke-Schaub et al., 2008; Bubb, 1992; Johnson, 2003; Schlick et al., 2010). They are of special importance to an HMI as they impact on both, human and technical system, and thus increase uncertainty. For example, ambient noise or flashing lights can interfere on human perception and thus disrupt an interaction (e.g. Johnson, 2003, p. 66). Further, changes of climate can lead to elongations of materials and work pieces, which can interfere on product quality. Table 2-6 presents brief definitions for the physical environmental factors.

Table 2-6. Definition and description of physical environmental influencing factors.

Factor	Definition	Additional Literature
Climate	Climate describes the interaction of air temperature, humidity, wind speed and thermal radiation, which physiologically and psychologically affect a human (Schlick et al., 2010, p. 861).	Schlick et al., 2010, pp. 861–884
Harmful Substances	Harmful substances include all chemical, physical or biological solid, fluid or gaseous substances and materials which may interfere with human physiology, psychology and perception.	Schlick et al., 2010, pp. 907–934.
Illumination	Illumination refers to the amount and type of light within the environment, which is needed for visual perception. Illumination thereby addresses both, natural and artificial light.	Schlick et al., 2010, pp. 885–906.
Mechanical Vibrations	Mechanical vibrations are translational and rotational, time-dependent motions of solid bodies around a resting position (Dupuis, 1981).	Schlick et al., 2010, pp. 790–804.
Noise	Noise is defined as an undesired, annoying or even harmful sound event (Szadkowski, 1984) with regard to work. As the given definition of noise adheres only to a negative perception of sound, the definition is extended to include all perceived sound events, which can result into a shift of attention or an injury and thus may affect human action.	Schlick et al., 2010, pp. 772–789.
Radiation	Within physics, radiation designates the free, undirected propagation of energy in terms of particles or waves (Schlick et al., 2010, p. 805).	Schlick et al., 2010, pp. 805–860.

In contrast to the physical environmental influencing factors, the social environmental influencing factors are less agreed upon. Additionally, a further classification of the social factors into organizational, individual, legislative and cultural factors may be possible. But as the focus of the present work is upon the human subsystem and not on the environmental conditions, only a brief overview of identified social factors without further classification is given in Table 2-7. As a first exemplary list the factors acknowledgement, social norms, labor organization, leadership style, monitoring and supervision, other people and bystanders, policies, responsibility and social compatibility are covered.

Table 2-7. Definition and description of social environmental influencing factors.

Factor	**Definition**
Acknowledgement	Acknowledgement represents the positive or negative feedback of other persons (colleagues, management or society) in relation to one's work or the fulfillment of a given task.
Social Norms	Social norms represent established and socially desired patterns of behavior of a specific group of people. Thereby, social norms may differ between groups depending on education, cultural background or place of residence.
Labor Organization	Labor organization largely addresses the coherent structure of working processes as well as the shift schedule of a specific person (cf. Schlick et al., 2010, pp. 433–494).
Leadership Style	Leadership style describes the type of relation between a person and a possible manager within an organization. Classical styles are authoritarian, laissez-fair and cooperative. Leadership style is known to have a high impact on motivation of employees and the success of teams and organizations (e.g. Schmidt-Huber, Dörr, & Maier, 2014).
Monitoring and Supervision	Monitoring and supervision represents the amount and type of control or surveillance of a person by another person or entity. For example, the action of a person could be recorded on video. This factor only affects human action if the actor is aware of being monitored or supervised.
Other People and Bystanders	Other people and bystanders addresses the possibility of other humans within the vicinity of a human interacting with a system. Thereby, possible disturbances range from direct conversation with bystanders to the mere awareness of other people possibly observing someone's actions.
Policies	Policies represent fixed rules which regulate or suggest certain kinds of behavior for a given environmental context.
Responsibility	Responsibility describes the possible effect an action can have on other people. A pilot for example is responsible for the safe transport of his passengers as well as the cabin crew. High responsibility may correlate with high psychological demands and strain.
Social Compatibility	Social compatibility represents the overall social opinion towards an action. In contrast to acknowledgement, social compatibility does not necessarily involve a direct and personal feedback. For example, an

	employee may get positive feedback from his management for the work done within a nuclear power plant, whereas working within a nuclear power plant is socially regarded with skepticism.

2.6 Summary and Deficit Analysis

First, the concepts of human reliability and risk were found to focus on human error, which only gives information about failure, generally leading to malfunction or even destruction of a technical system. Therefore, the application of the concept of uncertainty for the description of HMI seems appropriate, allowing for a continuous description of performance on both human and technical side. Uncertainty includes failure but further accounts for each state before failure and beyond. Models for the description of HMI, of human information processing and a model to evaluate and characterize different sources of human error were presented. Further, the term of uncertainty was defined and the term of human induced uncertainty was introduced to account for the uncertainty of HMIs. Concluding, more than 60 influencing factors involved in HMIs were presented and discussed briefly.

Even though concepts for the assessment of human error and for the uncertainty of mechanical systems exist, no approach for the investigation of the human impact on the stress of technical systems through HMI and the related human induced uncertainty could be found. But knowledge about human induced uncertainty is crucial, as it leads to insights for the optimization of HMIs, represents a basis for the implementation of resilience systems and lastly leads to the conservation of resources (Oberle, Helfert, König, & Bruder, 2017). To achieve this goal, human induced uncertainty first must be characterized explicitly. Therefore, the general model of HMIs according to Bubb (2005, p. 355) represents a foundation, but lacks further insights into the human part of HMIs. Thus, additional information concerning possible sources of human induced uncertainty regarding human information processing as well as incorporating specific human and general influencing factors is needed. Based on a characterization of human induced uncertainty a methodic approach for its investigation, assessment and quantification of can be developed. Only if the knowledge about human induced uncertainty is increased, systemized and quantified, measures for its control can lastly be derived.
The described circumstance can be condensed to the following three research questions:

1. How can human induced uncertainty be characterized?
2. How can human induced uncertainty be assessed and quantified methodically?
3. How can human induced uncertainty be controlled?

Based on the presented research questions, the methodological approach of this work is derived in three subsequent steps, which are aggregated in Figure 2-11.
First, a model for the characterization of human induced uncertainty in the context of HMIs is developed based on the presented literature. Scope of the model is to further detail the human part of HMI within the context of the environment and the technical subsystem. Further, the identified influencing factors for all three HMI instances must be situated within the model with the goal to constitute possible sources of uncertainty. Thus, the developed model first details the uncertainty of HMIs and their potential sources. Based on the model for its characterization, a method for the systematic assessment of human induced uncertainty is developed. The method centers on the structured definition of an observed task on which basis the involved elements (human, environment and technical subsystem) are specified and facilitates the empirical assessment of human induced uncertainty (see chapter 3).

Second, the derived method is evaluated to investigate its applicability to characterize, assess and quantify human induced uncertainty. Therefore, two studies investigating different types of tasks with different complexities are conducted. Relevant influencing factors are selected according to the method and their impact on the resulting stress of the technical subsystem is assessed. Possible correlations between the influencing factors and the resulting uncertainty are identified. Thus, the human induced uncertainty for the exemplary tasks is generally described through the resulting variation of the technical subsystem's stress and further detailed by giving information about the source of uncertainty based on the model. Based on the results of the first two studies first suggestions for controlling human induced uncertainty are derived and discussed (see chapter 4 and 5).

Third, another study is conducted to further investigate possible approaches for reducing and controlling human induced uncertainty. It is investigated, if human induced uncertainty can be controlled by actively designing the HMI and especially the human-machine interface with the goal to reduce uncertainty. If such an approach is applicable, human induced uncertainty can be controlled without an expansive analysis of possible operators of an HMI and thus represents an opportunity for a user-independent control of uncertainty (see chapter 6).

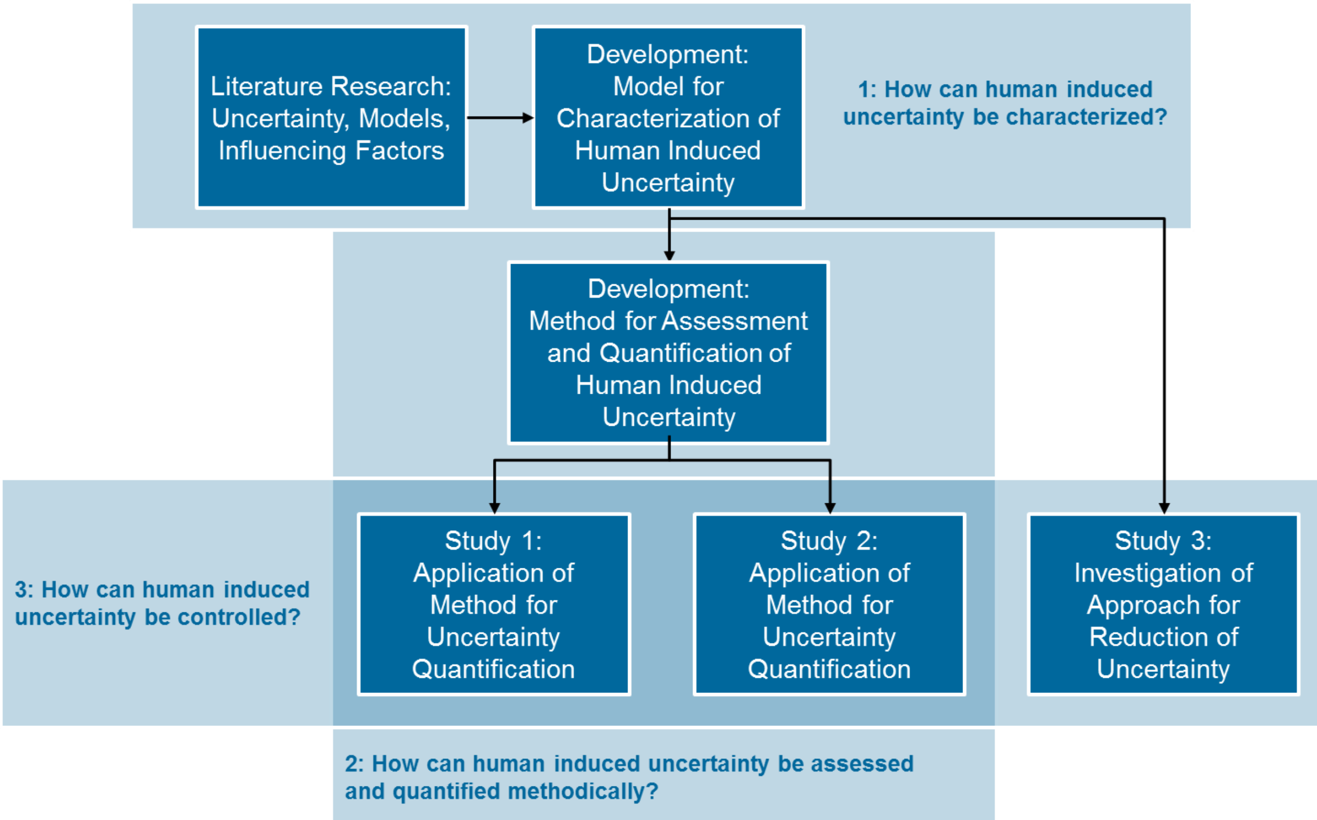

Figure 2-11. General methodological approach.

3 Model and Method for the Description of Human Induced Uncertainty

Within this chapter the treatment of the first research question is presented. Therefore, a literature based model for the description of HMIs regarding human induced uncertainty is developed, followed by the allocation and integration of the prior identified influencing factors. Based on the developed model, human induced uncertainty is characterized. Subsequently, a method for the structured investigation of human induced uncertainty of HMIs is derived from the model. The chapter concludes with a summary.

3.1 Model Development

For the description of uncertainty, a holistic model is needed. The model must describe the general HMI and further detail the human part of an HMI. To identify possible sources of uncertainty, the influencing factors must be integrated into the model.

Common for the description of human machine interaction is a separation into the three subsystems environment, technical system or machine and human (cf. chapter 2.2). The model of Bubb (2005) further adds the elements *task*, which is the cause for an interaction, as well as *result* and *feedback*, which return the achieved result to the human. This allows for the explanation of the evolvement of repeated task execution and for building a sequence of different repetitions or sequential tasks, increasing the flexibility of the model's application. Therefore, the model of human machine interaction as described by Bubb (2005) is used as a frame for the further development.

The models for human information processing generally divide the human action into three or four steps. The models based on four steps are mostly equal and for example differentiate between the steps of sensory processing, perception, response selection and response execution (cf. Wickens et al., 2012, p. 4). Further, Damböck (2013) allows the steps of recognition and decision to be pooled as information processing, resulting in the three meta processes of information acquisition, information processing and information execution. These resulting steps are textual equal to the model of Welford (1968), who distinguishes between perceptual mechanism, translation mechanism and central effector mechanism. Overall, a three-step based description of human information processing represents a common and basic concept within the literature. A three-step approach further matches the categorization of human influencing factors into perceptual, mental and physical factors (see chapter 2.5.1.1). Thus, a three-step approach is chosen for the further description of the human part of HMIs.
Through the adoption of human information processing for the detailed description of the human part of an HMI, the input of the model is changed from general cues and signals to *task*, as used within the frame model. Based on this change, the application of the model is shifted to connect the three human sub-processes to the sequential execution of a given task instead of general information processing. Further, the first sub-process is designated as perception, in concordance to the model of Welford and the categorization of the human influencing factors. To account for the changed application of the human information process to describe task execution, the second and third sub-processes are renamed *choice of action* and *execution of action*.

The described models in chapter 2.3 include various influencing factors. However, the mentioned factors are widely generalized by integrating whole concepts like *memory* or *resources*. To create a description of HMI focused on the human part of interaction, the human influencing factors are first regarded as a

black-box, interacting with all three human sub-processes. The black-box contains all influencing factors as described in chapter 2.5.1.
The resulting human centered model for the description of HMI is depicted in Figure 3-1.

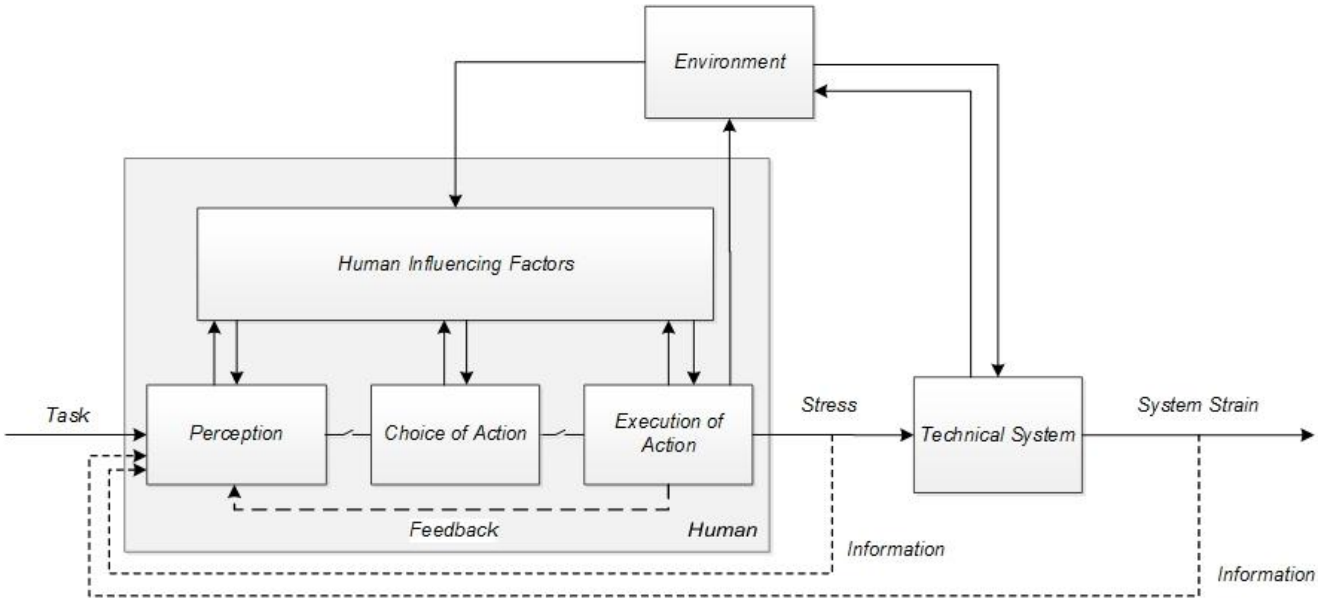

Figure 3-1. Human centered model for the description of human-machine interaction.

An HMI begins with a *task*, which defines the wished goal of the interaction. The task is first perceived by the human, who interprets the task. The step of *perception* is affected by human influencing factors (e.g. attention), information concerning the technical subsystem (e.g. current state or working mode) and influences from the environment, in which the interaction takes place (e.g. weather). After interpreting the task regarding personal, technical and ambient conditions, an action is chosen. *Choice of action* depends on the prior perception and further on human influencing factors (e.g. experience). Then, the chosen action is executed. Besides the obvious impact of choice of action, again the human influencing factors (e.g. strength) impact on the *execution of action*. The action finally represents and defines the interaction with the technical subsystem and leads to some amount of stress onto the system. Thereby, system stress is not solely defined and created through the human part of the interaction but may further originate from the environment. Also, the environment can be affected by the executed action. With the execution of action, a direct feedback is transferred within the human, which is further processed for a first evaluation of the executed task in correspondence to the initial task. Additionally, the resulting system stress is looped back as an external source of feedback, yielding additional information regarding the outcome to the processed interaction. The technical subsystem transforms the incoming stress into a system-specific amount of strain, which can be looped back to the human in form of information. Like the internal feedback, information itself is further processed through perception. Thereby, perception defines if and to which degree the returned results of the executed action and its impact on the technical subsystem are perceived and subsequently impact on the human influencing factors or even lead to another sequence of choice and execution of action if the initial task remains unaccomplished. The technical subsystem further affects and is affected by the environment.
It must be noted that the connections between the three human sub-processes are optional. A given task could pass unnoticed due to a lack of attention on the human side or the choice of action may not lead to an action execution. Thus, not all human sub-processes are necessarily processed for every input of

task, which is represented through the switch-connections between the human sub-processes. Thus, a given task not always leads to an active interaction between human and technical system. It must be noted that the omission of action execution may also result into system stress and must be considered when investigating human induced uncertainty.

3.2 Allocation of Influencing Factors within the Model

The above described model is subsequently further described by detailing and defining the single aspects of the model. Further, the influencing factors described in chapter 2.4 are allocated to the specific model aspects.

3.2.1 Human

As described in chapter 2.5.1, the human influencing factors can be categorized into the four groups of perceptual, mental, physical and ambiguous factors. As touched upon in chapter 3.1, the categories of the human influencing factors appear to match with the defined human sub-processes *perception*, *choice of action* and *execution of action*. An allocation of the defined human influencing factors to the corresponding human sub-process seems possible. Only the fourth group of ambiguous factors must be investigated concerning their possible influence on two or all three of the human sub-processes.

The human sub-process of *perception*, which is defined as the transformation of physical or chemical stimuli into mentally processed information (Badke-Schaub et al., 2008, p. 61), is consequently based on the sensory modalities. Thus, a direct allocation of the perceptual factors to the sub-process of perception can be confirmed.
Regarding the sub-process *choice of action*, a strong relation to mental factors exists. Wickens, Gordon, Liu, and Lee (2014, p. 143) describe the process of decision making as based on working memory and long-term memory (cf. Allport, 1993; Baddeley, 1993). The mental influencing factors largely address several aspects of memory itself (e.g. knowledge) and capabilities to process stored information (e.g. intelligence). Thus, mental factors are hence associated with the sub-process choice of action.
Accordingly, the third category of physical factors is associated with the sub-process *execution of action*. Factors like anthropometry (e.g. reach of a person) are known to directly interfere with the manner of action execution (e.g. VDI, 1980), supporting the association of physical factors to execution of action.
Now only the ambiguous factors remain for allocation. When regarding the factors, a distinction between factors only affecting two of the sub-processes and factors affecting all three sub-processes seems possible. Thereby, the latter group relates to fundamental factors, which itself interact with and impact on a broad variety of other factors, like sex or age. The specific allocation of each ambiguous factor is presented and reasoned in Table 3-1.

Table 3-1. Allocation of ambiguous human influencing factors to the human sub-processes.

Allocation	Ambiguous Factor	Reasoning
Choice and Execution of Action	Personality	As defined, personality are inter alia an individual's behavioral patterns (Schlick et al., 2010, p. 112). As such, it can be argued that behavioral patterns are rooted within the memory, which according to Luczak (1975) is not connected to perception, but

		only to the subsequent information processing steps. Thus, personality is allocated to choice and execution of action, but not to perception.
	Practice	Through practice, choice of action and the execution of actions can be affected (e.g. Jeske, 2013). As perception instead addresses the active processing of external cues, but without a direct connection to memory, practice is not allocated to perception.
	Training	See reasoning for practice.
All three sub-processes	Age	Age affects nearly every other human influencing factor. For example, the auditory perception undergoes a shift of perceivable frequencies (e.g. Schlick et al., 2010, p. 779) and intelligence (e.g. Cahan & Cohen, 1989) as well as anthropometry (e.g. Perissinotto, Pisent, Sergi, Grigoletto, & Enzi, 2002) evolve through age. Thus, at least a secondary effect on all three human sub-processes can be confirmed.
	Attention	As per definition, attention directs the awareness to the environment as well as the current thoughts and operations (see chapter 2.5.1.2). Certain models further support the positioning of attention as an influencing factor for perception (cf. Wickens, Gordon, & Liu, 2004, p. 163). Thus, affecting all three human sub-processes.
	Emotion	Emotions are known to affect inter alia on arousal, cognitive processes and behavioral tendencies (e.g. Zimbardo et al., 2003) and thus relates to all three human sub-processes.
	Ethnic Origin	Like age, the ethnic origin impacts on several influencing factors over all three sub-processes (e.g. Edwards, Fillingim, & Keefe, 2001; Wing, Adams-Campbell, Marcus, & Janney, 1993).
	Fatigue	Fatigue is known to impact on overall performance (e.g. Hacker, 1984) and thus affects all three human sub-processes.
	Genetics	Like age and ethnic origin, genetics impact fundamentally on various influencing factors (e.g. Deary, Spinath, & Bates, 2006; Levy & Nagylaki, 1972; Plomin, DeFries, Knopik, & Neiderhiser, 2013).
	Health	Health is defined the state of complete physical, mental and social well-being (cf. WHO, 1946) and thus is relevant for all three sub-processes.
	Metabolism	Metabolism covers all chemical processes of the body (cf. Schlick et al., 2010, p. 266) and therefore impacts on the whole body and as such on all three sub-processes.

	Motivation	Motivation relates to the degree and personal commitment of goal fulfillment (cf. Sansone, 2007) and thus impacts on all three human sub-processes.
	Rhythmology	As for metabolism, rhythmology addresses biology-driven periodic fluctuations of the body (cf. Schlick et al., 2010, p. 167) and thus interferes with all three sub-processes.
	Sex	Sex defines general properties of the human body (e.g. Schlick et al., 2010, pp. 91–95) and thus impacts on all three sub-processes.

It must be noted that even though the influencing factors are associated with the human sub-processes in the above described manner, impact from one category of influencing factors to a different sub-process is not completely impossible. The allocation of factors represents a first simplification and approach for the further assessment of human induced uncertainty. Generally, all influencing factors affect all three sub-processes, but the established allocation highlights the most probable influencing factors for each human sub-process.

Even after allocating the factors to the human sub-processes, for each sub-process a high number of factors remains. As indicated in chapter 2.5.1.3, human performance and performance variability relates to the resulting stress of a technical subsystem.
Based on the above described variability of human influencing factors, intra- and interindividual differences of performance are explainable. Thus, factors of the constitutional and dispositional group are more relevant when investigating differences of performance between different populations and persons. With increasing variability, assessment of influencing factors and their effect on performance is transferred to be relevant for assessing performance variability within one person. In this case, adaptable as well as qualifying and educational factors are more likely to impact on human induced uncertainty. Thus, variability of human influencing factors can be used to focus on prominent influencing factors and to reduce the number of potential factors for an investigation. This allows for the identification of possible sources of uncertainty prior to an explicit investigation. So far, the categorization model depicted in Figure 2-9 (see chapter 2.5.1.3) does not include all identified influencing factors. To complete the allocation, the distribution of the remaining factors is reasoned in Table 3-2.

Table 3-2. Allocation of human influencing factors to the categories for variability over time.

Allocation	**Factor**	**Reasoning**
Constitutional Factors	Handedness	Even though a person may be trained to use a different instead of the performance dominant hand, the handedness of a person generally remains fixed after familiarization (cf. Schmauder, 1999). Although, the innate preference for one hand persists. Thus, handedness is regarded as a constant and constitutional factor.
Dispositional Factors	Attitude	Attitudes are based on experiences and thus object to learning processes (e.g. Wilson, 1963, p. 247). But further, attitudes are also built and formed primarily throughout adolescents,

		remaining more or less constant thereafter, which is the reason for their allocation to the dispositional factors.
	Creativity	Creativity is based on knowledge, but the ability to create new ideas is also based on certain individual traits and abilities (cf. Amabile, 1983). Even though creativity can be trained to some extent (e.g. Scott, Leritz, & Mumford, 2004), due to its general relation to personal traits creativity is regarded as a dispositional factor.
	Dexterity	Dexterity may be trainable to a certain degree, but in terms of comparability, effects resulting from a change of dexterity are majorly related to interindividual differences, which is the reason for an allocation to the dispositional factors.
	Metabolism	Even though the metabolism can be affected through certain substances like drugs or alcohol, the way the body reacts to such substances and the general conversion of chemical substances evolves slowly. Thus, metabolism is allocated to the dispositional factors.
	Morality	As discussed by Turiel (2007), formation of morality is based on certain character traits as well as on the internalization of emotions. Further, differences of morality depending e.g. on sex, age and cultural background are known, emphasizing the interindividual character of morality. As morality is not a constant concept it is allocated to the dispositional factors.
	Sensory Modalities[4]	The sensory modalities are neither constant nor trainable, but may change with the age of a person or through certain external events and influences. Like age, they are therefore regarded as dispositional factors.
	Strength	Like dexterity, differences of strength are majorly related to interindividual differences.
Qualifying and Educational Factors	Mental Model	Per definition, mental models change over time and are based on knowledge (cf. Märki et al., 2016), which implicates that mental models can be learned, trained and altered. Thus, mental models are allocated to the qualifying and educational factors.
	Mode Awareness	Mode awareness refers to the ability of a user to comprehend and predict system behavior (cf. Sarter & Woods, 1995). As this comprehension is learnable and related to the knowledge and prior experiences of the user the factor is determined as a qualifying and educational.

[4] For the allocation of the perceptual factors the sensory modalities are handled collectively, as they are conceptually equal.

	Situation Awareness	Like mode awareness, situation awareness is based on the perception, comprehension and projection of the environment (cf. Endsley, 1995, p. 36) and thus allocated to the qualifying and educational factors.
	Training	As training represents the willingly and planned repetition of actions with the goal to improve performance, training represents a modality by which the qualifying and educational factors are changed and thus itself belongs to the mentioned group.
Adaptable Factors	Attention	Per definition attention is directed willingly and unwillingly to direct attention onto objects, operations and thoughts (Badke-Schaub et al., 2008, p. 64). With this, attention can be shifted in short time periods, which leads to its allocation to the adaptable factors.
	Emotion	Emotions are highly changeable and may vary in short time periods, rendering them a factor for intraindividual analysis (e.g. Sbarra & Emery, 2005).

Now each factor can be associated with the human sub-processes as well as characterized through its variability over time. The latter further leads to a possible distinction between inter- and intraindividual factors.

The resulting taxonomy of the human influencing factors based on both, the three human sub-processes and the three levels of performance, is illustrated in Figure 3-2. Thereby, the factors age, sex genetics and ethnic origin are depicted separately at the top of the taxonomy. A direct connection of these four factors to the three human sub-processes seems implausible. Instead, the four factors represent general attributes of a human and itself affect nearly every other human influencing factor. For example, age defines the continuous evolvement of factors like intelligence, knowledge, anthropometry, visual perception, health, etc.. Because of this, the four factors are important concerning human induced uncertainty, but are already represented through other factors due to their indirect influence.

Based on the taxonomy, a reduction of human influencing factors for a certain case seems possible. For example, when investigating the intraindividual variation of performance and the resulting uncertainty, adaptable as well as qualifying and educational factors are predominantly important. Still, a high number of factors remains. Further distinction of the human influencing factors may be possible for future research, but the resulting taxonomy represents a first approach for the systematic analysis of human induced uncertainty and its possible sources.

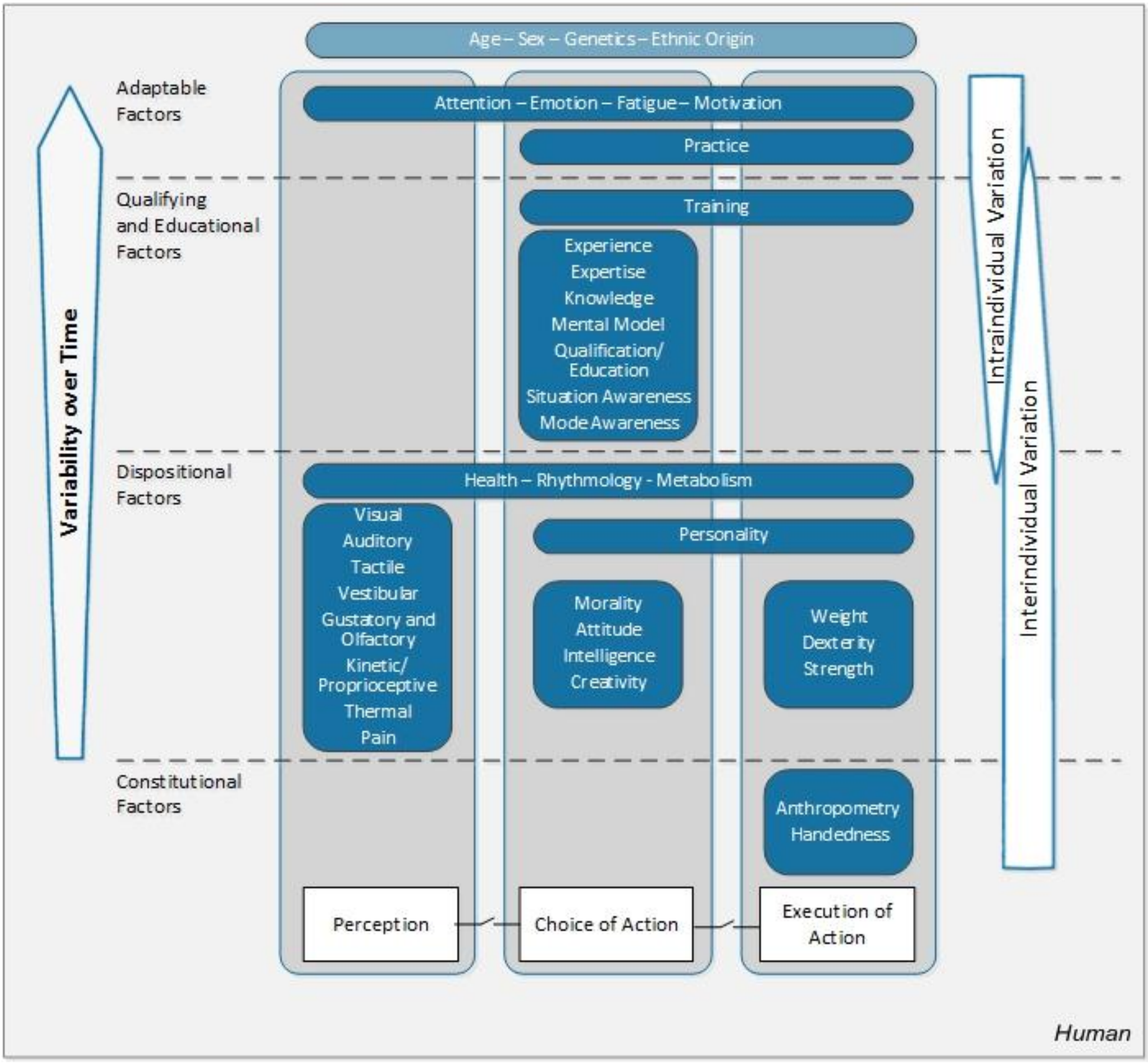

Figure 3-2. Taxonomy of human influencing factors allocated in relation to the human sub-processes and their variability over time.

3.2.2 Technical Subsystem

The focus of the present work is to investigate the human impact on the uncertainty of a system's stress resulting from an interaction. Therefore, a detailed description of possible technical influencing factors is not a part of this work. Thus, for detailed information on technical uncertainty the work of the CRC 805 is referenced (see chapter 2.5.2). Generally, possible influencing factors of the technical subsystem are system specific and difficult to generalize and must be derived individually.

Instead of discussing possible influencing factors, the possibility to combine the HMI model described in chapter 2.5.2 with the process model of the CRC 805 is presented and discussed briefly. By joining both models, an overall description of uncertainty is possible and the methods used and developed within the CRC 805 can be applied for a detailed description and identification of systemic influencing factors. Figure 3-3 depicts the combined models.

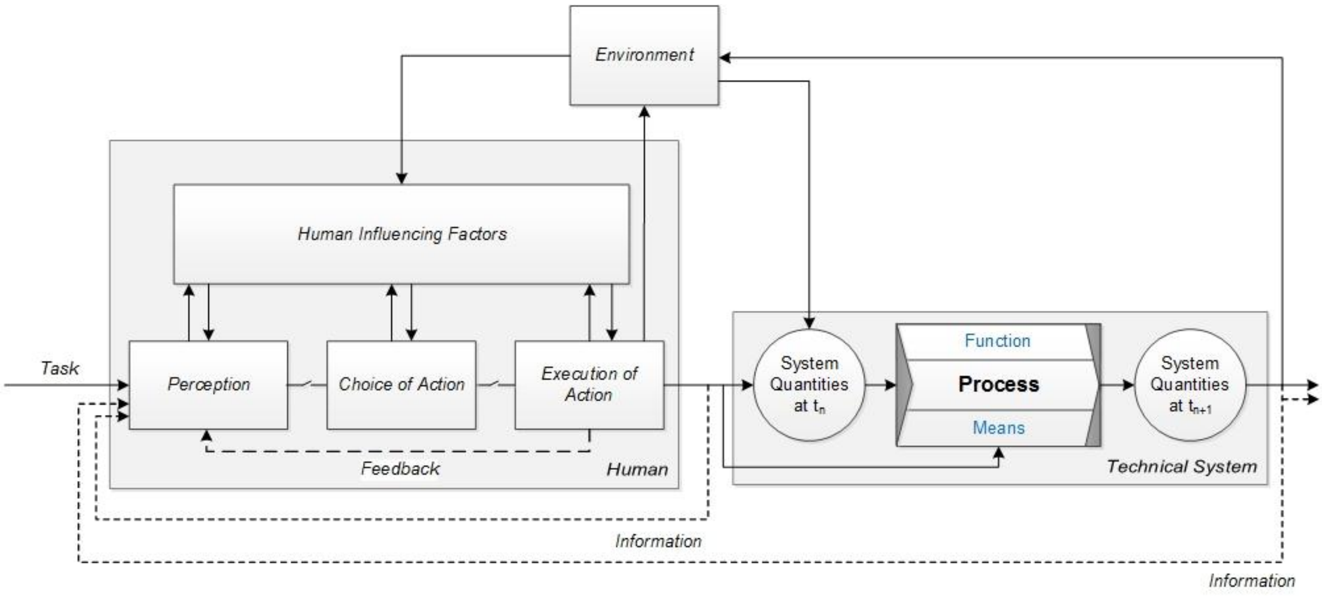

Figure 3-3. Combination of the model for the description of HMI and the process model of the CRC 805.

Based on the combined model, the resulting stress of an executed action impacts on the system quantities. For the application of the process model it must be discerned whether the human action is the direct cause for the initiation of a technical process or if the human action represents a manipulation of system quantities and is thus a secondary cause for a transformation of the system quantities. For example, prior to the technical process of milling, the human interaction aims to input the specifications of the milling process, but not directly operates the milling process itself (indirect interaction). Contrary, when using a hand press, the human interaction itself directs the technical process of forming (direct interaction). Besides the human, also the environment impacts on the initial system quantities. The through a system process transferred system quantities impact onto the environment and represent a source for information, e.g. for the human. Thus, the major in- and outputs of the process model are specified and further connected to the other elements of an HMI. Thereby, resources and disturbances are incorporated within the input of the initial system quantities. Input of information into the technical process is not depicted explicitly for reasons of clarity, but would also be located as input to the initial system quantities.

3.2.3 Environment

As described in chapter 2.5.3, the environment and its influencing factors can be distinguished between social and physical factors. The environment affects both, technical subsystem and human and is vice versa affected by those two elements. Unlike the physical influencing factors, the social influencing factors almost exclusively affect the human element of an interaction. Whereas both elements, human and technical subsystem, are exposed to the physical environment.

Figure 3-4 depicts the allocation of influencing factors of environment.

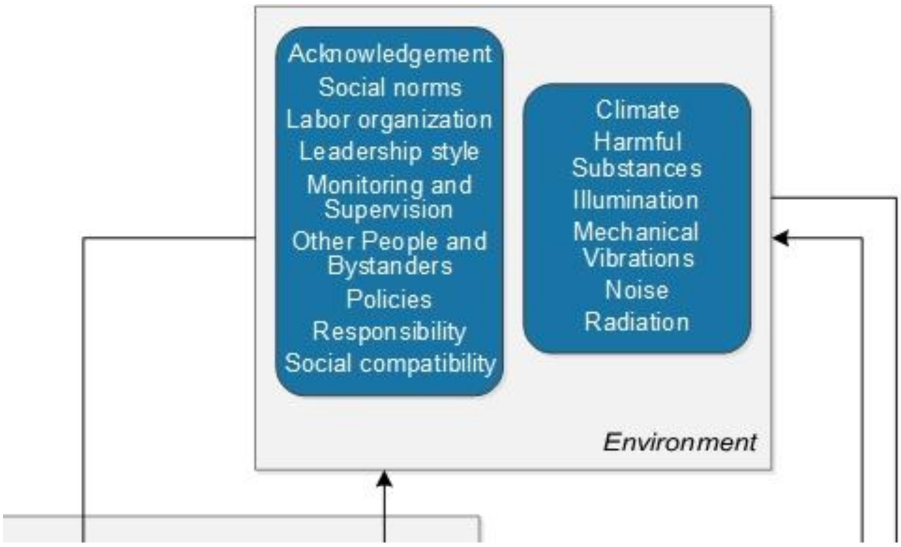

Figure 3-4. Environmental influencing factors.

3.2.4 Task, System Stress and System Strain

Until now, no characteristics of task, system stress and system strain were defined. Following, influencing factors deriving from those three model elements are identified and discussed.

The term task is defined in chapter 2.1 as a "part of work or a performed process which has to be done to achieve a certain goal" (p. 6). Thus, goal represents a possible influencing factor of a task. Besides a goal, further characteristics of a task can be found. An overview over relevant parameters for the characterization of a task based on Badke-Schaub et al. (2008, p. 117) and Bubb (1992) are defined in Table 3-3. All given definitions are derived from the field of human factors and ergonomics and thus closely related to work assignments. Terminologically it must be noted that the described factors are characteristics of a task, but represent influencing factors in relation to the human sub-processes and to the general HMI.

Table 3-3. Definition and description of task characteristics and influencing factors onto the human sub-system.

Factor	Definition
Goal	Goal defines the optimal and intended result of a task or the reason to perform it (Wickens et al., 2014, p. 19).
Instruction	Instructions represent the way a task is introduced to a person. An instruction generally incorporates a definition of a task's goal and possibly some annotations of how to achieve the goal. Instructions can be given through every type of media, from direct verbal communication to a video tutorial or a written work plan. Further information on instruction can be found in Richland, Linn, and Bjork (2007).
Time	Time represents the given time or allowed duration for a task's fulfillment. Time also addresses a possible cycle in case of a repeated task.

Complexity	Complexity describes the range and difficulty of a task. Within this work complexity especially adheres to the spatial dimensionality of a task, whereat an increase of possible manipulative dimensions involves an increase of complexity. Further, complexity is increased if a task can be structured into self-contained subtasks.
Degree of freedom	Degree of freedom describes the amount of personal control over the interpretation and execution of a task. For example, a task where every decision and movement is predetermined would bear no left degree of freedom. An increased degree of freedom generally leads to a consecutive increase of complexity.

System stress represents the impact of an executed action onto the technical subsystem. The characteristics of the system stress derive directly from the parameters of action execution and are thus represented through physical units. The following parameters describe the human action and the resulting stress on a system: force, mass, velocity, acceleration, final position of a movement, line of movement, time and duration of the executed action, angles of limbs and resulting torque (based on Diaz Meyer, 2008). Besides affecting the technical system, the same parameters affect the human, too. This is represented through *feedback* and discussed in chapter 3.2.5. Again it is noted, that the effect of the resulting stress onto the technical system depends on the degree of interaction. Thus, a distinction between monitoring, indirect and direct interaction can be made. Even though monitoring not actively results into an interaction, system stress still may occur due to the omission of a necessary interaction[5]. Figure 3-5 depicts the allocation of the above described influencing factors for task and system stress.

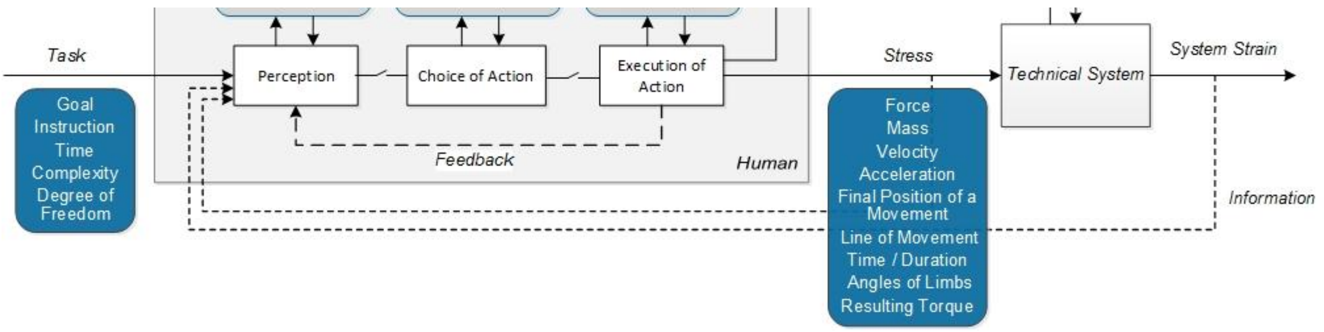

Figure 3-5. Allocation of influencing factors of task and system stress.

System strain is, like the overall technical subsystem, dependent of the actual observed system. Thus, as for the technical subsystem itself, no specific influencing factors are derived. In terms of uncertainty the resulting system strain is lastly the value needed to define the amount of uncertainty. Generally, chosen parameters for its description represent critical aspects of the system. For example, when observing a table, its legs represent the critical element regarding the system's strain and adequate physical units for the description of the specific resulting strain must be defined for an investigation.

[5] For the distinction between indirect and direct interaction please refer to chapter 3.2.2.

3.2.5 Feedback and Information

Both, feedback and information, represent a crucial part of HMIs. Thereby, feedback describes information, which directly derives from the execution of action like the personally perceived reaction of an exerted force or the resulting position of a used limb. Feedback further involves the amount of individual strain generated through the execution of an action, which lastly affects the human influencing factors like fatigue or motivation. Feedback involves perceptual and physical cues and affects both, mental and physical influencing factors. The fed back information is thereby generated temporally during the execution of an action and consequently during an interaction and as well before and during the impact of the interaction onto the technical subsystem. The involved factors are the same as described for system stress and thus not listed again.

The information loop derives from the resulting system strain and contains information about the reaction of the technical subsystem in succession to the operated interaction. An exemplary information could be the evolvement of cracks on the surface of a table's legs accompanied by a cracking sound in case of an overstraining. In contrast to feedback, information primarily relies on perceptual cues and is temporally generated after the interaction. Like feedback, information can affect mental and physical influencing factors alike. The amount and type of information depends highly on the design of the observed technical subsystem and can involve interfaces solely integrated for informational feedback. Thus, no explicit factors are listed or defined.

The derived cues and signals derived from feedback and information lastly are detected and processed by the human sub-process of perception. This means that their adequate detection is not guaranteed and if detected, their impact onto the influencing factors or subsequent actions is dependent to interpretation.

3.3 Characterization of Uncertainty within the Model

By combining the general model for the description of HMIs (see chapter 3.1) with all discussed influencing factors (see chapter 3.2), a complete model for the description of HMIs is derived as depicted in Figure 3-6. The model represents an overview over the elements involved in an HMI as well as depicting the related influencing factors and parameters for each element of an HMI. Even though the model itself helps to understand HMI and thus represents a possibility to reduce uncertainty, several kinds of uncertainty still exist within the model. Thus, the following chapter gives some thoughts about the immanent uncertainty situated within the model and within HMIs.

First, the uncertainty situated within the influencing factors is discussed. In the case of the human influencing factors, the taxonomy helps relating each factor to a specific human sub-process and further allows for a selection based on the focus of an investigation for within or between designs. As mentioned before, the taxonomy represents a first simplification for the reduction of influencing factors, but generally all factors are involved to some degree in human actions. Albeit with sometimes unmeasurable effects. Even in case the taxonomy would lead to a perfect selection of relevant factors for a specific task, uncertainty remains as an immanent part of the factors itself. To asses and quantify human induced uncertainty in relation to influencing factors, each factor must be measured, resulting in uncertainty concerning the measurement. Not only is the measurement of most human influencing factors difficult and always afflicted with measurement inaccuracy, additionally, the factors change over time. For example, when measuring emotions, which by itself is a difficult task, the assessed values must not necessarily stay the same when the actual interaction occurs. Further, the relation of the influencing factors is at best complex and which factor, possibly subject to change, may affect and interact with other factors remains indistinct. The issue of precise assessment is not unique to the human influencing factors, but concerns all influencing factors within an HMI.

Regarding the inherent uncertainty of measurements, the issue is known and can be considered using established methods like error calculation. The issue regarding the variability of influencing factors and the fact, that a measured value could have changed before its effect is measured, is already addressed within the model. Thus, this issue is primarily relevant for factors of the adaptable and secondary to the factors of the qualifying and educational type, which demonstrate a high variability. Dispositional and especially constitutional factors remain relatively unaffected by this bias as they generally are considered constant throughout a measurement. Based on the same reasoning, the effect of the interdependencies between influencing factors can be weakened. Again, adaptable as well as qualifying and educational factors are more likely to be affected by other influencing factors during an investigation. Thus, the issue of variability and interdependency is highly important when investigating intraindividual effects on uncertainty. Therefore, investigation of intraindividual effects on human induced uncertainty should consider to further reduce the number of influencing factors, e.g. through the experimental design by providing constant and equal environmental conditions.

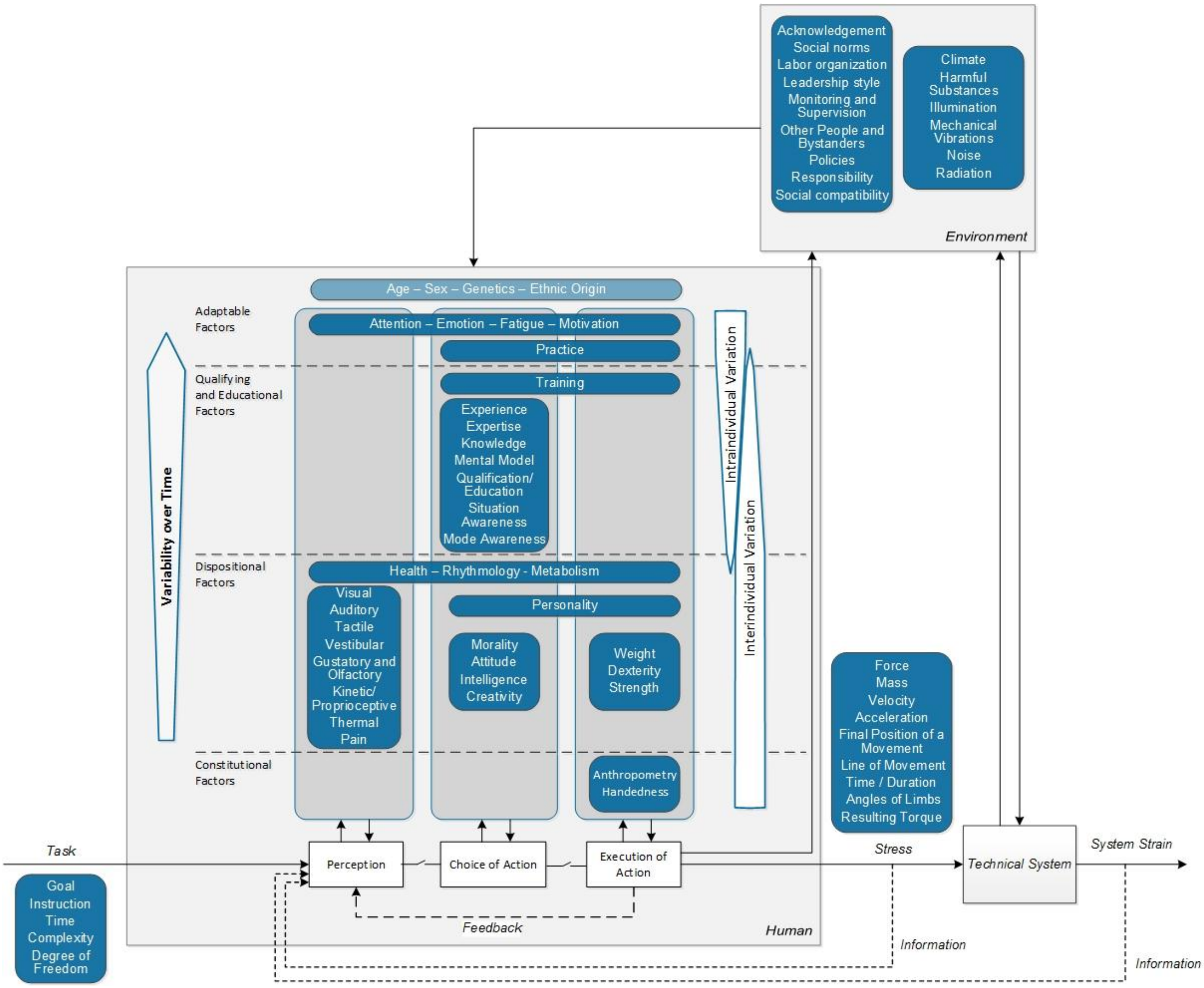

Figure 3-6. Model for the description of human induced uncertainty of HMI with allocated influencing factors.

Second, the uncertainty embedded within the three human sub-processes and their contribution to the resulting uncertainty of an HMI is discussed.
The step of *perception* is responsible for the initial detection of external cues and their identification in relation to the environmental conditions and the given task. Sources for uncertainty are thus the possibility to incorrectly detect important cues, not detect them at all or to be overexerted due to a flood of information (Johnson, 2003, pp. 66–67). Additionally, detected information may be identified incorrectly and thus trigger uncommon or wrong choices of action. The core of perceptual uncertainty is hence to not act at all when an action is necessary or to confound a subsequent choice of action. Quantification of perceptual uncertainty is complicated and mostly possible by assessing the uncertainty of the subsequent processes and relating them to the perceived information.
Uncertainty of *choice of action* manifests itself in two different manners. First, in case of a single action or independent task, the uncertainty is based on the amount of possible actions to the given task. To quantify the involved uncertainty, all possible actions can be assessed and quantified by their relative probability of occurrence. Thereby, the complexity to thoroughly assess all actions increases with the general amount of possible actions. Lastly, some uncertainty always remains due to the constant existence of yet unobserved and thus unexpected actions, which cannot be quantified. Regarding prior perception, one case of uncertainty for choice of action is not to choose an action at all. This uncertainty is simply covered by considering no action as a possible action when assessing the relative probability. Second, if a sequence of actions is needed for the fulfillment of a given task, the uncertainty is subject to the single sub-actions and their possible sequence. Such uncertainty can be described by assessing the probability of all possible action sequences. A possibility for an assessment is the application of Markov models (cf. Luczak, 1974, p. 86; Norris, 2006, c1997). In this case, the additional assessment of the uncertainty for each single sub-action's execution may be reasonable.
The uncertainty of *execution of action* manifests itself directly through the measurement and assessment of the prior mentioned factors for system stress (chapter 3.2.4). Quantification of uncertainty is achieved by generating distribution functions for each factor through repeated measurement. Thereby, a variation within each factor will always be present, as no perfectly equal repetition of the same action is possible. Like the uncertainty for execution of action, the resulting system stress and strain can be measured and quantified by their distribution.
An exemplary characterization of uncertainty for specific model elements is depicted in Figure 3-7.

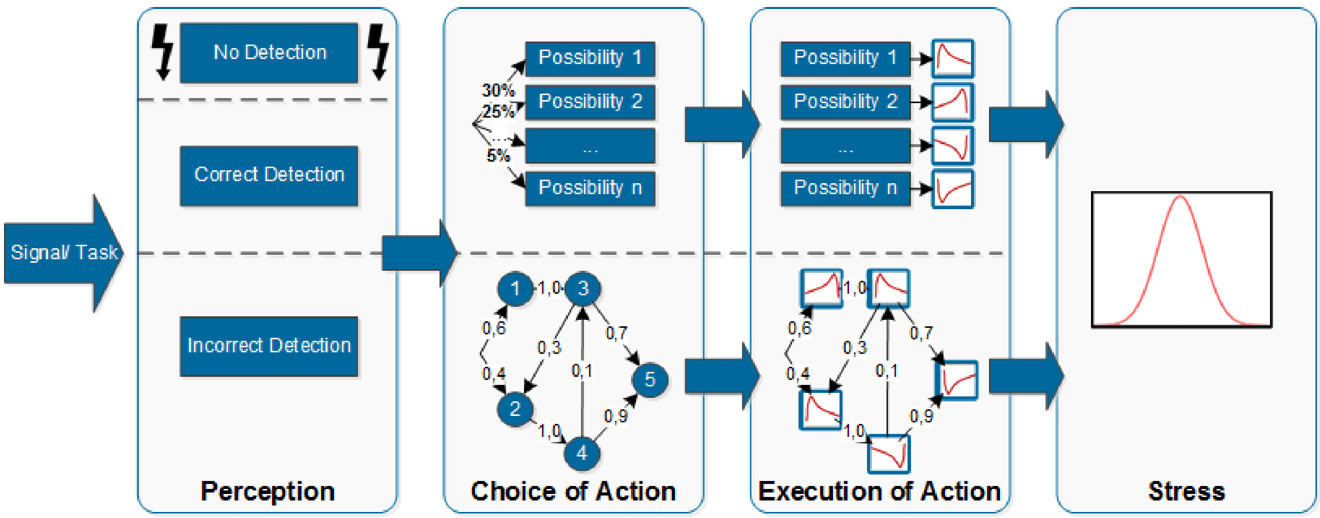

Figure 3-7. Exemplary characterization of uncertainty for specific model elements.

The resulting system stress in succession of an interaction can be systematically analyzed using the combined model (see Figure 3-6) for the description of human induced uncertainty. Based on the general model, a working model for the investigation of a specific HMI can be derived. Therefore, the focus of the investigation regarding inter- or intraindividual differences and thus influences can be selected as well as a predominant source for human induced uncertainty in form of one of the three human sub-processes. For example, when investigating a task with focus on the direct execution of action based on intraindividual factors, the according human influencing factors can be selected based on the model. The derived working model for the mentioned case is exemplarily depicted in Figure 3-8[6].

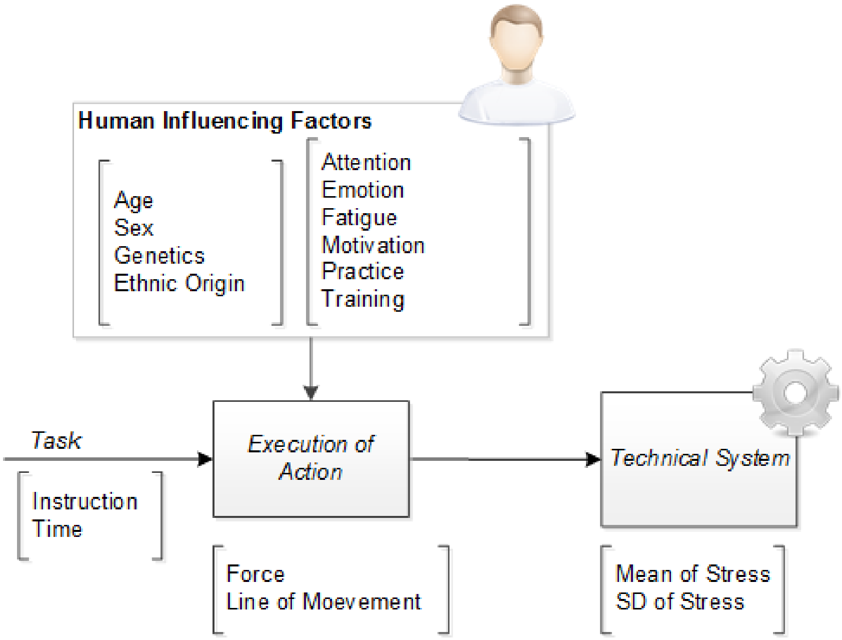

Figure 3-8. Exemplary working model for an intraindividual analysis of human induced uncertainty of execution of action.

In a subsequent step, an experimental investigation based on the selected influencing factors as represented within the derived working model can be conducted to quantify their impact on human induced uncertainty. As a result, the resulting system stress can be characterized through a distribution function (see exemplary depiction in Figure 3-7). Through the use of regression analysis, the resulting distribution can be analyzed in relation to the selected influencing factors, to identify and quantify the impact of each single factor. Relevant for the final description of human induced uncertainty is the formalization of the resulting mean and standard deviation of system stress as exemplified in equation (3.1) and (3.2).

Mean of stress: $$mean_{stress} = f(Factor_1, Factor_2, \ldots, Factor_n) \quad (3.1)$$

Standard deviation of stress: $$SD_{stress} = f(Factor_1, Factor_2, \ldots, Factor_n) \quad (3.2)$$

Based on such equations, potential variation of the resulting stress based on the involved influencing factors is predictable for future applications.

For such an application of the human uncertainty model, it must be discerned whether the human action is the direct cause for the initiation of a technical process or if the human action represents a

[6] To focus on the selection of human influencing factors, factors from the environment are eschewed for the exemplary depiction. For *task* and *execution of action* only a choice of possible factors is selected.

manipulation of system quantities and is thus a secondary cause for a transformation of the system quantities. For example, prior to the technical process of milling, the human interaction aims to input the specifications of the milling process, but not directly operates the milling process itself. Contrary, when using a hand press, the human interaction itself directs the technical process of forming. Depending on the involvement of the human within an HMI, certain human sub-processes may not be executed. For example, in case of a monitoring task an operator would only act if uncommon data or system states are observed. Thus, the main HMI focuses on the sub-process of perception.

Finally, the uncertainty relating to feedback and information is discussed. Thereby, the importance of feedback and information within an HMI based on existing knowledge is focused. Quantification of the uncertainty deriving from feedback and information is lastly only possible by assessing the uncertainty of the human sub-processes and relating them to different types of feedback and information. To conclude the importance of feedback and information for the uncertainty of HMIs, following statements are presented:

- The element of information has a high impact on system understanding, human error and thus on human induced uncertainty of HMIs (cf. Degani, 2004; Sheridan, 2010, p. 57; Wickens et al., 2014, p. 156).
- The design of human-machine interfaces is crucial for the resulting amount of uncertainty, where at the quantity, content and presentation mode of information impacts on the success of human perception (Johnson, 2003, p. 65).
- Appropriate feedback on system behavior supports the development of mental models (Norman, 1990).
- Correct design of human-machine interfaces empowers the human to act as a safety factor and thus contributes to the reduction of uncertainty (Grote & Roy, 2009, p. 104).
- Communication between human and machine should be designed according to human requirements to facilitate information processing (Völkel, 2005, p. 4).
- Generally, feedback and information should be delivered temporally adjacent to the execution of action (Wickens et al., 2012, p. 232). This emphasizes the importance of information, as it is temporally located after the execution of an action, whereas feedback occurs concurrent to task execution leading to issues of dual tasking and an increase of perceptual uncertainty.

3.4 Method for the Analysis of Human Induced Uncertainty

Within chapter 3.3, various sources for human induced uncertainty as well as potential steps for its assessment and quantification were presented. Following, a method for the systematic investigation and assessment of the described uncertainty is presented. The following method functions as a guidance for the derivation of a working model, containing and specifying all dependent and independent relevant variables, for an experimental investigation.

As the task contains the actual goal and reason for an interaction, defining the task is of primary importance to understand and further specify an HMI (Wickens et al., 2014, p. 19). Thus, step one represents the specification of the task. As second step, the involved subsystems, meaning the characteristics of the technical subsystem as well as the environmental conditions, are specified. Thereby, specification of the technical subsystem involves the aspect of information which is fed back to the human, as the manner of information representation is specified by the design of the system interfaces. The third step involves the selection of the uncertainty mode and the specification of human influencing factors regarding the human element of an HMI. With this, all elements involved within the observed HMI are specified and the empirical investigation and quantification of human induced uncertainty is carried out. Step four thus starts with deriving the working model, now only involving the prior identified and specified influencing factors and uncertainty mode, and then proceeds with the conception and execution of the study. Lastly, the assessed data is analyzed within step five regarding the resulting human induced uncertainty. The analysis thereby follows a general statistical approach by first operating a descriptive analysis of the data, followed by the statistical quantification of the human induced uncertainty and its impact on the stress of the system. This further involves the direct association of specific influencing factors to the resulting uncertainty.

Following, the five above described methodological steps, as depicted in Figure 3-9, are explained in detail. The developed method is subsequently referred to as Human Uncertainty Modes and Effects Analysis (HUMEAn).

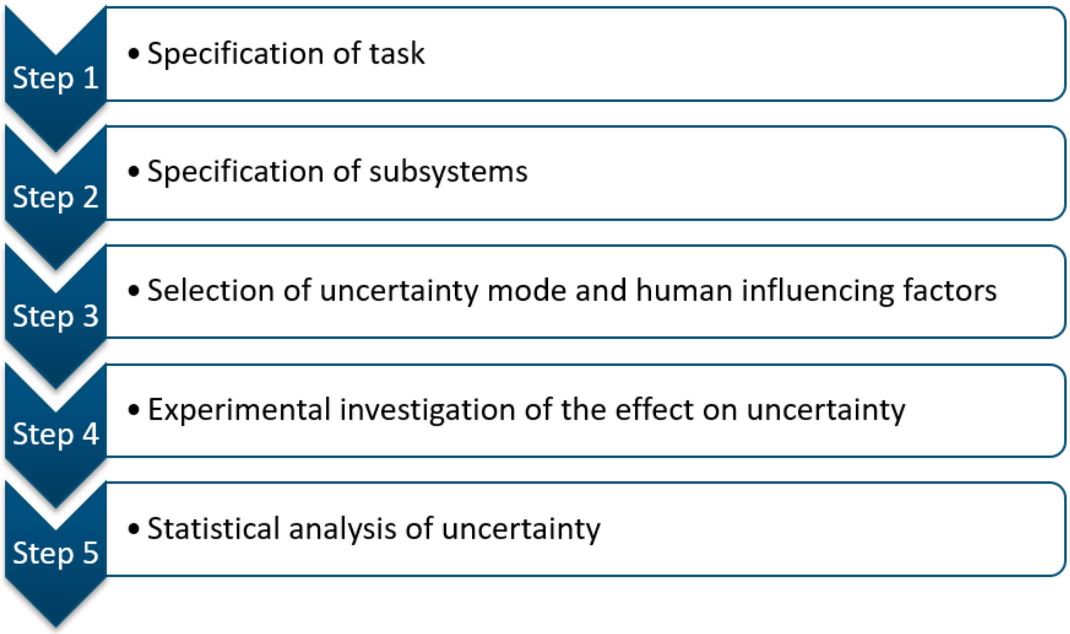

Figure 3-9. Steps of the Human Uncertainty Modes and Effects Analysis.

3.4.1 Specification of Task

As mentioned above, the task incorporates the reason to start an interaction. Task and especially a task's goal predefine the following human sub-processes, which are started for the task's fulfillment. Thereby, the task further entails how the human should interact with the technical subsystem under the present environmental conditions, which is why specification of the task represents step 1 of the HUMEAn.
Of major importance for the proceeding steps is the evaluation of whether the observed task can or even must be divided into distinct subtasks. This distinction is foremost influenced by time and complexity of the task. As a rule of thumb, in case of high task durations and/ or high complexity a further distinction into subtasks is advisable. Additionally, the distinction must be made regarding the possible impact of subtasks on the human induced uncertainty. For example, the task of placing a semi-finished product within a milling machine could be separated into the subtasks: grip part, lift part off the ground,

transport weight over to the machine and fit part within the milling machine. Of all these subtasks, only the last (fit part within the milling machine) directly leads to an interaction with the technical subsystem. This does not implicate that the prior subtasks have no impact on the resulting uncertainty at all, but assessment of their impact is just near impossible. This task example further entails low complexity combined with a relatively short duration. In conjunction, a distinction of this task is rather inappropriate.

If the task is divided into single subtasks, the investigation may be applied for each subtask independently. Further, the sequence of the subtasks represents another source for uncertainty, as outlined in chapter 3.3. Thus, a distinction into single subtasks leads to an increased effort for the uncertainty analysis.

Additionally, the general level of interaction must be defined. As pointed out in chapter 3.3, a distinction between a monitoring, indirect or direct interaction is possible. In case of a monitoring interaction, the further investigation mainly focuses on perception as well as the fed back information from the technical system. The distinction between direct and indirect interaction does not implicate a focus on a human sub-process, but affects the later specification of stress and the corresponding factors. For a direct interaction, stress is initially best defined through the mentioned factors (see chapter 3.2.4), like force and/ or velocity. For indirect interactions the resulting parameters for stress are prominently represented through the system quantities, like a set machine program or the input value of a knob.

After definition of the elementary attributes of the task and dependent interaction, the influencing factors are specified. This involves the operationalization of each single characteristic of task, which are the factors *goal*, *instruction*, *time*, *complexity* and *degree of freedom* (see chapter 3.2.4). Operationalization thereby involves the specification of a measurement method for each factor and the according scale (nominal, ordinal or ratio) on which a factor's value is assessed. As a special case, it could also be specified to actively manipulate one or more of the factors, to investigate their impact on human induced uncertainty. Besides the operationalization, the relevance of each factor regarding the investigation should be checked. A detailed description of each factor is only needed if the impact of the task onto the human induced uncertainty is the focus of the investigation. Otherwise and especially if the factors remain unchanged throughout the investigation, a ruff specification is sufficient and the factors can be neglected onwards.

The single elements of step one are depicted as a flowchart in Figure 3-10.

It must be noted that within the field of human factors and ergonomics a broad collection of methods for task analysis exist (e.g. Kirwan & Ainsworth, 1992). The above described approach is not directly based on existing task analysis methods, even though a sameness of elements may exist, but merely represents a simplification and rudimental way of defining the general principles of an observed HMI. Further, the task analysis methods within literature generally pursue a different goal, like the initial design and layout of an HMI for product design (Wickens et al., 2014, pp. 19–30).

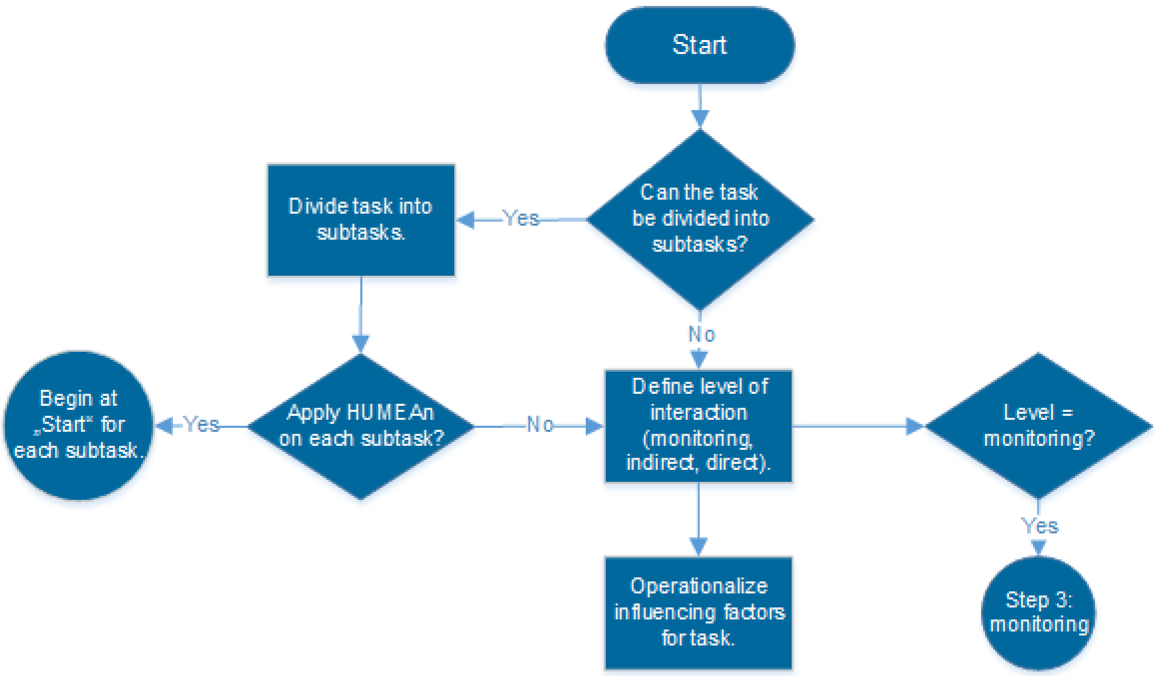

Figure 3-10. Flowchart for step one of the HUMEAn.

3.4.2 Specification of Subsystems

Step 2 focuses on the specification of the environment and the technical subsystem. Like for task, this primarily involves the operationalization of the according influencing factors.
In case of the environment, the operationalization of the social and physical factors should not solely focus on their initial state, but further consider possible alterations over time. If the environmental conditions cannot be controlled or kept constant during the experimental investigation, constant tracking of these conditions is required. If the environmental factors are constant throughout the uncertainty assessment, the results only apply for the same conditions, but may differ for different ones. In case that single social or physical factors are always constant for the investigated HMI they can be neglected onwards.
As discussed, the technical influencing factors are not covered within the present work. For operationalization of technical influencing factors the work and methods of the CRC 805 are referred to (cf. chapter 3.2.2). Fundamentally, the technical influencing factors are only important if they are prone to frequent change. This is the case if a human interacts with several systems of the same kind but which slightly differ within their specifications. Or if the impact of the technical influencing factors onto human induced uncertainty is the focus of the investigation. Otherwise, the same system is generally used for an investigation, which allows for neglecting most of the technical influencing factors.
Still, two aspects generally not represented by technical influencing factors are of major importance. First, this involves the system parameters which represent the resulting stress on the system due to an interaction. Like other influencing factors, these parameters must be identified and operationalized for later assessment. Second, the interface of the technical subsystem, which defines the possible inputs and outputs of the system, must be specified. Thereby, the resulting stress can derive directly from the human, e.g. through the exertion of a certain amount of force, or indirectly by initiating an intra-systemic process or by manipulating system parameters (see chapter 3.4.1). Concurrent to the specification of inputs into the system, the feedback returning to the human is specified by the law of *action equals*

reaction. Through the specification of the system output, the information which is returned to the human after the interaction is defined. Thereby, the allocation of output devices to the human perceptual influencing factors is recommended.
Figure 3-11 depicts all single elements of step two as a flowchart.

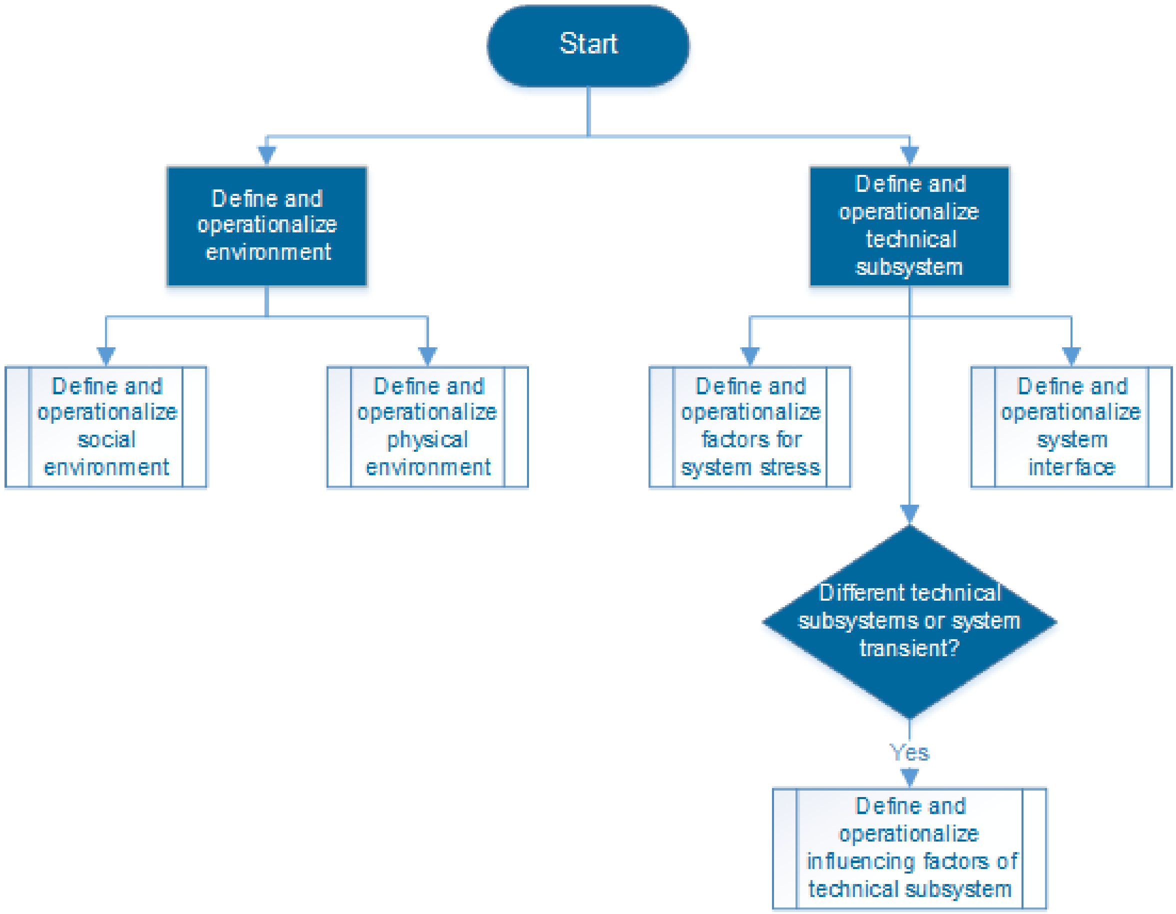

Figure 3-11. Flowchart for step two of the HUMEAn.

3.4.3 Selection of Uncertainty Mode and Human Influencing Factors

The term “uncertainty mode” refers to the identification and selection of one or more of the three human sub-processes in conjunction with the choice of intra- or interindividual uncertainty analysis for a given task and HMI. Depending on the chosen mode, relevant human influencing factors are selected. Thus, the selection of an uncertainty mode represents a crucial step of the HUMEAn.

Selection of the uncertainty mode is first done based on the task as defined in step 1, which is assigned according to the classification of work as depicted in Figure 3-12, based on the model of mental work by Luczak (1975). The task is thus analyzed for the probable bottleneck regarding human performance. For a complete coverage of work, the basic model for mental work is extended by physical work, which is attributed to the sub-process *execution of action*. The remaining task types are already represented within the original model and thus already described in chapter 2.3.4.
By selecting the uncertainty mode, one, or in case of sensory-motor or creative work, two human sub-processes are identified as the predominant source for uncertainty. For the investigation of human induced uncertainty, measures for assessing the variation of the human sub-processes must be identified and operationalized.

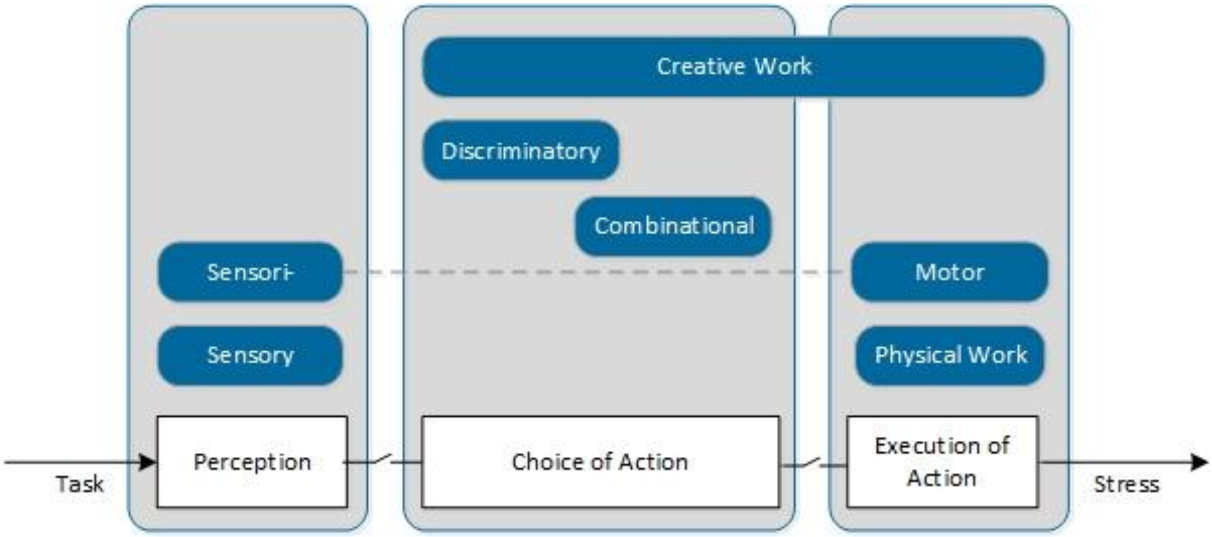

Figure 3-12. Interrelation of task type and human sub-processes based on Luczak (1975).

The direct metrological assessment of perception is difficult and can hardly be measured without the use of invasive measurement methods. As this is generally not an option, perception can be assessed through observation or interrogation of the task's execution. Also, the use of head- or eye-tracking is a common method to infer on perception.

For choice of action, two possibilities for the assessment of variation exist. If a sequence of subtasks is identified within step 1 as the major source for uncertainty, the method of Markov models, as proposed by Sheridan (2010, p. 58) and by Luczak (1974, p. 86), is suggested for assessing the uncertainty resulting from possible action sequences. In case that only a single task is observed, the relative probability for each possible action is suggested for uncertainty assessment.

The sub-process execution of action is assessed through operationalization of the influencing factors associated with system stress (see chapter 3.2.4). For measurement, methods like EMG or motion-tracking can be applied.

Next, the uncertainty mode is further selected through the choice between intra- and interindividual analysis of human induced uncertainty. In case the task is highly repetitive and generally operated by the same persons, focusing on intraindividual aspects is advisable. Contrary, in case of an interaction with constantly changing human operators an interindividual perspective is probably best.

With this the uncertainty mode is completely selected and the human influencing factors can be reduced according to the corresponding sub-process(es) and the intra- or interindividual focus. Subsequently, all selected human influencing factors must be operationalized to allow for their assessment within the experimental study. Concurrently, further selection and elimination of human influencing factors based on expert knowledge or literature is advisable. Same as for excluding factors, unselected factors may be included if a probable impact on human induced uncertainty is assumed due to additional knowledge. When operationalizing the factors, a categorization into independent variables (actively manipulated or focused as predominant for the resulting uncertainty), covariates (effect of variable cannot be eliminated and thus must be observed), controlled variables (kept constant, e.g. through the experimental design) and excluded variables (eliminated) should be done as preparation for the experimental investigation.

Besides a selection of relevant influencing factors, each selected factor should be defined in detail. The given definitions for the human influencing factors (see chapter 2.5.1.2) represent a first step to the understanding of each factor, but do not involve every aspect. Thus, a chosen factor like emotion should be analyzed and further specified into single emotions like love, anger or hate as accurate for the given task and HMI. Based on the general orientation of the task as predominantly mental or physical, some factors may further be specified. For example, when investigating a physical task, the physical aspect of the factor health could be more relevant then the mental aspect of health. This implies that two independently investigated tasks could lead to an equal selection of human influencing factors, but with different specifications and consequences for a following analysis.
A flowchart of step three of the HUMEAn is depicted in Figure 3-13.

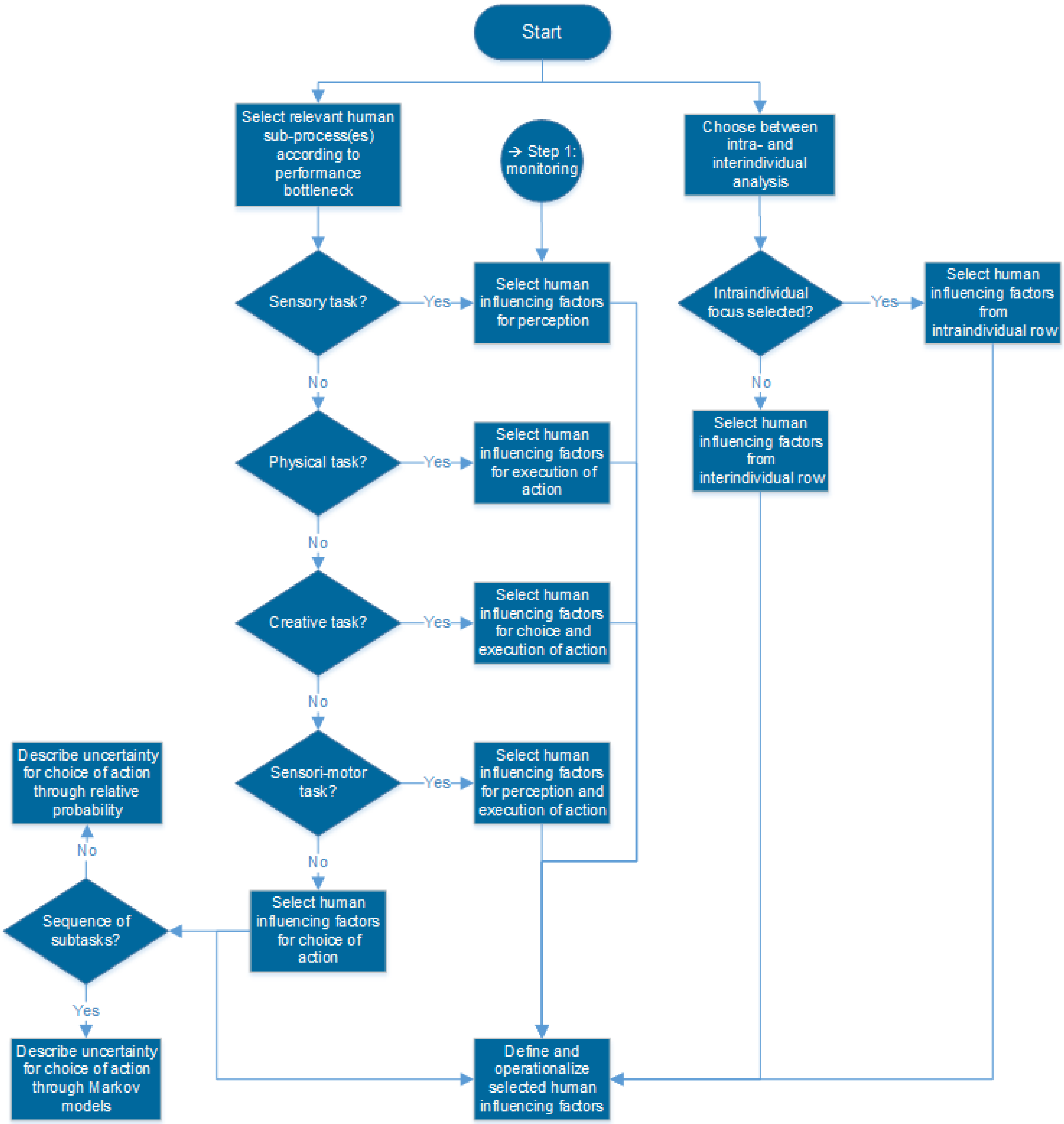

Figure 3-13. Flowchart for step three of the HUMEAn.

3.4.4 Experimental Investigation of the Effect on Uncertainty

As the initial step of the experimental investigation, all prior steps are summarized by transforming the results of each single step into a working model. The working model lastly describes the investigated HMI by representing only the remaining influencing factors of the remaining model elements for the selected uncertainty mode and their relation (cf. Figure 5-5).
Based on the prior steps and the derived working model, the experimental investigation is planned and conducted. This involves the selection of additionally methods for the measurement of variables, of the test apparatus and test procedure, choice for an adequate sample size and population of subjects, potentially the conduction of a pre-study and lastly the conduction of the experimental investigation.
As the described procedure strongly depends on the investigated task and is thus unique, no detailed explanation can be given. For a detailed description of experimental design the relevant literature is recommended (e.g. Wickens et al., 2014, pp. 490–504).
Figure 3-14 depicts the single parts of step four as a flowchart.

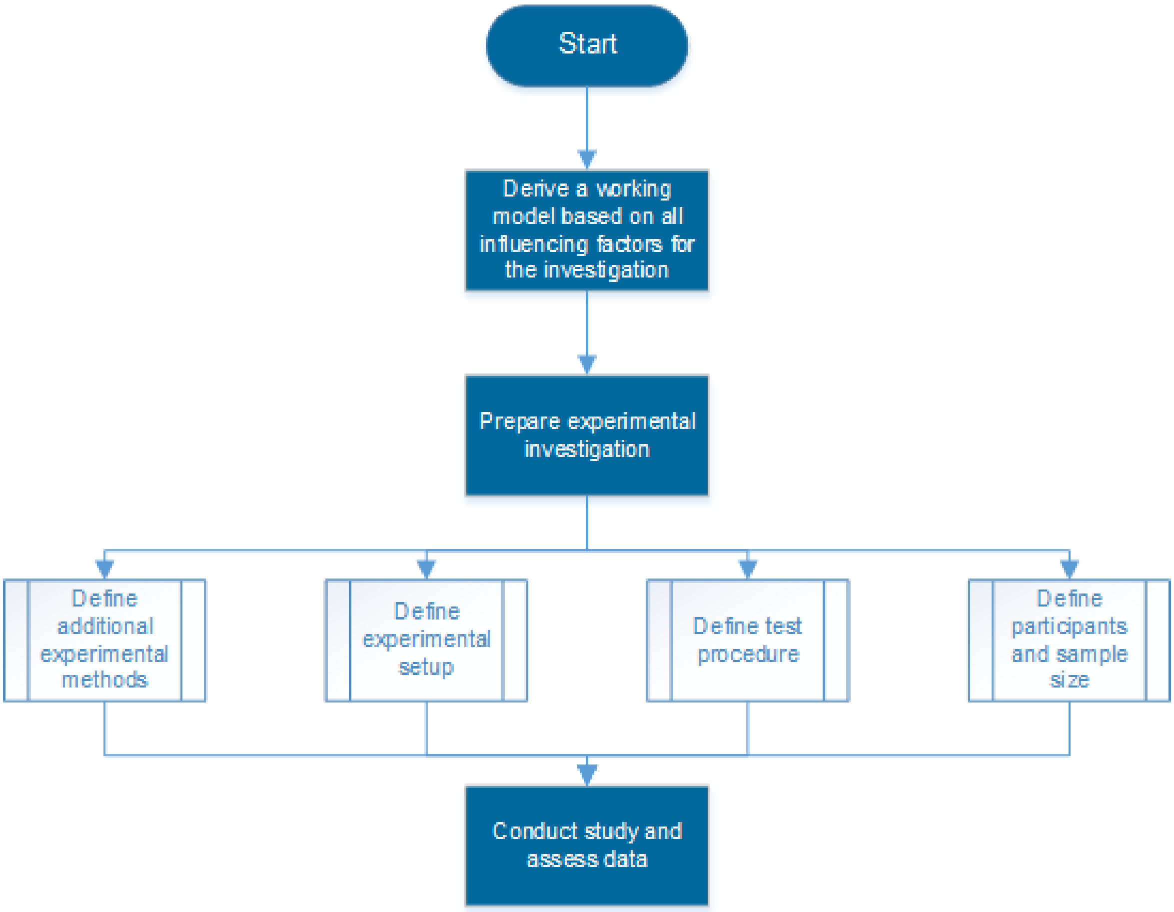

Figure 3-14. Flowchart for step four of the HUMEAn.

3.4.5 Statistical Analysis of Uncertainty

The statistical analysis of uncertainty involves two subsequent steps and is done based on the assessed data of the experimental investigation. The two steps are thereby oriented on common statistical analysis methodology and first involve a statistical description of the resulting uncertainty, followed by a statistical quantification of the effects of the influencing factors on uncertainty. The latter can be done by testing for statistical correlations between the single elements of the derived working model or further by using regression analysis to identify if certain influencing factors can be used as predictors for the resulting uncertainty.

For additional information on possible statistical tests the relevant literature is recommended (e.g. Wickens et al., 2014, pp. 497–504). A general approach for step five is depicted in Figure 3-15 as a flowchart.

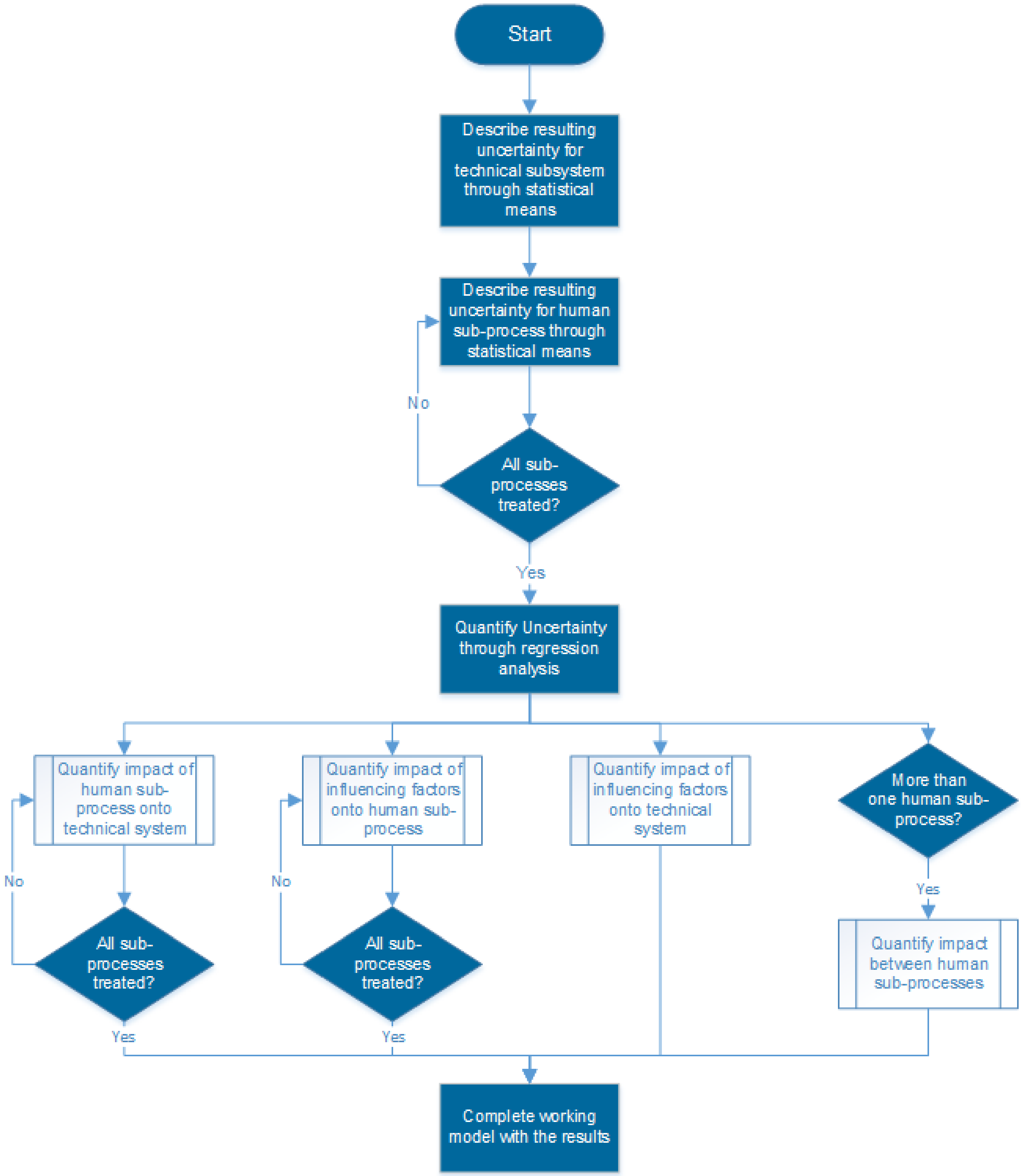

Figure 3-15. Flowchart for step five of the HUMEAn.

3.5 Summary Chapter 3

Within chapter three a model for the description of HMIs with focus on human induced uncertainty was developed. Special emphasis was laid upon the allocation of influencing factors to all elements of the model to facilitate the identification of sources for uncertainty. The uncertainty situated within the developed model was discussed and characterized. Based on the model, a methodological approach for the systematic investigation and quantification of human induced uncertainty was derived and named HUMEAn. Through stepwise specification of the model elements, certain characteristics of HMIs can be identified, the number of influencing factors reduced and their impact assessed. Thus, a working model consisting of the case relevant model elements and influencing factors can be derived. Finally, regression analysis, based on the working model and an empirical investigation, can be conducted to lastly quantify the amount of human induced uncertainty regarding the identified sources for uncertainty.
Therefore, the method in conjunction with the model represent means for the characterization of human induced uncertainty and thus an answer to the first research question of the present work.

Subsequently, the HUMEAn is applied to evaluate its applicability for the quantification of human induced uncertainty. For this reason, three different studies are conducted. Thereby, the first two studies focus on different human sub-processes and associated human influencing factors as a source for human induced uncertainty. The first study investigates a simple task relating to execution of action, whereat the second study investigates a more complex one, focusing on a sequence of choices of action. If for both tasks HUMEAn is applicable and a quantification of the resulting human induced uncertainty succeeds, the second research question, how human induced uncertainty can be assessed and quantified methodically, could be answered. The third study investigates the impact of feedback and information on human induced uncertainty, independent of specific human influencing factors. Then, all three studies are discussed regarding their contribution to the control of uncertainty regarding the third research question.

4 Application of HUMEAn for Execution of Action

Within the following chapter the prior derived method of human uncertainty modes and effects analysis (HUMEAn) is applied for a first uncertainty analysis. First, the application example for the study is presented. The following five sub-chapters represent the steps of the HUMEAn, as described in chapter 3.4. Thus, the elements of the HMI for the investigated task are defined and operationalized and then investigated within an experimental study. Based on the study, the human induced uncertainty is analyzed statistically and lastly quantified. The chapter concludes with a discussion on the findings of the study, especially regarding the applicability of the HUMEAn and ends with a summary.

4.1 Application Example of Study One

The objective for a first application of HUMEAn is to evaluate whether a reduction of human influencing factors based on the selection of one of the three human sub processes and further by distinguishing between an intra- or interindividual assessment is applicable for the description of human induced uncertainty. Thus, it seems advisable to focus on a simple example within a highly-controlled environment and study conditions. Also, the selection of a simple task, which is executable without prior training and within a short period, seems advisable. Thus, an example from a pre-study is chosen (Oberle & Bruder, 2014). The pre-study used a tripod[7] in combination with the task to place a weight on its top. Thereby, three different types of instructions were used for an initial investigation of human induced uncertainty. For the following study the experimental setup is adapted[8] and extended to include different weights in addition to three different types of instructions. Thereby, the actual results for human induced uncertainty of the chosen example majorly promote the applicability of the method and are itself of secondary importance.
Following, the single steps of the HUMEAn are traversed for the chosen example.

4.2 Specification of Task for Study One

As the first step of the HUMEAn the task which is investigated needs to be specified. As described above, the simple task of lifting and placing a weight on top of the tripod is chosen. With the general definition of the task, the subsequent steps for the complete specification of the task are processed.
Due to the simplicity of the task, no further division into subtasks is needed. Thus, the HUMEAn is processed only once for the single task.
The interaction level is specified as direct, as the subjects directly interact with the technical subsystem and thus impact on the technical process (see chapter 3.2.2). Therefore, the factors describing stress are applicable and should directly relate to the system's strain.
With this, the influencing factors of task are operationalized.
The goal of the task is to pick up a weight and place it on top of the tripod. Based on the pre-study (Oberle & Bruder, 2014) the content of the *goal* is varied to investigate the impact of a changing task focus. Therefore, the weights placed on top of the tripod as well as the content of instruction are varied (see chapter 4.5.2). The mode of *instruction* is fixed throughout the experiment. As mode of presentation a written instruction presented on a screen is chosen. No specific requirements regarding the available

[7] See chapter 4.5.2 for a detailed description of the tripod and the overall experimental setup.
[8] Adaptations concern the experimental setup and used equipment. The adaptations are described within chapter 4.5.

time for the task's execution are defined. *Complexity* and *degree of freedom* are simple and controlled for the task. This is achieved by giving explicit instructions and regulations for the manner the task must be executed.
Concluding, the factor goal, which is characterized through weight and content of instruction, represents an independent variable. Instruction, time and complexity are neglected within the experiment, as these factors are kept constant and thus should not impact on uncertainty. Degree of freedom represents a controlling variable. Even though precise instructions regarding the manner of task execution are given, it must be checked if each subject adhered to the given regulations.
With this, the task is fully specified and the second step of the HUMAEn is addressed.

4.3 Specification of Subsystems for Study One

Within the second step of the HUMEAn the subsystems of the HMI, addressing the environment and the technical subsystem, are specified.
As indicated in chapter 4.1, the experimental investigation is done under controlled laboratory conditions. Thus, the *physical environment* is actively kept constant and controlled throughout the experiment and neglected onwards. The *social environment* is controlled, too, apart from possible variations regarding the investigator. To reduce influences deriving from changing investigators, the procedure of the experimental study is controlled using checklists and scripted conversations (see chapter 4.5.3). Thus, social environment is likewise neglected onwards.
As the same, static technical subsystem is used, only factors for the assessment of stress as well as potential *system interface* must be specified. Latter is nonexistent for the tripod and thus neglected. Regarding factors for the *system stress*, the tripod allows for a direct measurement (see chapter 4.5.2). The stress is thereby characterized through the resulting maximum force on placing the weight on its surface and the eccentricity of the placed weight in relation to the center of the tripod. Low eccentricity signifies an equal force distribution of the static weight after placement. These two measures further represent the dependent variables of the study.
With this, step two of the HUMEAn is completed.

4.4 Selection of Uncertainty Mode and Human Influencing Factors for Study One

Now all aspects of the observed HMI have been addressed and defined, except for the human part. Thus, the dominant human sub-process followed by the decision for intra- or interindividual analysis of uncertainty is selected. With this, the number of human influencing factors can be reduced and operationalized for the later investigation.
The selection of one or more human sub-processes is done according to the bottleneck-oriented approach by Luczak (1975) as presented in Figure 3-12. As the task focuses on the manipulation of weights and thus is dominantly oriented on physical actions, a declaration as sensory task seems inappropriate. Also, the creative, discriminatory and combinational task types can be excluded, as the goal of the task is simple, defined in detail and controlled (see chapter 4.2), leaving the possibility for a sensorimotor or pure physical task. As the interaction precludes additional interfaces for information and feedback presentation and the task is executed with the complete arm instead of the precise motion of single fingers, the sensorimotor task type is excluded, too. The task is thus characterized as a physical task. Consequently, the human sub-process *execution of action* is selected. Thereby, the exerted *acceleration* of each participant's movement as well as the exerted *finger forces* to retain the placing weights are

measured to assess the variation of execution of action. Thus, both measures represent the dependent variables for execution of action.

Generally, an investigation of both, intra- and interindividual impact on uncertainty, is possible for the given task. In case of an intraindividual analysis, a small number of participants would repeat the task over a long time period, which would address factors like practice and fatigue as primary sources for uncertainty. An interindividual analysis would focus on general differences in performance between different people, addressing factors like strength or anthropometry as primary sources for uncertainty. For a first application of the HUMEAn, an interindividual approach is chosen. Based on an interindividual analysis, findings could be used to select people for a future task execution allowing for a first reduction of uncertainty. An intraindividual approach would make sense to further reduce uncertainty based on pre-selected operators and thus represents a second step.
Concluding, the uncertainty mode is characterized through focus on the intraindividual impact on the system deriving from the execution of action. Assessment of uncertainty is thereby directly related to the human performance variability of action execution. Figure 4-1 depicts the selected human influencing factors for and interindividual analysis of execution of task. Following, all factors are discussed one by one to discern whether they are eliminated (e.g. through experimental design), controlled (probably unimportant, but still measured to control for a possible impact) or regarded as an independent variable to investigate their impact on system stress. To reduce possible impact of unselected influencing factors, the disregarded factors pertaining to execution of action are treated, too.

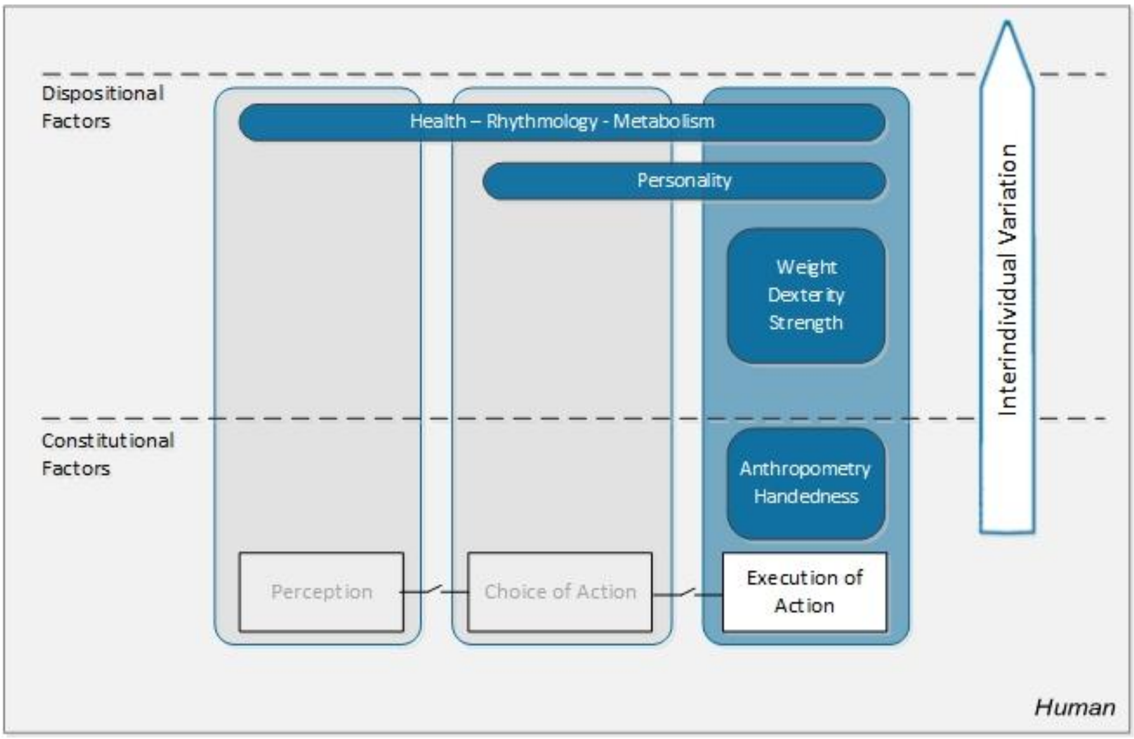

Figure 4-1. Remaining human influencing factors for the uncertainty mode *execution of action* and *interindividual* analysis.

Dispositional Factors

Health is of major importance regarding human performance. Generally, it must be expected that participants not feeling well would not participate voluntarily. Additionally, a questionnaire item is included asking for physical impairments, current and recently. Thus, health is characterized as a covariate.

As circadian effects like sleep deprivation impact on fatigue, *rhythmology* and fatigue are related (Johnson, 2003, p. 63). Therefore, further consideration of rhythmology is neglected.

Metabolism represents a highly individual factor, which is further affected by food, liquids and other stimulating substances. To cope with this, participants are advised to visit the toilet before starting the experiment. Further, food and drinks are offered to retain hunger or thirst. As no further control of metabolism is possible without relying on invasive techniques, metabolism is characterized as eliminated and thus neglected.

Personality may impact on uncertainty due to different notions regarding conscientiousness of keeping to the exact instructions as well as to willingly manipulate the study. As the assessment of personality generally involves extensive questionnaires, which would further increase the time on experiment for every participant, no direct assessment of personality is conducted. Instead, the mentioned difficulties are coped through thorough observation of the participant's behavior according to the study guidelines. Thus, personality itself is neglected.

The observed task relies on the use of one arm for placing the weight on top of the tripod. Therefore, the body *weight* of the participants is not expected to directly interfere on the placement, as the exerted force predominantly derives from the arm and not from the whole body. Still, the weight of the participants is assessed through a questionnaire and thus regarded as a covariate for later verification.

Due to the predominant physical aspect of the task and regarding the dependent variables, impact from each participant's *strength* and *dexterity* is expected. Further, both factors are nearly impossible to control through experimental design, which would involve a preselection of participants according to their strength and dexterity. As this already involves the measurement of both factors, strength and dexterity are actively selected as independent variables in addition to the prior discussed content of instructions and the placing weights.

Constitutional Factors

The factor *anthropometry* can be subdivided into parameters like height or reach of the participants. Different body dimensions therefore lead to different distances to the tripod or a different angle of view onto the top of the tripod. To negate such effects, the experimental setup is adjusted, as described in chapter 4.5.1. Thus, the factor of anthropometry is generally regarded as controlled. Still, participant's height is assessed through the questionnaire as a covariate.

According to Annett (1985), about 10% to 15% of all people are left handed. Therefore, obtaining left handed participants is more difficult than obtaining right handed participants. To enhance later comparability of the data only right-handed participants are included for the experiment. Thus, *handedness* is eliminated.

Background Factors

Age is a major influencing factor for other influencing factors. For example, age is stated as an interindividual factor impacting on the maximum, possible exerted force (e.g. Wakula et al., 2009). Age also impacts on dexterity (e.g. Mathiowetz, Volland, Kashman, & Weber, 1985). To cope with this influence, participants are selected by age, only allowing for subjects between 20 to 24 years[9] to participate at the study. Additionally, the age of the participants is assessed through a questionnaire. Thus, age characterizes as a covariate.

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[9] This range is selected as one of the used tests for the assessment of dexterity (see chapter 4.5.1.2) features table data for this specific group.

Like age, *sex* is known to impact on both, strength (e.g. Wakula et al., 2009) and dexterity (e.g. Mathiowetz et al., 1985). Thus, the first investigation focuses on male participants only, neglecting sex as an influencing factor.
For the factors *genetics* and *ethnic origin* no measures for assessment or controlling are derived. Even though both factors may impact on strength and dexterity of the participants, this impact is only secondary and already assessed through the direct measurement of these factors. Therefore, genetics and ethnic origin remain disregarded throughout the experiment.

Adaptable Factors

Fatigue is generally of importance concerning experimental investigations. Thereby, a distinction must be made between mental and physiological fatigue. For the investigated task, latter is of higher importance. Total elimination of physiological fatigue is mere impossible, as every exerted force impacts on the involved muscles. But physiological fatigue can be countered by implementing sufficient time for recovery (cf. Schlick et al., 2010, p. 202). Therefore, adequate time for recovery from physiological fatigue is provided within the experiment. The needed time for recovery was determined within a small pre-test[10]. Still, a questionnaire item is included for the repeated assessment of perceived effort to cope for remaining fatigue effects. Thus, fatigue is characterized as a covariate. Besides effects from fatigue, monotony represents a major issue for the experiment, as the task to place a weight on a tripod, which must be repeated several times for each combination of instruction and weights, is simple and without major variation. Thus, monotony could affect fatigue impacting on the results. Within the pre-test, the number of task repetitions for each variation of goal regarding monotony effects was evaluated. A total of 6 repetitions were found to be adequate. Still, a questionnaire item on the perceived concentration on the task is included to control for possible effects due to monotony.
Like fatigue, *motivation* is of importance for experimental investigations. As motivation embodies a highly individual factor, different levels of motivation within the participants are to be expected. As a countermeasure, participants are presented with a small compensation for their participation. Further, a ranking of the assessed values for strength, dexterity and performance at placing the weights is generated and handed out to every participant to evoke competition. Both countermeasures should increase the level of motivation. Still, a questionnaire item is included for the repeated assessment of each participant's motivation throughout the experiment to cope with remaining influences. Like fatigue, motivation is characterized as a covariate.
The factors *attention* and *emotion* remain disregarded. First, like for personality, measurement of attention would require extensive methods like eye-tracking. Second, attention is partially considered through fatigue of the participants. Emotions are also difficult to assess and thus not justifiable as the focus is upon interindividual factors. Further, emotions partially correspond to motivation. Therefore, additional consideration of both factors is neglected.
The task of placing a weight on top of a tripod was chosen because it is simple and does not involve any practicing or training periods. Simplicity of the chosen task was confirmed by the pre-test, as even after 20 repetitions no practicing effects were identified. Further, the task does not give advantage for a certain group of people due to previous knowledge or experience. Still, the assessed data is checked for practicing effects, characterizing *practice* as a covariate.

[10] The pre-test was conducted with the support of Antos, Garcia, Yorur, Yazir, and Zhao (2015).

Qualifying and Educational Factors

As mentioned above, the observed task is of a generic nature, wherefore all factors of the *qualifying and educational* group are likely unimportant as prior knowledge and experience in relation to the task is unlikely. Still, to further reduce possible unsuspected influences, the sample size is reduced to include only university students. Further, assessment of prior apprenticeships as well as the subject of study are added to the questionnaire.

Concluding step 3, all influencing factors, their operationalization and the corresponding measurement methods are summarized in Appendix A.

4.5 Experimental Investigation of the Effect of Uncertainty of Study One

Following, the experimental methods, the experimental setup, the used procedure and the participants who participated at the study are presented[11]. In conjunction with the chosen uncertainty mode and the operationalized influencing factors, a working model for study one is derived, as depicted in Figure 4-2.

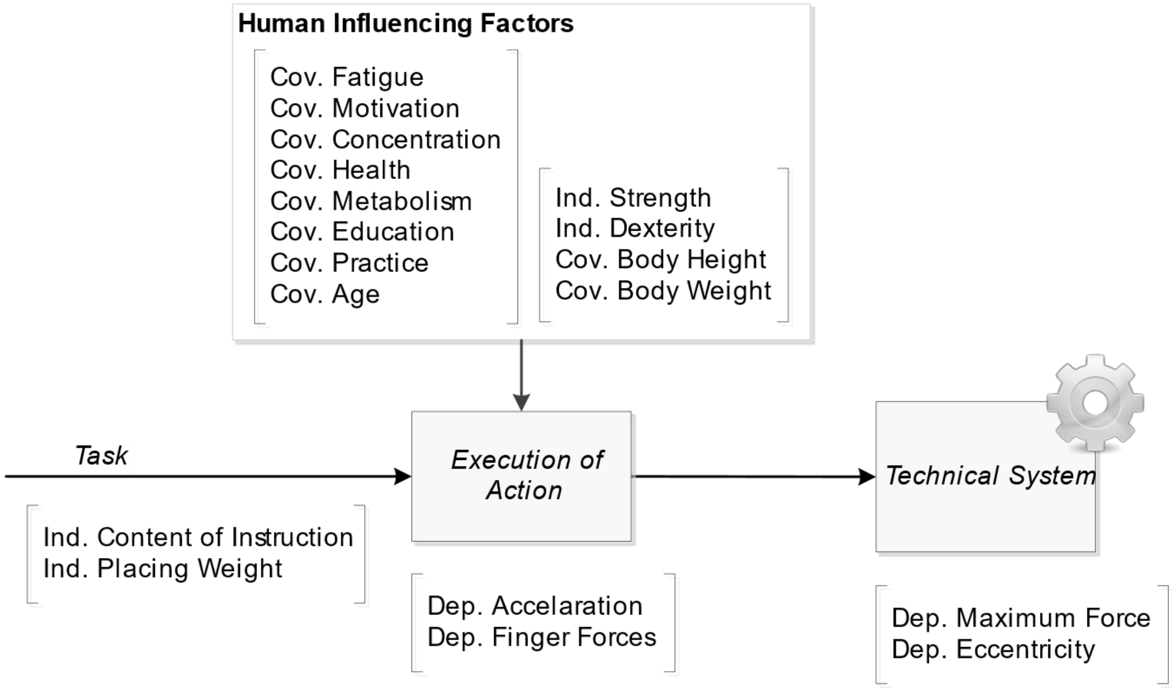

Figure 4-2. Derived working model for the investigation of human induced uncertainty of study one.

4.5.1 Experimental Methods of Study One

In the following subchapters, the applied methods for the measurement of strength and dexterity, the questionnaire for the assessment of demographic and subjective data as well as the utilization of the Captiv measurement equipment for the assessment of variations within *execution of action* are introduced.

[11] The experimental study was supported by the work of Hu (2016), Pertz (2016) and Sprenger (2016).

4.5.1.1 Strength Measurement

For the assessment of the dependent variable *strength* a force measurement rig, as described and implemented by Wakula et al. (2009, pp. 38–41), is used. The force rig is depicted in Figure 4-3. The force measurement rig was developed for the assessment of whole body forces for different positions and classifies as a subjective/ direct force measurement method (Mainzer, 1982). For this purpose, the position for the two force sensors, one for each hand, can be adjusted and the piezo-electric sensors can assess forces in all three spatial directions.

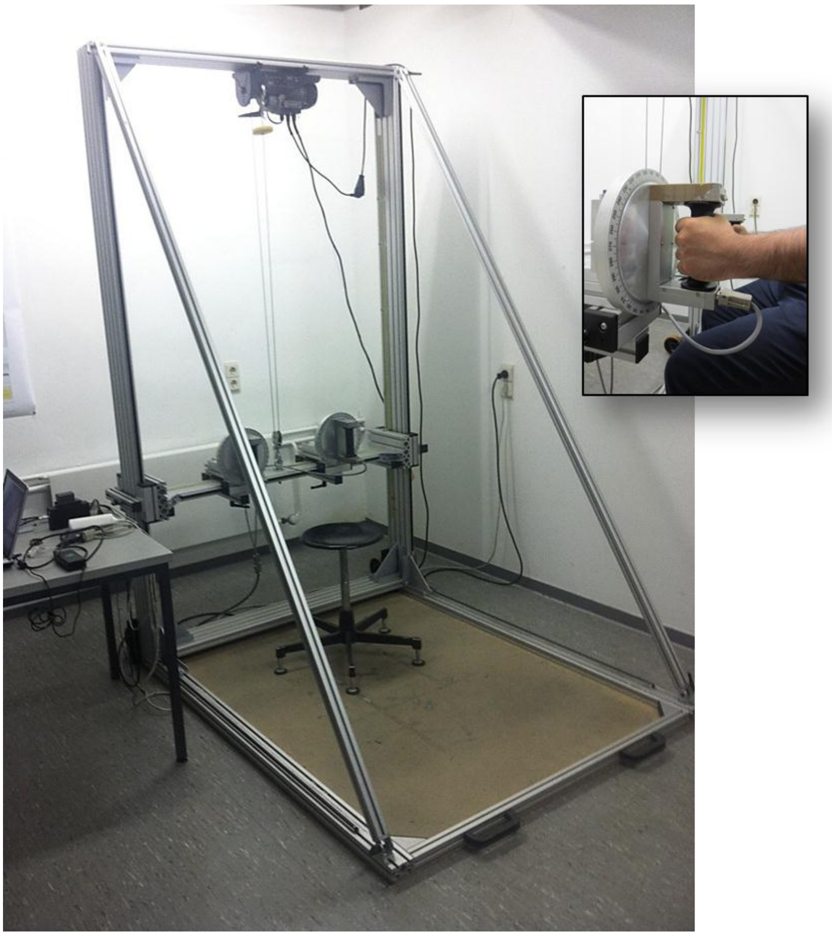

Figure 4-3. Setup of the force measurement rig.

The planned task consists of four single movements for the participant. First the weight must be picked up from its original position. Second the weight has to be lifted in the direction of A+, according to the definition of force direction by Wakula et al. (2009), as can be seen on the left in Figure 4-4. Third the weight must be moved over to the new position in direction of C+ and fourth placed on the surface again, moving in the direction of A-. Generally, the maximum possible force which can be exerted by humans differs depending on the posture and direction of force exertion (Wakula et al., 2009). But as participants are working against gravity for the third movement (in direction A-), for a soft placement forces are exerted in A+. Thus, only the directions A+ and C+ are assessed. Both directions are measured using both hands simultaneously, as the use of only the right hand would lead to an asymmetric force exertion, negatively influencing the resulting values.

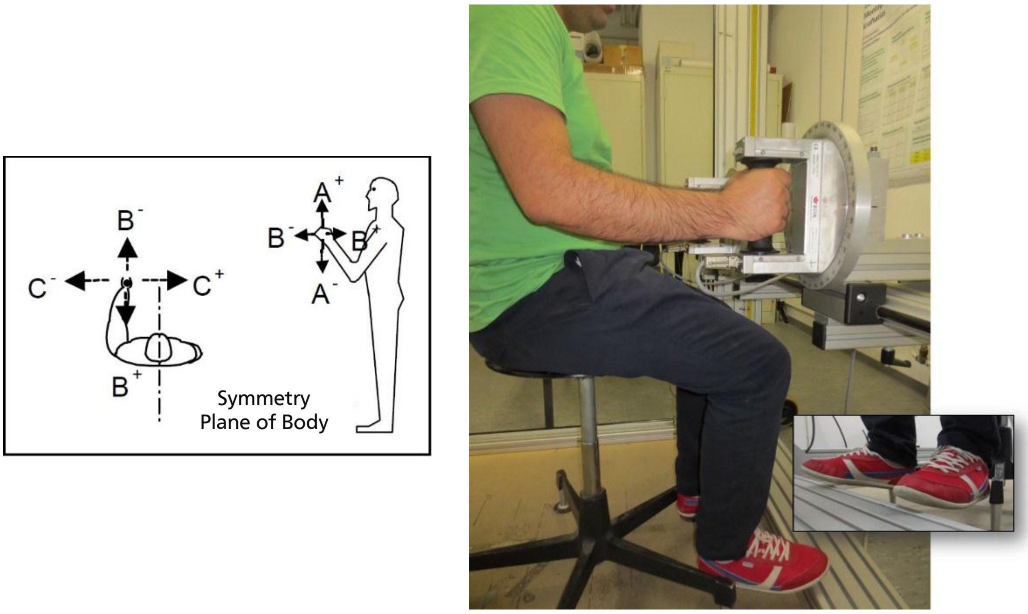

Figure 4-4. *Left*: Definition of force direction according to Wakula et al. (2009); *Right*: Resulting posture of participants during force measurement.

The analog signals of the force sensors are converted to a digital signal and assessed with the WIDAAN software[12], with a frequency of 50 Hz. Each participant must exert their maximum possible force in the above discussed directions over a period of 4 seconds as is the custom for the measurement of maximum forces (cf. Wakula et al., 2009). The resulting value is determined as the maximum of a moving average covering 1.5 seconds.

As the measurement of forces itself is prone to several influencing factors, especially height and build of participants, the position of force application within the rig is adjusted according to each participant's proportions. Further, to prevent participants from making use of additional strength through their legs, participants are seated and advised to lift their feet off the ground. The resulting position can be seen on the right in Figure 4-4. Another influencing factor on the exerted force is represented by the body weight of the participants. As force exertion is measured in direction A+, each participant must lift the weight of his own arm. Due to the complexity for a direct assessment of arm weights, equation (4.4), based on equations (4.1) to (4.3) by Saziorski (1984, p. 46), is used to calculate the arm weight based on each participant's body weight. This value is than multiplied by gravity and the resulting force is added to the measured arm force for correction. Measurement of maximum force in C+ remains uncorrected.

Weight of hand:	$y = 0.109 + 0.0046\,x$	(4.1)
Weight of forearm:	$y = 0.165 + 0.0139\,x$	(4.2)
Weight of upper arm:	$y = 0.0003\,x^2 + 0.0786\,x - 1.96$	(4.3)
Weight of arm:	$y = -1.686 + 0.0971\,x + 0.0003\,x^2$	(4.4)

[12] WIDAAN software was developed at the IAD for data acquisition based on the force measurement rig.

4.5.1.2 Dexterity Measurement

For the assessment of the dependent variable dexterity, two different tests are used. Both tests are only applied to assess the dexterity of the right hand.

As a first approach, the standardized Box-and-Block-Test (BBT) introduced by Mathiowetz et al. (1985) for the assessment of manual dexterity is applied. The BBT consists of a box, filled with 150 wooden cubes of 2.5 cm square. The box is divided into two equal compartments by a partition, 25.4 cm high. At the beginning of the test, all cubes are in the compartment at the right-hand side of the participant. After a standardized instruction and a 15-second trial period the main test is started. The participants have 60 seconds to transfer blocks over the partition and into the second compartment. The number of transitions is counted and represents the resulting dexterity score. Thereby, participants can transfer more than one block at a time. Participants are instructed to score as much transitions as possible.

The BBT was chosen due to its short application time of less than 5 minutes to assess the dexterity of the right hand, including instructions and trial. Further, the BBT possesses a high reliability as well as validity and offers basic data for different age, sex and hand dominance (Mathiowetz et al., 1985; Mathiowetz, Federman, & Wiemer, 1985). Latter allows for a comparison of the assessed scores to the existing data. The test was constructed according to the specifications of Mathiowetz et al. (1985)[13] and is depicted in Figure 4-5.

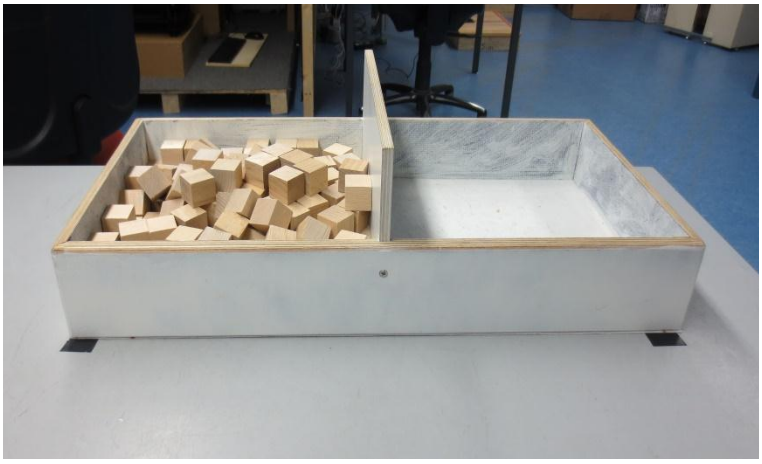

Figure 4-5. Box-Block-Test for dexterity assessment.

In addition to the BBT, a second dexterity test is used, based on the well-known hot-wire game for children. The test was exclusively build for the experiment and used to assess a dynamic type of dexterity. The hot-wire test consists of a base plate on which a thick and conductible wire is fixed. As a counterpart, a second wire, fitted within a handle and formed into a loop enclosing the thick wire, is used. Participants must trace the course of the thick wire with the loop, starting from the lower left side and ending at the lower right side (see Figure 4-6) as fast as they can and with as few contacts as possible. For dexterity assessment, the time to complete the course as well as the number of contacts are counted. To account for mishaps and for practicing effects, each participant must complete six runs. As direct conversion between time and contacts is impossible, a single ranking score is derived for each participant.

Execution of both tests was recorded with a camera to ascertain the assessed data.

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[13] The construction of the BBT was supported by the work of Rösner, Kaupe, Li, Zierk, and Mautes (2015).

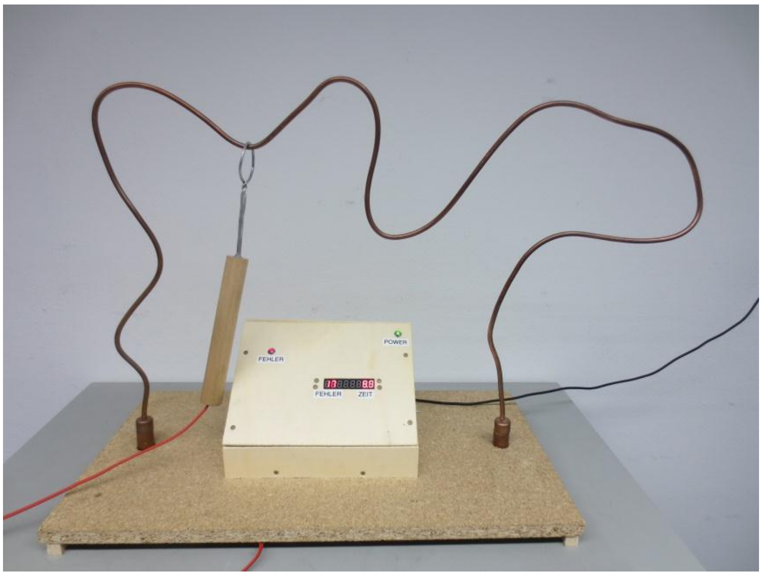

Figure 4-6. Hot-Wire test for additional dexterity assessment.

4.5.1.3 Questionnaire for the Assessment of Demographic Data

A questionnaire was constructed to assess demographic data and covariates, as pointed out in chapter 4.4. The questionnaire was further extended to include additional items for control for possible impacts on the study. Thus, two questions to assess the sportiness of the participants, asking how regularly they do sports and if they did sports prior to the experiment, were included. Further, a question concerning the subject of study was added. The complete questionnaire is depicted in Appendix B.

4.5.1.4 Captiv Measurement Equipment

For the assessment of factors form *execution of action* the Captiv measurement equipment by the company TEA was used. Captiv represents a measurement software for continuous data recording. A series of different sensor types can be combined with the software.
The factor of acceleration was directly assessed using an acceleration sensor placed on top of the placing weights. Thus, the movement of each participant while placing the weights is assessable, whereat the sensor must not be repositioned for each participant.
For the assessment of the finger forces a force sensor entailing three patches for force assessment was applied. The patches were attached to defined points of each participant's hand. The positions for the sensors were evaluated within a small pre-study[14] to ascertain that the chosen positions were applicable for force assessment. The pre-study showed that positioning of the patches is difficult, as each participant gripped the weights slightly different. Still, fixed positions for each sensor patch were derived, accepting the chance of being outside the flow of forces for some participants. Additionally, directives for the participants were included to facilitate a universal grip position.

4.5.2 Experimental Setup of Study One

Besides the aforementioned methods, which were integrated into the overall procedure, the actual experimental design consists of four elements: the tripod, the weights, an experimental table and the measurement software. The experimental setup was identic to the setup used in Oberle, Sommer, and

[14] The pre-study for detecting the best position of the force sensors was supported by the work of Antos, Garcia, Yorur, Yazir, and Zhao (2015).

König (2017, p. 48), except for the placing weights. Following, a brief overview of the setup will be given, as depicted in Figure 4-7.

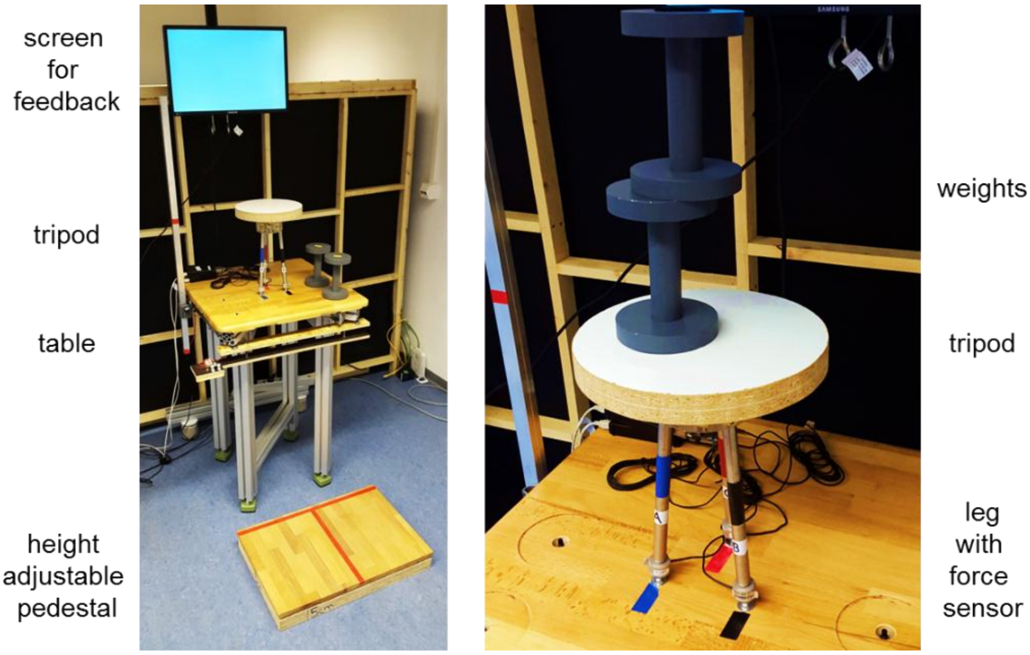

Figure 4-7. Experimental setup of study one. Left: Height adjustable pedestal, table, tripod and screen for presentation of the instructions. Right: Weights and tripod (close-up) with its three legs each with a force sensor.

The tripod represents a circular platform, 25 cm in diameter, which rests on three legs, allocated in 120° steps. On each leg's base a force sensor is installed, allowing the independent measurement of forces of up to 400 N for each leg with a set frequency of 10 Hz. The tripod can be seen on the right of Figure 4-7. Two different weights were custom-built to best fit the requirements of the experiment. The weights were designed to weigh 1 kg (precise resulting weight: 1074 g) and 3 kg (precise resulting weight: 2959 g)[15]. Thereby, the values of the weights were chosen with the goal to confront the participants with different weights resulting into different performance requirements, but without causing muscular fatigue during the experiment, as the latter would address intraindividual differences. The given task classifies as manual material handling when regarded with analysis tools for ergonomic risk assessment[16]. In this context, the weight of 3 kg represents a common limit when investigating the risk of manual material handling (e.g Bernard, 1997; Chiang et al., 1993; Silverstein, Fine, & Armstrong, 1986), which is the cause for its selection as the higher weight. Thus, the weight of 3 kg is high enough to represent a physical challenge for the participants without high possibilities of causing muscular fatigue. The second weight is selected as 1 kg to represent a low physical challenge and to build a contrast to the other weight.

Through the use of different materials, aluminum and iron, both weights were built with equal geometry. This was done to prevent impacts from dissimilarly shaped weights. Both weights are shaped like a barbell, whereas the middle-bar was designed according to DIN 33402-2 to allow for the 95th percentile of male and female hand sizes to fit easily.

[15] Design and manufacturing of the placing weights was supported by the work of Wang, Coskun, Da, and Bahyl (2014).

[16] Exemplary methods for ergonomic risk assessment are the European Assembly Worksheet (e.g. Schaub, Caragnano, Britzke, and Bruder, 2013) or the NIOSH equation (e.g. Waters, Putz-Anderson, Garg, and Fine, 1993).

The experimental table was built for several purposes. One of the purposes was to fix the position of the weights and the tripod on the table surface to ascertain that all participants are confronted with the identic test layout. This was achieved by cutting notches on the table surface. Further, the table was designed to be robust against vibrations, as the force sensors are sensitive to vibrations. Therefore, dampening mounting foots were installed and the table legs were isolated with a cork mat from the tabletop. At last, a height adjustable pedestal was built. Through measurement of the elbow height and arm length in relation to the position of the tripod on the table, height and distance of the pedestal were adjusted to prevent the participant's anthropometry from impacting onto the experiment.
For data acquisition the sensors were connected via analog digital converters to a notebook, on which a measurement-software was installed, allowing for a continuous (10 Hz) data assessment.
Two HD cameras were used to record the experiment for each participant. One camera was located as a bird's eye view directly above the tripod, the second camera was located on the right of the participants for a lateral view.

4.5.3 Procedure of Study One

The experiment started with a short introduction and settling of formalities, like filling out a declaration of consent. Thereafter, participants were transferred to the force measurement rig for strength assessment. Prior to the main experiment, participants answered the questionnaire, the Captiv equipment was vested and the experimental table was adjusted to height and reach of the participants with help of the pedestal. This gap between strength assessment and main experiment was intentional to provide sufficient recovery time.
The main experiment was structured into six parts due to possible combinations of weight and content of instruction (see Table 4-1). For each part, 6 repeated placings had to be operated to control for outliers, resulting in a total of 36 placements for each participant. Changes between the combinations were always operated by a change of weight, resulting in a possible sequence of AECDBF. To reduce sequence effects, the order of the experimental parts was permuted between participants. Between each part a short break was added to ascertain that no effects due to fatigue showed up. Thereby, each break equaled the time of the last part's exertion, which according to Rohmert and Rutenfranz (1983, p. 92) is sufficient to account for fatigue effects. To account for effects from perceived changes of motivation, effort and concentration, a separate questionnaire was handed in after two parts, after four parts and finally after six parts. A 7-pointed Likert-scale was used for the assessment of each item.

Table 4-1. Parts of experiment resulting from the possible combinations of weight and instruction.

Instruction (task goal) \ Weight	**1kg**	**3kg**
"Place the weight as softly as possible."	A	D
"Place the weight as centrally as possible."	B	E
"Place the weight as softly and centrally as possible."	C	F

The main experiment was followed by the Box-Block Test and the Hotwire test for the assessment of dexterity. This sequence was used due to organizational issues caused by the vesting of the Captiv equipment and the strength assessment. Concluding, each participant received a small compensation for participating and was bid farewell. Table 4-2 gives an overview of the steps and their planned duration.

Table 4-2. Steps of test procedure with specific durations.

Step	Duration [min]
Reception of participant, introduction and formalities	3
Force measurement with the force measurement rig	5
Questionnaire on demographic and additional data	2
Vesting of Captiv equipment	5
Adjustment of the pedestal to negate participant's height and reach	2
Placement of weights on tripod (run 1 and 2)	6
Assessment of motivation, effort and concentration 1	1
Placement of weights on tripod (run 3 and 4)	6
Assessment of motivation, effort and concentration 2	1
Placement of weights on tripod (run 5 and 6)	6
Assessment of motivation, effort and concentration 3	1
Box-Block Test	5
Hotwire test (6 runs for each participant)	5
Concluding formalities and farewell	2
Total duration	50

Every step of the experiment was monitored and tracked using a checklist[17], which also contained prescribed phrases for instructing the subjects. Prior to the main study, the described experimental setup and procedure were evaluated within a small pre-study.

4.5.4 Participants of Study One

Fifty-eight male students from the TU Darmstadt ranging in age from 19 to 25 years (M = 22.3 years, SD = 1.6 years) participated in the experiment. As the students aged 19 (N = 4) and 25 (N = 2) were few and all less than two months away from the desired age of 20-24 years, none was excluded. Students were approached personally at the campus and invited to participate for an expanse allowance of about 10€. All students were right-handed. Twenty-seven students studied mechanical engineering, eighteen students applied for different natural science-programs (i.e. physics or industrial engineering) and thirteen studied architecture. One participant stated to have had physical impairments, but as they were cured and concerned only the legs the participant was not excluded. All participants exerted all six task types as described in 4.5.3. The experiment took about 50 minutes for each participant.

4.6 Statistical Analysis of Uncertainty of Study One

Following, the assessed data is analyzed to evaluate the human induced uncertainty on the stress of the tripod. First, the resulting uncertainty is described statistically and second, the effect of the influencing factors on uncertainty is quantified. Test-tables, figures and results which do not appear within the following subchapters can be found in Appendix D.

[17] See Appendix C.

4.6.1 Statistical Descripition of Uncertainty for Study One

First, the resulting uncertainty concerning the stress of the tripod is described statistically. Second, the uncertainty of the human sub-process *execution of action* is described.

4.6.1.1 Uncertainty of Technical Subsystem

As described in chapter 4.3, the stress of the tripod is assessed by measuring the maximum exerted force on all three legs during placing of the weight (dynamic component) and the resulting force distribution after placement (static component), which is described by the absolute distance from the center of the placed weight in relation to the center of the tripod, called eccentricity. As each participant operated 6 placements per combination of instruction and weight, average values for each participant were calculated. Thus, Maximum Force and Eccentricity are described each by their mean value and standard deviation (SD), resulting into four measures for stress. The mean values characterize the amount of stress, whereat the SD values characterize the individual variation of resulting stress. To improve comparability, the proportion of Maximum Force resulting from the heaviness of the weights was subtracted from the measured forces prior to calculating mean and SD. Figure 4-8 and Figure 4-9 depict histograms for the distribution of all four dependent variables.
As can be seen, all four histograms exhibit a skewed distribution. Test of normality confirms that all four variables are not normally distributed. Regarding the statistical use and general characterization of the resulting uncertainty, skewed distributions cannot be specified by stating of their mean and SD. For example, the boundary values for the 99.7%-confidence interval for Mean of Maximum Force would be between -3.111 N to 9.411 N. As a value of 0 N represents the absolute minimum for the stress, negative values are not applicable. Further, the upper boundary would mean that only 2.5% of the expected values are above 9.411 N. But the histogram depicts more than 2.5% above that boundary. Concluding, the observed human induced uncertainty of the resulting stress is not characterized by a normal distribution.

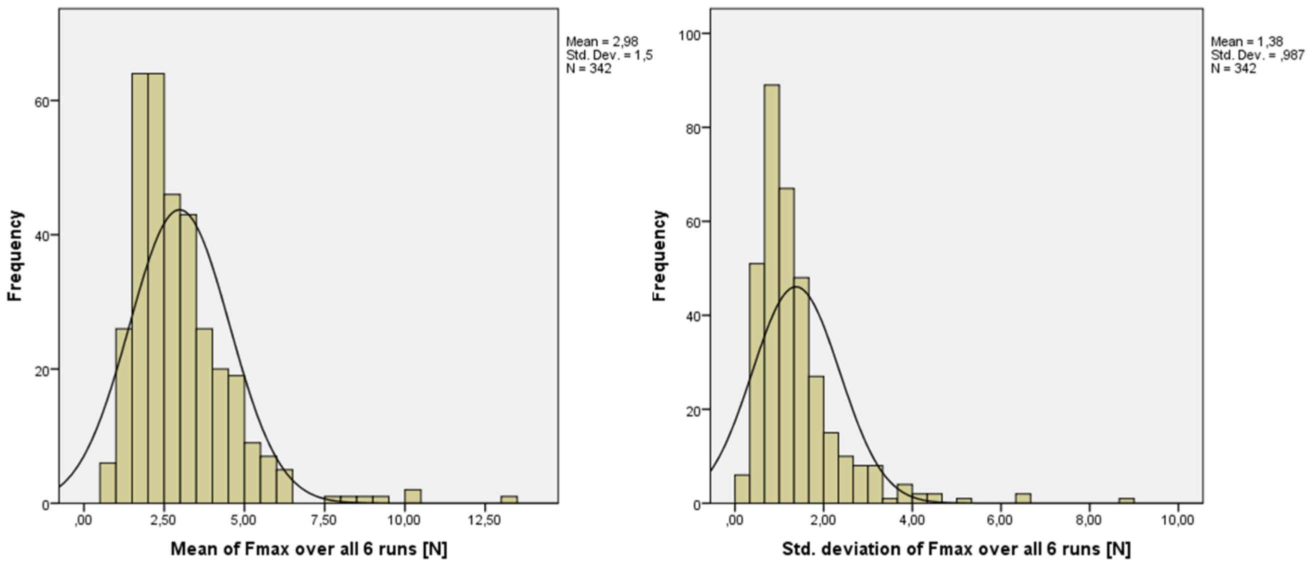

Figure 4-8. Histograms for mean and standard deviation of Maximum Force over all 6 runs.

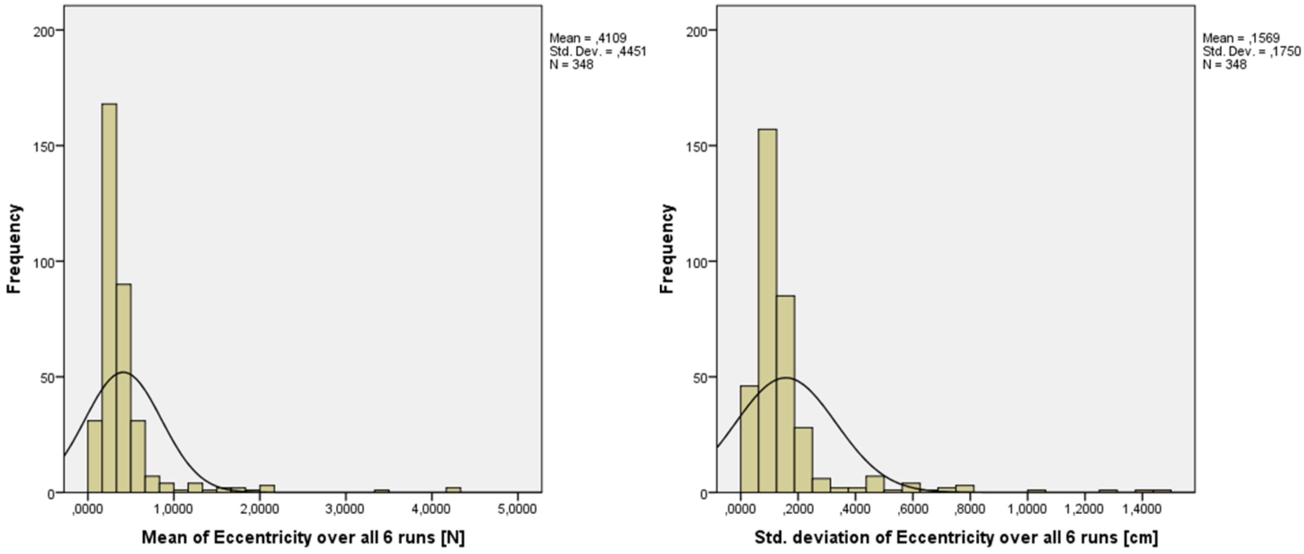

Figure 4-9. Histograms for mean and standard deviation of Eccentricity over all 6 runs.

Therefore, all four variables were tested against a lognormal distribution. A lognormal distribution is characterized by the fact that for a variable X not the variable itself, but Ln(X) is normally distributed. Thus, testing is done by transforming the values to the logarithmic scale and retesting them for normality. Also, a Probability-Probability Plot (P-P Plot) against a lognormal distribution function is used to visually test for a possible fit of the data to a lognormal distribution. In Figure 4-10 a P-P Plot for Mean of Maximum Force (left) and a histogram for the logarithmically transformed distribution for Mean of Maximum Force are given. Both graphs suggest a lognormal distribution. Test of normality confirmed a lognormal distribution for all four variables.

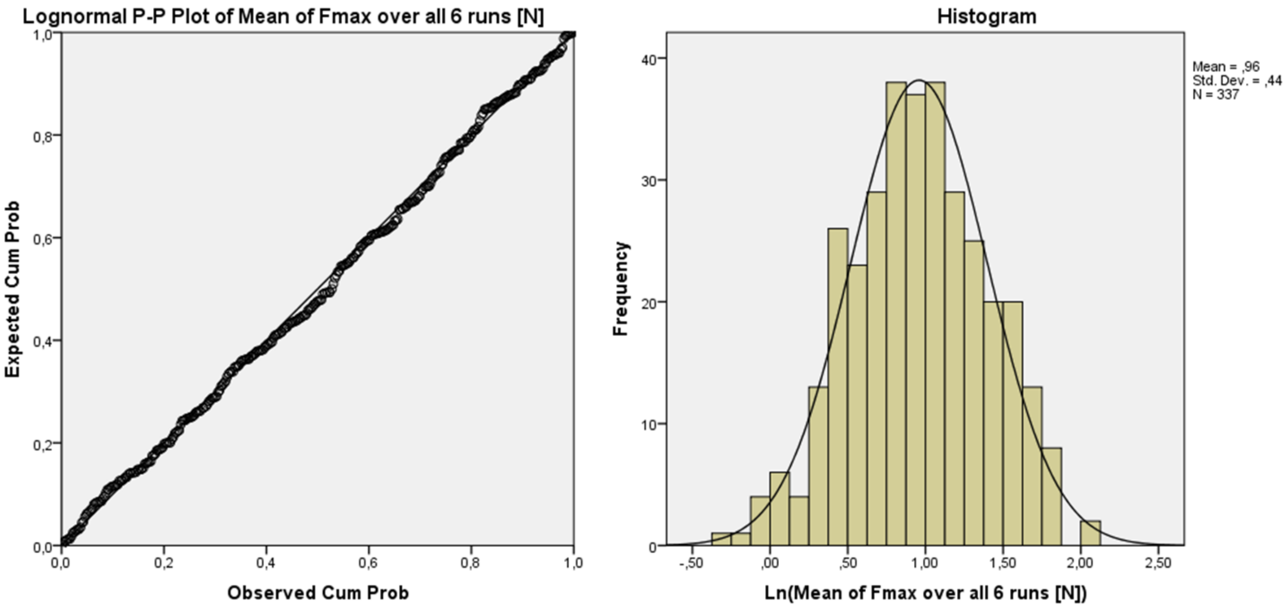

Figure 4-10. Left: P-P Plot for the evaluation of fit of Maximum Force to a lognormal distribution. Right: Histogram for logarithmized mean of Maximum Force.

For statistical description of the resulting uncertainty mean and SD of the lognormal distribution were retransformed. Table 4-3 shows the retransformed mean value and boundaries for the 95%- and 99.7% confidence intervals. The data highlights the applicability of a lognormal distribution for statistical means. When compared to the mean value, the lower boundaries show a relatively small difference whereat the upper boundaries deviate strongly.

Table 4-3. Retransformed mean values and boundaries for 95% and 99.7% intervals for mean of Maximum Force and Eccentricity as well as SD of Maximum Force and Eccentricity.

Variable	Mean	Boundaries for 95%-Interval	Boundaries for 99.7%-Interval
Mean Maximum Force [N]	2.731	0.994 to 7.502	0.600 to 12.434
SD Maximum Force [N]	1.176	0.350 to 3.948	0.191 to 7.235
Mean Eccentricity [cm]	0.327	0.102 to 1.048	0.057 to 1.875
SD Eccentricity [cm]	0.120	0.033 to 0.433	0.017 to 0.824

4.6.1.2 Uncertainty of Execution of Action

Analysis of the Captiv data for the tracked acceleration of movements and the finger forces revealed that both measures were unfeasible for evaluation.
In case of the acceleration sensor, the resolution of data acquisition showed to be too small for reliable measures. The sensor assesses acceleration in fractions of g with a resolution of about 0.11 g. As the task generally demands the weights to be placed softly, participants produced only small accelerations, which were beyond the data noise of the sensor. Therefore, adequate detection and identification of the exerted accelerations was impossible and had to be dropped.
In case of the sensors for measuring finger forces during the placements, the in chapter 4.5.1.4 mentioned problem regarding the flow of force could not be prevented. Only about one quarter of the participants yielded suitable data for finger forces, which still showed broad variations due to minimal differences of the applied grip on the weight. Thus, investigation of the finger forces was dropped, too.
In total, investigation of the uncertainty of *execution of action* could not be assessed. Thus, the following quantification of uncertainty is done without further involvement of execution of action.

4.6.2 Quantification of the Impact of Influencing Factors on Uncertainty for Study One

The following chapter treats the results of the statistical analysis of the relationship between the elements of the derived working model (cf. Figure 4-2) regarding the resulting stress of the tripod. First, the approach for the following data analysis is presented. Second, the strength and dexterity measurements are validated regarding mediating effects e.g. from fatigue. Third, the impact of influencing factors on the tripod is assessed. Concluding, the resulting regression model is presented. As mentioned above, the data for the description of execution of action was unfeasible, which is why execution of action remains disregarded.
Again, test results and graphs not depicted within the following subchapter can be found in Appendix D. An alpha level of .05 was used for all statistical tests if not stated differently.

4.6.2.1 Approach for Data Analysis

As initial step, a test of normality on the respective variables was run to determine the selection of parametric or nonparametric tests for the proceeding steps. The independent variables were then tested for high correlations with $r > 0.7$ (cf. Zöfel, 2011, p. 151) as multi-collinearity between independent variables can impact on the calculation of regression. In case of high correlation, only one of the correlating independent variables was used onwards. The remaining variables were then corrected for outliers, which can have a high impact on regression, too. According to Hoaglin, Iglewicz, and Tukey (1986, p. 998) outliers can be identified by multiplying the inter quartile range (IQR) with a factor of 2.2. Lower/ upper boundaries for excluding outliers can be calculated by subtracting/ adding the calculated value from/ to the median. Afterwards, the regression model was calculated, followed by tests for normal distribution of the residuals, independence of observation, homoscedasticity and again for possible multi-collinearity. Except the test for multi-collinearity, the other requirements can be tested visually. For the residuals, a histogram with a comparative normal distribution was plotted. Independence of observation and homoscedasticity were checked by creating a scatterplot with the standardized predicted values on the x-axis and the standardized residuals on the y-axis. Thereby, the plot should not contain patterns and balanced distances regarding the centerline. According to Menard (2002), multi-collinearity is problematic for a tolerance below 0.2. Further, a variance inflation factor (VIF) above 10 suggests the existence of multi-collinearity (e.g. Bowerman & O'Connell, 1990; Myers, 1990). If none of the above stated requirements were violated, the regression model was accepted and the results allocated to the working model.

4.6.2.2 Validation of Data and Controlling for Secondary Effects

Validation of Strength Measurement

Based on personal communication (Wakula, personal communication, 2016) the mode for strength assessment was changed after participant 42. For the first 42 participants, strength was assessed in direction A+ and C+, bi-manual and with the feet of the participants allowed to touch the ground. The personal communication suggested strength measurement in A+, single-handed and with feet off the ground, as the observed interaction with the tripod was also exerted single-handed and participants could use their feet for additional force exertion. Before changing to the modified assessment, a Pearson product-moment correlation was run to determine the relationship between the exerted forces in direction of A+ and C+. The data showed no violation of normality, linearity or homoscedasticity. There was a high, positive correlation between exerted force directions, which was statistically significant ($r = .551$, $n = 42$, $p < .005$). Due to the correlation, measurement of C+ was dropped. Instead of measurement in C+, a second measurement in A+ was conducted, whereat participants had to exert the force single-handed and with the feet lifted off the ground, like suggested. Again, a Pearson product-moment correlation was run to determine the relationship between the exerted forces with two hands (symmetric force exertion) and one hand (asymmetric force exertion). The data showed no violation of normality, linearity or homoscedasticity. There was a high, positive correlation between two-handed and one-handed force exertion, which was statistically significant ($r = .911$, $n = 16$, $p < .0005$). This means that regarding the regression, only one of the two values was needed. As initial assessment for A+ was assessed for all participants, this measure was used henceforth as with the high correlation potential violations through the measurement mode were dispelled.

Additionally, the assessed data was checked for high impact of parasitic forces, which are a common artifact of strength measurements (cf. Rohmert et al., 1992, p. 13). A Pearson product-moment correlation was run to determine the relationship between the exerted force with two hands in direction of A+ and the resulting force regarding all three spatial axes. The data showed no violation of normality, linearity or homoscedasticity. There was a high, positive correlation between the two force values, which was statistically significant ($r = .998$, $n = 58$, $p < .0005$). Thus, the influence of parasitic forces was negligible, validating the use of the measured forces in A+ for the further analysis.

As described in chapter 4.5.1.1, the resulting values were corrected for the calculated influence of arm weight.

Validation of Dexterity Measurement

First, the assessed data from the BBT was compared to the table data from Mathiowetz et al. (1985). A one-sample t-test against a BBT-Score of 88.0 was run to determine whether the BBT-Score in the recruited subjects was different to the table data. BBT-Scores were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$). Mean BBT-Score ($M = 77.09$, $SD = 8.27$) was lower than the normal BBT-Score of 88.0, with a statistically significant mean difference of 10.914, 95% CI [8.74 to 13.09], $t(57) = -10.055$, $p < 0.0005$. This means that participants achieved a significantly lower score regarding the table data from 1985. Additional effects from the subject of study were found. BBT-Scores for participants studying mechanical engineering were statistically significantly lower (74.22 ± 8.65) compared to the other participants (79.58 ± 7.15), $t(56) = 1.783$, $p = 0.012$. But the mean score for the other participants was still lower than the table data.

Further, a Spearman's rank-order correlation was run to determine the relationship between BBT-Score and Hotwire Rank. No statistically significant correlation was found ($r_s(56) = -.036$, $p = .788$). This supports the prior decision to run two tests to account for different types of dexterity.

Controlling for Practicing Effects

Even though the task was chosen to reduce possible influences from practice or previous knowledge, the measured data was checked for remaining effects. A Friedman’s test was run, which is applicable for nonparametric variables with repeated measurements. There was no statistically significant difference in achieved eccentricity for all 6 runs, $\chi2(5) = 6.986$, $p = .222$, as well as for maximum force for all 6 runs, $\chi2(5) = 8.618$, $p = .125$. Overall, no training effects on participants’ performance were found.

Controlling for Effects of Motivation, Effort and Concentration

First, the three measurements for motivation, effort and concentration were checked for alterations throughout the experiment. Test of normality indicated no normal distribution for all factors, wherefore a Friedman’s test was run for each variable.

There was a statistically significant difference in perceived effort ($\chi2(2) = 43.197$, $p < .0005$) and in perceived motivation ($\chi2(2) = 15.662$, $p < .0005$) during the three measurement points. Generally, an increase in effort by a concurrent decrease of concentration can be noted. Concerning motivation, the median for all three measurements points remains equal, but when observed in detail some participants perceive an increase and some a decrease in motivation. This implies that still after careful planning and pre-tests, fatigue and motivational effects were not completely removed. Therefore, the variables Change of Motivation and Change of Effort were calculated, which represent the difference of each score between their first and last assessment. Change of Motivation and Effort were henceforth used to evaluate possible effects on the stress of the tripod, as these variables were no longer regarded as controlled.

4.6.2.3 Impact of Influencing Factors on Technical System

Based on the initially presented process for data analysis, predictors for all four dependent variables were searched within the independent variables[18] and the covariates[19].

[18] Placing Weight, Instruction Softly, Instruction Centrally, Strength in A+, BBT-Score and Hotwire Rank.

[19] Perceived Change of Motivation, Perceived Change of Effort, Age, Subject of Study, Sporting Activity and Sport Today.

A multiple, stepwise regression was run to predict Ln Mean Maximum Force from the remaining influencing factors. The factors Placing Weight, Instruction Softly, Change of Perceived Motivation and Subject of Study were found to statistically significantly predict Ln Mean Maximum Force, $F(4, 326) = 36.139$, $p < .0005$, adj. $R^2 = .299$. Thereby, increased weight and Change of Motivation as well as participants studying mechanical engineering lead to a higher Maximum Force on placing the weight. Instruction to place the weight as softly as possible leads to a decrease of maximum force.

A multiple, stepwise regression was run to predict Ln SD Maximum Force from the remaining influencing factors. The factors Placing Weight, Instruction Softly, Arm Strength in A+ and Change of Perceived Motivation were found to statistically significantly predict Ln SD Maximum Force, $F(4, 320) = 18.561$, $p < .0005$, adj. $R^2 = .178$. Increased weight, strength and Change of Motivation result into a higher deviation of Maximum Force. Again, instruction to place the weight softly decreases the deviation of maximum force.

A multiple, stepwise regression was run to predict Ln Mean Eccentricity from the remaining influencing factors. The factors Instruction Softly, Strength in A+, BBT-Score, Age and Perceived Change of Effort were found to statistically significantly predict Ln Mean Eccentricity, $F(5, 316) = 18.752$, $p < .0005$, adj. $R^2 = .217$. Increased strength and the instruction to place the weight softly leads to a higher Eccentricity, whereat an increase of BBT-Score, Age and Change of Perceived Effort reduces Eccentricity.

A multiple, stepwise regression was run to predict Ln SD Eccentricity from the remaining influencing factors. The factors Instruction Softly, BBT-Score and Sport Today were found to statistically significantly predict Ln SD Eccentricity, $F(3, 314) = 13.252$, $p < .0005$, adj. $R^2 = .104$. Thereby, a high BBT-Score and having done sports on the day of experiment reduces the variation of Eccentricity. The instruction to place the weight softly instead increases the deviation for Eccentricity.

Concluding, the impact of the influencing factors on the resulting stress of the tripod is described through the following regression equations:

*Ln Mean Maximum Force = 0.490 + 0.213 * Placing Weight – 0.113 * Instruction Softly + 0.107 * Change Perc. Motivation + 0.090 * Subject of Study*

*Ln SD Maximum Force = -0.528 + 0.203 * Placing Weight + 0.001 * Arm Strength – 0.114 * Instruction Softly + 0.072 * Change Prec. Motivation*

*Ln Mean Eccentricity = -0.139 + 0.336 * Instruction Softly + 0.001 * Arm Strength - 0.007 * BBT-Score - 0.047 * Age – 0.062 * Change Effort*

*Ln SD Eccentricity = -1.819 + 0.283 * Instruction Softly – 0.007 * BBT-Score – 0.171 * Sport Today*

4.6.2.4 Resulting Regression Model

Figure 4-11 depicts the resulting model for the description of the relation between influencing factors and technical system for study one. As no feasible data for *execution of action* could be investigated, the regression model shows the direct relation to the influencing factors onto the technical system. Predictors for all four dependent variables were found.

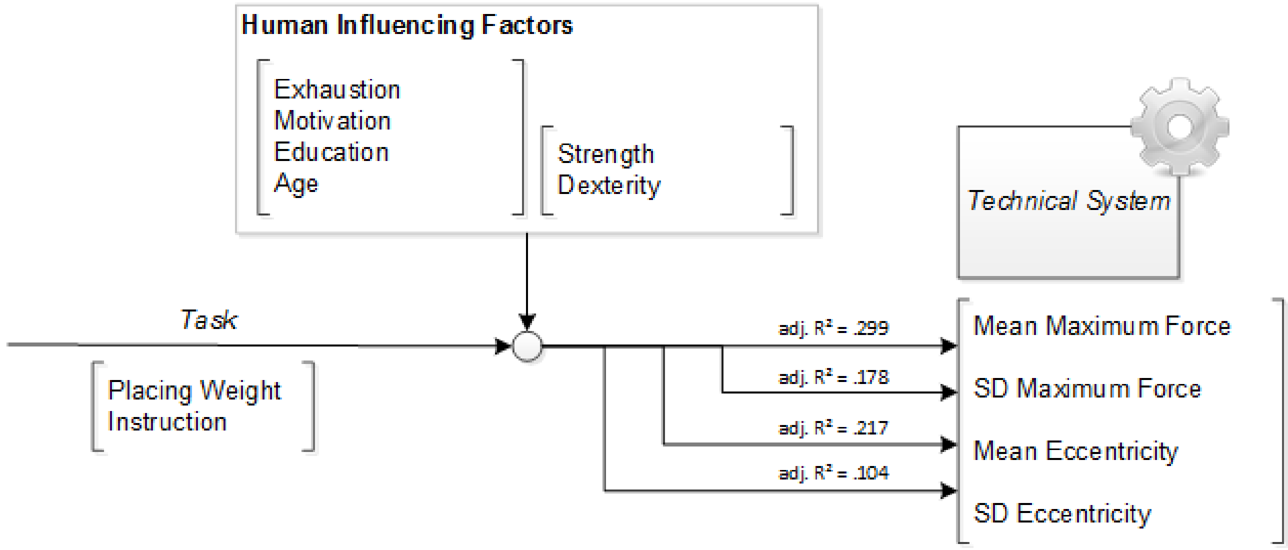

Figure 4-11. Regression model for the description of the relationship between the influencing factors and the resulting stress on the system for study one.

4.7 Discussion of Results of Study One

The statistical analysis of the resulting stress of the tripod showed a lognormal distribution. All four dependent variables possess a minimum value regarding the stress; an absolute zero point. A lognormal distribution suggests that only a few values reside close to the absolute zero, whereas the majority resides close to the mean value with an existing tale of values reaching far above the mean value. Applied to uncertainty and stress, only few people achieved low values for stress, the majority evoked moderate stress and a third group achieved high values far off the mean value. In terms of human error, the last group is the most likely to provoke failure. Examples for lognormal distributions for the description of human behavior were already found for other contexts, like the length of comments in internet discussions (Sobkowicz, Thelwall, Buckley, Paltoglou, & Sobkowicz, 2013), a user's dwell time on online articles (Yin, Luo, Lee, & Wang, 2013) or for modelling repair times of maintainable systems (O'Connor & Kleyner, 2012). For a generalization of the assumption that human induced uncertainty is represented by a lognormal distribution of the resulting stress, further investigations are needed.

The factor Placing Weight was found to be of major importance for Maximum Force. This implicates that heavier weights are more difficult to handle, with an impact on both resulting stress and variation of stress. In contrast, no impact from weight on eccentricity was found. Thus, a soft placement is more difficult with heavier weights, whereat positioning of the weights is not affected, at least until weights of 3 kg.
A second factor of importance for Maximum Force was the Perceived Change of Motivation, which impacted on stress and variation of stress. High values for change of motivation, which stand for a decrease of motivation from first to third assessment, led to an increase of stress and variation. This seems logical, as less motivation generally corresponds to a lower performance. Again, motivation only affected Maximum Force, but not Eccentricity. This could mean that the task component of placing the weight softly was of less importance than the component of a centered placement or that a centered placement was still achieved randomly, even unmotivated.
People with high strength can potentially apply higher forces. It seems as this also infers on regulation of their strength, as stronger participants tended to higher variation regarding SD of Maximum Force as

well as a less central placement of the weights. To receive higher impact of strength on the resulting stress, surely using weights above 10 kg seems more applicable. This was avoided deliberately, because higher weights are prone to result into higher impact on perceived effort and muscle fatigue during the experiment.
Already with the low weights of 1 kg and 3 kg, an increase of perceived effort was noted, which further impacted on Mean of Eccentricity. Participants who registered an increase of perceived effort placed the weights less centrally, which is as expected.
Dexterity, as measured by the BBT, was found to impact on both mean and deviation of Eccentricity. Thereby, a higher BBT-Score resulted into lower Eccentricity, meaning that more dexterous participants could place the weight more centrally. This effect was as expected. Curious was the finding that participants within the study achieved overall BBT-Scores more than 10 points below the scores assessed for the comparison group in 1985 (Mathiowetz et al., 1985). As the BBT was built and operated according to the official and standardized instructions, this may implicate a shift of dexterity within the group of 20- to 24-year-old right-handed males. That would mean that the table data is outdated and should be reassessed. Further research is needed to confirm the possible change of dexterity.
Concerning the Hotwire test, no correlations were found. One reason could be a difference between the assessed and needed type of dexterity. Further, no prior applications of a hotwire for the assessment of dexterity are known. Perhaps the Hotwire test does simply not relate to dexterity or at least the used approach of combining time and number of failures as a rank is not expedient. Further investigations are needed to implement the Hotwire test as an applicable method for the assessment of dexterity.
Another interesting finding was the positive influence on variation of eccentricity for participants who did sport during the day prior to the experiment. Perhaps sports already stimulated the metabolism and activated the muscles, facilitating a more constant performance.
The results the pre-study (Oberle & Bruder, 2014) regarding the content of instruction was confirmed. Thereby, focus on placing the weight softly reduces the Maximum Force, mean as well as SD. In contrast, instruction to place the weight softly also increases mean and SD of Eccentricity. The fact that no direct predictors based on the instructions centrally or centrally and softly were found, implicates that Maximum Force was solely regarded when explicitly addressed. Apparently, participants were predominantly concerned with a central placing than a soft one. Thus, the use of instructions to focus on a specific sub-goal is a possibility to reduce uncertainty. But in case of two equivalent sub-goals, participants seem to focus only on one of them.

Further, when regarding the complete measured stress on the tripod, the highest stress was measured during the removal of the prior placed weights, as no instructions or restrictions for this part of the experiment were given. Thus, only the variation of instruction for the experiment did not yield any statistic effects. Compared to not focused parts of the observed process, instructions seem to be highly relevant.

Concluding, all findings are only valid for the investigated sample – 20- to 24-year-old male, right-handed students. For generalization of the findings, further research for other populations is needed.

Based on the results of study one, applicability of HUMEAn for the quantification of human induced uncertainty is verified. Based on the single steps of the method, the elements of the HMI could be characterized one by one. Further, the number of human influencing factors could be reduced and their impact on the stress of the system could be quantified successfully. Based on the findings, a reduction of uncertainty for further executions of the observed task could be done by selecting possible operators. Thereby, people with a high dexterity and a lower level of strength are to be preferred regarding the resulting uncertainty.

4.8 Summary of Chapter 4

Within chapter four, a study for the analysis of human induced uncertainty on the example of a simple task, which consisted of placing a weight on an object, was conducted. Thereby, the method of HUMEAn was applied successfully. Based on the method the human induced uncertainty represented by the resulting system stress was quantified. Thereby, the human impact on the resulting stress seems to be represented statistically by a lognormal distribution in case of the existence of an absolute zero-point for the resulting stress. Further, the impact of specific influencing factors onto the resulting stress and likewise onto the human induced uncertainty was proven and quantified. Based on the findings, first implications for the reduction of human induced uncertainty through the selection of operators could be derived. Thus, the second and third research question received first answers. Still, for a comprehensive evaluation of the HUMEAn further research is needed.

Subsequently, a second study is conducted to investigate the applicability of the HUMEAn regarding the human sub-process choice of action.

5 Application of HUMEAn for Choice of Action

Within the following chapter the HUMEAn is applied for the investigation of uncertainty of a second task. After presenting the application example of study two, again all five steps of the HUMEAn are processed. Like in study one, the chapter concludes with a discussion on the findings of study two as well as on the general applicability of the HUMEAn. Finally, the chapter is summed up and the current state of the research questions is discussed.

5.1 Application Example of Study Two

The first experiment focused on an abstract and simple task example for developing an applicable approach for the human uncertainty modes and effects analysis. A more practical example is selected for the evaluation of HUMEAn. As stated in chapter 1.1 of this work, the field of aviation is leading in human factors and especially human error analysis. Consequently, it seems reasonable to choose an example from the field of aviation for an application of the HUMEAn. Figure 5-1 depicts accident statistics by flight phases. As can be seen, the phases of approach and landing adhere to the highest probability of accidents (e.g. Boeing, 2016, p. 20; Dambier & Hinkelbein, 2006, p. 267; Scheiderer & Ebermann, 2011, p. 6). On the technical side the landing gear represents the most burdened part of the airplane during landing (cf. Thurston, 1995). Concluding, it seems reasonable to apply the HUMEAn on the task of landing an airplane to investigate the human impact on the uncertainty of the landing gear's stress during touchdown. The investigation is operated within a flight simulator to prevent personal harm of the participants.

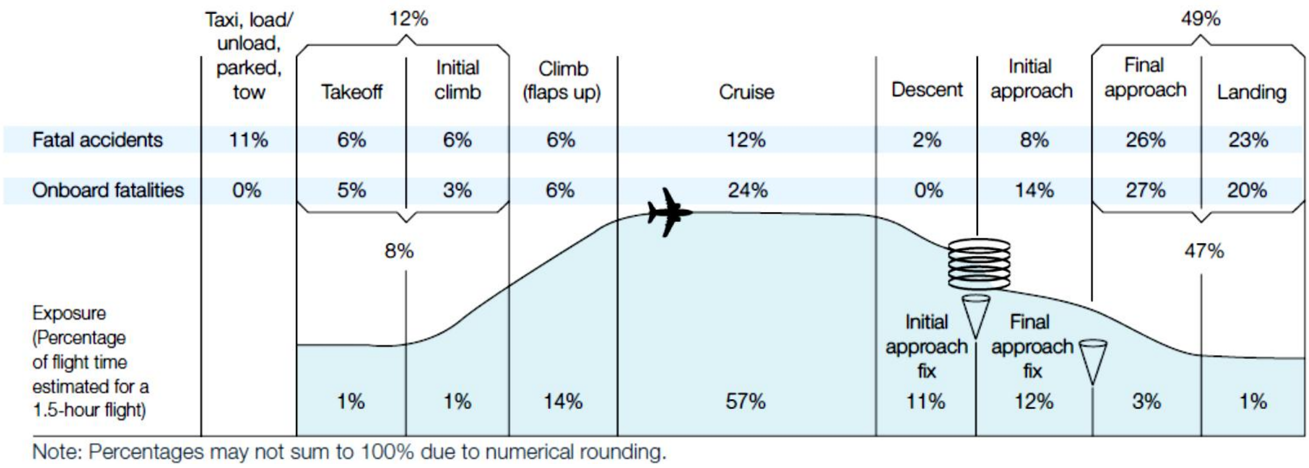

Figure 5-1. Percentage of fatal accidents and onboard fatalities by phase of flight from 2006 to 2015 (Boeing, 2016, p. 20).

5.2 Specification of Task for Study Two

Based on the selected example, the human task can generally be described as "landing an airplane". As can be seen in Figure 5-1, a flight is divided into several phases. Therefore, the question arises at which point the task of "landing an airplane" starts, demanding a closer look onto the landing maneuver.

On one hand, the landing phase and especially the moment the airplane makes direct contact to the runway are of high concern for the human induced uncertainty regarding the stress of the landing gear. On the other hand, prior manipulation of flight parameters, like reducing altitude and airspeed, contribute to the resulting stress, advocating a broader definition of the landing phase. The next earlier phase, called (final) approach, describes the moment in which the airplane is already positioned for final touchdown on the runway (Crane, 1997), a moment still close to the actual landing. Thus, including the phase of descent as a possible influencing part of a landing maneuver seems reasonable. Concluding, the task of “landing an airplane” is defined to start with the exit of cruise flight and includes the phases of descent, initial approach, final approach and landing.

As by this definition, the task of “landing an airplane” consists of several subtasks stretching over a longer time, a specific breakdown of the task is sensible. Therefore, a process model for a landing maneuver[20] is developed (Oberle & Bruder, 2015) and further adjusted to describe the task of landing an airplane (Zocholl et al., 2015). The resulting process model is depicted in Figure 5-2.

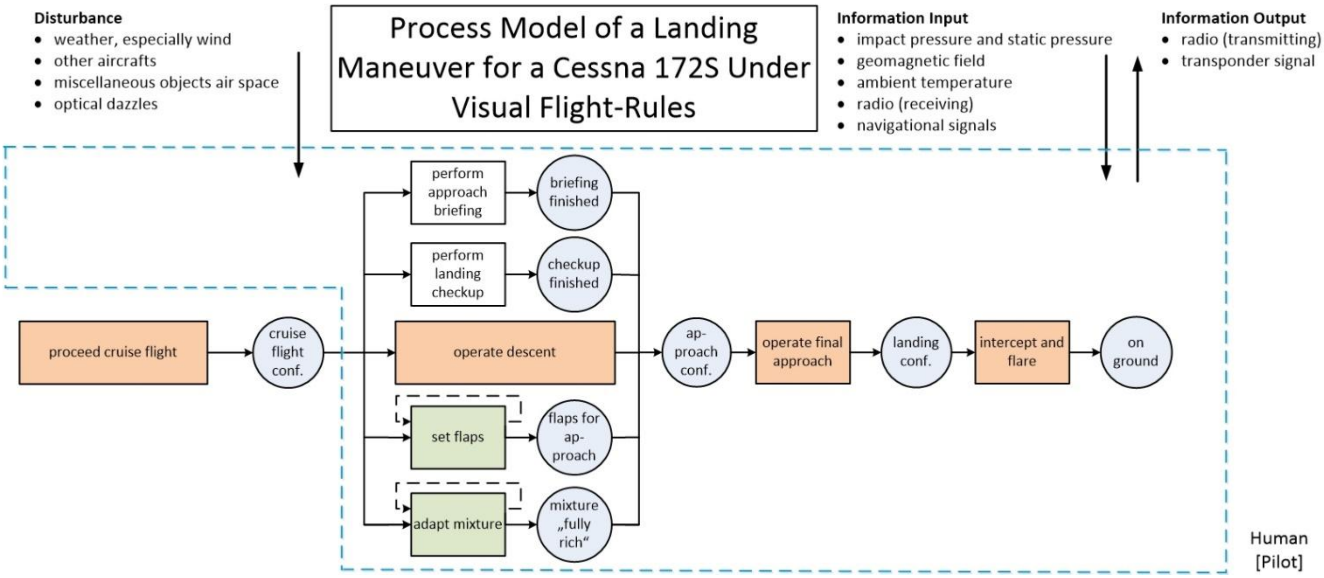

Figure 5-2. Process model of a landing maneuver for a Cessna 172S under visual flight rules based on Zocholl et al. (2015) as well as Oberle and Bruder (2015). Circles: system states, rectangles: subtasks. White rectangles: cognitive processes, red rectangle: processes for the control of the airplane, green rectangles: processes for the configuration of the airplane.

With the process model, the complete task of landing an airplane is divided into several subtasks, which are classified within three categories: cognitive tasks, main aviation tasks and configurational tasks. The cognitive tasks account for internal tasks which the pilot must process as prerequisites for subsequent tasks. They include *performing approach briefing* and *performing landing checkup*. Cognitive tasks are diverse to the other tasks, as they don’t involve a direct HMI and are majorly included for completeness. The main aviation tasks refer to the continuous control of the airplane, like manipulating airspeed or altitude by use of the yoke. They are divided into *operate descent*, *operate final approach* as well as *intercept and flare* and represent the above discussed flight phases. Lastly, the configurational tasks are divided into *set flaps* and *adapt mixture* and account for interaction with airplane controls other than yoke or pedals. In conjunction, the three defined categories correspond to the three different levels of interaction, whereat cognitive represent monitoring, configurational represent indirect and main aviation represent direct interactions (see e.g. chapter 3.2.2 for the levels of interaction).
The next question is whether to apply the HUMEAn on each subtask individually or on all tasks at once. The landing gear represents the critical part of the technical subsystem. Thus, all tasks are investigated within one approach of the HUMEAn as only the subtask intercept and flare involves the landing gear.

[20] The development of the process model for a landing maneuver was supported by the work of Wolf (2013).

Regarding the influencing factors of the task, all participants will be confronted with the identical setup and procedure. Therefore, all factors are regarded as constant and with this neglected for the experimental investigation. No further operationalization is needed and the first step of the HUMEAn finished.

5.3 Specification of Subsystems for Study Two

After defining the task, the technical subsystem and the environment is specified within the second step of the HUMEAn.
Due to the difficulty of real and in-flight data assessment, especially regarding comparable and constant environmental factors, a controlled environment within a laboratory[21] is chosen. No influences from communication with air-traffic control and crew as well as influences due to passengers are investigated. Due to the controlled environment, environmental influencing factors are regarded as constant and are therefore neglected.
The general technical subsystem is represented by the complete airplane. But regarding the given task, focus can be put onto the cockpit where the HMI takes place and the landing gear of the airplane, which represents the burdened system part. The instruments within the cockpit represent the given interface for the HMI. Thereby, the elements yoke, mixture, thrust, flap switch and pedals represent the dominant input instruments. The output is dominantly defined by the six-pack, consisting of the altimeter, airspeed indicator, vertical velocity indicator, attitude indicator, heading indicator and turn indicator[22].

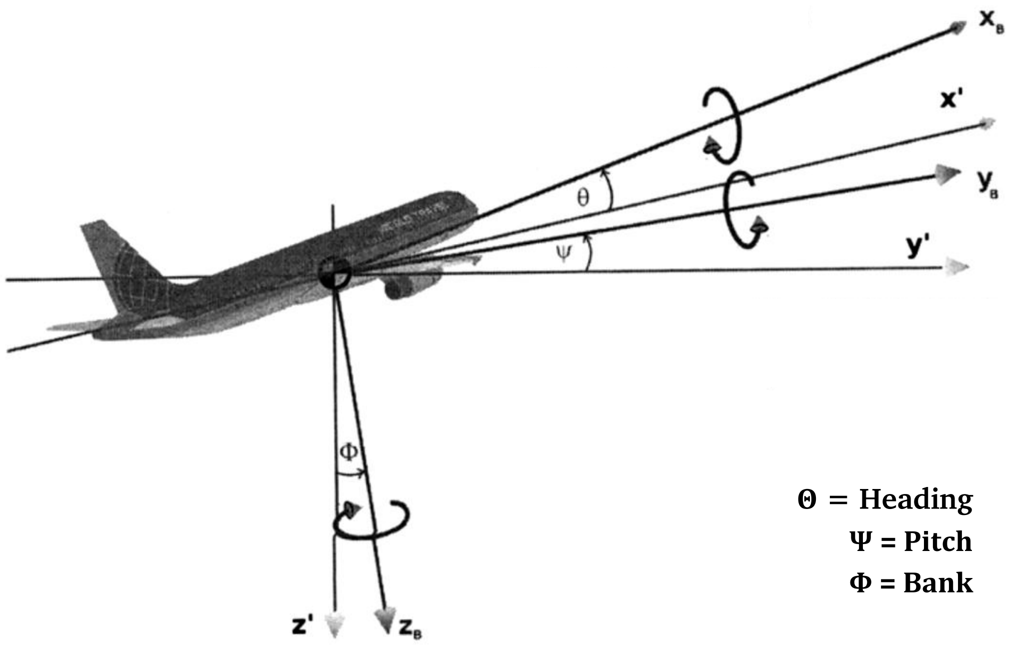

Figure 5-3. Depiction of the angles pitch, bank and heading for a body-fixed system of coordinates of an airplane (according to Schulte, 2012, p. 239).

The resulting stress on the landing gear would be typically measured by the resulting forces (in all three spatial directions) on touchdown. Unfortunately, the simulation software does not supply a direct digital measure for the forces on the landing gear. Therefore, a comparable and existing variable must be chosen

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[21] The used flight simulator and the simulated environment is further discussed in chapter 5.5.1.
[22] A detailed depiction of all elements can be found in chapter 5.5.1 within Figure 5-6.

for stress assessment. The most closely related and available measure is represented by the velocity in vertical direction. Thus, instead of a direct force, the velocity is used, which physically relates to the impulse on touchdown, which is equal to the force impact. The relation of force and velocity is described through the following equation: $F * t = m * v$. Additionally, the angles pitch, bank and heading at the moment of touchdown are assessed. This is done to account for the spatial direction of a possible force during touchdown. Figure 5-3 depicts the relation of the three angles regarding an airplane.
With this, definition of the environment and the technical subsystem is completed.

5.4 Selection of Uncertainty Mode and Human Influencing Factors for Study Two

As first part of step three of the HUMEAn the relevant human sub-process needs to be selected. According to Osman (2010), the task of landing an airplane can be characterized as a control task, which involves complex and sequential decision making. Regarding the different task types, the types of sensory, sensorimotor and physical can thus be neglected. Further, operating an airplane represents a task with high demands on expertise and training as well as adhering to set procedures. Therefore, the creative task type can be neglected, too, which is only addressed in case of emergency. Concluding, the task of landing an airplane is best represented by the discriminatory and combinational tasks types, wherefore the human sub-process *choice of action* is selected.
Due to the task characteristic, which is divided into several subtasks, the resulting uncertainty for choice of action and the taken action sequence is described and evaluated using Markov models. Based on the resulting Markov model, direct measures for the description of specific sequences and their probability can be derived. One such measure is the *most probable path*, which represents the most probable sequence of traversed Markov states within the model. A second measure is the *most probable path probability*. This value results from multiplying the single probabilities for each state transition, when following the highest probability for each state. Thereby, low values of most probable path probability correspond with high variations of the action sequence. The value is calculated based on the resulting Markov model for each pilot, based on the operated flights. Third, the measure *followed most probable path* is introduced, a dichotomous value which is true, if a pilot's individual most probable path equals the overall most probable path.
As the human process *choice of action* is followed by *execution of action*, measures for the description of the latter must be derived, too, to evaluate the complete progression until the resulting stress. For this reason, *flight duration* is measured as well as the *cumulated amount of yoke inputs* as factors of execution of action.
For the given task, a focus on practicing pilots is sensible. Generally, pilots are trained experts and decades of human factors research have led to a multitude of rules and prescribed procedures. As this group already implicates a certain homogeneity, an *intraindividual* focus is chosen for the following investigation. With this, qualifying and educational as well as adaptable factors are focus of investigation. The resulting selection of human influencing factors is depicted in Figure 5-4. Following, each influencing factor is operationalized and checked for their relevancy within the given context and categorized as dependent variable, covariates (need to be observed), controlled variables (need to be controlled through the experimental design) and excluded variables (are not considered). Again, to prevent impact from disregarded factors, the unselected factors for choice of action are also discussed regarding their possible control or elimination.

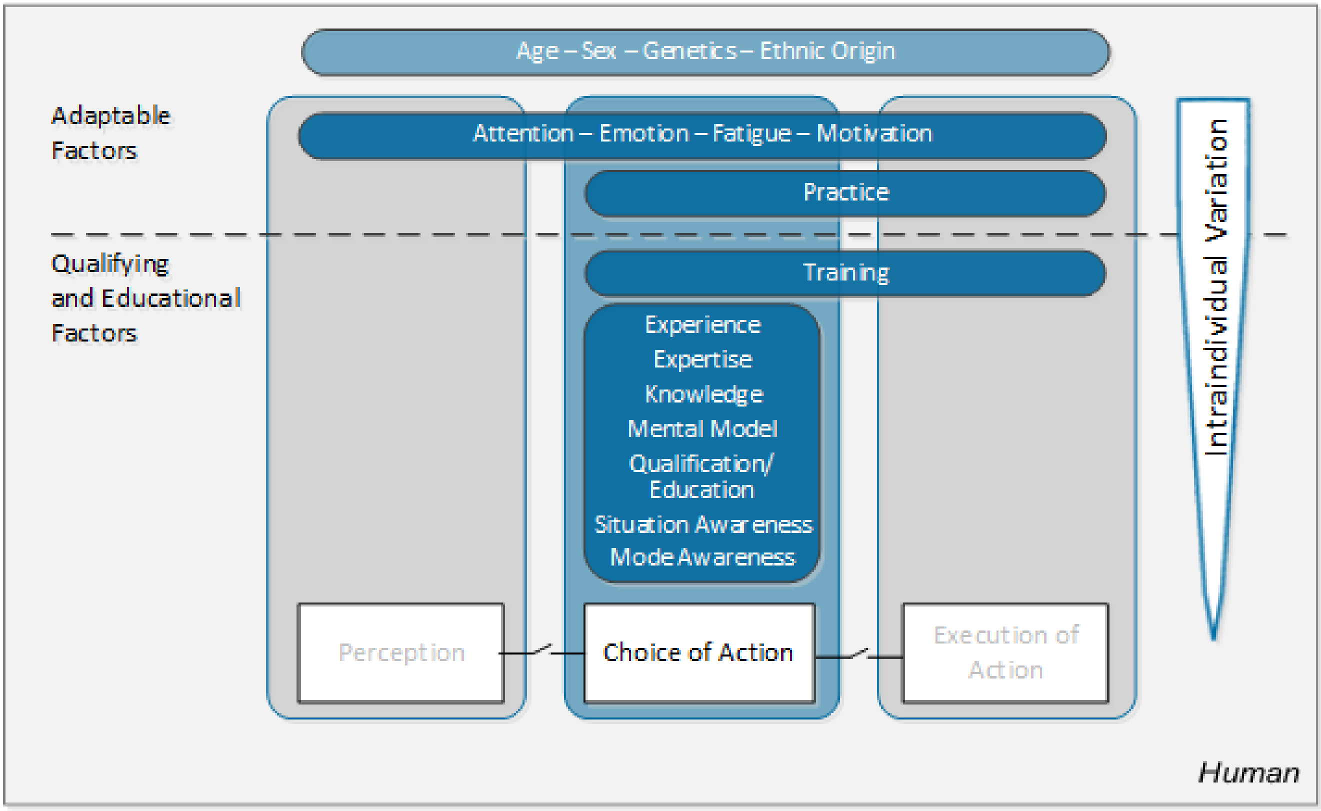

Figure 5-4. Relevant human influencing factors for uncertainty mode *choice of action* and *intraindividual* focus.

Adaptable Factors

Attention is of major importance in vigilance tasks (Strayer & Drews, 2007, p. 39). Even though aviating requires vigilance for external disturbances, e.g. other airplanes within the airspace, vigilance is of minor importance within the experiment due to the controlled environment. Also, measuring attention infers high effort as the general method is to use eye tracking techniques. All in all, attention is neglected.

As stated before, *emotion* is difficult to measure. Furthermore, emotions are connected to other cognitive factors and especially to motivation (Zimbardo et al., 2003). Therefore, the factor emotion is marginally accounted for through handling the factor of motivation and itself neglected.

Fatigue represents a major issue and threat to aviation safety and even pilots state that fatigue is a common problem (Rosekind, Co, Gregory, & Miller, 2000, p. 11). Fatigue represents a major factor, especially in the context of laboratory studies. Therefore, fatigue is classified as an independent variable. For measurement, the Karolinska Sleepiness Scale (KSS) (Akerstedt & Gillberg, 1990), a 9-point verbally anchored scale, is used. Through repeated application during the experiment, change of fatigue can be measured, which additionally functions a measure for perceived effort (Akerstedt, Anund, Axelsson, & Kecklund, 2014).

Like fatigue, *motivation* also represents a major issue for experiments. Initially, the motivation to operate a landing as best as possible is of importance. Also, the motivation to cooperate within the study is important, as low motivation could e.g. lead to false answers within questionnaires, both willingly and unwillingly. As the pre-study (Oberle & Bruder, 2015) showed, the subjects participated voluntarily and were highly motivated for and interested in the study. Therefore, the general assumption of equal motivation among the participants is expected, as they participate voluntarily due to their interest in research and aviation. Motivation is therefore assumed to be controlled.

Practice is always relevant regarding experimental investigation as participants need time to accustom themselves to the new situation. Practicing effects are, if not a direct focus for the investigation, treated within the experimental design by giving each participant sufficient time to adapt to the given setup. The idea is that after an explicit practicing time, adaptation and practicing effects already occurred and are kept to a minimum henceforth. A practicing phase was already implemented and tested within the pre-study[23] showing no further effects on the main experiment. Still, the assessed data are checked for remaining practicing effects before final analysis, classifying practice as a covariate.

Qualifying and Educational Factors

Due to the general complexity flying and piloting, constant *training* is a relevant factor (Vidulich et al., 2010, p. 197). Training is consequently regarded as an independent variable, which can be assessed through the number of flight hours within the last twelve months prior to the experiment (Casner, 2010, p. 602).

Experience is known as a relevant factor for pilot's decision making process (Khoo & Mosier, 2005, p. 578). Further, a connection between experience and knowledge concerning the relationships of external signals exists (Schriver, Morrow, Wickens, & Talleur, 2008, p. 865). Therefore, experience is declared as an independent variable. Measurement of experience in aviation is generally done by assessing the total number of flown hours (cf. Molesworth & Chang, 2010, p. 848). Since practicing pilots must keep a logbook about their flown hours, experience, represented by flight hours, can be accurately measured. Additionally, Yacavone, Borowsky, Bason, and Alkov (1992, p. 72) state that chances of accidents are higher for the first 500 hours on a new aircraft model, independent of prior experience. To accommodate for this effect, flight hours on the overall aircraft type and specific model used within the experiment are assessed additionally as independent variables.

In relation to pilot performance, *expertise* is found to have only a weak correlation and even an insignificant correlation to accident rates (Tsang, 2003). Further, expertise is known to be important when deciding the course of action for novel, unknown and complex situations (Dismukes, 2010, p. 339). Due to the controlled environment and the weak importance for pilot performance, expertise is neglected.

Due to the above stated relation of experience and *knowledge* for a pilot's decision making, the factor of knowledge will not be assessed further and is thus neglected.

Mental models are known to channel expert pilots' attention (Schriver et al., 2008, p. 865). Mental models therefore impact the scan pattern of the instruments for information acquisition. Again, determining mental models is a frail work, which e.g. can be done by using the structure formation technique (Scheele & Groeben, 1988), imbuing a lot of effort. Due to the fixed environment and non-observance of perception in combination with the high effort for the assessment, mental models are neglected.

One way to measure *qualification* is to ask for certificates and ratings. In case of pilots this refers to the different license types, like private pilot license (PPL) or commercial pilot license (CPL). Qualification coincides with experience as measured by flight hours, as certain license types need for a specific number of total and yearly flight hours to remain active and thus represent a possible impacting factor (Casner, 2010, p. 603). Qualification is classified as an independent variable. The aspect of *education* is unknown for impacting on flight performance. But as a quick check for each participant's education can be done by asking for their highest level of education, it can easily be incorporated as a covariate.

[23] The pre-study was supported by the work of Peinemann and Keil (2014).

The factor *situation awareness* is of major importance with regard to aviation, accounting for about 30% of all accidents (Ebermann & Scheiderer, 2013, p. 35). Still, other factors like communication and especially decision-making account for a higher number of accidents. Further, Wickens (2007) states that situation awareness supports the response to the unexpected and is especially of use in dynamic and evolving situations. As the environment is controlled and no unexpected interruptions are planned for the pilots, situation awareness is neglected.

Mode awareness is of major importance with increased amount of automation. By keeping the experiment and flight situation simple without systems like an auto pilot, mode awareness should be unimportant. Further, assessing mode awareness generally implies the interruption of an action to question the participant about the current mode of the system. As interruptions itself would represent an influencing factor onto the experiment, mode awareness is neglected.

Background Factors

Age and *sex* are typically assessed for most experiments as standard demographic data. For age, significant and linear changes of psychomotor and information processing speed for pilots are known (Hardy, Satz, D'Elia, & Uchiyama, 2007). But still, intraindividual differences are highlighted. Therefore, both variables are classified as covariates.

Once more, the factors *genetics* and *ethnic origin* remain disregarded throughout the experiment, as no direct effect on choice of action is to be expected (cf. chapter 4.4).

Dispositional Factors

Health is assessed by a short question asking for any physical impairments or current illnesses which could interfere with a participation. No further investigations are run, classifying health as controlled.

Rhythmology is partly accounted for by the measurement of fatigue. Further control or assessment of rhythmology factors would reduce the experiment to a limited, daily timeframe. Due to the partially assessment and the effort for further assessment, rhythmology itself is neglected.

Same as rhythmology, *metabolism* is difficult to assess or to control. Measurement would further imply invasive techniques. Therefore, metabolism is neglected (cf. chapter 4.4).

According to Chidester, Helmreich, Gregorich, and Geis (1991), pilot performance partially depends on *attitude* and *personality* factors. Even though some relations between personality and pilot performance exist, an accurate prediction of performance based on personality and attitude remains vague. Thus, both factors are neglected.

As discussed initially, the task of landing an airplane represents a highly trained and structured process. Further, no unexpected occurrences are planned within the experiment. Thus, the factors *intelligence* and *creativity* are unimportant.

After the Germanwings crash on March 27th in 2015, the issue of *morality* in aviation was addressed medially. Even though morality is of importance in real aviation, the observed task is operated within a flight simulator, which yields no risk to personal well-being. Thus, morality is neglected.

All independent variables and covariates are assessed within a questionnaire, except for practice, which is tested based on the data. Concluding step three of the HUMEAn, all influencing factors, their operationalization and the corresponding measurement methods are summarized in Appendix E.

5.5 Experimental Investigation of the Effect of Uncertainty of Study Two

Within Figure 5-5 all relevant variables for the experimental investigation are summarized as a working model for the study. A detailed description of each factor, its measure, how it was assessed and its scale can be found in Appendix E.

Following, the used experimental setup is explained.

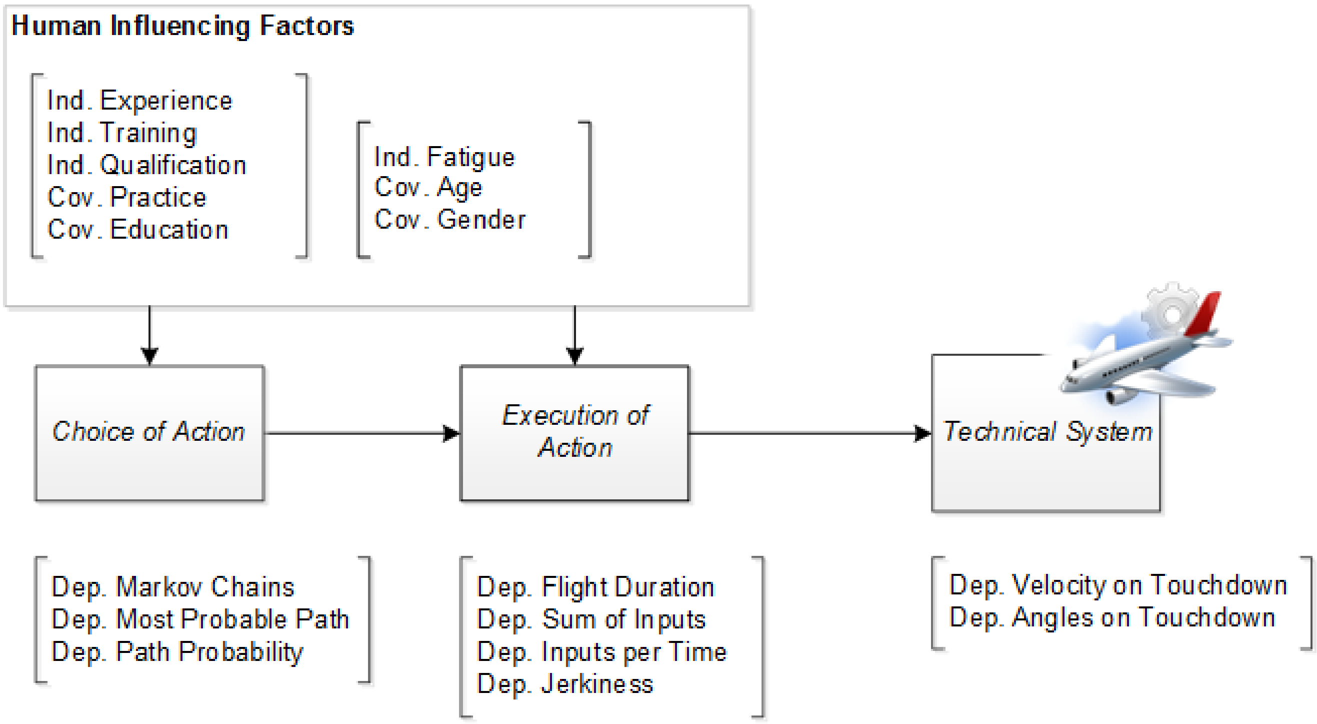

Figure 5-5. Derived working model for the investigation of human induced uncertainty of study two.

5.5.1 Experimental Setup of Study Two

For the experimental investigation, a flight simulator was constructed[24]. A detailed description of the flight simulator and the used flight scenario can be found in Oberle, König, and Bruder (2017). Summarizing, a mock-up according to a Cessna 172 Skyhawk was build, as a Cessna represents the most successful light aircraft of all times (Smith, 2010), increasing chances for familiarity with the airplane model. Accurate replications for instruments and controls were implemented. Three 24” monitors enable 120° of view, which is further enhanced through the implementation of a head-tracking system. A tablet is used to simulate a GPS system communicating through a virtual server. The complete layout is focused on the pilot, instruments for a co-pilot are not implemented as the experiment is designed for only one pilot. The complete setup can be seen in Figure 5-6.

[24] The development and construction of the flight simulator was supported by the work of Büddefeld et al. (2013).

Figure 5-6. Mock-up of the flight simulator, replicating a Cessna 172S.

Microsoft's *Flight Simulator X* (FSX) and the add-on module *FS Recorder 2.1*, allowing for a digital record of each flight as well as the measurement of 30 in-flight parameters with a sample rate of 24 Hz, were used for simulation and data assessment. According to EASA (2012, p. 5) the entire setup would specify as a "flight training device".

The flight scenario for the experiment started over the sea at a height of 2.500 ft, 10 nautical miles away from a small airport at the northern coastal line of Germany (*Norden-Norddeich*). For all flights, equal and easy to fly weather conditions (no wind, no clouds) without other air traffic were simulated. A complete pre-story, including map material and a flight plan, was invented for a higher identification with the scenario. A compilation of the used documents can be found in Appendix F.

Physical build of the mock-up, behavior of the simulated Cessna and the implemented scenario were evaluated and enhanced with the help of a flight expert[25].

5.5.2 Procedure of Study Two

As for the experimental setup, a detailed description of the procedure can be found in (Oberle, König et al., 2017). Generally, the experiment was structured in four phases: initial phase, practice phase, main phase and concluding phase. The initial phase is used for the reception of the participants and to introduce them to the experiment. As the name suggests, practicing phase is used to accommodate the participant to the flight simulator with the goal to reduce possible practicing effects during the main phase, at which the actual experiment is run. During the concluding phase a brief interview is conducted

[25] Trained pilot (PPL) and research associate in the field of flight systems.

to assess the subjective flight behavior and perceived difficulty of conducting the simulated landing. Then the participant is bid farewell.

Structure, duration and the single steps of the procedure are summarized in Table 5-1. The complete experiment takes about two hours for each participant. Throughout the experiment all steps are documented using a checklist to minimize inequalities within the procedure and to annotate special occurrences or commentaries. The material used for directing the experiment as well as the used questionnaires can be found in Appendix F and Appendix G. The entire experiment was evaluated and enhanced within a pre-study[26] with seven practicing pilots absolving three landings each (Oberle & Bruder, 2015).

Table 5-1. Steps of test procedure with specific durations.

Step	**Duration [min]**
Reception of participant, introduction of experiment and formalities	5
[Questionnaire on demographic data, flight qualification and experience]	[15]
Indication of possible simulator sickness and following test procedure	2
Preparation of practice phase (paper-based)	8
Instruction on flight simulator	8
Practice phase (aerodrome traffic circuit and downwind)	30
Preparation of flight scenario (paper-based)	8
Questionnaire 1 on fatigue (KSS)	1
Flight 1	10
Flight 2	10
Flight 3	10
Questionnaire 2 on fatigue (KSS)	1
Flight 4	10
Flight 5	10
Questionnaire 3 on fatigue (KSS)	1
Concluding interview, formalities and farewell	8
Total duration	121 / [136]

5.5.3 Participants of Study Two

44 pilots participated in the experiment[27]. All pilots were recruited with the help of bulletins and e-mails to four aviation clubs, three in Egelsbach and one in Aschaffenburg. Only male pilots registered voluntarily. As age was measured as a grouped variable in 10-year steps, the median age was between 41 to 50 years, spanning from 19 to over 70 years. In total, 30 pilots held private pilot licenses (PPLs), 9 held commercial pilot licenses (CPLs) and 5 pilots held other license types, e.g. for gliders. The total number of overall flight hours for assessing flight experience had a high variation from 60 hours to a maximum of 24.000 hours (mean: 1924 hours, median: 320 hours). 4 pilots had no experience with flight simulation, 12 were experienced solely with simulations, 5 solely with professional simulators and 21 were experienced with both.

[26] The pre-study was supported by the work of Peinemann and Keil (2014).

[27] The execution of the experiment was supported by the work of Manalili (2014) and Keitz (2014).

As the focus of the study is the assessment of human induced uncertainty, in this case represented by the stress of the landing gear, only flights which ended with a regular landing (no crashes) were evaluated. Thus, two pilots were excluded completely, as no adequate number of regular landings (less than three) was operated. Another pilot had to be excluded from the Markov analysis, as calculation of the pilots Markov model crashed due to the amount of repeating mid-air circles. The following analysis is therefore based on 42 participants for the general analysis and 41 participants for the analysis related to Markov models. All remaining pilots completed the procedure as described and without any sorties due to simulator sickness.

Even though the used sample size of study two allows for the application of statistical means, a bigger sample is generally recommended for a multiple regression analysis. Green (1991) states that as a general rule a number of *N >= 50 + 8 * Number of predicting variables* is needed, when interested in R^2. If the interest is upon calculation of beta-weights, as is the case for the construction of predictive functions, at least *N >= 104 + Number of predicting variables* is proposed. Even though the calculations for study one were based on more than 300 values for the overall uncertainty due to the repeated measurement for variation of goal and placing weights, calculations of study two are based on only 44 subjects. Still, acquisition of trained pilots represents a difficult task and thus 44 participants already are more than expected. Anyway, the exact results must be regarded with care and hold a predominantly explorative character.

5.6 Statistical Analysis of Uncertainty of Study Two

Following, the assessed data is analyzed to evaluate the human induced uncertainty on the stress of the landing gear. First, the resulting uncertainty is described statistically and second, the effect of the influencing factors on uncertainty is quantified. The statistical analysis thereby follows the same procedure as in study one.

5.6.1 Statistical Description of Resulting Uncertainty for Study Two

First, the resulting uncertainty concerning the stress of the landing gear is described statistically. Second and third, the uncertainty within the human sub-processes is further described, starting with *choice of action* and lastly focusing on *execution of action*. Test-tables, figures and results which do not appear within the following subchapters can be found in Appendix I.

5.6.1.1 Uncertainty of Technical Subsystem

The resulting stress on the landing gear is characterized by the vertical velocity and the angles pitch, bank and heading, all assessed at the moment of direct touchdown. The factors of vertical velocity are lastly described with two variables, mean velocity on touchdown for each pilot and standard deviation of velocity on touchdown for each pilot. To facilitate processing, the three angles are transformed into a single rank for each pilot, representing a comparative measure for the quality of landing[28]. Figure 5-7 depicts the histogram for the distribution of mean velocity and standard deviation of velocity[29].

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[28] For reasons of brevity, the calculation of a single rank for the angles pitch, bank and heading is described in Appendix H.

[29] The distribution of the resulting ranking for the angles is not depicted, as build ranks generally depict a constant distribution.

For study one, a lognormal distribution for the resulting stress was found (cf. chapter 4.6.1). This led to the assumption that human induced uncertainty can be generally described by means of a lognormal distributed, if an absolute zero point for the stress exists. Regarding velocity, again skewed distributions can be noted. Statistical tests confirm that mean and SD of velocity are not normally distributed. To test the assumption of lognormal distribution, mean and SD of velocity are transformed to lognormal values[30] and tested once more for normality. For both transformed variables the Shapiro-Wilk test confirms the assumption of normality. Therefore, the hypothesis of lognormal distributed human induced uncertainty remains valid. Figure 5-8 depicts the distribution for mean of velocity and SD of velocity after lognormal transformation.

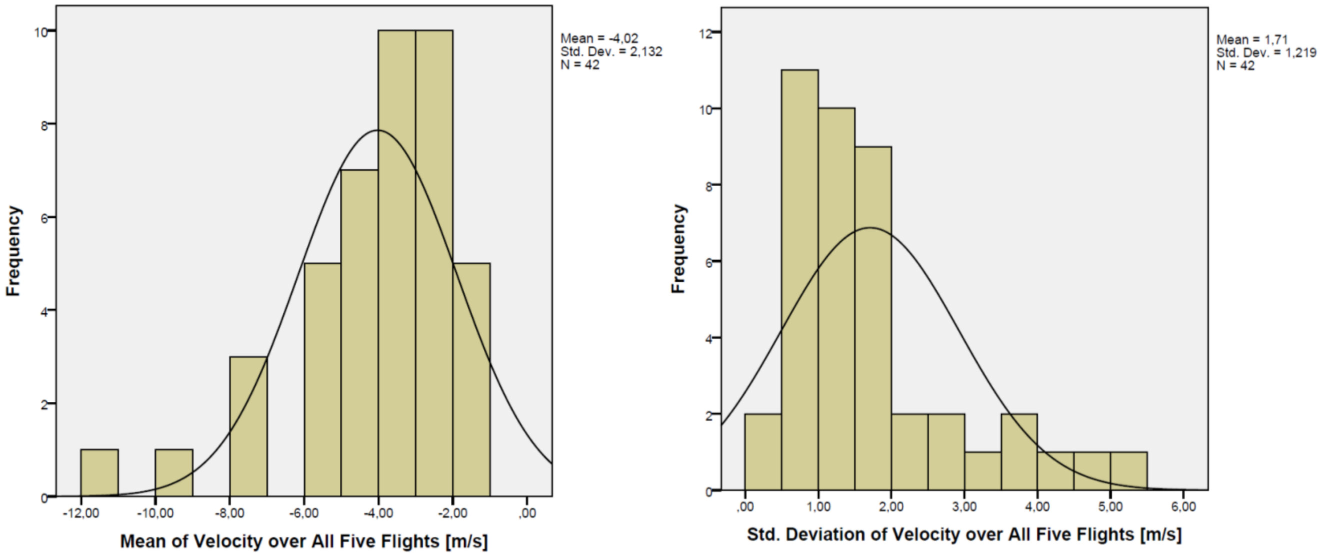

Figure 5-7. Histograms for mean and standard deviation of velocity over all five flights.

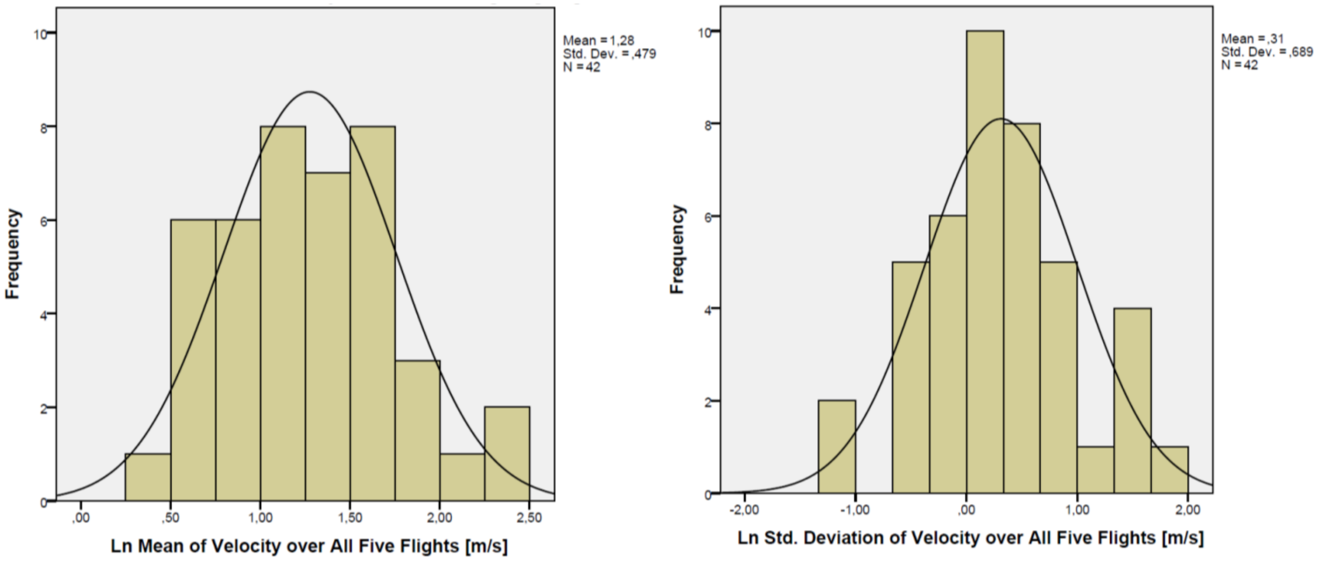

Figure 5-8. Histograms for lognormal transformed mean and standard deviation of velocity over all five flights.

A description of the resulting uncertainty has thus to be based on the lognormal values and then retransformed for practical application. Of course, retransformed values can only be used for the practical description and not for further statistical analysis. Table 5-2 lists the retransformed values for

[30] Ln(mean_velocity) and Ln(SD_velocity) is calculated.

mean and SD of velocity. The retransformed boundaries illustrate the range of variation for the resulting stress.

Table 5-2. Retransformed mean values and boundaries for 95% and 99.7% intervals for mean velocity and SD velocity.

Variable	Mean [m/s]	Boundaries for 95%-Interval [m/s]	Boundaries for 99.7%-Interval [m/s]
Mean Velocity	-3.597	-1.380 to -9.375	-0.855 to -15.135
SD Velocity	1.363	0.344 to 5.409	0.173 to 10.773

The results further imply that parametric tests can be applied for statistical analysis of velocity. For the angle ranking nonparametric tests must be applied due to the ordinal scale.

5.6.1.2 Uncertainty of Choice of Action

A detailed description of the development and analysis of the Markov model is given by Oberle, and König et al. (2017)[31]. Generally, the concept of Markov models was successfully applied to describe and analyze the variations within choice of action, resulting into different action sequences. Figure 5-9 depicts the resulting Markov model for all pilots with a most probable path following the states of 1-2-3-5-7-9-10-11 with a most probable path probability of 39.7%. The comparably low probability to follow the most probable path signifies major variations of the action sequence between all pilots.

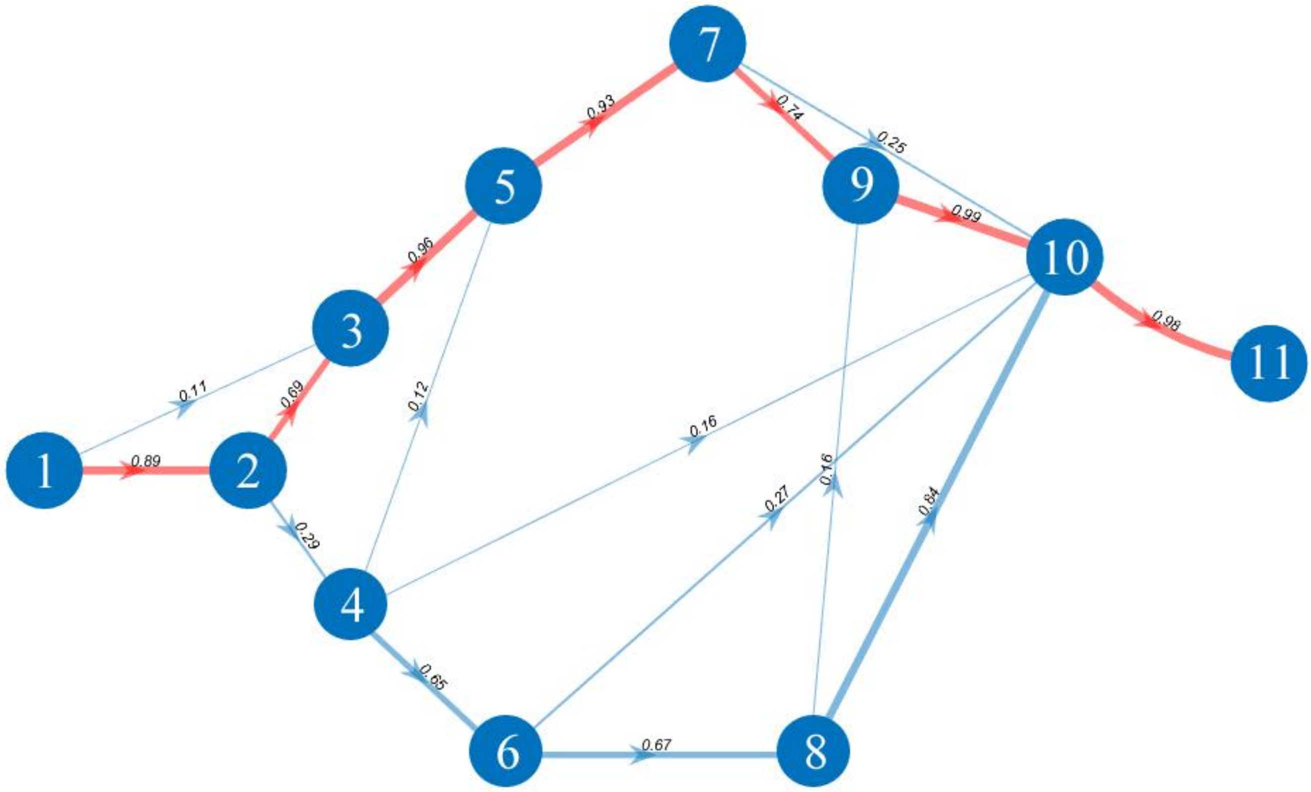

Figure 5-9. Markov model for all pilots and flights. States are counted from 1 to 11. The size of the connections corresponds to the transition probability; whereat low probabilities are depicted with a thin connection. The red connections represent the most probable path within the model. The probability for the most probable path for all pilots and flights is 39.7%. Transitions with a probability below 10% were neglected.

[31] The development of the Markov model was supported by the work of Wang (2016).

Also, differences of the Markov model, when calculated for different groups of qualification, were identified, as depicted in Table 5-3. For example, pilots holding a CPL (n = 9) followed the same path as for all pilots, but with a probability of 58.7%, signifying a more consistent action sequence.

Table 5-3. Resulting most probable path and path probability for all Pilots in comparison to different Qualification.

Group	Path	Probability
All Pilots	[1 2 3 5 7 9 10 11]	39,7%
CPLs	[1 2 3 5 7 9 10 11]	58,7%
PPLs	[1 2 3 5 7 9 10 11]	38,8%
Other Licenses	[1 2 4 6 10 11]	20,8%

5.6.1.3 Uncertainty of Execution of Action

The process *execution of action* represents the link between *choice of action* and the resulting stress on the system, for which reason the uncertainty within this process is assessed, too. The assessed variables Flight Duration, Sum of Inputs, Inputs per Time and Jerkiness are determined once as the mean value over all five flights and once as the standard deviation over all five flights, resulting in 8 different variables for the description of execution of action. First, tests of normality were run to determine the character of distribution. Only Mean Inputs per Time tends to be normally distributed ($p = 0.091$). Therefore, all factors were tested for lognormal distribution. Test of normality for the transformed variables yielded proof for lognormal distribution, except for Mean Flight Duration, SD Flight Duration and SD Inputs per Time. Therefore, Probability-Probability Plots (P-P Plots) for all eight variables were generated for a comparison between the fit to normal and lognormal distribution. Exemplary, Figure 5-10 depicts the comparing P-P Plots for SD of Flight Duration. Visual analysis showed higher compliances for the lognormal distribution. Therefore, all variables were henceforth used after transformation to lognormal values.

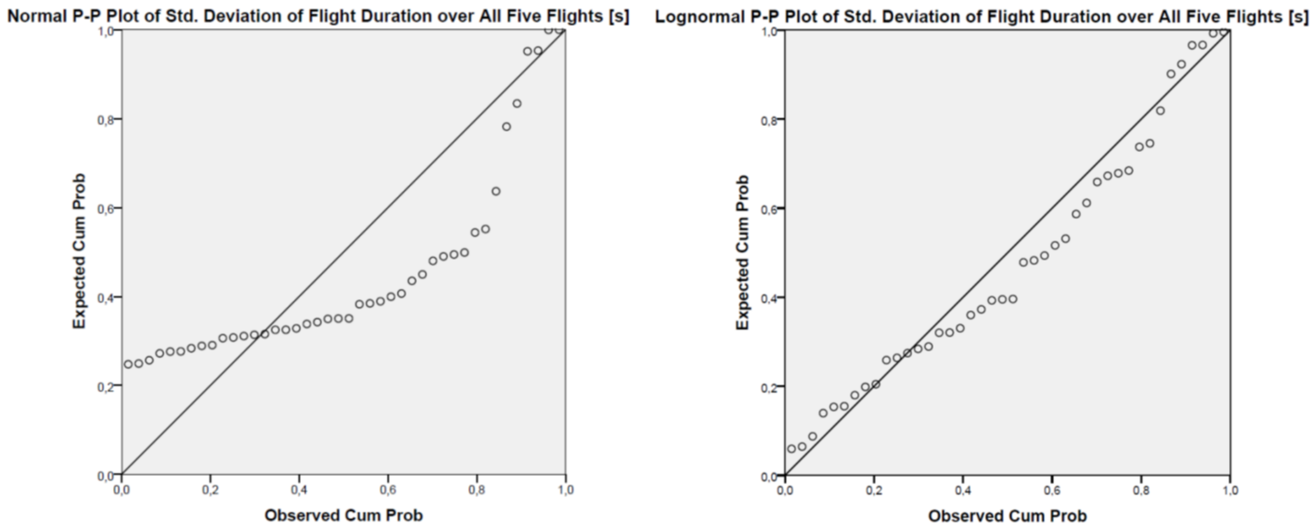

Figure 5-10. Comparing P-P Plot for SD of Flight Duration against normal (left) and lognormal (right) distribution.

Table 5-4 lists the retransformed values for all eight dependent variables of *execution of action* for practical analysis. Like for velocity, retransformation illustrates the vast range of variation and uncertainty of the variables.

Table 5-4. Retransformed mean values and boundaries for 95% and 99.7% intervals for all dependent variables of *execution of action*.

Variable	Mean [m/s]	Boundaries for 95%-Interval [m/s]	Boundaries for 99.7%-Interval [m/s]
Mean Flight Duration	564.9	413.6 to 771.4	354 to 901.4
Mean Sum of Inputs	45352998	20158022 to 102038505	13439059 to 153053453
Mean Inputs per Time	79845	40466 to 157547	28807 to 221305
Mean Jerkiness	3007	1371 to 6595	925.5 to 9768
SD Flight Duration	36.85	7.271 to 186.8	3.23 to 420.5
SD Sum of Inputs	9225630	1435077 to 59308501	565998 to 150375608
SD Inputs per Time	14779	4048 to 53951	2119 to 103081
SD Jerkiness	442.6	130.9 to 1497	71.18 to 2752

5.6.2 Quantification of the Effect of Influencing Factors on Uncertainty for Study Two

Within the following chapter, the relationship between the single elements of the derived working model (see Figure 5-5) are analyzed statistically, especially regarding the resulting stress on the technical system. First, the data is controlled for possible practice effects and effects due to changes of fatigue. Second, the impact of *execution of action* onto the technical system, third of *choice of action* onto *execution of action*, fourth of *choice of action* onto technical system, fifth of the human influencing factors onto *choice* and *execution of action* and sixth of the human influencing factors onto the technical system are investigated. Finally, all single tests are summarized within a regression model to depict the found predictors for each factor.

5.6.2.1 Approach for Data Analysis

The statistical approach for the impact analysis follows the same steps as described in chapter 4.6.2.1 regarding the preparation and processing of the regression analysis. Additional test results and graphs can be found in Appendix I. An alpha level of .05 was used for all statistical tests if not stated differently.

5.6.2.2 Controlling for Practicing and Fatigue Effects

To control for possible practicing effects, the central tendency for velocity on touchdown between all five single flights was compared and tested for significant differences. Thus, tests of normality for all five variables were run. As all instances of velocity were not normally distributed, Friedman's test for comparing a continuously scaled dependent variable with repeated measurements was run. There was no difference in velocity on touchdown for all five landings, $\chi2(4) = 3.200$, $p = .525$. Accordingly, no practicing effect was found, wherefore all five flights were used for the further analysis.

Following the same procedure, the three measurements for fatigue were checked for alteration throughout the experiment. Test of normality indicated no normal distribution. Friedman's test found a statistically significant difference in perceived fatigue throughout the experiment, $\chi2(2) = 24.929$, $p < .0005$. Post hoc analysis with Wilcoxon signed-rank tests were conducted with applied Bonferroni correction, resulting in a significance level set at $p < 0.017$. Median (IQR) perceived fatigue KSS-values before flights, after three flights and after all five flights were 3 (2.75 to 4), 3 (2.75 to 5) and 4 (3 to 5), respectively. There were no significant differences between before and after three flights trials ($Z = -1.532$, $p = 0.125$). However, there was a statistically significant increase in fatigue for after three flights vs after five flights trial ($Z = -3.506$, $p < 0.0005$) and in before flights vs after five flights trial

(Z = -3.819, p < 0.0005). Therefore, the variable Change of Fatigue was calculated, which represents the difference of KSS score before flights to after five flights. Change of Fatigue was used henceforth to assess a possible influence of perceived increase of fatigue on the dependent variables.

5.6.2.3 Impact of Execution of Action on Technical System

Pearson product-moment and Spearman's rank-order correlation were run to determine the relationship between the measures for *execution of action*. The data showed no violation of normality (in the case of Pearson), linearity or homoscedasticity. There was a strong, positive and statistically significant correlation between Ln Mean Sum of Inputs for all flights and both, Ln Mean Inputs per Time (r = .921, n = 42, p < .0005) and Ln SD Sum of Inputs (r = .747, n = 42, p < .0005). Further, a strong, positive correlation between Ln SD Inputs per Time and Ln SD Sum of Inputs, which was statistically significant ($r_s(39) = .881$, p < .0005), was found. Due to high correlations, only one of each correlating factor was used for regression, wherefore the factors Ln Mean Inputs per Time, Ln SD Sum of Inputs and Ln SD Inputs per Time were excluded.

A multiple, stepwise regression was run to predict Ln Mean Velocity from Flight Duration, Sum of Inputs and Jerkiness. Ln Mean Flight Duration statistically significantly predicted Ln Mean Velocity, F(1, 40) = 5.269, p = .027, adj. $R^2 = .094$. Increase of flight duration therefore impacted on the resulting stress on touchdown.

A multiple, stepwise regression was run to predict Angle Ranking from Flight Duration, Sum of Inputs and Jerkiness. Ln SD Flight Duration statistically significantly predicted Angle Ranking, F(1, 40) = 10.176, p = .003, adj. $R^2 = .183$. Pilots with high variation of flight duration generated a higher stress on touchdown.

The impact of *execution of action* on the landing gear was described through the following regression equations:

*Ln Mean Velocity = -5.376 + 1.050 * Ln Mean Flight Duration*
*Angle Ranking = -3.055 + 6.808 * Ln SD Flight Duration*

5.6.2.4 Impact of Choice of Action on Execution of Action

A multiple, stepwise regression was run to predict Ln Mean Sum of Inputs from Most Probable Path Probability and Followed Most Probable Path. Most Probable Path Probability statistically significantly predicted Ln Mean Sum of Inputs, F(1, 39) = 4.362, p = .043, adj. $R^2 = .078$. Therefore, pilots with low variations of their action sequence needed less inputs to operate a landing maneuver. No further predictors for the impact of *choice* on *execution of action* were found.

The resulting regression equation was:

*Ln Mean Sum of Inputs = 17.248 + 0.552 * Most Probable Path Probability*

5.6.2.5 Impact of Choice of Action on Technical System

Investigation of the resulting system stress due to variations of *choice of action* was assessed for two levels. First, the derived variables from the Markov model are used to predict the resulting stress, checking if the overall sequence of action interacts with the resulting stress. Second, each single state of the Markov model, which itself can be characterized as a single *execution of action* with corresponding variables, is tested for its impact on the resulting stress.

A multiple, stepwise regression was run to predict Ln SD Velocity from the variables derived from the overall Markov model. Followed Most Probable Path statistically significantly predicted Ln SD Velocity, $F(1, 39) = 5.817$, $p = .021$, adj. $R^2 = .107$. Pilots who followed the overall most probable path were found to elicit a decreased amount of variation for the resulting velocity on touchdown. No further predictors were found.
Impact of *choice of action* on the landing gear was described through the following regression equation:

*Ln SD Velocity = 0.567 - 0.497 * Followed Most Probable Path*

A complete review on the evaluation of the impact of single states onto the resulting stress can be found in Oberle, and König et al. (2017). Summarizing, predictors for the resulting stress were found within the states 4, 8, 10 and 11. Following regression equations described the impact of single states on the stress of the landing gear:

$Ln\ Mean\ Velocity = 1.876 - 0.116 * Mean\ Duration_{State\ 11}$
$Angle\ Ranking = 146.448 - 3.704 * Mean\ Altitude_{State\ 10}$
$Ln\ Mean\ Velocity = 0.562 - 0.243 * Mean\ Pitch_{State\ 8}$
$Ln\ SD\ Velocity = -0.753 + 0.005 * Mean\ Altitude_{State\ 8}$
$Ln\ Mean\ Velocity = 0.769 + 0.010 * Mean\ Duration_{State\ 4}$
$Ln\ SD\ Velocity = -0.566 + 0.020 * Mean\ Duration_{State\ 4}$
$Angle\ Ranking = 7.523 + 0.276 * Mean\ Duration_{State\ 4}$

5.6.2.6 Impact of Human Influencing Factors on Choice and Execution of Action

A Spearman's rank-order correlation was run to determine the relationship between the human influencing factors. Several high, positive and statistically significant correlations were found, which led to the exclusion of Number of Operated Flights in Last Twelve Months, Cumulated Single Engine Flight Duration, Cumulated Single Engine Flight Duration in the Last Twelve Months, Cumulated Time Using FSX and Cumulated Time on Professional Flight Simulator regarding the regression analysis.
A multiple, stepwise regression was run to predict Ln Mean Flight Duration from the remaining human influencing factors. The factors Cumulated Flight Duration on Cessna and Realistic Flight Behavior[32] were found to statistically significantly predict Ln Mean Flight Duration, $F(2, 11) = 8.249$, $p = .006$, adj. $R^2 = .527$. Increased experience with flying a Cessna and a less realistic flight behavior led to higher flight durations.
A multiple, stepwise regression was run to predict Ln SD Flight Duration from the remaining human influencing factors. The factors Cumulated Flight Duration on Cessna and Realistic Flight Behavior were found to statistically significantly predict Ln SD Flight Duration, $F(2, 11) = 12.857$, $p = .001$, adj. $R^2 = .646$. Increased experience with flying a Cessna and a less realistic flight behavior led to higher variation of flight duration.
A multiple, stepwise regression was run to predict Ln Mean Sum of Inputs from the remaining human influencing factors. Perceived Difficulty of Landing Maneuver statistically significantly predicted Ln Mean Sum of Inputs, $F(1, 12) = 6.078$, $p = .030$, adj. $R^2 = .281$. Pilots perceiving the task of landing

[32] The variable Realistic Flight Behavior was assessed within the interview of phase four. Thereby, the participants were asked to rate their flight behavior on a five-point Likert-scale reaching from "as in reality" to "different to reality".

an airplane within the simulator more difficult than in reality needed a higher number of inputs to operate the landing.
A multiple, stepwise regression was run to predict Ln Mean Jerkiness from the remaining human influencing factors. Qualification PPL, Flight Simulation Experience and Age statistically significantly predicted Ln Mean Jerkiness, $F(1, 10) = 27.385$, $p < .005$, adj. $R^2 = .859$. Jerkiness increases with age, but decreases with experience with flight simulators as well as for pilots holding a PPL.
A multiple, stepwise regression was run to predict Ln SD Jerkiness from the remaining human influencing factors. Qualification CPL statistically significantly predicted Ln SD Jerkiness, $F(1, 12) = 4.865$, $p = .048$, adj. $R^2 = .229$. Pilots holding a CPL showed higher variations of their jerkiness.
The impact of human influencing factors on *execution of action* was described through the following regression equations:

*Ln Mean Flight Duration = 6.111 + 0.001 * Cumulated Flight Duration on Cessna + 0.089 * Realistic Flight Behavior*
*Ln SD Flight Duration = 2.081 + 0.007 * Cumulated Flight Duration on Cessna + 0.595 * Realistic Flight Behavior*
*Ln Mean Sum of Inputs = 15.741 + 0.459 * Perceived Difficulty of Landing Maneuver*
*Ln Mean Jerkiness = 8.535 – 1.197 * Qualification PPL – 0.150 * Flight Simulation Experience + 0.232 * Age*
*Ln SD Jerkiness = 65.033 + 1.187 * Qualification CPL*

Even though low correlations between human influencing factors and *choice of action* were found, no predictors could be derived (Oberle, König et al., 2017). Thus, human influencing factors have only a low impact on *choice of action*.

5.6.2.7 Impact of Human Influencing Factors on Technical System

A multiple, stepwise regression was run to predict Ln Mean Velocity from the remaining human influencing factors. The factors Change of Fatigue, Level of Education and Age were found to statistically significantly predict Ln Mean Velocity, $F(3, 10) = 13.694$, $p = .001$, adj. $R^2 = .746$. Increased Age and Level of Education in combination with a decrease of Change of Fatigue resulted into a higher stress.
A multiple, stepwise regression was run to predict Ln SD Velocity from the remaining human influencing factors. Cumulated Overall Flight Duration in Last Twelve Months statistically significantly predicted Ln SD Velocity, $F(1, 12) = 5.630$, $p = .035$, adj. $R^2 = .263$. Increased overall training time led to a decreased variation of resulting stress.
A multiple, stepwise regression was run to predict Angle Ranking from the remaining human influencing factors. Cumulated Overall Flight Duration in Last Twelve Months statistically significantly predicted Angle Ranking, $F(1, 12) = 4.969$, $p = .046$, adj. $R^2 = .234$. Increased overall training time led to a lower rank regarding the angles on touchdown, signifying a decrease of the resulting stress.
The impact of human influencing factors on the resulting stress on the landing gear was described through the following regression equations:

*Ln Mean Velocity = -0.367 - 0.381 * Change of Fatigue + 0.248 * Level of Education + 0.185 * Age*
*Ln SD Velocity = 0.527 - 0.014 * Cumulated Overall Flight Duration in Last Twelve Months*
*Angle Ranking = 27.651 - 0.241 * Cumulated Overall Flight Duration in Last Twelve Months*

5.6.2.8 Resulting Regression Model

Figure 5-11 depicts the resulting working model for the description of the interrelations between human influencing factors, *choice of action*, *execution of action* and technical system for study two. Regression models and predictors for all relations were found, except for the relation between human influencing factors and *choice of action*. In this case, only low correlations were found.

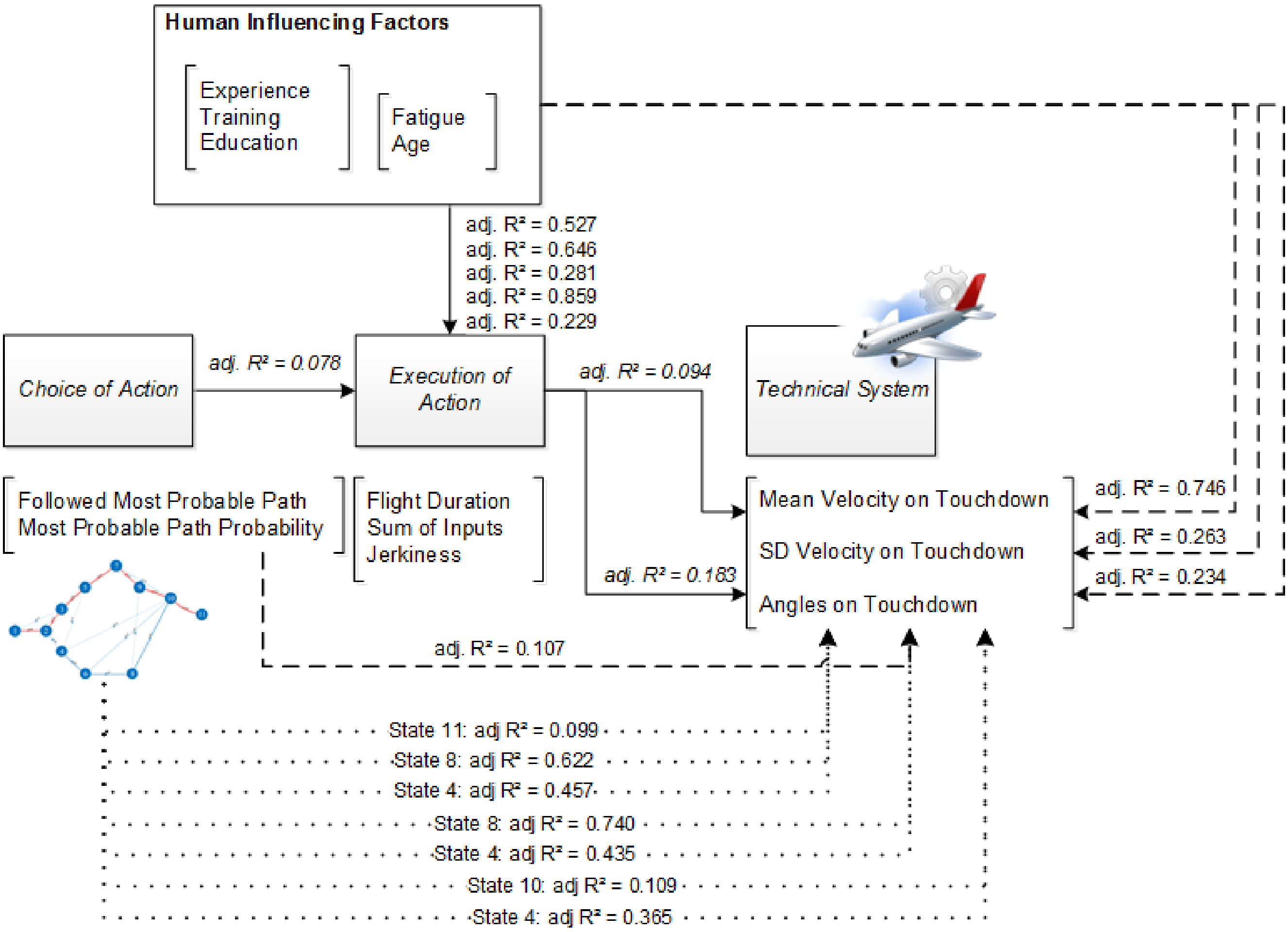

Figure 5-11. Regression model for the description of the relationship between the influencing factors and the resulting stress on the system.

5.7 Discussion of Results of Study Two

Study two yields several findings. For one instance, the overall resulting stress was identified and quantified to be lognormal distributed. Also, all variables characterizing the variation of *execution of action* were identified to be lognormal distributed. Quantification of these variables therefore showed a skewed distribution with most values close to a minimum stress, but also with broad interval boundaries leading to single and high possible values compared to the actual mean. This again supports the hypotheses that human induced uncertainty is best described through means of a lognormal distribution, with the restriction of an existing absolute zero point for the uncertainty.

Summarizing, Mean Velocity was predicted by the flight duration and the combination of age, level of education and change of fatigue. The impact of flight duration seems reasonable, since pilots taking more time for the landing imply to have difficulties handling the aircraft or orienting themselves to find the airport. These insecurities impact on flight performance and stress on touchdown. Also, the factor age was already mentioned to possibly interfere with flight performance (cf. Hardy et al., 2007), thus, impact on stress seems reasonable, too. For the level of education, no previous data indicated a possible impact. Unexpected is the fact that higher education correlated with higher stress. The factor Change of Fatigue was expected to impact on stress (cf. Rosekind et al., 2000). But again, data showed that with high change of fatigue, representing an increase of fatigue over the experiment, correlated with a reduction of stress, not the other way around as would be expected. An interpretation could be that pilots who stated to have perceived an increase of fatigue possess a higher ability of self-assessment and by noticing an increase of fatigue also started to concentrate more on the task to negate effects of perceived fatigue.

SD Velocity was predicted by overall training time and by following the most probable path. Both findings are reasonable. Training was expected to be an impacting factor prior to the experiment (cf. Vidulich et al., 2010). Following the overall most probable path, which represented the suggested path (cf. Oberle & Bruder, 2015), implies that pilots were accustomed to flight procedures and were not distracted by experimental conditions. Thus, having the capability to focus on the landing maneuver itself and reducing the variation of resulting stress.

As for the dependent variable Angle Ranking the factors SD Flight Duration and again overall training time were found as predictors, the latter confirming its importance for flight performance. Like the overall flight duration, high variation of flight duration led to an increased stress. High variation of flight duration implies unfamiliarity with flight procedures or the flight simulator, which surely impacts on the resulting stress.

For the process *execution of action,* the predictors Most Probable Path Probability, experience on a Cessna and Perceived Difficulty of Landing Maneuver were found. Thereby, pilots who exhibited low variation of the taken sequence of action throughout all flights needed less inputs on the yoke to operate the landing. This seems reasonable, as this implies increased familiarity with flight procedures, as already discussed above for the factor Followed Most Probable Path. Experience on Cessna impacted both on mean and variation of flight duration. Pilots familiar with the Cessna are expected to need less time to accommodate to the simulator and further would be expected to fly more intuitively, on a skill-based level (Rasmussen, 1983). Therefore, needing less time to land is reasonable. Finally, pilots who stated landing within the simulator to be more difficult than in reality, needed more inputs on the yoke to do so. This seems reasonable. Even though, as the perceived difficulty was assessed after all flights, it is hard to discern if the higher number of inputs is cause for or effect of perceived difficulty.

Regarding the Markov model, predictors for the resulting stress were found within specific states. As the states 10 and 11 are congruent to the flight phases of final approach and landing (cf. Figure 5-1), it seems reasonable that factors of these states are predictors for the resulting stress. Even though, relying on a predictor from state 11 is not applicable, as the state ends with the actual touchdown and possible interventions based on a predictor would come too late to adhere to. More so, the predictors found within the states 8 and 4 seem useful for application, but are limited because both states are only operated when not following the suggested action sequence.

Concluding, based on the regression model and the above stated equations, prediction of the resulting stress is facilitated and the uncertainty of the resulting stress due to human interaction is further explained.

Nevertheless, the results must be handled carefully. For instance, to run a regression analysis a bigger sample size would be favorable and was only done due to the explorative character of the study. Therefore, conducting a study with a higher sample size is advisable prior to an application of the assessed data.

Also, a possible impact of the used flight simulator on the data must be considered, which was indicated by the measures Perceived Difficulty of Landing. A majority of 83.4% of the participating pilots stated that operating a landing maneuver within the simulator was more difficult than operating a landing maneuver in real. Of course, for this statement it is hard to discern whether pilots performed poorer because using the simulator was trying or if the pilots who thought about their landings to have gone amiss used this rating as a kind of excuse. Still, some pilots commented that the head tracking system used for the enhancement of view was rather irritating.

Even though 66,7% of the pilots stated that they behaved similar within the simulator compared to operating a real landing, simulation is likely to foster unrealistic behavior. This is due to the negligible consequences of failure and unsafe behavior within a simulation. The fact is somehow confirmed by the number of crashes which happened during the experimental flights (13 crashes compared to a total number of 210 operated flights). It is to be hoped that within a real world experiment no crashes would have occurred and that pilots would have stopped the approach when feeling unsure about landing unharmed.

Generally, all results must be regarded with care when trying to apply the findings to real world landings. To be precise, all data just state which factors and to which amount contribute to the stress of the landing gear when operated within the used flight simulator. Therefore, the investigated task wasn't "landing an airplane", but "landing an airplane within a flight simulator". For this reason, further research is needed to see if the findings can be applied to a landing maneuver operated within the real world.

Concluding, the method of HUMEAn was applied successfully for study two. Also, display of the uncertainty for *choice of action* using the concept of Markov models was appropriate. Based on the findings for the intraindividual assessment of human induced uncertainty recommendations for its reduction can be derived. Thus, increased training of the pilots or applying for more complex pilot licenses leads to a reduction of uncertainty. Besides, findings regarding the action sequence could be applied to develop additional human-machine interfaces, which inform the pilot about the current state of his landing maneuver and implicate possible outcomes for the resulting stress on touchdown. The general idea to implement additional human-machine interfaces for the reduction of the resulting human induced uncertainty is addressed in study three (see chapter 6).

5.8 Summary of Chapter 5

Within the past chapter, a second study for the evaluation of the HUMEAn was conducted. Thereby, the complex task of landing an airplane was investigated and divided into several subtasks. The task was identified as predominantly discriminatory, independent of real or simulated, and thus the human sub-process *choice of action* in combination with a focus on intraindividual influences was selected as the uncertainty mode. HUMEAn was applied successfully and the resulting human induced uncertainty was quantified. Like for study one, the human induced uncertainty was represented as a lognormal distribution. Additionally, several predictors for the resulting uncertainty were identified from the group of influencing factors as well as for certain states of the Markov model. Based on the findings, implications for the future reduction of human induced uncertainty regarding the investigated context were derived.

Concluding, study one and study two both contributed to answer the second research questions. The developed method of HUMEAn thus represents an applicable methodology for the assessment and quantification of human induced uncertainty. Also, first implications for the third research question, how human induced uncertainty can be controlled, were identified. For a final treatment of the third research question a third study is conducted to investigate the impact of additional human-machine interfaces for the reduction of uncertainty.

6 Reduction of Human Induced Uncertainty through Appropriate Interaction Design

Within the following chapter, a third study for the investigation of the impact of appropriate feedback design is conducted. First, the objective and the investigated hypotheses are presented. Second, the method used for the development and design of the appropriate feedback system, the experimental setup, procedure and the sample size are discussed. Third, the results of the study are presented and fourth discussed. The chapter concludes with a summary.
It must be noted, that the following chapter only represents a brief overview over the third study. A complete account can be found in Oberle, and Sommer et al. (2017).

6.1 Objective and Hypotheses of Study Three

Based on the various references concerning the importance of feedback and especially human-centered feedback design for HMIs (e.g. Bainbridge, 1983; Grote & Roy, 2009; Johnson, 2003; Neufville & Weck, 2004; Norman, 1990; Völkel, 2005), study three[33] investigates the impact of different types of feedback onto human induced uncertainty. Based on the references literature, the following two main hypotheses[34] are derived and tested:

H1: *Additional feedback results into a reduced system stress as well as a reduced amount of uncertainty in comparison to natural feedback.*

H2: *Appropriate feedback, designed with regard to the user-needs, results into a reduced system stress as well as a reduced amount of uncertainty in comparison to feedback not designed with regard to the user.*

For this purpose, the tripod introduced in study one is applied again as the technical system. Thereby, the task is adopted to the stacking of two identical weights, where at different types of feedback are presented to the participants after the first placement to inform them about their impact on the system. As the focus of study three solely relies on the impact of the different feedback types, independent of direct human influencing factors, the first three steps of the HUMEAn are treated brevity.
Regarding the specification of the task, only the above stated adaption of the task goal is performed. As the task is kept constant throughout the experiment, all influencing factors of the task are neglected. The task is not divided into subtasks.
Again, the environmental factors are neglected as the task is executed within a laboratory study. Regarding the technical subsystem, the resulting system strain is assessed through the mean and standard deviation of the resulting maximum force as well as on the mean and SD of eccentricity. The maximum force is thereby focused on the resulting maximum force during the placement of the second weight. Instead of the resulting static weight distribution after the second placement eccentricity is calculated as the proportional improvement of the distance from the center between the first to the second placement[35]. Regarding the technical subsystem, the human-machine interface differs from study one, as a monitor is installed for the presentation of feedback. Thus, the output of the system is changed to visual information.

[33] The conduction of the feedback study was supported by the work of Sommer (2016).
[34] For a better legibility, the null hypotheses are not specified.
[35] $Eccentricity_{\%} = \frac{Distance_{first\ weight} - Diestance_{both\ weights}}{Distance_{first\ weight}}$.

As the focus of study three is on the interface design, not on the direct human impact on uncertainty, step three of the HUMEAn is neglected. No specific uncertainty mode is selected as well as no human influencing factors. Still, to reduce possible influences, the sample size is reduced to right-handed male aging from 18 to 30.

6.2 Experimental Investigation of Study Three

Following, the experimental investigation of study three is described. Initially, the experimental setup is described, presenting the different types of feedback. Then, the test procedure and the participants are presented.

6.2.1 Experimental Setup of Study Three

The used experimental setup resembles the setup presented in chapter 4.5.1 and involves the placement of weights onto the surface of the tripod. In contrast to study one, the weights remain unchanged at 1.7 kg and the task is fixed to place the weights as centrally and softly as possible. To allow the possibility to change the resulting stress on the tripod in compliance with given feedback, the task is further changed to the stacking of two identical weights, whereat a possible feedback is given after the first placement.

Three different types of feedback are used. The first type does not involve any additionally feedback and thus subjects must rely on their sensory modalities to evaluate the first placement (referred to as *NoFeedback*). Second, a digital feedback is presented on a monitor, which depicts the measured forces as a time-continuous graph for each leg of the tripod (referred to as *Feedback1*). This mode of presentation is thereby directly derived from the original measurement-software of the tripod (see Figure 6-1).

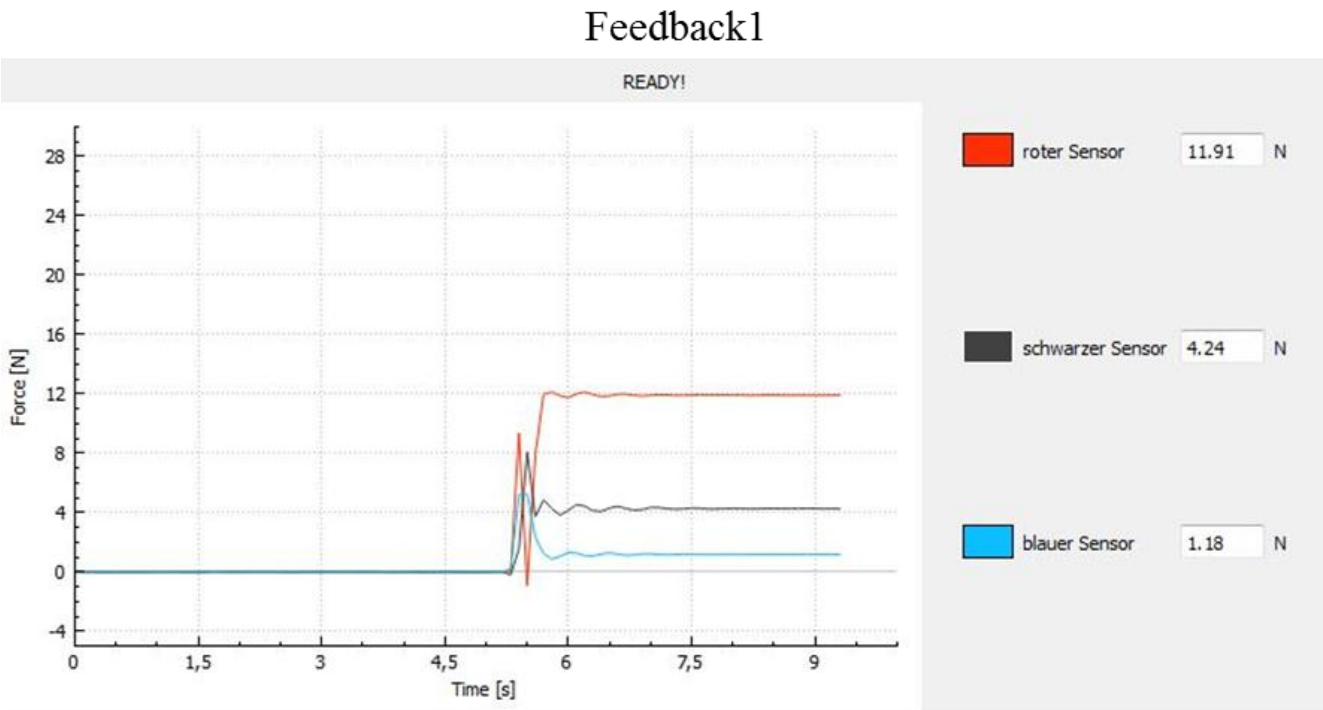

Figure 6-1. Feedback1, consisting of a curve chart depicting exerted force per leg across time as well as maximum of exerted forces.

Third, another digital feedback is presented on a monitor (referred to as *Feedback2*), which is specifically designed according to the human-centered design process (cf. DIN EN ISO 9241-210, 2011)[36]. Thereby, the resulting stress of the tripod is presented dedicated to each sub-goal as a bar-diagram (softness) and an optical representation of the relative position of the first weight on the tripod's surface (centrality). The mode of presentation is depicted in Figure 6-2.

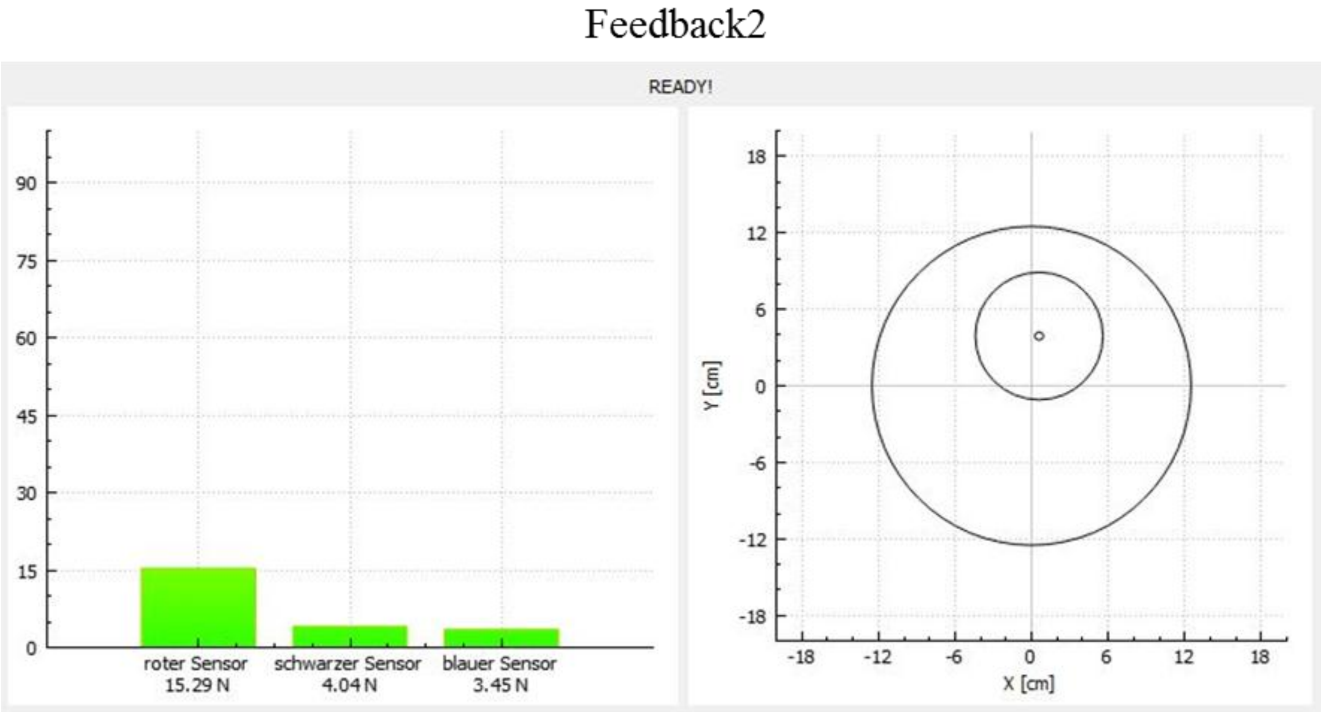

Figure 6-2. Feedback2, consisting of a bar chart depicting force per sensor (left) and an optical representation of the position of the weights in relation to the tripod (right).

6.2.2 Procedure of Study Three

The test procedure is structured into four sequential phases: introduction, preparation, test execution and farewell.

Within the first phase of introduction, the participant is welcomed and the objective and procedure of the experiment is presented. Then the participant is introduced to the setup, the weights and the general task.

Within the second phase, the participant is handed a questionnaire, asking for demographic data. Meanwhile, the first run of the experiment is prepared.

During phase three, the actual experiment takes place. Prior to each run, the participant is handed another questionnaire, giving instructions on the tested feedback type as well as checking the understanding of the current type through a small test. Thereafter, each participant has two trials to actively test the presented feedback type. Then, the actual test starts and each participant must stack the weights three times. This procedure is repeated three times, once for each feedback type. After all runs, the participant is handed a final questionnaire asking for a subjective rating of the three different feedback types.

[36] The development and evaluation of the third feedback version was supported by the work of Guseva (2015).

Within the fourth phase, the participant is given a small compensation for his participation and bid farewell.

To ensure comparable study conditions and reduce secondary effects, the sequence of the feedback type is permuted between participants. Further, a checklist is used to track all steps of the study, also containing standardized phrases for instruction. The questionnaires and materials of study three are presented in Appendix J.

6.2.3 Participants of Study Three

A total of 32 right-handed men with an age ranging from 19 to 29 years (M = 23.8, SD = 2.5) participated at the study. The complete experiment took about 45 minutes for each participant. For the analysis, one participant had to be excluded due to missing data, reducing the number of valid measurements to 31.

6.3 Results of Study Three

The descriptive results for the human induced uncertainty in relation to the three different types of feedback are depicted in Figure 6-3. Descriptively, the different types of feedback did not impact on the exerted maximum force of the tripod (softness). For the resulting eccentricity, an improvement can be seen for both digital feedback types, whereas *Feedback2* further depicts a higher, positive effect than *Feedback1*.

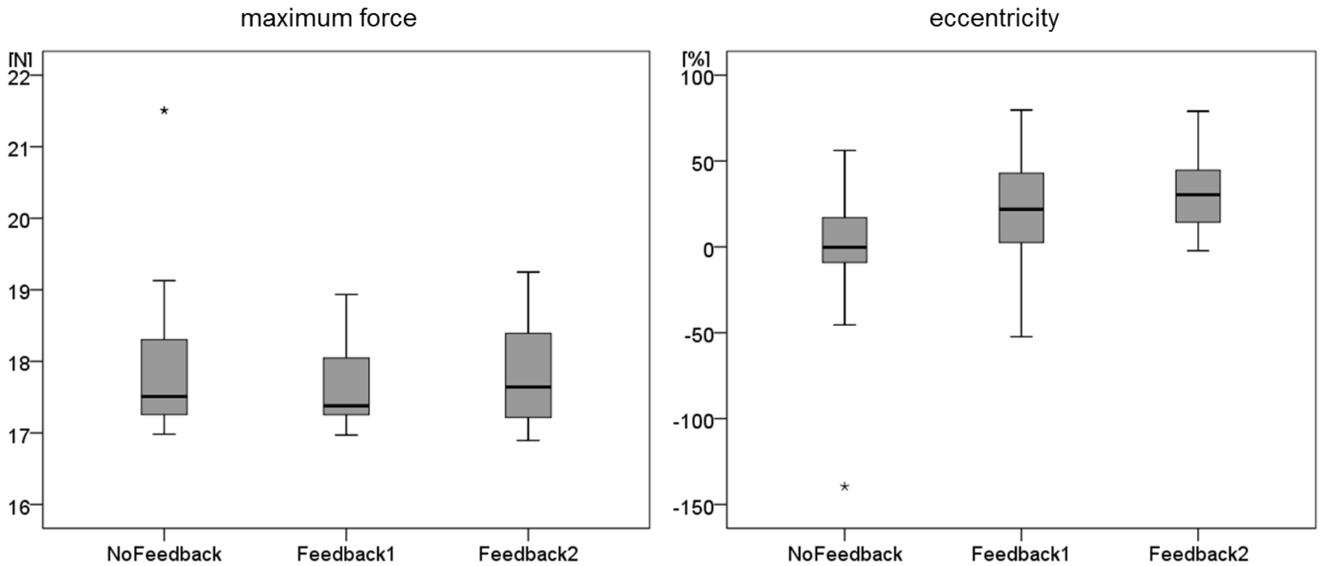

Figure 6-3. *Left:* Boxplot depicting the mean of the maximum force for each feedback type for the placing of the second weight; *Right:* Boxplot depicting the mean proportional improvement of eccentricity after placing the second weight.

Statistical analysis confirms that the different feedback types have no significant impact on the resulting maximum force (softness). In case of eccentricity, hypothesis H1 can be confirmed, as a highly significant difference of the mean values exists between the natural feedback and both digital feedback types ($p < .001$)[37]. Regarding hypothesis H2, only a marginally significant effect ($p = .058$) was found and

[37] A complete review of the results of study three can be found in Oberle, Sommer, and König (2017).

thus the hypothesis remains unconfirmed. Otherwise, analysis of the questionnaire data showed a high subjective preference of *Feedback2* over *Feedback1*.

6.4 Discussion of Results of Study Three

Concluding, the study shows that through the implementation of appropriate feedback the resulting human induced uncertainty can be affected and respectively reduced. Thereby, enhancing the amount of information concerning an HMI lead to a decrease of uncertainty.
However, it should be noted that mere enhancement of the amount of information may also lead to an increase of complexity and likewise uncertainty. Thus, the importance of human-centered feedback-design is highlighted.

6.5 Summary of Chapter 6

Within chapter 6, a brief review of study three was given. Thereby, the task of stacking two weights on a tripod with varying types of feedback was to evaluate the possible impact of appropriate interaction design onto human induced uncertainty. The study was successful and confirmed the positive impact of feedback onto the reduction of uncertainty.
Concluding, study three adds to the third research question concerning possible means to control uncertainty by introducing the possibility to actively design human-machine interfaces for the reduction of uncertainty.

7 Discussion and Conclusion

Following, the results of the present work are discussed. As the specific results of the studies were already discussed in the chapters 4.7, 5.7 and 6.4, the following chapter concentrates on a general discussion of the applicability of the HUMEAn as well as limitations of the method and the used methodological approach. First, the applicability of the human uncertainty modes and effects analysis, based on the conducted studies, is discussed. Second, the limitations of the HUMEAn are debated. Third and last, the present work is concluded.

7.1 Discussion on the Applicability of HUMEAn

Based on the studies described within this work, a general applicability of the developed method is confirmed. Thereby, the results depict the possibility to quantify the amount of human induced uncertainty, especially regarding the studies one and two (see chapters 4 and 5). Further, it is confirmed that the human induced uncertainty can be ascribed to specific influencing factors, allowing for a prediction of uncertainty if the identified factors are known. Thereby, the approach of the HUMEAn for the reduction of possible influencing factors based on task characteristics holds validity. Based on the results of the HUMEAn, suggestions for the reduction and control of human induced uncertainty through selection, training or, as exemplified with study three, through appropriate interface design can be derived.

An interesting result of all studies was the fact that the resulting human induced uncertainty was represented by a lognormal distribution. As discussed before, this circumstance is first only supported in case of an existing zero-point for the resulting system stress.

Even though a quantification of the impact of the human sub-processes *choice of action* and *execution of action* onto the human induced uncertainty was possible within the second study, the human influencing factors were found to affect the human induced uncertainty far more effectively. Additionally, the human influencing factors were found to have a high impact on *execution of action*, whereas the prior sub-process *choice of action* showed only a marginally effect. Generally, this is positive for applicability, as knowing the influence of human factors facilitates prediction prior to an observation. Predictions may therefore be done independently of an analysis. On the other hand, this may indicate a false selection of parameters for the description of the inherent uncertainty of the two human sub-processes.

Another explanation for the fact that the human sub-processes were less relevant for the overall human induced uncertainty within study two in comparison to the direct impact of the human influencing factors may be reasoned with the general complexity of the observed task. As the main task was subdivided into several subtasks, both, *choice of action* and *execution of action*, were represented through the single subtasks. Thus, confounding of the overall impact of the sub-processes in comparison to the impact of single and specific subtasks seems probable. At this, the concept of Markov models was successfully applied to describe and quantify the uncertainty within the human sub-process *choice of action*. Also, a relation between action patterns and personal traits was found and within four states of the assessed Markov model predictors for the resulting stress on touchdown were identified. The latter supports the hypotheses that for a sequence of actions, single sub actions have a higher explained contribution to human induced uncertainty than the overall parameters of human sub-processes.

Additionally, the further application of the HUMEAn to investigate the impact of feedback highlights the importance of adequate information exchange between human and machine regarding uncertainty. Thus, implementation of appropriate feedback, designed specifically regarding the needs of an operator and the related task, results into a significant reduction of human induced uncertainty. The positive influence of feedback onto HMI is not a novelty and thus already addressed within the literature (e.g. Degani, 2004; Dismukes, 2010; Johnson, 2003; Norman, 1990; Wickens et al., 2014). The evaluation with HUMEAn allows for a quantification of the impact of appropriate feedback design. Even though prediction of human induced uncertainty based on mode of uncertainty or even regarding the impact of specific influencing factors allows for measures like prior selection or adequate training of operators, the use of appropriate feedback represents an easy and holistic approach. As feedback was found to reduce uncertainty independently of further influencing factors, appropriate interface design may lead to a general reduction of uncertainty without prior investigations. Of course, a prior analysis of the human influence may positively affect the appropriate design and successful implementation of feedback and information systems. Therefore, a combination of both approaches seems most promising for a reduction of uncertainty.

The conducted studies and their findings are valid for the observed tasks, within the specific environments and regarding the employed population of subjects. The applicability of the results to real tasks without a controlled field has yet to be evaluated, but can be expected to yield different results due to further influences onto task execution. This represents one limitation of this work's results and is discussed in detail within the following chapter.

7.2 Limitations of HUMEAn and the methodological approach

As indicated above, the work so far focused on laboratory studies including selective samples for the controlled assessment of uncertainty. Thus, the findings are valid for the investigated tasks, study conditions and subject populations. For example, when changing weather conditions of study two to windy and clouded, different results for uncertainty are to be expected, even when investigated with the same flight simulator. As this was a necessity to allow the measurement of the impact of single influencing factors onto human induced uncertainty, further field applications of the approach need to regard a higher number of factors, which would increase complexity. Transferability of the proposed approach for the assessment of human induced uncertainty within field investigations has to be evaluated.

Further, systemic investigations are generally limited to the inherent simplification of an observation, as stated in chapter 2.1 when defining the concept of systems. Thus, simplifications represent a necessary evil. Without simplifications, investigations would need to include every detail and aspect, resulting in unmeasurable complexity. On the other hand, simplification always results into a loss of information. Regarding the HUMEAn, the reduction of human influencing factors according to a selected uncertainty mode holds the danger to erroneously neglect an import factor. Regarding the studies, influence of the selected factors was assessed and confirmed or refused. But this does not eliminate the possibility that a neglected factor might also contribute to human induced uncertainty. Still, verification is only possible by conducting a study involving all influencing factors, which contradicts the approach of this work to facilitate uncertainty investigation and finally leads to an impossible study design due to an untreatable sample size. As the studies showed, application of the developed method for the reduction of the experimental complexity is valid. Expansion of the number of selected influencing factors is therefore only necessary, if no effect on the human induced uncertainty is assessable based on the initially selected factors.

Concerning the model for the description of human induced uncertainty (see Figure 3-6), the contained influencing factors represent a first accumulation of possibly relevant factors. As argued in chapter 2.4, more influencing factors can possibly be added to the model, especially for the environment which was of minor importance for the present work. Also, additional distinction and definition of the influencing factors are possible. Furthermore, the inherent relations and interdependencies of the influencing factors remain disregarded so far. Systematic investigation of those interdependencies could lead to supplemental insights concerning possible immediate or intermediate effects between the factors and thus onto uncertainty. Still, the presented model and the derived HUMEAn represent a first, valid approach for the systematic assessment of human induced uncertainty.

7.3 Conclusion

The present work focused on the investigation of the human impact onto the uncertainty of human-machine interaction. After an initial literature research, certain deficits concerning the knowledge about the human contribution to uncertainty were identified as represented by the following research questions:

1. How can human induced uncertainty be characterized?
2. How can human induced uncertainty be assessed and quantified methodically?
3. How can human induced uncertainty be controlled?

For the characterization of human induced uncertainty, a descriptive model was developed including a total of 67 influencing factors allocated to specific model elements. Based on the model, the methodological approach of the human uncertainty modes and effects analysis was derived. The HUMEAn allows for the selection of an uncertainty mode as well as the selection of predominant influencing factors based on the type of investigated task.
Based on the HUMEAn, the human induced uncertainty for the task of placing weights onto a tripod was assessed and successfully quantified within a first study. Thereby, several influencing factors, like strength, dexterity and placed weight, were identified as significant predictors for the resulting uncertainty. A second study was conducted for the application of HUMEAn for the investigation of the complex task of landing an airplane within a simulator. Based on the selected uncertainty mode, the variation of taken actions and the resulting sequence were successfully assessed through the development and use of a Markov model. Again, several influencing factors, like experience and fatigue, were identified as significant predictors of the resulting uncertainty. Additionally, specific Markov states were identified as predictors, too. At last, another study was conducted to quantify the impact of feedback onto the resulting human uncertainty. The findings implicate that appropriate feedback of the resulting system stress, which is designed according to the needs of an operator, results into a significant reduction of uncertainty. Appropriate feedback is thus found as a promising approach to reduce human induced uncertainty through a stronger involvement of the operator. Also, identified predictors onto human induced uncertainty can be manipulated, e.g. through intensive training or selection of operators, to treat and reduce uncertainty.
The present work further confirmed the working paradigm of the CRC 805 that uncertainty occurs in processes. This was shown especially with study two, where the resulting stress on the system could be

predicted by measures from the human sub processes of *choice of action* and *execution of action*. Thereby, the quantified uncertainty of the conducted studies confirms the general possibility for a structured and methodologic assessment of human induced uncertainty in relation to specific influencing factors.
The assumption that the human induced uncertainty is best characterized by a lognormal distribution in case of an existing absolute zero point for a system's stress remains valid and was supported by study one and two (see chapters 4.6.1 and 5.6.1). If approved prospectively, implications are essential for the work with human induced uncertainty, as resulting stress always incorporates a skewed distribution. Thus, high values of stress far off a regarded mean must be considered as probable, but may be characterized and calculated based on a lognormal distribution.
Further, the sole knowledge of the HUMEAn and the associated model represents an opportunity to treat and reduce uncertainty, especially for engineers not proficient with human factors. Through the definition of the observed task and the connected selection of the uncertainty mode, influencing factors are promoted and can be regarded with care during product development. Further, the overall model depicts the different sources of uncertainty and thus helps to understand the human contribution, negative as well as positive, to the resulting stress of technical systems and the underlying uncertainty.
In contrast to the concept of risk, dealing with and reducing uncertainty not solely focuses on (human) error, but further investigates the general human influence on a system's stress. Thereby, increasing knowledge about HMIs still leads to the reduction and prevention of errors but additionally sheds light onto the positive effects of the human part of HMIs. The concept of uncertainty therefore addresses a broader field than risk and its application on HMIs further contributes to the resilience of a system.

Concluding, the present work contributes to the treatment of uncertainty through the development of knowledge concerning the human influence on uncertainty of HMIs and further presents a new tool for the methodologic assessment, quantification and control of human induced uncertainty. With this, the stated research questions were treated successfully.
Still, the present work represents only a first contribution to the understanding of the human impact on uncertainty. Thus, new questions arose during the work, which are topic of the following chapter.

8 Implications for Future Work

Following, implications for the application of the findings of the present work and for future research discussed.

8.1 Implications for Application

Based on the conducted studies, first implications for the application can be derived. Thus, study one showed that the factors strength and dexterity affect predominantly physical tasks. Further, the importance of the task definition itself was shown. A reduction of human induced uncertainty can thus be achieved through proficient manipulation of a task's goal, like the content of instructions.
Regarding study two, the identified predictors based on the Markov model could be applied for the development of a feedback interface for pilots. Thereby, the interface could inform pilots whether the current state of the landing maneuver would probably lead to an increased stress of the system. Additionally, knowledge about the human influencing factors and their impact on uncertainty could be applied to discern different types of information presentation, e.g. based on the expertise of the current pilot. Unexperienced pilots would thus be presented with more information and possible countermeasures to reduce the resulting stress, whereat proficient pilots are confronted with less information, possibly increasing the acceptance of such a system.
Anyway, direct application of the study results and the identified predictors for uncertainty should be done with care due to the laboratory character. Besides this, further implications for the application of the present work's findings exist.

Besides the specific application of the assessed data within this work, generated data and predictors using the HUMEAn are applicable for several purposes. For example, found predictors based on human influencing factors could be used to specifically train possible operators of an HMI to achieve a reduction of uncertainty. Besides training, also the selection of operators may be a possible solution for high-risk environments and situations.
Furthermore, identified and proved influencing factors can be regarded within product design to eliminate possible influences. Independent of a human operator, predictors found within the three human sub-processes can be used to establish real-time feedback loops to further support the human operator. Appropriate feedback design and implementation may enable a human to positively contribute to uncertainty. Also, the design approach is independent of humans and with this interesting if prior training or selection of operators is impossible.
Additionally, results of uncertainty analysis can be transferred to other fields, like CAD construction (cf. Zocholl et al., 2015). Quantified human induced uncertainty can be used as input for FEM-analysis of a system's stress and thus introduce the option to simulate the human impact on uncertainty.

Further to the direct application of data assessed through HUMEAn, the development of a database for the accumulation and exchange of quantified human induced uncertainty is suggested. One source for uncertainty relies within the fact that for several influencing factors no comprehensive data exists or is accessible. Thereby, a database could contribute to the development of knowledge on several levels. For instance, a database would possess the possibility to easily add definitions or specify existing definitions of influencing factors, add information about their relation to other factors and facilitate the above-mentioned rating of inherent attributes. Further, conducted studies could be related to each observed influencing factor, including their impact on the quantified uncertainty. Thus, comparison of influencing factors and their overall importance and occurrence for specific uncertainty modes could be tracked, leading to additional insights concerning human induced uncertainty.

Apart from the above, the HUMEAn proved itself to be valuable for the planning and design of experimental studies. Based on this approach, consideration and operationalization of variables is facilitated and the chance to overlook relevant influencing factors for an experiment is reduced due to the catalogue of allocated factors.

8.2 Implications for Future Research

As discussed in chapter 7.2, the conducted studies are subject to limitations regarding the used sample size, restricted population and the general constraints of laboratory studies. Thus, repetition of the conducted experiments with an increased sample size to confirm the findings is suggested. Also, the expansion of the studies to involve a broader population would lead to a broader understanding of the human induced uncertainty. Finally, the transfer of the studies into real situations would lead to new insights. For example, the conduction of an experiment with real aircrafts under genuine conditions is suggested. Through comparison of the data assessed in the field to the data assessed under controlled laboratory conditions the general transferability of laboratory studies to genuine applications could be investigated.

Besides further studies to evaluate the findings of this work, additional studies should be conducted to further apply the method of HUMEAn on different tasks. Especially the investigation of tasks relating to the human sup-process of *perception* remain disregarded. So far, the applicability of the HUMEAn for such task types remains unsettled. Same applies to tasks related to *choice of action*, which are not subdivided into single subtasks. Also, an application to investigate the uncertainty of creative tasks constitutes an interesting yet challenging topic for further research, because in this case nearly all influencing factors must be regarded. Successful application for creative tasks would further allow for an expansion of HUMEAn to the phase of product development. Additionally, further studies are needed to investigate whether the lognormal distribution of human induced uncertainty remains unchallenged and can thus be raised to a new paradigm.

The influencing factors represent another field for prospective research. Further possibilities for the categorization of influencing factors are imaginable. As noted in chapter 2.4, the factors could be arranged according to a primary or secondary effect on human induced uncertainty. Therefore, the interdependencies between the influencing factors need to be addressed and clarified in detail.

Diversification of the environmental factors regarding the current group of social factors is suggested. New aspects like team work or a distinction into organizational, individual and cultural aspects seem reasonable and were only postponed due to the focus on the human contribution to uncertainty.

Also, categorization of all influencing factors in compliance with their specific attributes could lead to an improved knowledge of uncertainty[38]. Additional attributes of the influencing factors could be their

[38] A first investigation of such an approach was already tried within the student work of Stolz (2015). Findings depicted that the derived categories are generally reasonable, but allocation of each influencing factor failed due to the complexity to rate each factor within all categories.

measurability, the amount of information known about a specific factor (existing studies, possible distribution within a specific population) and the external suggestibility.

Another possibility for further research is the transfer of the HUMEAn for the assessment of human induced uncertainty for the phase of product manufacturing. Therefore, characterization of the uncertainty for the human sub-process *execution of action* could be applied on predetermined motion time systems, like MTM UAS. Instead of focusing on the defined time values, a quantification of human induced uncertainty for each basic motion could be investigated. For example, the component "grab" could be investigated regarding specific characteristics and their relation to the resulting uncertainty based on different parameters like weight, shape or texture of the grabbed object. In case quantification of uncertainty would be successful, such predetermined motion time systems could be expanded to include predictors for human induced uncertainty for each basic motion in addition to the predetermined time values, allowing for a prior estimation of uncertainty during construction planning. Still, extraction of uncertainty for single motions seems difficult due to the varying execution and influences between different individuals.

A further field of research is represented by the detailed investigation of feedback for the treatment and reduction of human induced uncertainty. Besides additional studies to confirm the positive effect of feedback onto uncertainty, a systematic approach for the development of an uncertainty-driven and human oriented product development process is suggested. Through systematic variation of interface designs, the uncertainty of specific concepts could be quantified with the help of the HUMEAn. Also, the impact of certain influencing factors onto the understanding of feedback could lead to new insights. Based on such studies, successful design elements and human-machine interfaces could be identified, abstracted and lastly transformed into a methodological approach for the derivation of design measures.

Regarding the work of the CRC 805, two additional topics for prospective research exist. First, the latest version of the process model of the CRC 805 could be combined with the model for the description of human induced uncertainty to further consider working appliances (see chapter 3.2.2). Thus, investigation regarding the influence of working appliances onto the human induced uncertainty can be conducted. Second, a holistic investigation of uncertainty of HMIs regarding all elements (human, environment and technical subsystem) has yet to be conducted. Even though this represents a challenging approach due to the multitude of involved influencing factors and thus would need careful planning and preparation.

Finally, further research for an uncertainty unrelated topic is proposed. Within the first study, the data of the Box-and-Block Test, which was used to assess the dexterity of the subjects, showed a significant offset to the table data attached to the BBT (see chapter 4.7). It was discussed that this effect could be related to a decrease of manual dexterity of present generations in comparison to the data assessed 30 years past. Therefore, conduction of a study to investigate whether the table data of the BBT continues to be valid for present generations as well as for women is suggested.

Concluding, the present work represents a small contribution to the development of knowledge concerning human induced uncertainty, its assessment and its treatment. No matter how much studies are conducted and influencing factors investigated, in the end, uncertainty will prevail. As initially stated by David Hume:

> "All knowledge resolves itself into probability."
>
> \- David Hume (*A treatise of Human Nature*, 1739)

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A Operationalization of Variables for Study One

Type	Variable	Measurement Method	Unit/ Categories	Scale
Independent	Placing Weight	Active Variation	1 kg; 3 kg	Nominal
	Instruction	Active Variation	centrally; softly; centrally & softly	Nominal
	Arm Strength in A+	Force Measurement Rig	N	Ratio
	BBT-Score	Box-and-Blocks Test	Transitions in 60 seconds	Ratio
	Hotwire Rank	Hotwire Apparatus	Rank of Time and Errors	Ordinal
Dependent	Mean of Fmax over all 6 runs	Tripod - Force Sensors	N	Ratio
	Std. deviation of Fmax over all 6 runs	Tripod - Force Sensors	N	Ratio
	Mean of Eccentricity over all 6 runs	Tripod - Calculation through force distribution	cm	Ratio
	Std. deviation of Eccentricity over all 6 runs	Tripod - Calculation through force distribution	cm	Ratio
Covariate	Age	Questionnaire	Years	Ratio
	Body Weight	Questionnaire	kg	Ratio
	Body Height	Questionnaire	cm	Ratio
	Sporting Activity	Questionnaire	no sport; monthly; weekly; daily	Ordinal
	Sporting Activity Today	Questionnaire	Yes; No	Nominal
	Caffeine Consumption Today	Questionnaire	Yes; No	Nominal
	Perceived Effort	Questionnaire	7-pointed Likert Scale	Ratio
	Perceived Concentration	Questionnaire	7-pointed Likert Scale	Ratio
	Perceived Motivation	Questionnaire	7-pointed Likert Scale	Ratio
	Pedestal Height	Direct Measurement	cm	Ratio
	Initial Task	Checklist	A, B, C, D, E or F	Nominal
	Degree Program	Questionnaire	Text	Nominal

B Questionnaire of Study One

Laufnummer	001	Name	
Datum		Alter	
Gewicht		Größe	

1. Probandencode

Um die beantworteten Fragen später den entsprechenden Messwerten aus dem Versuch zuordnen zu können, wird jedem Probanden ein individueller Probandencode zugewiesen. Des Weiteren kann dadurch in Zukunft festgestellt werden, ob der Proband an weiteren Versuchen am Dreibein teilnimmt. Durch den Probandencode kann nicht auf die Identität des Probanden geschlossen werden.

1. Bitte gebe die letzten beiden Buchstaben des Vornamens deiner Mutter an.
   Beispiel: Ihre Mutter heißt Sandra. Bitte gebe „ra" an.

   ____

2. Bitte gebe den Tag an, an dem du geboren wurdest.
   Beispiel: Du wurdest am 08.12.1989 geboren. Bitte gebe „08" an.

   ____

3. Bitte gebe die ersten beiden Buchstaben deines Geburtsortes an.
   Beispiel: Du wurdest in Darmstadt geboren. Bitte gebe „Da" an.

   ____

2. Fragebogen: Vor dem Versuch

1. Treibst du regelmäßig Kraft- und/oder Ausdauersport?

   ☐ Ja, täglich

   ☐ Ja, wöchentlich

   ☐ Ja, monatlich

   ☐ Nein

2. Hast du heute Sport betrieben?

   ____

3. Hast du heute Koffein oder ähnliche Mittel zu dir genommen?

   ☐ Ja:

   ☐ Nein

4. Hast du körperliche Einschränkungen?

   ☐ Ja:

   ☐ Nein

Laufnummer 001 | Datum: 1

5. Wie bist du auf uns aufmerksam geworden?
   ☐ Plakat
   ☐ Flyer
   ☐ persönlicher Kontakt
   ☐ Soziale Netzwerke
   ☐ Sonstiges

6. Was studierst du?
   ____

7. Hast du bereits an einem Dreibein Versuch teilgenommen?
   ☐ Ja
   ☐ Nein

3. Nach dem 2. Durchgang

Wie anstrengend findest du den Versuch bisher?

gar nicht anstrengend — sehr anstrengend

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie konzentriert bist du auf den Versuch?

gar nicht konzentriert — sehr konzentriert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie motiviert bist du, den Versuch weiterzuführen?

gar nicht motiviert — sehr motiviert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

4. Nach dem 4. Durchgang

Wie anstrengend findest du den Versuch bisher?

gar nicht anstrengend — sehr anstrengend

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie konzentriert bist du auf den Versuch?

gar nicht konzentriert — sehr konzentriert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie motiviert bist du, den Versuch weiterzuführen?

gar nicht motiviert — sehr motiviert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Laufnummer 001 | Datum: 4

5. Nach dem 6. Durchgang

Wie anstrengend findest du den Versuch bisher?

gar nicht anstrengend — sehr anstrengend

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie konzentriert bist du auf den Versuch?

gar nicht konzentriert — sehr konzentriert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

Wie motiviert bist du, den Versuch weiterzuführen?

gar nicht motiviert — sehr motiviert

O	O	O	O	O	O	O
1	2	3	4	5	6	7

C Checklist and Additional Material for Study One

1. Vorbereitungen für Probanden

Geschicklichkeitstests
- ☐ Kamera für den BBT ausrichten.
- ☐ Kamera für den Hotwire ausrichten.
- ☐ Alle Blöcke auf eine Seite bringen.
- ☐ Zähler auf null stellen.

CAPTIV
- ☐ Desinfizieren aller Geräte/Sensoren.
- ☐ Sensoren anschalten.
- ☐ Zuordnung der Sensoren zu den T-LOG Kanälen.
- ☐ Sensornummer und zugeordneter Kanal notieren.
- ☐ Hansaplast-Streifen vorbereiten

Sensornummer	Nummer in T-Log
Kraftsensoren	
FS-0069	
Bewegungssensoren	
MO-0148	
MO-0150	
MO-0151	
MO-0152	
Pulsmessgerät	
CF-0081	
Beschleunigungssensor	
AC-0064	

Allgemein
- ☐ Schild raushängen.
- ☐ Auf Ordnung im Labor achten: Stehen die Stühle richtig? Ist aufgeräumt?

Probandencode: ___________________________-

Laufnummer 006 | Datum: 1

2. Einführung des Probanden

- ☐ Begrüßung des Probanden, Vorstellung (Eric, Jan, Sylvia)
- ☐ „Bist du Rechtshänder und zwischen 20 und 24 Jahre alt?"
- ☐ Den Proband darauf hinweisen, dass es Kekse und etwas zu trinken gibt.
- ☐ „Mach es dir bequem, deine Tasche kannst du hier abstellen."
- ☐ Einverständniserklärung
- ☐ „Jetzt werde ich dir kurz etwas zum Versuch erzählen. Du wirst heute mehrere kleinere Versuche durchführen. Dazu gehören das Kraftmessgestell, das Dreibein und der Hot-Wire- sowie der Box-Block-Test.
  Der Sonderforschungsbereich 805 untersucht die Unsicherheit in lasttragenden Systemen des Maschinenbaus. Wenn Unsicherheit beherrscht werden kann, kann auch die Qualität der Produkte erhöht werden. Unsicherheit ist ein Phänomen, das überall vorkommt. Unsicherheit bedeutet nichts anderes als einen Mangel an Informationen. Das IAD betrachtet dabei die Unsicherheit im menschlichen Handeln. Deswegen machen wir heute einen Versuch, um die Unsicherheit quantifizieren zu können. Ihr leistet also mit eurer Teilnahme einen Beitrag zur Beherrschung der Unsicherheit im Maschinenbau. Das Ziel unserer Bachelorarbeiten ist es, verschiedene menschliche Einflussgrößen (Kraftvermögen, Armbewegung, Geschicklichkeit) und deren Wirkung auf die Belastung des Dreibeins zu untersuchen. Hast du noch Fragen dazu?"
- ☐ „Bist du bereit ununterbrochen den ca. 50-minütigen Versuch durchzuführen oder möchtest du vor dem Versuch auf die Toilette?"
- ☐ „Schalte bitte dein Handy jetzt auf lautlos."

Laufnummer 006 | Datum: 2

3. Kraftmessgestell

- ☐ Begrüßung des Probanden und Präsentation des Kraftmessgestell
- ☐ Die Höhe der Querstrebe an den Probanden anpassen
- ☐ Achten, dass der Proband nicht das Kabel der Sensoren berührt
- ☐ Ellenbogen im 90°, Unterarm senkrecht zum Oberkörper und gerader Rücken
- ☐ Entfernung zwischen Proband und Sensorik überprüfen
- ☐ Anweisung an Proband:
  „Bitte mit maximaler Kraft und festem Zugreifen in Richtung A+/C+ drücken. Dabei die Kraft nur aus der Arm und nicht aus dem Oberkörper nehmen, d.h. der Körper sollte sich nicht bewegen. Maximalkraft bedeutet, dass es unangenehm ist, aber nicht weh tut."
- ☐ Rückfragen vom Probanden beantworten
- ☐ Beim WIDAAN Client auf „Start" klicken (Proband 1, aufrecht A+, Messung 4s)
- ☐ Nach der Messung öffnet sich wieder ein neues Fenster → Tabelle schließen

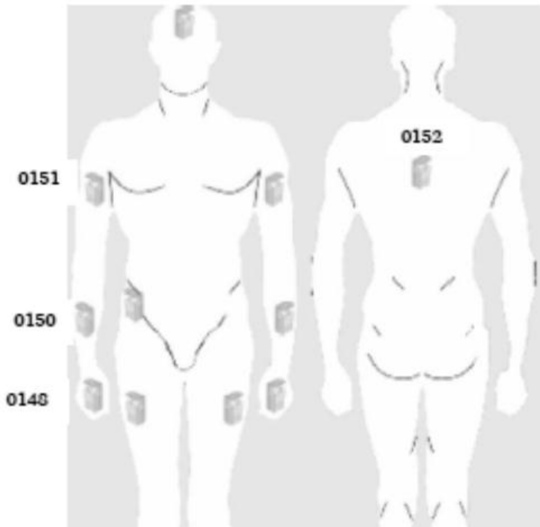
- ☐ Name der abgespeicherten Datei für A+ notieren

- ☐ Zurückkehren zum WIDAAN Client
- ☐ Beim WIDAAN Client auf „Start" klicken (Proband 1, aufrecht C+, Messung 4s)
- ☐ Nach der Messung öffnet sich wieder ein neues Fenster → Tabelle schließen

- ☐ Name der abgespeicherten Datei für C+ notieren

4. Captiv-System

	Anbringen des Captiv-Systems	Erledigt?
1	Anbringen des Pulsmessgeräts an der Brust mit Fixierung	
2	Befestigen der Kraftsensoren mit Textilhautklebeband (sensitiv)	
3	Keine Knicke im Kabel, nicht zu straff	
4	Prüfen, ob Kupplungsstellen der Sensorkabel isoliert sind	
5	Handschuh anziehen	
6	Prüfen, ob Sensornummer notiert ist.	
7	Sensoren befestigen - Nacken - Oberarm -Unterarm -Hand	
8	Beschleunigungssensoren an Gewichte anbringen	
9	Auf aufrechte Körperhaltung achten, entspannte Hand - Kalibrieren	



5. Dreibein

- ☐ Position der Beine überprüfen und Anweisungen auf Bildschirm anzeigen lassen.
- ☐ Begrüßung des Probanden am Versuchsstand. Wenn alles in Ordnung ist, wird die Tür geschlossen.
- ☐ Versuchsleiter: „Bevor wir mit dem Versuch beginnen, muss der Versuchstisch an deine Körpermaße angepasst werden."
- ☐ Versuchsleiter: „Stell dich bitte mit der rechten Seite zum Stab an den Versuchstisch."
- ☐ Nun wird die Verstellung des Podestes in z-Richtung vorgenommen. Dazu wird der vertikale Abstand zwischen der Tischplatte und der Unterkante des Handgelenkes des Probanden mit Hilfe eines Messstabs bestimmt.
  Versuchsleiter: „Winkel den Unterarm in einem 90° Winkel an." Am Messstab kann direkt die notwendige Podesthöhe abgelesen werden.

  Podesthöhe ☐

- ☐ Versuchsleiter: „Anschließend streckst du deinen Arm auf Schulterhöhe aus und entfernst dich soweit vom Tisch (in x-Richtung), dass du den Stab bequem greifen kannst."
- ☐ Die Abstandsvorrichtung des Versuchsstandes mit dem Laser wird nun so weit ausgefahren, dass der Laserstrahl die Fußspitzen des Probanden berührt.
- ☐ Nun stellt der Versuchsleiter das Podest in x- und z-Richtung anhand der vorher bestimmten Werte ein. Die Abstandsvorrichtung wird wieder in ihre Ausgangsposition gebracht.

- ☐ Versuchsleiter: „Nun beginnt der Hauptversuch. Bitte stell dich so auf das Podest, dass deine Fußspitzen die rote Markierung berühren. Die Anweisungen werden dir auf dem Monitor angezeigt. Starte erst, wenn ich „los" sage. Danach hast du 10 Sekunden Zeit, die Masse abzustellen. Es gibt 6 Anweisungen, die jeweils 6 Mal ausgeführt werden. Für das Auflegen und Abstellen geben wir dir jedes Mal ein Signal. (Auflegen und Ablegen der Gewichte nur bei ‚Ready'. Bei ‚Please wait' keine Aktion vornehmen.)

- ☐ Rückfragen des Probanden beantworten.
- ☐ T-Log Hauptmenü: Record Data on SD Card → Record
- ☐ Kamera anschalten.

- ☐ Laufnummer in die Kamera halten.

- ☐ Für 4s möglichst fest die Hantel am Griff packen (Maximal beim Zupacken)

- ☐ Flash zum Synchronisieren auslösen und in die vordere Kamera halten.
- ☐ Die Software GSVReVis öffnen → Settings → Path, File Name einstellen → Measurment → Start measuring → Recording (ab jetzt speichert das Programm die Datei) → „Los!" → nach 10 Sekunden: „Jetzt abstellen bitte."

- ☐ Zum Beenden Recording drücken

- ☐ „Gewicht runternehmen bitte." → Zurück zu 8. → Settings (2. Messung startet)

	Aufgaben nach dem Versuch	Erledigt?
1	Flash an T-Log erneut auslösen und in vorderne Kamera halten	
2	Aufnahme stoppen	
3	Kameras ausschalten	
4	Daten von Kamera und T-Log auf PC übertragen	
5	Sensoren abnehmen	

	1kg	Anzahl	3kg	Anzahl
sanft	A		D	
mittig	B		E	
sanft und mittig	C		F	

6. Box-Block-Test

	Aufgaben vor dem Versuch	Erledigt?
1	Alle Blöcke auf die rechte Seite bringen (unsortiert) – nicht stapeln!	
2	Prüfen, ob die Videokamera ausgerichtet ist	
3	Box muss mittig stehen	

- ☐ Prüfen, ob der Abstand zur Box stimmt: „Strecke bitte deine Arme aus!“
- ☐ „Wir testen beim Box Block Test deine Geschicklichkeit. Ziel ist es, die Blöcke so schnell wie möglich auf die andere Seite zu bringen.“
- ☐ „Heb‘ einen Block auf die andere Seite der Box und lass ihn dort fallen. Achte darauf, dass deine Fingerspitzen die Trennwand überqueren. Schau, ich zeige es dir.“ (Der Versuchsleiter zeigt es dem Probanden und hebt 3 Blöcke über die Trennwand.)
- ☐ „Wenn du mehrere Blöcke gleichzeitig rüberbringst, wird dies als ein Block gewertet. Wenn du Blöcke unabsichtlich auf den Boden fallen lässt, nachdem du sie über die Trennwand gehoben hast, zählen diese trotzdem. Verschwende keine Zeit damit diese aufzuheben. Wenn du Blöcke auf die andere Seite bringst ohne dass die Fingerspitzen die Trennwand überqueren, zählen diese Blöcke nicht. Bevor wir beginnen kannst du 15 Sekunden üben. Hast du noch Fragen?”
- ☐ „Leg die Hände links und rechts neben die Box. Beim Versuch bleibt die linke Hand bitte links neben der Box liegen. Zum Testbeginn sage ich zuerst ‚Fertig‘ und danach ‚Los‘.“
- ☐ Der Proband hat nun 15 Sekunden Zeit zu üben. Falls er dabei Fehler macht, so korrigiert der Versuchsleiter diese.
- ☐ Videokamera einschalten. Probandennummer auf dem Zettel in die Kamera halten.
- ☐ „Der Test beginnt jetzt und dauert 60 Sekunden. Es gelten die gleichen Anweisungen wie bei der Übung. Sei so schnell, wie du kannst. Fertig? Los!“ – Nach einer Minute: „Stopp“.

	Aufgaben nach dem Versuch	Erledigt?
1	Notieren, wie oft der Proband den Übergang gemacht hat	
2	Notieren, wieviele Klötzchen er rübergebracht hat	
3	Videokamera ausschalten	

Anzahl der Übergänge	
Anzahl der Blöcke	

Laufnummer 006 | Datum: 6

7. Hot-Wire-Test

- ☐ Prüfen, ob Kamera ausgerichtet ist.
- ☐ USB-Stecker an Hotwire und an den Laptop anschließen.
- ☐ Excel Tabelle öffnen und „Inhalt aktivieren“ oben im Fenster drücken.
- ☐ 2-3 Mal den obersten Schalter drücken, bis „Tasten rücksetzen“ steht.
- ☐ „Das Ziel ist es, die Öse so schnell wie möglich vom Anfang bis zum Ende des Drahtes zu führen und den Draht möglichst nicht zu berühren. Es wird dabei die Zeit und die Anzahl der Fehler gemessen. Bei einem Kontakt ertönt ein Signal. Die Zeit startet, sobald du den Startkontakt berührst und endet, sobald du den Endkontakt berührst.“ (Versuchsleiter zeigt dem Probanden die Start- und Endkontakte.)
- ☐ „Setz‘ dich bitte hin und strecke deinen Arm auf Schulterhöhe aus. Dein Arm sollte auf Höhe des Drahtes zwischen den Höckern des Kamels liegen. Ist das nicht der Fall, so kannst du den Stuhl hoch oder runterstellen.“
- ☐ „Achte bitte darauf, dass du den Startkontakt und den Endkontakt nicht zu lange berührst, da sonst das Programm spinnt. Ich sage dir Bescheid, ab wann du anfangen kannst. Hast du noch Fragen zum Vorgehen?“
- ☐ Kamera einschalten.
- ☐ „Du kannst jetzt anfangen.“
- ☐ Nachdem der Proband fertig mit dem Test ist, „Ergebnis abspeichern“ drücken.

	Aufgaben nach dem Versuch	Erledigt?
1	Zeit notieren	
2	Berührungen mit dem heißen Draht notieren	
3	Stab wieder an Anfang zurückführen	
4	Videokamera ausschalten	

	1	2	3	4	5	6
Zeit						
Anzahl der Fehler						
Auf Hotwire angezeigte Nummer						
Auf Hotwire angezeigte Zeit						

- ☐ Vergütungsbestätigung unterschreiben lassen
- ☐ Präsent übergeben

8. Nachbereitungen Proband:

Allgemein

- ☐ Schild abhängen.
- ☐ Laufzettel einheften.
- ☐ Vergütungsbestätigung einheften.
- ☐ Einverständniserklärung einheften.
- ☐ Digitalisieren der Laufzettel.

Geschicklichkeitstests

- ☐ Videos speichern und benennen.

Krassmessgestell

- ☐ Widaan-Daten auf externen Speichergerät sichern

D Additional Test-tables and Figures for Study One

Test of Normality of the four dependent variables

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Mean of Fmax over all 6 runs [N]	,158	348	,000	,701	348	,000
Std. deviation of Fmax over all 6 runs [cm]	,184	348	,000	,720	348	,000
Mean of Eccentricity over all 6 runs [N]	,269	348	,000	,469	348	,000
Std. deviation of Eccentricity over all 6 runs [cm]	,266	348	,000	,517	348	,000

a. Lilliefors Significance Correction

Test of normality for Ln(AVs)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ln(Mean of Fmax over all 6 runs [N])	,034	305	,200*	,996	305	,723
Ln(Std. deviation of Fmax over all 6 runs [cm])	,033	305	,200*	,993	305	,145
Ln(Mean of Eccentricity over all 6 runs [N])	,034	305	,200*	,994	305	,326
Ln(Std. deviation of Eccentricity over all 6 runs [cm])	,034	305	,200*	,994	305	,304

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Quantification of Uncertainty

Check Strength Measurement

Correlation A+ vs. C+

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
F_rightArm_A+	,067	42	,200*	,987	42	,917
F_rightArm_C+	,121	42	,128	,975	42	,489

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Correlations

		F_rightArm_A+	F_rightArm_C+
F_rightArm_A+	Pearson Correlation	1	,551**
	Sig. (2-tailed)		,000
	N	42	42
F_rightArm_C+	Pearson Correlation	,551**	1
	Sig. (2-tailed)	,000	
	N	42	42

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

Correlation single-handed vs. two-handed

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
F_rightArm_A+_twoHands	,123	16	,200*	,939	16	,341
F_rightArm_A+_oneHand	,147	16	,200*	,933	16	,275

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Correlations

		F_rightArm_A+_twoHands	F_rightArm_A+_oneHand
F_rightArm_A+_twoHands	Pearson Correlation	1	,911**
	Sig. (2-tailed)		,000
	N	16	16
F_rightArm_A+_oneHand	Pearson Correlation	,911**	1
	Sig. (2-tailed)	,000	
	N	16	16

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

Correlation A+ vs. Parasitic Forces

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
F_rightArm_kor_part	,055	58	,200*	,993	58	,985
F_rightArm_res_part	,052	58	,200*	,992	58	,964

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Correlations

		F_rightArm_kor_part	F_rightArm_res_part
F_rightArm_kor_part	Pearson Correlation	1	,998**
	Sig. (2-tailed)		,000
	N	58	58
F_rightArm_res_part	Pearson Correlation	,998**	1
	Sig. (2-tailed)	,000	
	N	58	58

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

Check Dexterity Measurement

Compare BBT-Score to Table-Data of Mathiowitz

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BBT-Score	,103	58	,198	,969	58	,150

a. Lilliefors Significance Correction

One-Sample Test

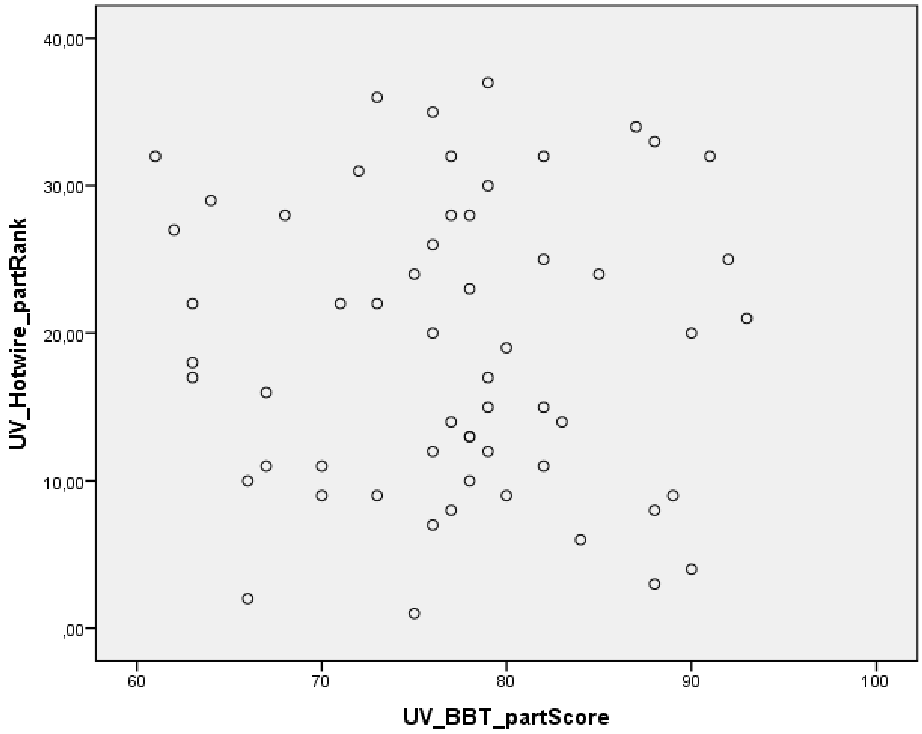
	Test Value = 88					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
UV_BBT_partScore	-10,055	57	,000	-10,914	-13,09	-8,74

Check influence of subject of study

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
BBT-Score	Equal variances assumed	1,783	,187	2,582	56	,012	5,358	2,075	1,201	9,516
	Equal variances not assumed			2,548	50,607	,014	5,358	2,103	1,136	9,581

Correlation between BBT and Hotwire



Correlations

			UV_BBT_partScore	UV_Hotwire_partRank
Spearman's rho	UV_BBT_partScore	Correlation Coefficient	1,000	-,036
		Sig. (2-tailed)	.	,788
		N	58	58
	UV_Hotwire_partRank	Correlation Coefficient	-,036	1,000
		Sig. (2-tailed)	,788	.
		N	58	58

Check for practicing effect

Practicing effect for eccentricity

Test Statistics[a]

N	337
Chi-Square	6,986
df	5
Asymp. Sig.	,222

a. Friedman Test

Practicing effect for Maximum Force

Test Statistics[a]

N	337
Chi-Square	8,618
df	5
Asymp. Sig.	,125

a. Friedman Test

Check for Effects form motivation, effort and concentration

Check for change of the factors

Descriptive Statistics

		Percentiles		
	N	25th	50th (Median)	75th
Effort_T1	58	1,00	1,50	2,00
Effort_T2	58	1,00	2,00	3,00
Effort_T3	58	2,00	2,00	3,00

Friedman Test

Ranks

	Mean Rank
Effort_T1	1,54
Effort_T2	2,05
Effort_T3	2,41

Test Statistics[a]

N	58
Chi-Square	43,197
df	2
Asymp. Sig.	,000

a. Friedman Test

Descriptive Statistics

	N	Percentiles		
		25th	50th (Median)	75th
Motivation_T1	58	5,00	6,00	7,00
Motivation_T2	58	5,00	6,00	7,00
Motivation_T3	58	5,00	6,00	7,00

Friedman Test

Ranks

	Mean Rank
Motivation_T1	2,18
Motivation_T2	2,05
Motivation_T3	1,77

Test Statistics[a]

N	58
Chi-Square	15,662
df	2
Asymp. Sig.	,000

a. Friedman Test

Impact of Influencing Factors on Strain

On Ln Mean Maximum Force

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Placing Weight	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Instruction_softly	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Change of Perceived Motivation	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	Mechanical Engineering Degree Progam vs. Others	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln(Mean of Fmax over all 6 runs [N])

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,484[a]	,235	,232	,38562	,235	100,818	1	329	,000
2	,499[b]	,249	,245	,38251	,015	6,376	1	328	,012
3	,545[c]	,297	,290	,37072	,048	22,198	1	327	,000
4	,554[d]	,307	,299	,36855	,010	4,855	1	326	,028

a. Predictors: (Constant), Placing Weight

b. Predictors: (Constant), Placing Weight, Instruction_softly

c. Predictors: (Constant), Placing Weight, Instruction_softly, Change of Perceived Motivation

d. Predictors: (Constant), Placing Weight, Instruction_softly, Change of Perceived Motivation, Mechanical Engineering Degree Progam vs. Others

e. Dependent Variable: Ln(Mean of Fmax over all 6 runs [N])

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14,992	1	14,992	100,818	,000[b]
	Residual	48,924	329	,149		
	Total	63,916	330			
2	Regression	15,925	2	7,962	54,421	,000[c]
	Residual	47,991	328	,146		
	Total	63,916	330			
3	Regression	18,976	3	6,325	46,025	,000[d]
	Residual	44,940	327	,137		
	Total	63,916	330			
4	Regression	19,635	4	4,909	36,139	,000[e]
	Residual	44,281	326	,136		
	Total	63,916	330			

a. Dependent Variable: Ln(Mean of Fmax over all 6 runs [N])

b. Predictors: (Constant), Placing Weight

c. Predictors: (Constant), Placing Weight, Instruction_softly

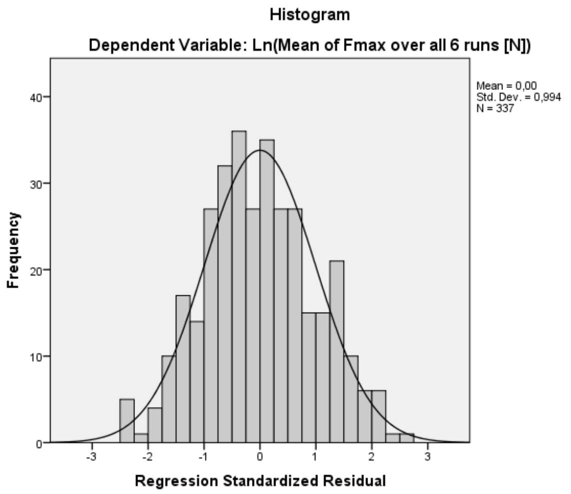
d. Predictors: (Constant), Placing Weight, Instruction_softly, Change of Perceived Motivation

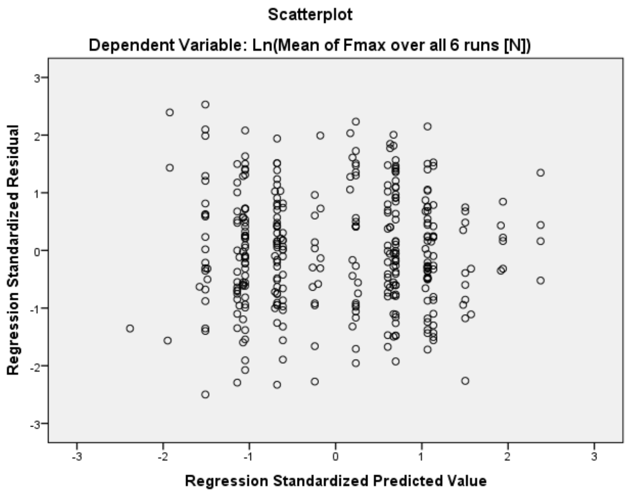
e. Predictors: (Constant), Placing Weight, Instruction_softly, Change of Perceived Motivation, Mechanical Engineering Degree Progam vs. Others

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	,533	,047		11,246	,000	,440	,626					
	Placing Weight	,213	,021	,484	10,041	,000	,171	,255	,484	,484	,484	1,000	1,000
2	(Constant)	,571	,049		11,571	,000	,474	,668					
	Placing Weight	,213	,021	,484	10,123	,000	,171	,254	,484	,488	,484	1,000	1,000
	Instruction_softly	-,113	,045	-,121	-2,525	,012	-,200	-,025	-,121	-,138	-,121	1,000	1,000
3	(Constant)	,529	,049		10,898	,000	,434	,625					
	Placing Weight	,213	,020	,484	10,445	,000	,173	,253	,484	,500	,484	1,000	1,000
	Instruction_softly	-,113	,043	-,121	-2,605	,010	-,198	-,028	-,121	-,143	-,121	1,000	1,000
	Change of Perceived Motivation	,114	,024	,218	4,711	,000	,066	,161	,218	,252	,218	1,000	1,000
4	(Constant)	,490	,052		9,511	,000	,389	,591					
	Placing Weight	,213	,020	,484	10,506	,000	,173	,253	,484	,503	,484	1,000	1,000
	Instruction_softly	-,113	,043	-,121	-2,621	,009	-,197	-,028	-,121	-,144	-,121	1,000	1,000
	Change of Perceived Motivation	,107	,024	,205	4,407	,000	,059	,154	,218	,237	,203	,983	1,018
	Mechanical Engineering Degree Progam vs. Others	,090	,041	,102	2,203	,028	,010	,171	,130	,121	,102	,983	1,018

a. Dependent Variable: Ln(Mean of Fmax over all 6 runs [N])





On Ln SD Maximum Force

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Placing Weight	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Arm Strength in A+ [N]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Instruction_softly	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	Change of Perceived Motivation	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln(Std. deviation of Fmax over all 6 runs [N])

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,390[a]	,152	,150	,47975	,152	57,955	1	323	,000
2	,405[b]	,164	,159	,47711	,012	4,586	1	322	,033
3	,418[c]	,175	,167	,47476	,011	4,197	1	321	,041
4	,434[d]	,188	,178	,47160	,013	5,319	1	320	,022

a. Predictors: (Constant), Placing Weight

b. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N]

c. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N], Instruction_softly

d. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N], Instruction_softly, Change of Perceived Motivation

e. Dependent Variable: Ln(Std. deviation of Fmax over all 6 runs [N])

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,339	1	13,339	57,955	,000[b]
	Residual	74,342	323	,230		
	Total	87,682	324			
2	Regression	14,383	2	7,191	31,592	,000[c]
	Residual	73,299	322	,228		
	Total	87,682	324			
3	Regression	15,329	3	5,110	22,670	,000[d]
	Residual	72,353	321	,225		
	Total	87,682	324			
4	Regression	16,512	4	4,128	18,561	,000[e]
	Residual	71,169	320	,222		
	Total	87,682	324			

a. Dependent Variable: Ln(Std. deviation of Fmax over all 6 runs [N])

b. Predictors: (Constant), Placing Weight

c. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N]

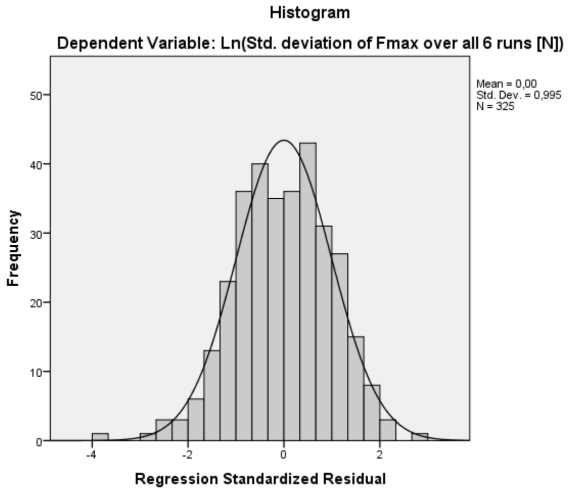
d. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N], Instruction_softly

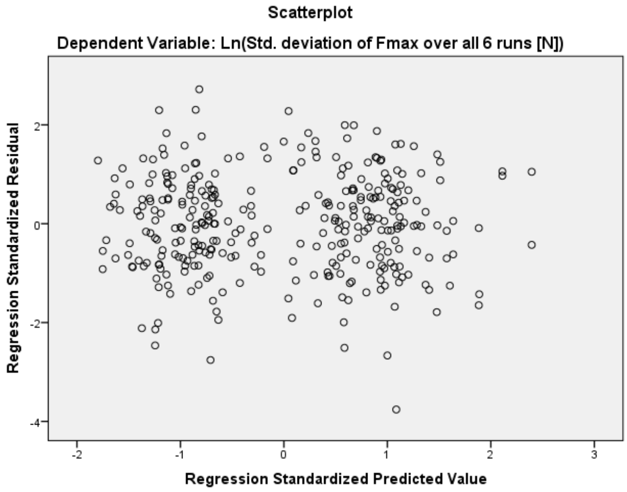
e. Predictors: (Constant), Placing Weight, Arm Strength in A+ [N], Instruction_softly, Change of Perceived Motivation

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,317	,060		-5,330	,000	-,434	-,200					
	Placing Weight	,203	,027	,390	7,613	,000	,150	,255	,390	,390	,390	1,000	1,000
2	(Constant)	-,570	,132		-4,314	,000	-,830	-,310					
	Placing Weight	,203	,026	,390	7,655	,000	,151	,255	,390	,392	,390	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,109	2,141	,033	,000	,002	,109	,118	,109	1,000	1,000
3	(Constant)	-,532	,133		-4,006	,000	-,794	-,271					
	Placing Weight	,203	,026	,390	7,693	,000	,151	,254	,390	,395	,390	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,109	2,152	,032	,000	,002	,109	,119	,109	1,000	1,000
	Instruction_softly	-,114	,056	-,104	-2,049	,041	-,224	-,005	-,104	-,114	-,104	1,000	1,000
4	(Constant)	-,528	,132		-3,997	,000	-,787	-,268					
	Placing Weight	,203	,026	,390	7,744	,000	,151	,254	,390	,397	,390	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,096	1,892	,059	,000	,002	,109	,105	,095	,987	1,013
	Instruction_softly	-,114	,055	-,104	-2,062	,040	-,224	-,005	-,104	-,115	-,104	1,000	1,000
	Change of Perceived Motivation	,072	,031	,117	2,306	,022	,011	,133	,128	,128	,116	,987	1,013

a. Dependent Variable: Ln(Std. deviation of Fmax over all 6 runs [N])





On Ln Mean Eccentricity

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Instruction_softly	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Arm Strength in A+ [N]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	BBT-Score	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	Age	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
5	Change of Perceived Effort	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln(Mean of Eccentricity over all 6 runs [cm])

Model Summary[f]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,377[a]	,142	,139	,39058	,142	52,915	1	320	,000
2	,401[b]	,160	,155	,38694	,019	7,044	1	319	,008
3	,425[c]	,181	,173	,38286	,020	7,837	1	318	,005
4	,464[d]	,216	,206	,37521	,035	14,106	1	317	,000
5	,478[e]	,229	,217	,37260	,013	5,442	1	316	,020

a. Predictors: (Constant), Instruction_softly

b. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N]

c. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score

d. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score, Age

e. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score, Age, Change of Perceived Effort

f. Dependent Variable: Ln(Mean of Eccentricity over all 6 runs [cm])

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8,072	1	8,072	52,915	,000[b]
	Residual	48,816	320	,153		
	Total	56,889	321			
2	Regression	9,127	2	4,563	30,479	,000[c]
	Residual	47,762	319	,150		
	Total	56,889	321			
3	Regression	10,276	3	3,425	23,367	,000[d]
	Residual	46,613	318	,147		
	Total	56,889	321			
4	Regression	12,261	4	3,065	21,774	,000[e]
	Residual	44,627	317	,141		
	Total	56,889	321			
5	Regression	13,017	5	2,603	18,752	,000[f]
	Residual	43,871	316	,139		
	Total	56,889	321			

a. Dependent Variable: Ln(Mean of Eccentricity over all 6 runs [cm])

b. Predictors: (Constant), Instruction_softly

c. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N]

d. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score

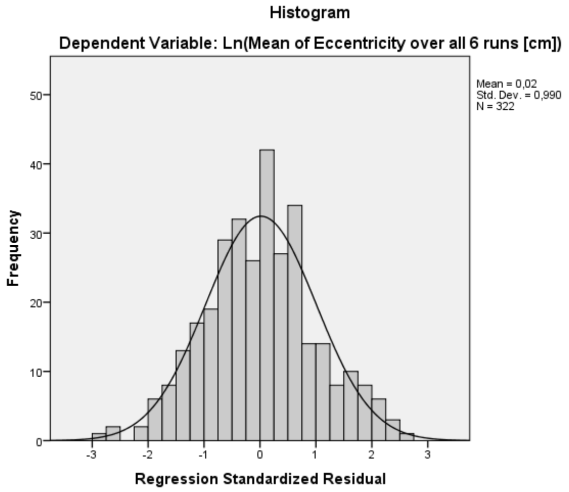
e. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score, Age

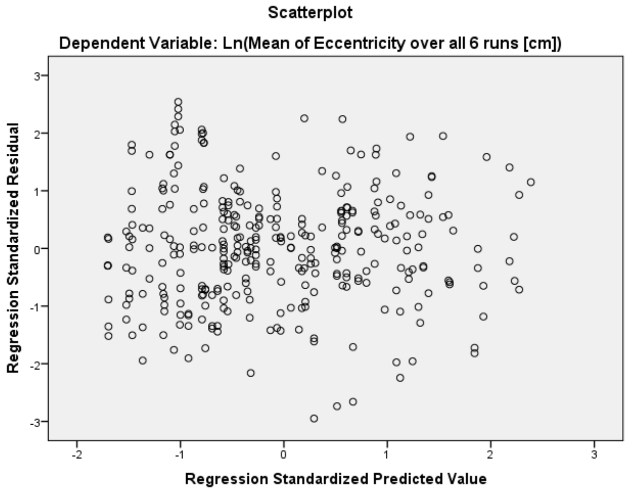
f. Predictors: (Constant), Instruction_softly, Arm Strength in A+ [N], BBT-Score, Age, Change of Perceived Effort

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-1,328	,027		-49,811	,000	-1,380	-1,275					
	Instruction_softly	,336	,046	,377	7,274	,000	,245	,427	,377	,377	,377	1,000	1,000
2	(Constant)	-1,584	,100		-15,856	,000	-1,780	-1,387					
	Instruction_softly	,336	,046	,377	7,343	,000	,246	,426	,377	,380	,377	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,136	2,654	,008	,000	,002	,136	,147	,136	1,000	1,000
3	(Constant)	-1,057	,212		-4,981	,000	-1,475	-,640					
	Instruction_softly	,336	,045	,377	7,421	,000	,247	,425	,377	,384	,377	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,159	3,095	,002	,000	,002	,136	,171	,157	,974	1,026
	BBT-Score	-,007	,003	-,144	-2,799	,005	-,013	-,002	-,119	-,155	-,142	,974	1,026
4	(Constant)	-,013	,347		-,038	,969	-,697	,670					
	Instruction_softly	,336	,044	,377	7,572	,000	,249	,423	,377	,391	,377	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,174	3,449	,001	,001	,002	,136	,190	,172	,968	1,033
	BBT-Score	-,007	,003	-,137	-2,708	,007	-,012	-,002	-,119	-,150	-,135	,973	1,028
	Age	-,049	,013	-,188	-3,756	,000	-,075	-,024	-,180	-,206	-,187	,991	1,009
5	(Constant)	-,139	,349		-,397	,692	-,825	,548					
	Instruction_softly	,336	,044	,377	7,625	,000	,249	,423	,377	,394	,377	1,000	1,000
	Arm Strength in A+ [N]	,001	,000	,175	3,482	,001	,001	,002	,136	,192	,172	,968	1,033
	BBT-Score	-,007	,003	-,129	-2,573	,011	-,012	-,002	-,119	-,143	-,127	,969	1,032
	Age	-,047	,013	-,179	-3,601	,000	-,073	-,021	-,180	-,199	-,178	,986	1,015
	Change of Perceived Effort	-,062	,027	-,116	-2,333	,020	-,115	-,010	-,135	-,130	-,115	,990	1,010

a. Dependent Variable: Ln(Mean of Eccentricity over all 6 runs [cm])





On Ln SD Eccentricity

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Instruction_softly	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	BBT-Score	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Sporting Activity Today	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln(Std. deviation of Eccentricity over all 6 runs [cm])

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,293[a]	,086	,083	,43654	,086	29,787	1	316	,000
2	,315[b]	,099	,094	,43409	,013	4,587	1	315	,033
3	,335[c]	,112	,104	,43160	,013	4,642	1	314	,032

a. Predictors: (Constant), Instruction_softly

b. Predictors: (Constant), Instruction_softly, BBT-Score

c. Predictors: (Constant), Instruction_softly, BBT-Score, Sporting Activity Today

d. Dependent Variable: Ln(Std. deviation of Eccentricity over all 6 runs [cm])

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5,676	1	5,676	29,787	,000[b]
	Residual	60,220	316	,191		
	Total	65,897	317			
2	Regression	6,541	2	3,270	17,356	,000[c]
	Residual	59,356	315	,188		
	Total	65,897	317			
3	Regression	7,405	3	2,468	13,252	,000[d]
	Residual	58,491	314	,186		
	Total	65,897	317			

a. Dependent Variable: Ln(Std. deviation of Eccentricity over all 6 runs [cm])

b. Predictors: (Constant), Instruction_softly

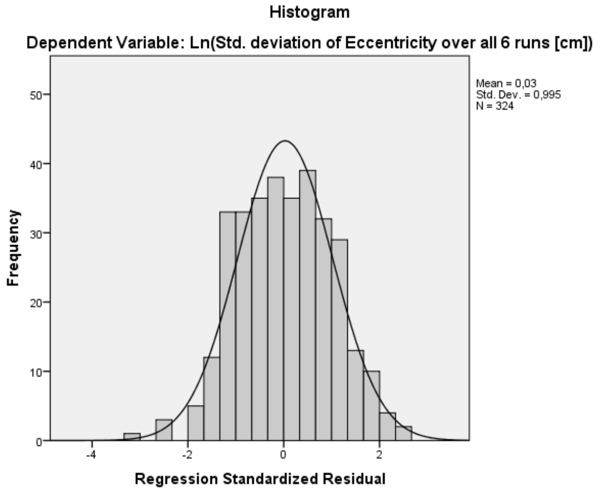
c. Predictors: (Constant), Instruction_softly, BBT-Score

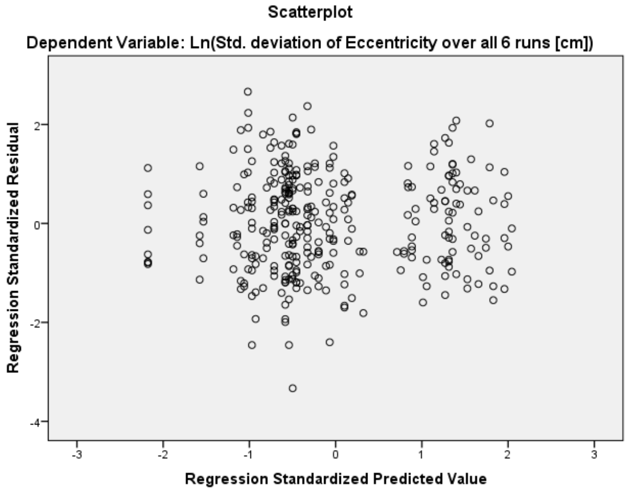
d. Predictors: (Constant), Instruction_softly, BBT-Score, Sporting Activity Today

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	-2,342	,030		-78,125	,000	-2,401	-2,283					
	Instruction_softly	,283	,052	,293	5,458	,000	,181	,386	,293	,293	,293	1,000	1,000
2	(Constant)	-1,852	,231		-8,019	,000	-2,306	-1,398					
	Instruction_softly	,283	,052	,293	5,489	,000	,182	,385	,293	,295	,293	1,000	1,000
	BBT-Score	-,006	,003	-,115	-2,142	,033	-,012	-,001	-,115	-,120	-,115	1,000	1,000
3	(Constant)	-1,819	,230		-7,903	,000	-2,272	-1,366					
	Instruction_softly	,283	,051	,293	5,520	,000	,182	,384	,293	,297	,293	1,000	1,000
	BBT-Score	-,007	,003	-,118	-2,220	,027	-,012	-,001	-,115	-,124	-,118	,999	1,001
	Sporting Activity Today	-,171	,080	-,115	-2,154	,032	-,328	-,015	-,111	-,121	-,115	,999	1,001

a. Dependent Variable: Ln(Std. deviation of Eccentricity over all 6 runs [cm])





E Operationalization of Variables for Study Two

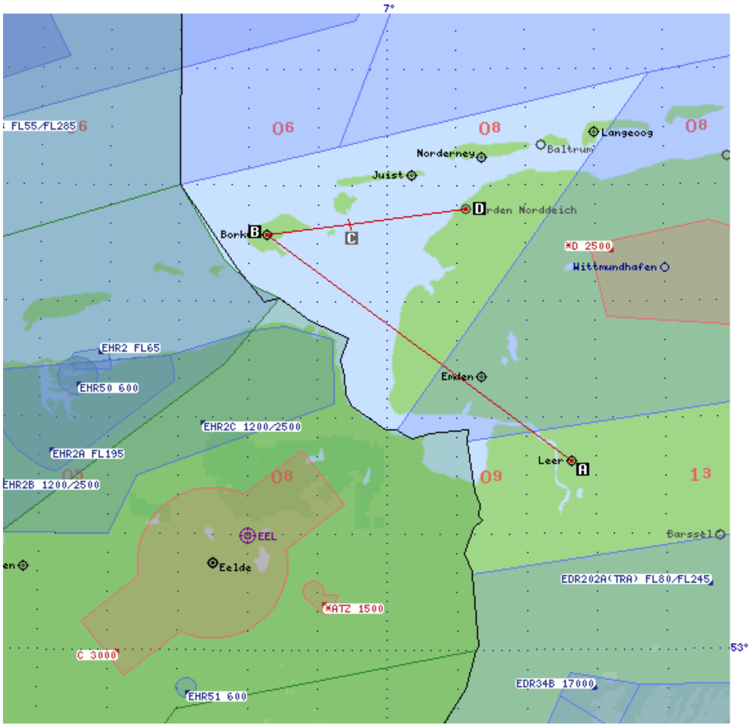
Type	Variable	Measurement Method	Unit/ Category	Scale
Independent/ Dependent	Mean Flight Duration	Flight Simulator	s	Ratio
	Mean Jerkiness	Flight Simulator	Inputs Yoke/ s	Ratio
	Mean of Inputs per Time	Flight Simulator	Inputs Yoke/ s^2	Ratio
	Mean of Input-Sum	Flight Simulator	Inputs Yoke	Ratio
	Std. Deviation of Flight Duration	Flight Simulator	s	Ratio
	Std. Deviation of Inputs per Time	Flight Simulator	Inputs Yoke/ s	Ratio
	Std. Deviation of Jerkiness	Flight Simulator	Inputs Yoke/ s^2	Ratio
	Std. Deviation of Input-Sum	Flight Simulator	Inputs Yoke	Ratio
	Most Probable Path Probability	Flight Simulator - Calculation Markov Model	%	Ratio
	Followed Most Probable Path	Flight Simulator - Calculation Markov Model	Yes; No	Nominal
Independent	Training - Flight Hours within Last Twelve Months on: - Overall - Single Engine Flights - Cessna	Questionnaire	h	Ratio
	Experience - Flight Hours: - Overall - Single Engine Flights - Cessna	Questionnaire	h	Ratio
	Simulation Training - Hours in Last Three Months: - Any Flight Simulation - FSX - Professional Flight Simulator	Questionnaire	h	Ratio

	Simulation Experience - Hours: - Any Flight Simulation - FSX - Professional Flight Simulator	Questionnaire	h	Ratio
	Fatigue	Questionnaire - Karolinska Sleepiness Scale	9-point Score on KSS	Ordinal
	Qualification	Questionnaire	PPL; CPL; Misc. License	Ordinal
Dependent	Mean of Velocity over All Five Flights	Flight Simulator	m/s	Ratio
	Std. Deviation of Velocity over All Five Flights	Flight Simulator	m/s	Ratio
	Ranking for All Flight-Angles over All Five Flights	Flight Simulator - Calculation of Ranks	Rank	Ordinal
Covariate	Age (grouped)	Questionnaire	Grouped in 10-Year-Steps	Ordinal
	Level of Education [Type]	Questionnaire	Text	Ordinal
	Self-assessment of Realistic Flight Behavior	Checklist	5-point Scale	Ordinal
	Perceived Difficulty of Landing Maneuver	Checklist	5-point Scale	Ordinal

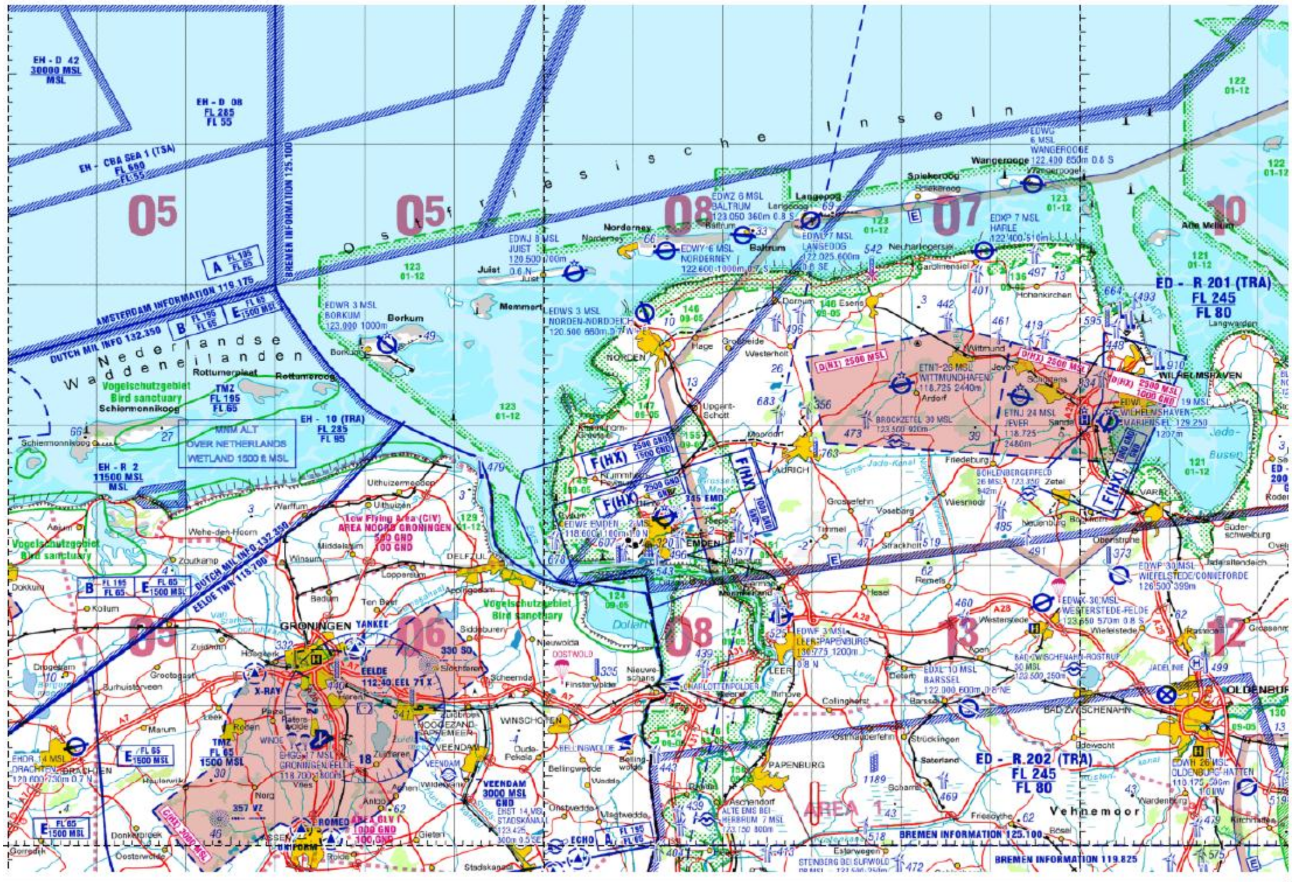
F Documents and Material for Scenario of Study Two

Material for Flight Scenario

Map of Flight Route



ICAO-Map of Region



19.12.2013

Flight Plan

Seite	Flugdatum	Von	Nach	LFZ-Muster	Kennzeichen	Strecke	Flugdauer	SR-30 Startort	SS+30 Zielort
1 von 2	06.08.2013	Leer	Norden Norddeich	C-172 S	G-BAFM	50 NM	0:27 h	03:24 UTC	19:49 UTC

FL95.de

COM-Frequenzen

EDWF - Leer Papenburg	
Leer Info (de)	**130.77**
EDWR - Borkum	
Borkum Info (en/de)	**123.00**
EDWS - Norden Norddeich	
Norddeich Info (de)	**121.40**

NAV-Frequenzen

Notizen

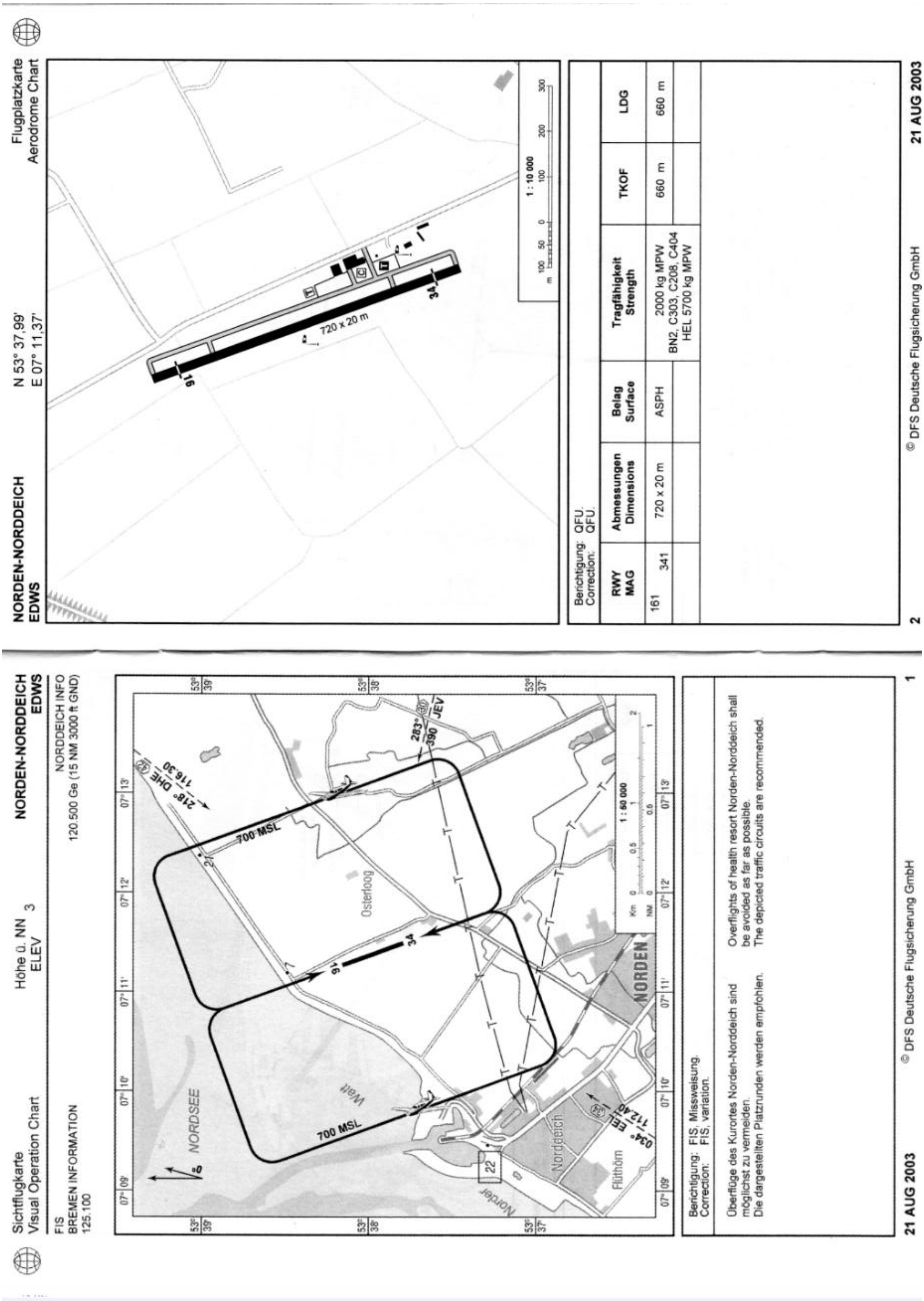
Off-Block: :

On-Block: :

Wegpunkt:	Restzeit	Restentf.	Name	(Navigation)	ETO	ATO
Etappe:	TC	Entf.	MSA / Navigation / Flughöhe	MH	Zeit	

Wind / Verbr. / Menge	TAS / GS	VAR / MC / WCA	Restzeit / TC	Restentf. / Entf.	Wegpunkt / MSA	Flughöhe	MH	Zeit	Notes
			Zeit für Abflug:		**A** Leer (3 ft)			:	Startzeit
Wind 360° / 0 kt; Verbr. 34,5 l/h; Menge 10,2 l	TAS 110 kt; GS 110 kt	VAR 1°E; MC 306°; WCA 0°	307°	32,6 NM	14 00 ft	2500 ft	306°	18 min	123.00 Borkum Info (en/de)
			0:09 h	17,2 NM	**B** Borkum (3 ft)				
Wind 360° / 0 kt; Verbr. 34,5 l/h; Menge 2,3 l	TAS 110 kt; GS 110 kt	VAR 1°E; MC 081°; WCA 0°	082°	7,2 NM	11 00 ft	2500 ft	081°	4 min	
			0:05 h	10,0 NM	**C** Südlich von Memmert				
Wind 360° / 0 kt; Verbr. 34,5 l/h; Menge 3,1 l	TAS 110 kt; GS 110 kt	VAR 1°E; MC 081°; WCA 0°	082°	10,0 NM	13 00 ft	2500 ft	081°	5 min	121.40 Norddeich Info (de); Platzrunde: 700 ft
			Zeit für Anflug:		**D** Norden Norddeich (3 ft)				Landezeit

Map of Norden-Norddeich



Additional Documents

Checklist

TECHNISCHE UNIVERSITÄT DARMSTADT

Protokoll

Versuchsdurchführung

SFB 805

Allgemeine Daten

Versuchsleiter:	
Assistent:	
Datum:	
Versuchsbeginn:	
Versuchsende:	
Probandencode:	

Checkliste Vorbereitung

Licht einschalten (Beide Lampen)		
Lüftung einschalten		
Verpflegung positionieren		
Eimer bereitstellen		
Erhalt des Fragebogens checken (e-mail)		
Mappe zusammenstellen		
	Protokoll Versuchsdurchführung	
	Gesprächsleitfaden	
	Einverständniserklärung	
	Fragebogen Qualifikation/ Erfahrung	
	Übungsunterlagen (☐ICOA- Karte, ☐Handbuch, ☐VFR- Karte, ☐METAR)	
	Briefingunterlagen (☐Instruktionen, ☐Flugplan, ☐Karte Flugplan)	
	Fragebogen Müdigkeit	
	Liste Verlosung/ weitere Versuche/ Benachrichtigung Versuchsergebnisse	
Mappe positionieren		

Seite 1/4 0001

Simulator starten (kurzer Funktionscheck?)		
	Startall.bat ausführen	
	Fly Now drücken	
	GPS: Server starten	
	GPS App starten (Tablet)	
	GPS: IP- Adresse überprüfen (Tablet)	
	GPS: App connecten (Tablet)	
	GPS: Stromanschluss Tablet überprüfen	
	Flug laden (Platzrunde)	
	M- Panel roter Knopf nach links	
	Alle G- Schalter nach oben	
	Yoke, Throttle, Mixture, Pedale, Trimmrad bewegen	
Maus/ Tastatur unter Simulator legen		
Funkmaus positionieren (incl. Batteriecheck)		
Kamera bereitstellen (Stromanschluss und Funktion überprüfen)		
Diktiergerät bereitlegen (incl. Batteriecheck)		
Kniebrett bereitlegen		

Checkliste Durchführung

Phase	Durch-geführt?	Anmerkungen
Begrüßung		
Vorstellung des Versuchs		
Einverständniserklärung		
Fragebogen Qualifikation/ Erfahrung		
Hinweis Simulatorkrankheit		
Einarbeitung Übungsflüge		Dauer:

Seite 2/4 0001

Einweisung Sitzverstellung, Headtracking		
Cockpiterklärung		
Ubungsflug Platzrunde		Dauer: Geflogene Manöver:
Übungsflug Gegenanflug (Mixture: 0,5; Throttle: 0,71)		Dauer:
Briefing		
Ermüdungsfragebogen_1		
Flug 1 (Mixture:0,475; Throttle:0,847)		
Flug 2		
Flug 3		
Ermüdungsfragebogen_2		
Flug 4		
Flug 5		
Ermüdungsfragebogen_3		
Exploration (kurzes Gespräch)		
Verlosung und Verabschiedung		

Seite 3/4 0001

Anmerkungen Exploration:

Sonstige Anmerkungen:

Kaffeeverzehr (Wann, wieviel?):____

Toilettenbesuch (Wann?):______________________________

Seite 4/4 0001

Conversation Guideline

Gesprächsleitfaden

Versuchsdurchführung

TECHNISCHE UNIVERSITÄT DARMSTADT

iaD

SFB 805

Begrüßung Hallo/Guten Morgen/Guten Tag Herr _______! Schön, dass Sie kommen konnten. Ich bin X, das ist mein Kollege Y. (Vornamen) Zunächst nochmal vielen Dank, dass Sie an unserem Versuch teilnehmen. Ihre Jacke können Sie hier ablegen, wenn Sie Durst und Hunger haben bedienen Sie sich einfach wann Sie wollen.	
Vorstellung Versuch Zu uns beiden: Wir sind beide Maschinenbau- Studenten und machen eine Versuchsreihe an diesem Flugsimulator als Bachelorthesis. Nochmal kurz zum Zweck des Versuchs, es geht generell um die Phase von Reiseflug bis zur abgeschlossenen Landung. Das Ziel ist es, realistische Landeverläufe nachzustellen. Damit soll bewertet werden, wie hoch der menschliche Einfluss (z.B. Ermüdung und Erfahrung) auf die Belastung des Fahrwerks bei der Landung ist. Das lässt sich natürlich nur sinnvoll untersuchen, wenn die Daten von wirklichen Piloten „erflogen" werden. Und, natürlich, dass Sie sich möglichst so verhalten, wie Sie es auch in einem richtigen Flugzeug machen würden. Die Flüge werden an diesem Simulator stattfinden. Es wurde das Cockpit einer C172S nachgebaut. Es gibt aber kleine Unterschiede zur Realität, dazu später mehr.	
Einverständniserklärung Zunächst mal müssten Sie diese Einverständniserklärung hier ausfüllen. Sie können sich gerne hier hinsetzen [Auf den Sitzplatz zeigen]. Fragen Sie bitte, wenn Ihnen etwas unklar ist.	
Fragebogen Qualifikation/ Erfahrung Haben Sie eigentlich den Fragebogen zu Erfahrung und Qualifikation, den wir ihnen zugeschickt haben, schon ausgefüllt? Wenn ja, können Sie mir den bitte jetzt geben? Wenn nicht, würden wir Sie bitten, das jetzt einfach schnell zu machen.	

Seite 1/4 0001

Kurz zu dem Probandencode: Der wird gebraucht, um die Versuchsteilnehmer anonym zu unterscheiden und bei einer weiteren Versuchsteilnahme die Daten zuzuordnen. Die Versuchsauswertung ist ja auch insgesamt komplett anonym. Wichtig wäre, dass Sie die Daten bitte vollständig und möglichst genau ausfüllen. Wenn irgendwas unklar ist, fragen Sie bitte nach.	
Hinweis Simulatorkrankheit Kennen Sie eigentlich die Simulatorkrankheit? Die kann auftreten, weil die Bewegungen von Bild und restlichem Cockpit im Simulator nicht übereinstimmen. Dabei kann es den Piloten übel werden. Wenn es Ihnen übel wird, sagen Sie bitte kurz bescheid, wir brechen dann den Versuch ab.	
Einarbeitung Übungsflüge Wir haben einiges Informationsmaterial zum Simulator und zum Flughafen für Sie vorbereitet: einige relevante Seiten aus dem Cessna- Handbuch inklusive der Landecheckliste, Kartenmaterial, in dem die Lage des Platzes ersichtlich ist und die aktuelle METAR Meldung des nahegelegenen Flugplatzes in Wittmundhafen. Der Zielflugplatz ist Norden-Norddeich (EDWS) an der Nordseeküste. Man kann sich gut an der Landschaft mit dem Hafenbecken orientieren. Nehmen Sie sich so viel Zeit wie sie brauchen, um sich alles anzusehen (vor allem falls Sie die 172SP noch nicht geflogen haben)	
Einweisung Sitz und Headtracking Wenn Sie fertig sind, setzen Sie sich bitte auf den Simulatorsitz. Den Sitz kann man hier einstellen. Die Mütze müssten Sie jetzt aufsetzen. Mit dem sogenannten Head- Tracking System kann man das Sichtfeld beim Fliegen vergrößern. Es erfasst die Kopfbewegung des Piloten. Man kann das System mit diesem Schalter hier zentrieren (G1). Schauen Sie am besten geradeaus nach vorne und schalten Sie dann einmal den Schalter zum einstellen.	
Cockpiterklärung Jetzt erkläre ich Ihnen mal den Cockpitaufbau (von rechts nach links): • Klappenhebel: Einmaliges Bedienen des Schalters ändert die Klappenstellung um 10°, Klappenstufen bei der 172 sind 10°, 20°, 30°. Der Hebel rastet nicht wie gewohnt ein. Mehrmaliges Drücken wird vom Panel registriert, d.h. bei zweimaligem Betätigen verstellen sich die Klappen auf 20° Position usw. Die Position kann am Panel abgelesen werden, 033=10°, 066=20°, 100=30°. • Das hier ist Mixture, das hier ist Throttle. In der Mitte ist der Prop-Hebel: der ist aber überflüssig bzw. real nicht vorhanden. Darauf muss man achten, da der Gemisch-Hebel bei der Cessna sonst direkt rechts neben dem Throttle ist. Wenn man die reale Anordnung gewohnt ist, bedient man eventuell Prop und nicht Mixture. Man kann sich aber an den standardisierten Griffen orientieren. • Der Tankwahlschalter fehlt • Landing Gear: Der Schalter ist überflüssig, die Cessna 172SP hat ja ein starres Fahrwerk	

Seite 2/4 0001

- „Switch Panel“: oben (von links nach rechts):
  Master: Battery, Alternator (beide rot), Avionics, (elektrische) Fuel Pump, De-Ice (in der Cessna aber nicht vorhanden) und Pitot Heat.
- Das Instrumentenbrett ist ein klassisches Sixpack; wie in Realität sind links Uhr und EGT, statt der Unterdruckanzeige (VAC) gibt es aber einen Drehzahlmesser, weil der für die Motoreinstellung wichtig ist, der wäre sonst rechts vom Sixpack
- Das GPS dient zur Orientierung. Die Karte lässt sich vergrößern man kann im Bild suchen.
- Funk gibt es in diesem Simulator nicht
- Beim Höhenmesser gibt es keine Einstellmöglichkeit, der ist aber in unseren Flügen schon auf den Zielflughafen eingestellt
- Und es gibt keine Steuerdrücke

Übungsflug Platzrunde

Wir haben jetzt eine Platzrunde zur Übung vorbereitet.

Generell bei allen folgenden Flügen herrscht Windstille und 15°C Temperatur. Das Flugzeug steht in Parkposition mit laufendem Motor. Sie können auf die Startbahn 34 rollen, um schonmal ein Gefühl für die Pedale zu bekommen. Wir schlagen vor, dass Sie eine Westplatzplatzrunde (Linksplatzrunde) mit Richtung 34 fliegen. Wir geben Ihnen dafür ungefähr zehn Minuten Zeit

(Vorschläge:

- Steigen bis 1500ft (Steigflug mit Steigflugkurven)
- Langsamflug
- Überziehübungen in Reiseflug- und Landekonfiguration
- Landeklappen
- Mixture
- Throttle
- Trim?
- Kurvenflug
- Sinken)

Übungsflug Gegenanflug

Zur weiteren Übung fliegen Sie jetzt einen Gegenanflug aus 700ft Höhe.

Briefing und Ermüdungsfragebogen_1

Wir hoffen, Sie konnten sich mit dem Simulator anfreunden. Jetzt kommen wir zu den eigentlichen Versuchsflügen. Würden Sie dazu bitte nochmal hier Platz nehmen? [Schreibplatz] Hier sind alle notwendigen Informationen zum Flugszenario. Das wird insgesamt fünfmal geflogen.

Wenn Sie sich ausreichend vorbereitet haben, füllen sie bitte noch diesen Bogen hier aus [Ermüdungsfragebogen_1 verdeckt auf den Tisch legen] und melden Sie sich dann einfach kurz bei mir.

Flug 1

Wenn Sie auf Toilette müssen, dann wäre jetzt der richtige Zeitpunkt, die nächste

Seite 3/4 0001

Möglichkeit wäre dann so ca. in einer guten Stunde. So, dann können wir jetzt anfangen. Bitte setzten Sie sich wieder in den Simulator. Wir schalten jetzt auch die Kamera ein. Nochmal die kurze Anmerkung: Bitte fliegen Sie einfach so, wie Sie es in Wirklichkeit auch machen würden.	
Flug 2 Dann starten wir jetzt den zweiten Flug.	
Flug 3 Dann starten wir jetzt den dritten Flug.	
Ermüdungsfragebogen_2 Bitte füllen Sie jetzt diesen Fragebogen [Ermüdungsfragebogen_2 reichen] aus.	
Flug 4 Dann starten wir jetzt den vierten Flug.	
Flug 5 Dann starten wir jetzt den fünften Flug.	
Ermüdungsfragebogen_3 So, dann sind wir jetzt fertig mit den Versuchsflügen. Sie können gerne nochmal hier [Schreibplatz] Platz nehmen. Füllen Sie dann bitte noch diesen Fragebogen [Ermüdungsfragebogen_3 reichen] hier aus.	
Exploration (kurzes, offenes Gespräch) Hoffentlich hat ihnen der Versuch Spaß gemacht. Wir hätten dann noch ein paar kurze Fragen an Sie: • Wie realitätsnah haben Sie sich im Flugsimulator verhalten? **Genau wie in der Realität** ○ ○ ○ ○ ○ **komplett verschieden** Wie haben Sie die Schwierigkeit einer Landung im Flugsimulator in Relation zur Realität empfunden? **im Simulator viel einfacher** ○ ○ **gleich =** ○ ○ **in Realität viel einfacher** ○ • Wie sind Sie eigentlich auf unseren Versuch aufmerksam geworden? • Und warum haben Sie an dem Versuch teilgenommen?	
Verlosung und Verabschiedung Dann bedanken wir uns nochmal, dass Sie teilgenommen haben. Als kleines Dankeschön haben wir noch was für Sie vorbereitet. [Geschenk überreichen] Dazu bräuchten wir dann hier noch eine Unterschrift aus Verwaltungsgründen.	

Seite 4/4 0001

G Questionnaire of Study Two

TECHNISCHE UNIVERSITÄT DARMSTADT

IAD

SFB 805

Fragebogen zu Erfahrung und Qualifikation

Dieser Fragebogen dient der anonymisierten Erfassung ihrer individuellen Daten, insbesondere Ihrer fliegerischen Qualifikationen und Erfahrungen.

Vorherige Versuchsteilnahme

Haben Sie bereits an einem Versuch im IAD- Flugsimulator teilgenommen?

O ja O nein

Demographische Daten

Alter:

O Bis 20 Jahre O 21-30 O 31-40 O 41-50
O 51-60 O 61-70 O Über 70 Jahre

Geschlecht:

O Weiblich O Männlich

Höchste Ausbildung:

O Hauptschulabschluss (Berufsreife)
O Realschulabschluss (Mittlere Reife)
O Berufsausbildung
O Fachabitur
O Abitur
O Hochschulabschluss

Seite 1/6 0002

Probandencode

(Der Probandencode dient zur anonymisierten Zuordnung Ihrer Versuchsergebnisse bei erneuter Teilnahme zu einem späteren Zeitpunkt.)

Bitte geben Sie die letzten beiden Buchstaben des Vornamens Ihrer Mutter an.
Beispiel: Ihre Mutter heißt Maria. Dann geben Sie bitte „ia" an.

____

Bitte geben Sie den Tag an, an dem Sie geboren wurden.
Beispiel: Sie wurden am 11.12.1970 geboren. Dann geben Sie bitte „11" an.

____

Bitte geben sie die ersten beiden Buchstaben Ihres Geburtsorts an.
Beispiel: Sie wurden in Berlin geboren. Dann geben Sie bitte „Be" an.

____

Lizenzen

Welche der folgenden Lizenzen besitzen Sie? Geben Sie auch Lizenzen an, die zurzeit ungültig sind.

- ☐ Segelfluglizenz
- ☐ Lizenz für Ultraleichtflugzeuge
- ☐ Motorfluglizenz
  - ☐ LAPL(A) nach Teil-FCL (EASA)
  - ☐ PPL(A) national/ PPL(N)/ PPL(A) nach LuftPersV
  - ☐ PPL(A) ICAO
  - ☐ PPL(A) nach JAR-FCL
  - ☐ PPL(A) nach Teil-FCL (EASA)
  - ☐ US-PPL(A)/ PPL(A) nach FAA
- ☐ Berufspilotenlizenz
  - ☐ CPL(A)
  - ☐ MPL
  - ☐ ATPL
- ☐ Sonstige Lizenz: ____________________.

Seite 2/6 0002

Berechtigungen:

Zusatzberechtigungen

Welche der folgenden Zusatzberechtigungen besitzen Sie? Bitte geben Sie für die Berechtigungen IR, CVFR und Nachtflug an, ob diese zurzeit gültig ist.

- ☐ IR: Instrumentenflugberechtigung
  - ☐gültig ☐nicht gültig
- ☐ CVFR: kontrollierter Sichtflug
  - ☐gültig ☐nicht gültig
- ☐ Nachtflug
  - ☐gültig ☐nicht gültig

FI: Lehrberechtigungen für Lizenzen

- ☐ Lehrberechtigung(en) für:
  - ☐ Segelflug
  - ☐ PPL(A)
  - ☐ CPL(A)
  - ☐ MPL
  - ☐ ATPL

CRI: Lehrberechtigung für Klassenberechtigungen (Class Ratings) und Instrumentenflug (IR):

- ☐ CRI Berechtigung(en) für:
  - ☐ SEP
  - ☐ MEP
  - ☐ TMG
- ☐ IRI: Lehrberechtigung für Instrumentenflug

Andere Lehrberechtigungen: ____

Seite 3/6 0002

Flugerfahrung

Bitte geben Sie nachfolgend möglichst genau die Zahl ihrer Flugstunden auf realen Flugzeugen (demnach ausgenommen Simulatorflugstunden) an.

<u>Gesamtflugzeit</u>
Wie viele Stunden sind Sie in Ihrem Leben insgesamt schon geflogen (auf allen Klassen)?
Ungefähre Stundenzahl: ______________

Davon innerhalb der letzten 12 Monate (Flugstunden auf allen Klassen):
Ungefähre Stundenzahl: ______________

<u>Flugstunden auf einmotorigen Motorflugzeugen mit Kolbentriebwerk (Klasse SEP):</u>
Wie viele Stunden sind Sie insgesamt auf einmotorigen Flugzeugen mit Kolbentriebwerk (Klasse SEP) geflogen?
Ungefähre Stundenzahl: ______________

Davon innerhalb der letzten 12 Monate (Flugstunden auf einmotorigen Flugzeugen mit Kolbentriebwerk/SEP)
Ungefähre Stundenzahl: ______________

<u>Flugstunden auf der Cessna 172</u>
Wie viele Stunden sind Sie insgesamt auf dem Flugzeugmuster „Cessna 172“ geflogen?
Ungefähre Stundenzahl: ______________

Davon innerhalb der letzten 12 Monate (Flugstunden auf dem Flugzeugmuster „Cessna 172“)
Ungefähre Stundenzahl: ______________

Seite 4/6 0002

Flugsimulatorerfahrung

Welche Flugsimulatoren haben Sie schon einmal genutzt?

- ☐ Keine
- ☐ Flugsimulatorsoftware:
  - ☐ Microsoft Flight Simulator X (FSX)
  - ☐ Andere Microsoftprodukte (z.B. Flight Simulator 2004)
  - ☐ Andere
- ☐ Professioneller Flugsimulator (mit Cockpitnachbau)
  - ☐ Motorflugzeug
  - ☐ Verkehrsflugzeug

<u>Hinweis:</u> Die folgenden Fragen müssen Sie nur beantworten, wenn Sie schon einmal einen Flugsimulator oder eine Flugsimulatorsoftware genutzt haben.

<u>Flugsimulatorsoftware</u>

Wie viele Stunden haben Sie in Ihrem Leben insgesamt eine Flugsimulatorsofware genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung einer Flugsimulatorsoftware)

Ungefähre Stundenzahl: _______________

<u>Microsoft Flight Simulator X</u>

Wie viele Stunden haben Sie in Ihrem Leben insgesamt die Software Microsoft Flight Simulator X genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung von Microsoft Flight Simulator X)

Ungefähre Stundenzahl: _______________

Seite 5/6 0002

Professionelle Flugsimulatoren (mit Cockpitnachbau)

Wie viele Stunden haben Sie in Ihrem Leben insgesamt einen professionellen Flugsimulator (mit Cockpitnachbau) genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung eines professionellen Flugsimulators)

Ungefähre Stundenzahl: _______________

Eingaberäte

Maus/Tastatur

Wieviele Stunden haben Sie in Ihrem Leben insgesamt Maus/ Tastatur als Eingabegerät für Flugsimulatoren genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung von Maus/ Tastatur)

Ungefähre Stundenzahl: _______________

Joystick (gegebenenfalls mit Seitenruderpedalen)

Wieviele Stunden haben Sie in Ihrem Leben insgesamt einen Joystick als Eingabegerät für Flugsimulatoren genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung eines Joysticks)

Ungefähre Stundenzahl: _______________

Steuerhorn (gegebenenfalls mit Seitenruderpedalen und/oder Cockpitnachbau)

Wieviele Stunden haben Sie in Ihrem Leben insgesamt ein Steuerhorn als Eingabegerät für Flugsimulatoren genutzt?

Ungefähre Stundenzahl: _______________

Davon innerhalb der letzten drei Monate (Nutzung eines Steuerhorns)

Ungefähre Stundenzahl: _______________

Seite 6/6 0002

Karolinska Sleepiness Scale

TECHNISCHE UNIVERSITÄT DARMSTADT

Fragebogen zur Müdigkeit

1. Müdigkeitsabfrage

Bitte bewerten Sie Ihre Müdigkeit in den letzten 10 Minuten, indem Sie den Kreis vor der entsprechenden Zahl markieren. Benutzen Sie auch die Zwischenstufen.

- 1. = sehr wach
- 2.
- 3. = wach
- 4.
- 5. = weder wach noch müde
- 6.
- 7. = müde, aber keine Probleme wach zu bleiben
- 8.
- 9. = sehr müde, große Probleme wach zu bleiben, mit dem Schlaf kämpfend

2. Müdigkeitsabfrage

Bitte bewerten Sie Ihre Müdigkeit in den letzten 10 Minuten, indem Sie den Kreis vor der entsprechenden Zahl markieren. Benutzen Sie auch die Zwischenstufen.

- 1. = sehr wach
- 2.
- 3. = wach
- 4.
- 5. = weder wach noch müde
- 6.
- 7. = müde, aber keine Probleme wach zu bleiben
- 8.
- 9. = sehr müde, große Probleme wach zu bleiben, mit dem Schlaf kämpfend

3. Müdigkeitsabfrage

Bitte bewerten Sie Ihre Müdigkeit in den letzten 10 Minuten, indem Sie den Kreis vor der entsprechenden Zahl markieren. Benutzen Sie auch die Zwischenstufen.

- 1. = sehr wach
- 2.
- 3. = wach
- 4.
- 5. = weder wach noch müde
- 6.
- 7. = müde, aber keine Probleme wach zu bleiben
- 8.
- 9. = sehr müde, große Probleme wach zu bleiben, mit dem Schlaf kämpfend

FB_M_N Probandencode: «ID_Nummer»

H Calculation of Rank for Pitch, Bank and Heading

The ranking represents a qualitative interpretation of all three angles on touchdown: pitch, bank and heading. The basic idea for the ranking is the fact that for each angle an ideal value exists. Thus, the resulting rank represents the deviation of a pilot from the ideal values. Thereby, a score for each single angle is derived first, on which basis the overall value for Angle Rank is calculated.
Following, the ideal value for each angle is defined.

For the angle pitch, no best value exists as depending on the chosen style of approach, different values are appropriate. But possible limits for pitch can be derived, as values above certain thresholds could damage the airplane as the rear would make contact first. The assessment of this value was done experimentally within the flight simulator by testing the safe margin during landing. A value of +0.5° for the pitch was identified best to prevent possible damage during touchdown. Regarding the rank/score for the angle pitch, only a penalty is introduced if the angle exceeds the defined limit. As further each pilot is rated regarding all five operated flights, lastly 6 different groups can be derived:

- Pilots without penalty
- Pilots with one penalty (within one out of the five flights the limit of +0.5° was exceeded)
- …
- Pilots with 5 penalties (when exceeding the limit on each flight)

Regarding bank, an optimal value can be defined at 0°. This signifies that the airplane is perfectly horizontally and thus both wheels of the landing gear hit the ground simultaneously. Thereby, the absolute difference between the ideal value and the actual value is calculated, meaning that -1° is the same as +1°. Further, a limit value is defined at an angle of ±20°, as with this angle the probability to hit the ground first with one of the wings is very high. Exceedance of the upper limit leads to a penalty of 1000.

For heading, the absolute difference to the angle of 340° is used as a quality indicator. Thereby, 340° represents the position of the runway. When landing at this angle the lowest shear forces act upon the landing gear, which is optimal regarding the stress. For heading, no upper limit exists.

In case a landing results into a crash, a penalty of 3000 points is awarded (1000 for each angle).

After defining the single rankings for each angle and each flight, the overall Angle Ranking is built by adding all values and dividing them through the number of absolved flights. Thus, all pilots can be related to each other regarding their quality of landing angles on touchdown.

I Additional Test-tables and Figures for Study Two

Uncertainty of Technical Subsystem

Tests for normality of velocity values

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Mean of Velocity over All Five Flights [m/s]	,127	42	,084	,865	42	,000
Mean of Flight Duration over All Five Flights [s]	,174	42	,003	,893	42	,001
Mean of Input-Sum over All Five Flights [Inputs]	,161	42	,008	,824	42	,000
Mean of Inputs per Time over All Five Flights [Inputs/s]	,128	42	,083	,954	42	,091
Mean of Jerkiness over All Five Flights [Inputs/s²]	,158	42	,010	,882	42	,000
Std. Deviation of Velocity over All Five Flights [m/s]	,180	42	,001	,842	42	,000
Std. Deviation of Flight Duration over All Five Flights [s]	,287	42	,000	,617	42	,000
Std. Deviation of Input-Sum over All Five Flights [Inputs]	,215	42	,000	,726	42	,000
Std. Deviation of Inputs per Time over all Five Flights [Inputs/s]	,135	42	,053	,904	42	,002
Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]	,167	42	,005	,845	42	,000

a. Lilliefors Significance Correction

Test for normality after transformation.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AV1_Ln_Mean_vel_over5	,074	42	,200*	,979	42	,610
AV1_Ln_SD_Vel_over5	,073	42	,200*	,980	42	,656
AV2_Ln_Mean_FDauer_over5	,150	42	,018	,946	42	,046
AV2_Ln_Mean_sum_inputs_over5	,090	42	,200*	,974	42	,441
AV2_Ln_Mean_inputs_perTime_over5	,080	42	,200*	,989	42	,947
AV2_Ln_Mean_jerkiness_over5	,141	42	,036	,966	42	,236
AV2_Ln_SD_FDauer_over5	,128	42	,082	,936	42	,021
AV2_Ln_SD_sum_inputs_over5	,060	42	,200*	,990	42	,974
AV2_Ln_SD_inputs_perTime_over5	,114	42	,197	,925	42	,009
AV2_Ln_SD_jerkiness_over5	,070	42	,200*	,979	42	,617

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Quantification of the Effect of Influencing Factors on Uncertainty

Controlling for Training Effects

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Geschwindigkeit beim Aufsetzen, Flug 1	,162	36	,018	,821	36	,000
Geschwindigkeit beim Aufsetzen, Flug 2	,136	36	,090	,926	36	,019
Geschwindigkeit beim Aufsetzen, Flug 3	,226	42	,000	,783	42	,000
Geschwindigkeit beim Aufsetzen, Flug 4	,146	41	,028	,937	41	,025
Geschwindigkeit beim Aufsetzen, Flug 5	,154	42	,014	,845	42	,000

a. Lilliefors Significance Correction

Ranks

	Mean Rank
Geschwindigkeit beim Aufsetzen, Flug 1	2,97
Geschwindigkeit beim Aufsetzen, Flug 2	2,59
Geschwindigkeit beim Aufsetzen, Flug 3	3,19
Geschwindigkeit beim Aufsetzen, Flug 4	3,22
Geschwindigkeit beim Aufsetzen, Flug 5	3,03

Test Statistics[a]

N	32
Chi-Square	3,200
df	4
Asymp. Sig.	,525

a. Friedman Test

Controlling for Training Effects

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Fatigue, Before First Flight [KSS-Rating]	,280	42	,000	,876	42	,000
Fatigue, After Three Flights [KSS-Rating]	,229	42	,000	,908	42	,003
Fatigue, After Five Flights [KSS-Rating]	,162	42	,007	,944	42	,039

a. Lilliefors Significance Correction

Ranks

	Mean Rank
Fatigue, Before First Flight [KSS-Rating]	1,73
Fatigue, After Three Flights [KSS-Rating]	1,83
Fatigue, After Five Flights [KSS-Rating]	2,44

Test Statistics[a]

N	42
Chi-Square	24,929
df	2
Asymp. Sig.	,000

a. Friedman Test

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum	Percentiles 25th	Percentiles 50th (Median)	Percentiles 75th
Fatigue, Before First Flight [KSS-Rating]	42	3,14	1,372	1	7	2,75	3,00	4,00
Fatigue, After Three Flights [KSS-Rating]	42	3,33	1,525	1	7	2,75	3,00	5,00
Fatigue, After Five Flights [KSS-Rating]	42	3,88	1,824	1	8	3,00	4,00	5,00

Ranks

		N	Mean Rank	Sum of Ranks
Fatigue, After Three Flights [KSS-Rating] - Fatigue, Before First Flight [KSS-Rating]	Negative Ranks	4[a]	5,00	20,00
	Positive Ranks	8[b]	7,25	58,00
	Ties	30[c]		
	Total	42		
Fatigue, After Five Flights [KSS-Rating] - Fatigue, Before First Flight [KSS-Rating]	Negative Ranks	3[d]	12,17	36,50
	Positive Ranks	22[e]	13,11	288,50
	Ties	17[f]		
	Total	42		
Fatigue, After Five Flights [KSS-Rating] - Fatigue, After Three Flights [KSS-Rating]	Negative Ranks	1[g]	8,00	8,00
	Positive Ranks	19[h]	10,63	202,00
	Ties	22[i]		
	Total	42		

a. Fatigue, After Three Flights [KSS-Rating] < Fatigue, Before First Flight [KSS-Rating]

b. Fatigue, After Three Flights [KSS-Rating] > Fatigue, Before First Flight [KSS-Rating]

c. Fatigue, After Three Flights [KSS-Rating] = Fatigue, Before First Flight [KSS-Rating]

d. Fatigue, After Five Flights [KSS-Rating] < Fatigue, Before First Flight [KSS-Rating]

e. Fatigue, After Five Flights [KSS-Rating] > Fatigue, Before First Flight [KSS-Rating]

f. Fatigue, After Five Flights [KSS-Rating] = Fatigue, Before First Flight [KSS-Rating]

g. Fatigue, After Five Flights [KSS-Rating] < Fatigue, After Three Flights [KSS-Rating]

h. Fatigue, After Five Flights [KSS-Rating] > Fatigue, After Three Flights [KSS-Rating]

i. Fatigue, After Five Flights [KSS-Rating] = Fatigue, After Three Flights [KSS-Rating]

Test Statistics[a]

	Fatigue, After Three Flights [KSS-Rating] - Fatigue, Before First Flight [KSS-Rating]	Fatigue, After Five Flights [KSS-Rating] - Fatigue, Before First Flight [KSS-Rating]	Fatigue, After Five Flights [KSS-Rating] - Fatigue, After Three Flights [KSS-Rating]
Z	-1,532[b]	-3,506[b]	-3,819[b]
Asymp. Sig. (2-tailed)	,125	,000	,000

a. Wilcoxon Signed Ranks Test

b. Based on negative ranks.

Impact of Execution of Action on Technical System

Check for Correlations – AVs Execution

Correlations

		Ln Mean of Input-Sum over All Five Flights [Inputs]	Ln Mean of Inputs per Time over All Five Flights [Inputs/s]	Ln Mean of Jerkiness over All Five Flights [Inputs/s²]	Ln Std. Deviation of Input-Sum over All Five Flights [Inputs]	Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]
Ln Mean of Input-Sum over All Five Flights [Inputs]	Pearson Correlation	1	,921**	,472**	,747**	,317*
	Sig. (2-tailed)		,000	,002	,000	,041
	N	42	42	42	42	42
Ln Mean of Inputs per Time over All Five Flights [Inputs/s]	Pearson Correlation		1	,581**	,617**	,381*
	Sig. (2-tailed)	,000		,000	,000	,013
	N	42	42	42	42	42
Ln Mean of Jerkiness over All Five Flights [Inputs/s²]	Pearson Correlation	,472**	,581**	1	,305*	,655**
	Sig. (2-tailed)	,002	,000		,049	,000
	N	42	42	42	42	42
Ln Std. Deviation of Input-Sum over All Five Flights [Inputs]	Pearson Correlation	,747**	,617**	,305*	1	,424**
	Sig. (2-tailed)	,000	,000	,049		,005
	N	42	42	42	42	42
Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]	Pearson Correlation	,317*	,381*	,655**	,424**	1
	Sig. (2-tailed)	,041	,013	,000	,005	
	N	42	42	42	42	42

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

*. Correlation is significant at the 0.05 level (2-tailed).

REGRESSION EXECUCTION of Action on Technical System

Mean Duration on Mean Velocity

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Ln Mean of Flight Duration over All Five Flights [s] -?-	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,341[a]	,116	,094	,45625	,116	5,269

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	40	,027

a. Predictors: (Constant), Ln Mean of Flight Duration over All Five Flights [s] -?-

b. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,097	1	1,097	5,269	,027[b]
	Residual	8,327	40	,208		
	Total	9,423	41			

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

b. Predictors: (Constant), Ln Mean of Flight Duration over All Five Flights [s] -?-

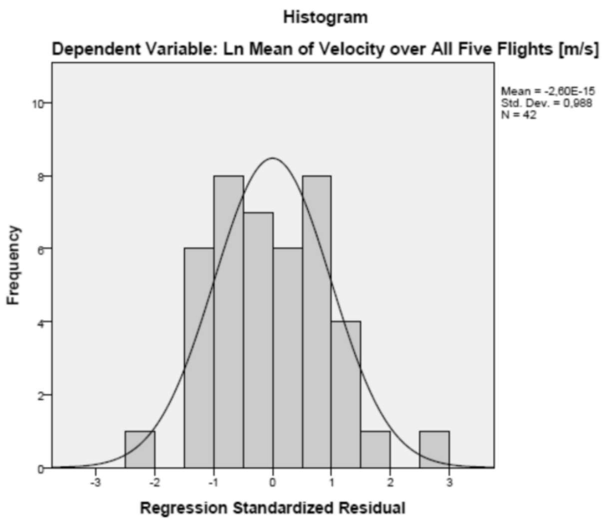
Coefficients[a]

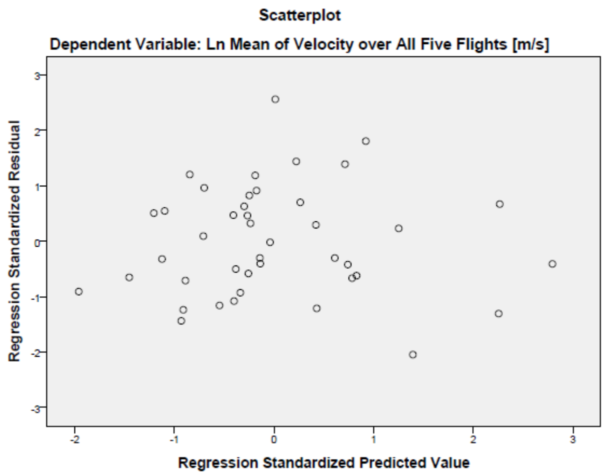
Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	-5,376	2,899		-1,855
	Ln Mean of Flight Duration over All Five Flights [s] -?-	1,050	,457	,341	2,295

Coefficients[a]

Model		Sig.	Collinearity Statistics	
			Tolerance	VIF
1	(Constant)	,071		
	Ln Mean of Flight Duration over All Five Flights [s] -?-	,027	1,000	1,000

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]





SD Duration on Ranking

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,450[a]	,203	,183	11,090	,203	10,176

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	40	,003

a. Predictors: (Constant), Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-

b. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1251,377	1	1251,377	10,176	,003[b]
	Residual	4919,123	40	122,978		
	Total	6170,500	41			

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

b. Predictors: (Constant), Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-

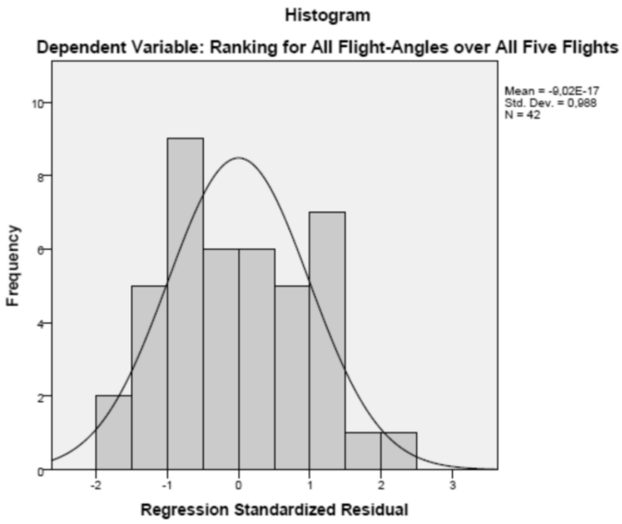
Coefficients[a]

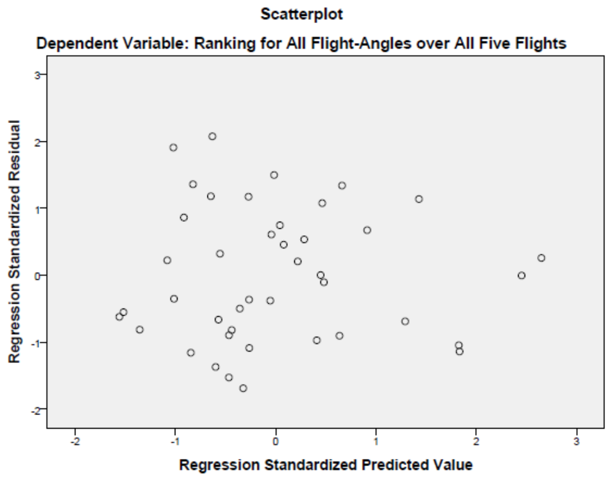
Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	-3,055	7,886		-,387
	Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-	6,808	2,134	,450	3,190

Coefficients[a]

Model		Sig.	Collinearity Statistics	
			Tolerance	VIF
1	(Constant)	,700		
	Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-	,003	1,000	1,000

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights





Impact of Choice of Action on Technical System

Markov Model on Technical System

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,360[a]	,130	,107	,65942	,130	5,817

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	39	,021

a. Predictors: (Constant), Followed most probable Path

b. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,530	1	2,530	5,817	,021[b]
	Residual	16,959	39	,435		
	Total	19,488	40			

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

b. Predictors: (Constant), Followed most probable Path

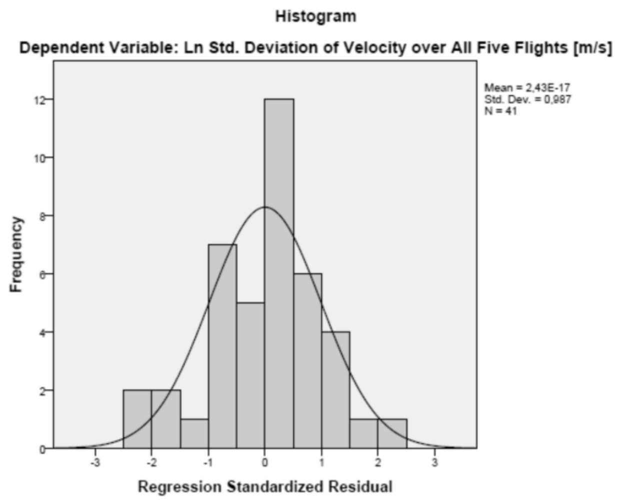
Coefficients[a]

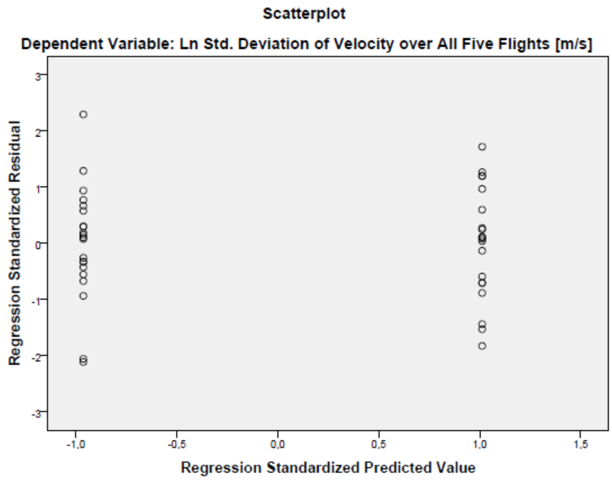
Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	,567	,147		3,845
	Followed most probable Path	-,497	,206	-,360	-2,412

Coefficients[a]

Model		Sig.	Collinearity Statistics	
			Tolerance	VIF
1	(Constant)	,000		
	Followed most probable Path	,021	1,000	1,000

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]





Markov States on Technical System

State 4

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	markov_duration_4	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,604[a]	,365	,323	10,106	,365	8,635	1	15	,010

a. Predictors: (Constant), markov_duration_4

b. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	881,834	1	881,834	8,635	,010[b]
	Residual	1531,930	15	102,129		
	Total	2413,765	16			

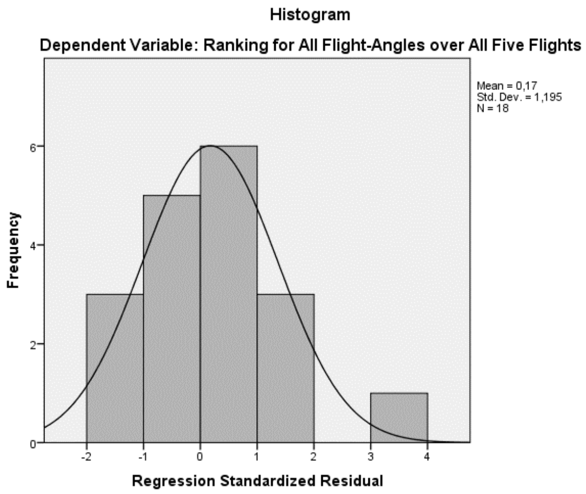
a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

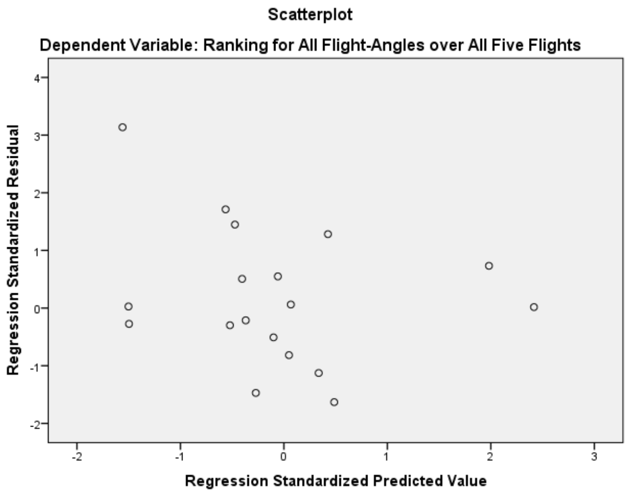
b. Predictors: (Constant), markov_duration_4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	7,523	4,868		1,545	,143		
	markov_duration_4	,276	,094	,604	2,938	,010	1,000	1,000

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights





Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	markov_duration_4	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,676[a]	,457	,421	,29502	,457	12,617	1	15	,003

a. Predictors: (Constant), markov_duration_4

b. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,098	1	1,098	12,617	,003[b]
	Residual	1,306	15	,087		
	Total	2,404	16			

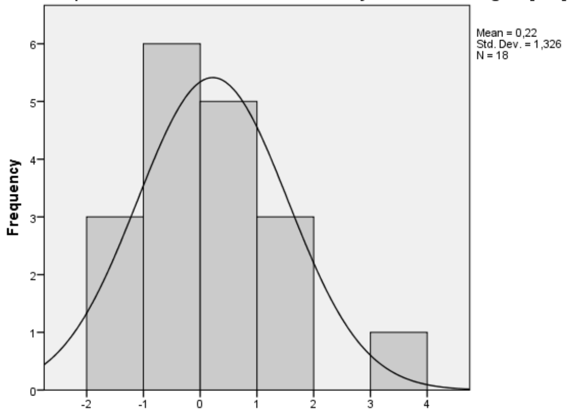
a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

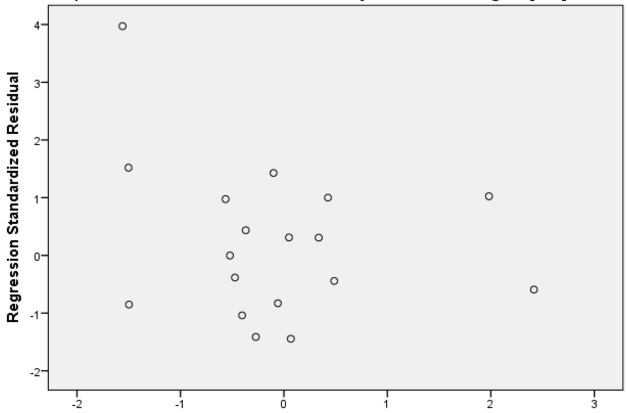
b. Predictors: (Constant), markov_duration_4

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,769	,142		5,413	,000		
	markov_duration_4	,010	,003	,676	3,552	,003	1,000	1,000

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]





Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	markov_duration_4	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	,688[a]	,473	,435	,55051	,473	12,565	1	14	,003

a. Predictors: (Constant), markov_duration_4

b. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3,808	1	3,808	12,565	,003[b]
	Residual	4,243	14	,303		
	Total	8,051	15			

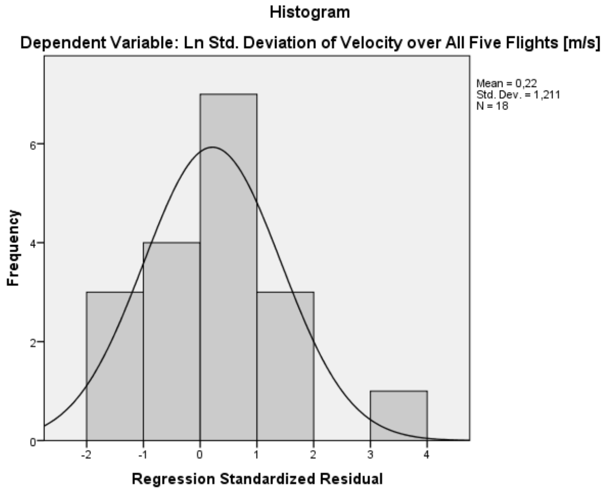
a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

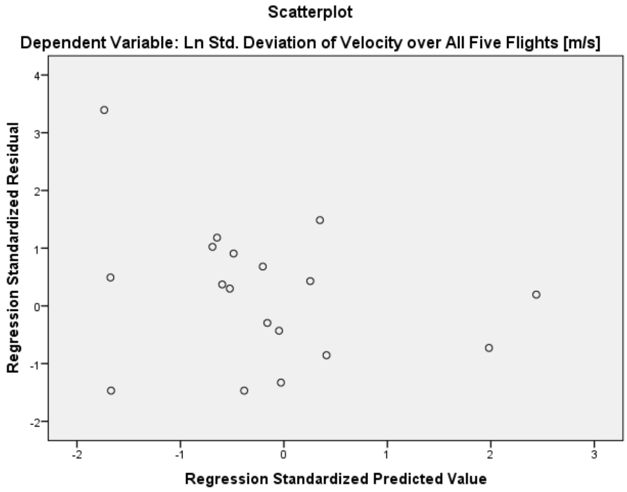
b. Predictors: (Constant), markov_duration_4

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-,566	,296		-1,911	,077	-1,202	,069		
	markov_duration_4	,020	,006	,688	3,545	,003	,008	,032	1,000	1,000

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]





State 8

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	markov_pitch_8	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,789[a]	,622	,580	,26812	,622	14,796	1	9	,004

a. Predictors: (Constant), markov_pitch_8

b. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,064	1	1,064	14,796	,004[b]
	Residual	,647	9	,072		
	Total	1,711	10			

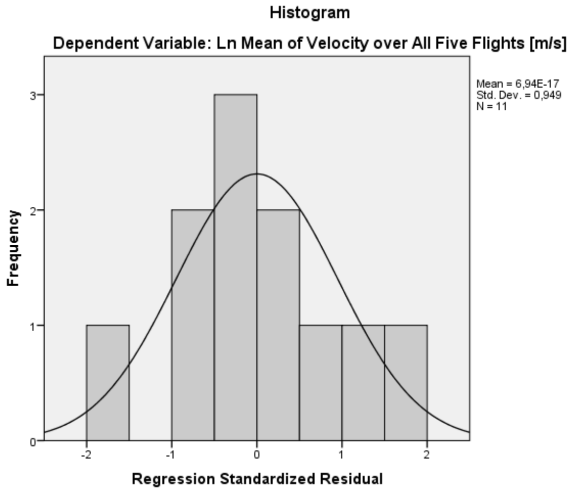
a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

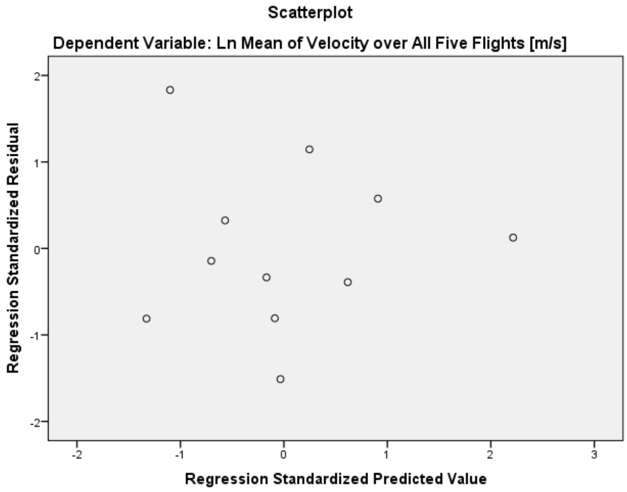
b. Predictors: (Constant), markov_pitch_8

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,562	,188		2,994	,015		
	markov_pitch_8	-,243	,063	-,789	-3,847	,004	1,000	1,000

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]





Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	markov_alt_mean_8	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change
1	,879[a]	,773	,740	,32669	,773	23,793	1	7	,002

a. Predictors: (Constant), markov_alt_mean_8

b. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,539	1	2,539	23,793	,002[b]
	Residual	,747	7	,107		
	Total	3,286	8			

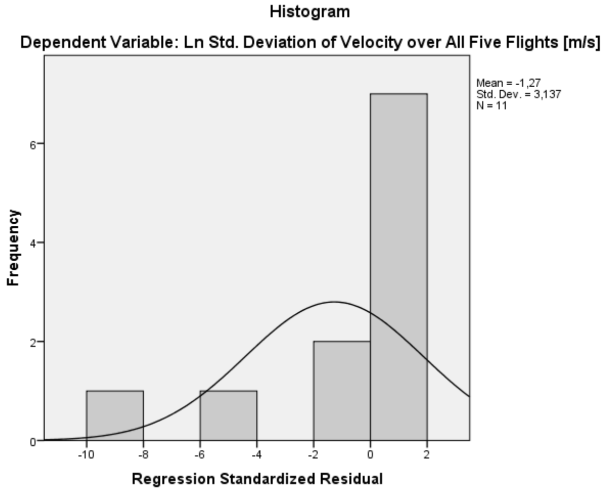
a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

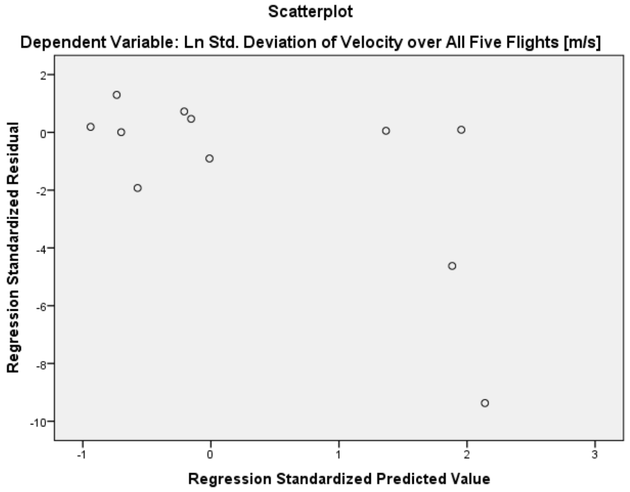
b. Predictors: (Constant), markov_alt_mean_8

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-,753	,292		-2,577	,037	-1,444	-,062		
	markov_alt_mean_8	,005	,001	,879	4,878	,002	,002	,007	1,000	1,000

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]





State 10

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Mean Altitude State 10	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,362[a]	,131	,109	11,424	,131	5,873

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	39	,020

a. Predictors: (Constant), Mean Altitude State 10

b. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	766,580	1	766,580	5,873	,020[b]
	Residual	5090,200	39	130,518		
	Total	5856,780	40			

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

b. Predictors: (Constant), Mean Altitude State 10

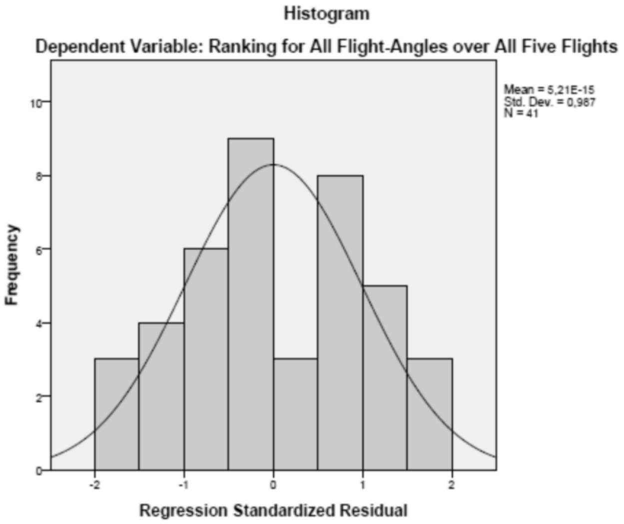
Coefficients[a]

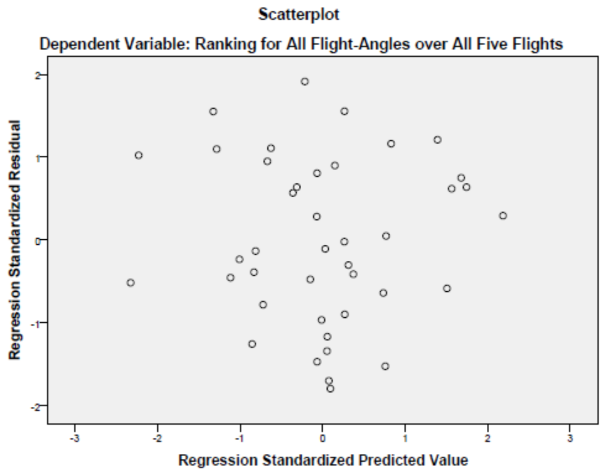
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	146,448	51,764		2,829	,007
	Mean Altitude State 10	-3,704	1,528	-,362	-2,424	,020

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Mean Altitude State 10	1,000	1,000

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights





State 11

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Mean Duration of State 11	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,349[a]	,122	,099	,45882	,122	5,407

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	39	,025

a. Predictors: (Constant), Mean Duration of State 11

b. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,138	1	1,138	5,407	,025[b]
	Residual	8,210	39	,211		
	Total	9,349	40			

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

b. Predictors: (Constant), Mean Duration of State 11

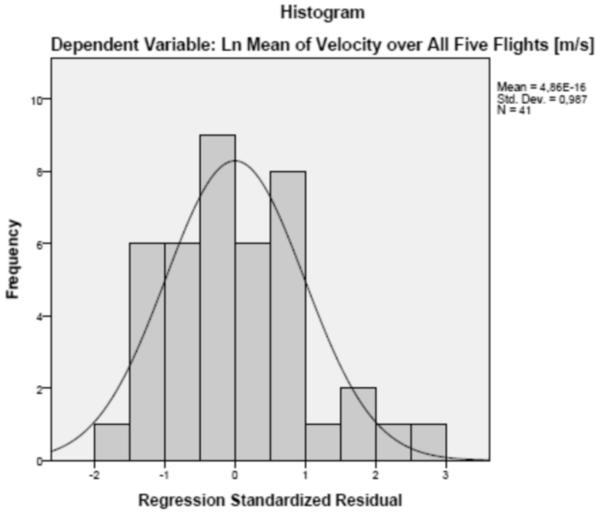
Coefficients[a]

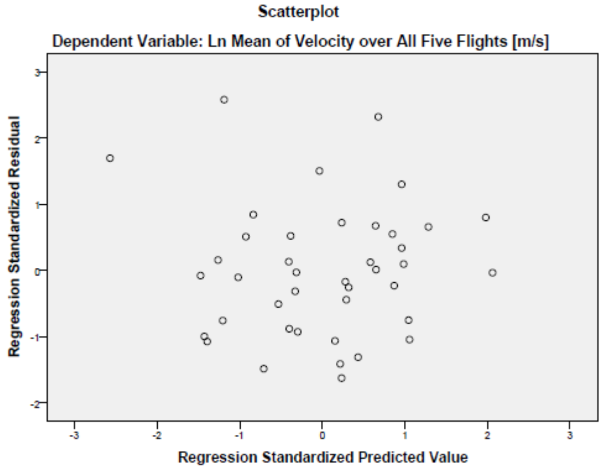
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t
1	(Constant)	1,876	,271		6,930
	Mean Duration of State 11	-,116	,050	-,349	-2,325

Coefficients[a]

Model		Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,000		
	Mean Duration of State 11	,025	1,000	1,000

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]





Impact of Choice of Action on Execution of Action

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change
1	,317[a]	,101	,078	,38940	,101	4,362
2	,322[b]	,104	,057	,39375	,003	,143

Model Summary[c]

Model	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change
1	1	39	,043
2	1	38	,707

a. Predictors: (Constant), Most Probable Path Probability [%]

b. Predictors: (Constant), Most Probable Path Probability [%], Followed most probable Path

c. Dependent Variable: Ln Mean of Input-Sum over All Five Flights [Inputs]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,661	1	,661	4,362	,043[b]
	Residual	5,914	39	,152		
	Total	6,575	40			
2	Regression	,684	2	,342	2,205	,124[c]
	Residual	5,892	38	,155		
	Total	6,575	40			

a. Dependent Variable: Ln Mean of Input-Sum over All Five Flights [Inputs]

b. Predictors: (Constant), Most Probable Path Probability [%]

c. Predictors: (Constant), Most Probable Path Probability [%], Followed most probable Path

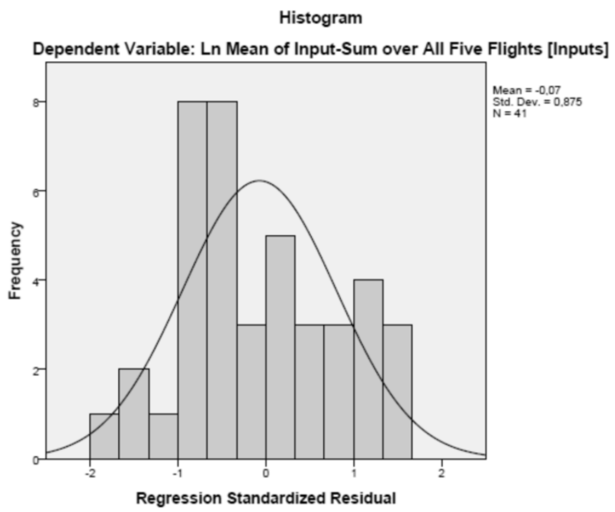
Coefficients[a]

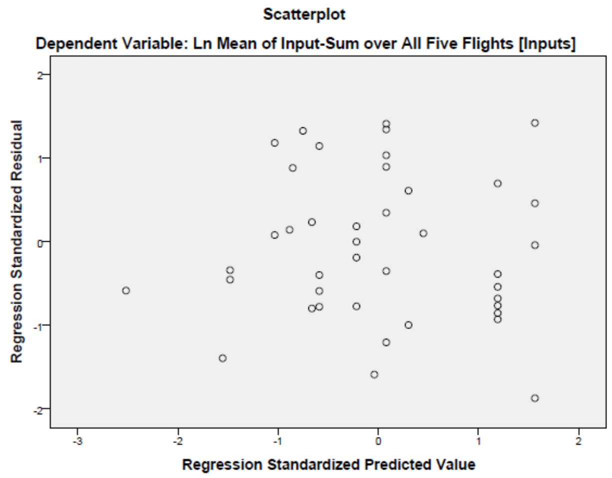
Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	17,248	,193		89,521
	Most Probable Path Probability [%]	,552	,264	,317	2,089
2	(Constant)	17,155	,314		54,574
	Most Probable Path Probability [%]	,582	,279	,335	2,087
	Followed most probable Path	,049	,128	,061	,378

Coefficients[a]

Model		Sig.	Collinearity Statistics	
			Tolerance	VIF
1	(Constant)	,000		
	Most Probable Path Probability [%]	,043	1,000	1,000
2	(Constant)	,000		
	Most Probable Path Probability [%]	,044	,917	1,090
	Followed most probable Path	,707	,917	1,090

a. Dependent Variable: Ln Mean of Input-Sum over All Five Flights [Inputs]





Impact of Human Influencing Factors on Choice and Execution of Task

Correlations

			Cumulated Overall Flight Duration in Last Twelve Months [h]	Cumulated Single Engine Flight Duration [h]	Cumulated Single Engine Flight Duration in Last Twelve Months [h]	Cumulated Time Using FSX [h]	Cumulated Time on Professional Flight simulator [h]
Spearman rho	Number of Operated Flights in Last Twelve Months [n]	Correlation Coefficient	,956**		,826**		
		Sig. (2-tailed)	,000		,000		
		N	22		22		
	Cumulated Overall Flight Duration [h]	Correlation Coefficient		,763**			
		Sig. (2-tailed)		,000			
		N		36			
	Cumulated Overall Flight Duration in Last Twelve Months [h]	Correlation Coefficient			,930**		
		Sig. (2-tailed)			,000		
		N			40		
	Flight simulation Experience [Type]	Correlation Coefficient					,863**
		Sig. (2-tailed)					,000
		N					38
	Cumulated Time on Flight simulation [h]	Correlation Coefficient				,732**	
		Sig. (2-tailed)				,000	
		N				35	

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

*. Correlation is significant at the 0.05 level (2-tailed).

ON MEAN Flight Duration

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,580[a]	,337	,281	,12721	,337	6,093
2	,775[b]	,600	,527	,10319	,263	7,238

Model Summary[c]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	12	,030
2	1	11	,021

a. Predictors: (Constant), Cumulated Flight Duration on Cessna [h]

b. Predictors: (Constant), Cumulated Flight Duration on Cessna [h], Self-assessment of Realistic Flight Behavior

c. Dependent Variable: Ln Mean of Flight Duration over All Five Flights [s] -?-

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,099	1	,099	6,093	,030[b]
	Residual	,194	12	,016		
	Total	,293	13			
2	Regression	,176	2	,088	8,249	,006[c]
	Residual	,117	11	,011		
	Total	,293	13			

a. Dependent Variable: Ln Mean of Flight Duration over All Five Flights [s] -?-

b. Predictors: (Constant), Cumulated Flight Duration on Cessna [h]

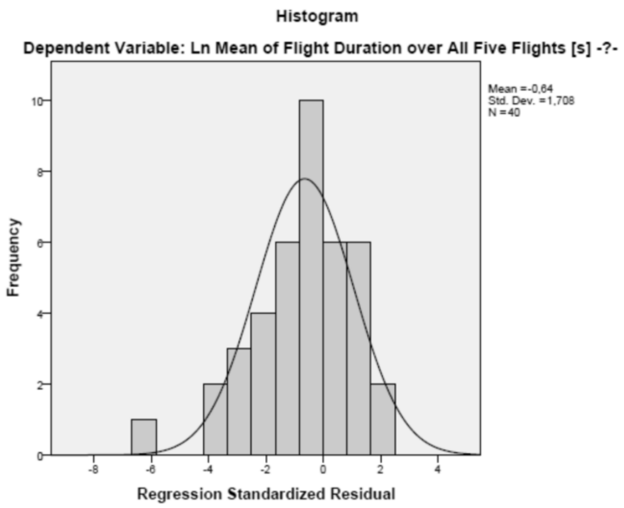
c. Predictors: (Constant), Cumulated Flight Duration on Cessna [h], Self-assessment of Realistic Flight Behavior

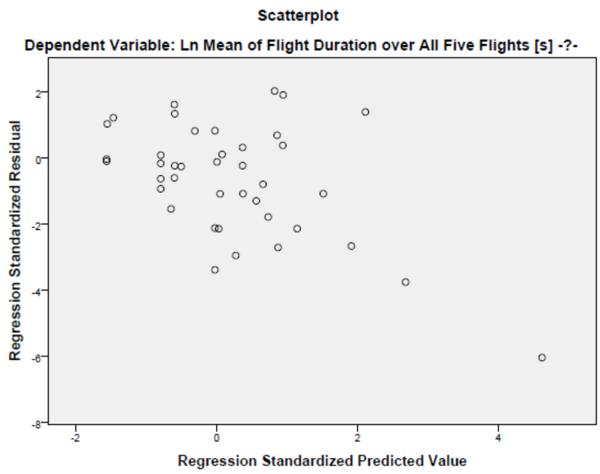
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	6,303	,047		134,997
	Cumulated Flight Duration on Cessna [h]	,001	,000	,580	2,468
2	(Constant)	6,111	,081		75,658
	Cumulated Flight Duration on Cessna [h]	,001	,000	,678	3,491
	Self-assessment of Realistic Flight Behavior	,089	,033	,522	2,690

Coefficients[a]

Model		Sig.	95,0% Confidence Interval for B		Collinearity Statistics
			Lower Bound	Upper Bound	Tolerance
1	(Constant)	,000	6,202	6,405	
	Cumulated Flight Duration on Cessna [h]	,030	,000	,002	1,000
2	(Constant)	,000	5,934	6,289	
	Cumulated Flight Duration on Cessna [h]	,005	,000	,002	,965
	Self-assessment of Realistic Flight Behavior	,021	,016	,162	,965





On SUM OF INPUTS

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,580[a]	,336	,281	,42493	,336	6,078

Model Summary[b]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	12	,030

a. Predictors: (Constant), Perceived Difficulty of Landing Maneuver

b. Dependent Variable: Ln Mean of Input-Sum over All Five Flights [Inputs]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,097	1	1,097	6,078	,030[b]
	Residual	2,167	12	,181		
	Total	3,264	13			

a. Dependent Variable: Ln Mean of Input-Sum over All Five Flights [Inputs]

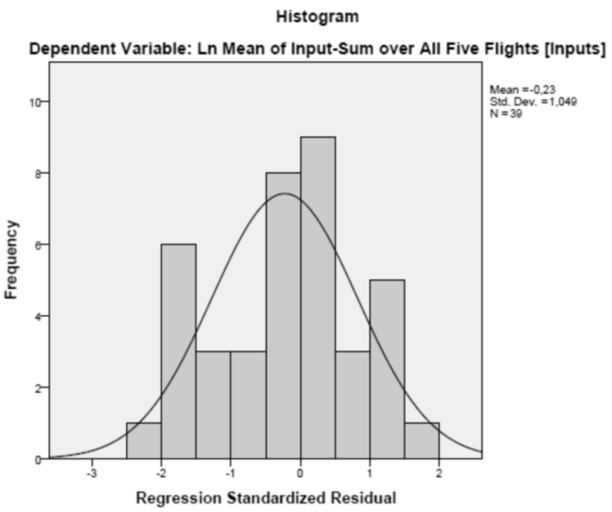
b. Predictors: (Constant), Perceived Difficulty of Landing Maneuver

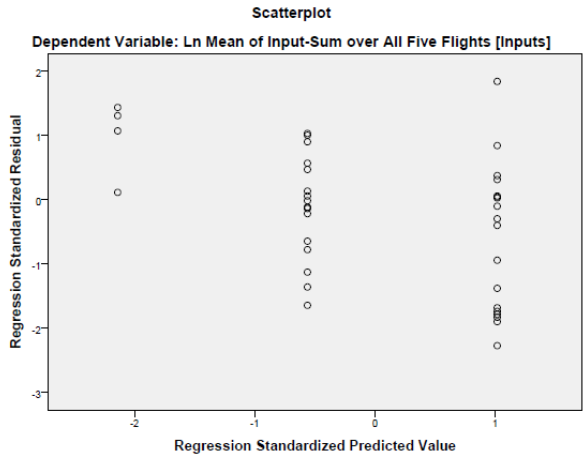
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	15,741	,819		19,227
	Perceived Difficulty of Landing Maneuver	,459	,186	,580	2,465

Coefficients[a]

Model		Sig.	95,0% Confidence Interval for B		Collinearity Statistics
			Lower Bound	Upper Bound	Tolerance
1	(Constant)	,000	13,957	17,525	
	Perceived Difficulty of Landing Maneuver	,030	,053	,864	1,000





On SD FLIGHT DURATION

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics	
					R Square Change	F Change
1	,619[a]	,384	,332	,74474	,384	7,465
2	,837[b]	,700	,646	,54227	,317	11,634

Model Summary[c]

Model	Change Statistics		
	df1	df2	Sig. F Change
1	1	12	,018
2	1	11	,006

a. Predictors: (Constant), Cumulated Flight Duration on Cessna [h]

b. Predictors: (Constant), Cumulated Flight Duration on Cessna [h], Self-assessment of Realistic Flight Behavior

c. Dependent Variable: Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4,140	1	4,140	7,465	,018[b]
	Residual	6,656	12	,555		
	Total	10,796	13			
2	Regression	7,561	2	3,781	12,857	,001[c]
	Residual	3,235	11	,294		
	Total	10,796	13			

a. Dependent Variable: Ln Std. Deviation of Flight Duration over All Five Flights [s] -?-

b. Predictors: (Constant), Cumulated Flight Duration on Cessna [h]

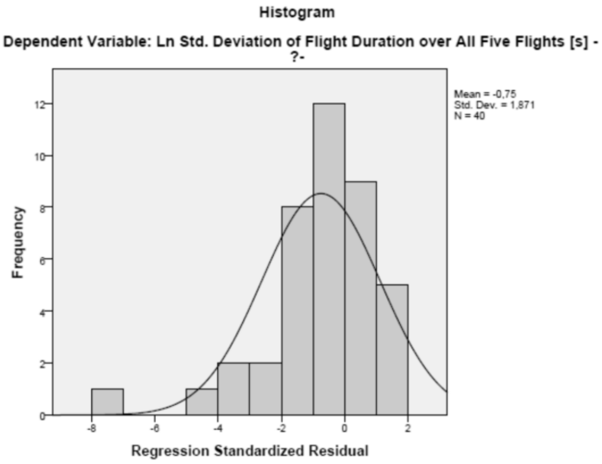
c. Predictors: (Constant), Cumulated Flight Duration on Cessna [h], Self-assessment of Realistic Flight Behavior

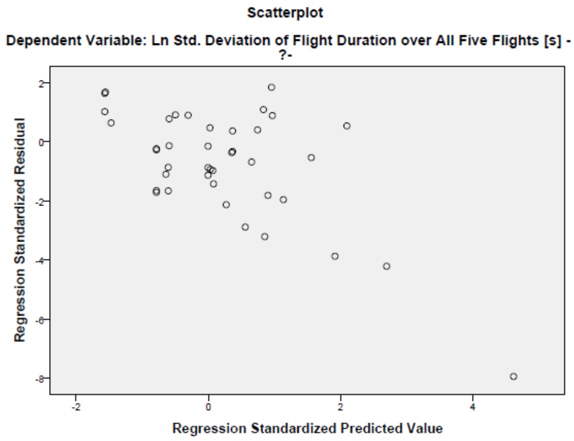
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	3,360	,273		12,292
	Cumulated Flight Duration on Cessna [h]	,006	,002	,619	2,732
2	(Constant)	2,081	,424		4,903
	Cumulated Flight Duration on Cessna [h]	,007	,002	,726	4,322
	Self-assessment of Realistic Flight Behavior	,595	,175	,573	3,411

Coefficients[a]

Model		Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance
1	(Constant)	,000	2,764	3,955	
	Cumulated Flight Duration on Cessna [h]	,018	,001	,011	1,000
2	(Constant)	,000	1,147	3,015	
	Cumulated Flight Duration on Cessna [h]	,001	,004	,011	,965
	Self-assessment of Realistic Flight Behavior	,006	,211	,979	,965





EGs on Mean Jerkiness

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Qual_PPL	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Flight simulation Experience [Type]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Age (grouped)	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Jerkiness over All Five Flights [Inputs/s²]

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,616[a]	,379	,327	,33561	,379	7,321	1	12	,019
2	,799[b]	,639	,573	,26727	,260	7,922	1	11	,017
3	,944[c]	,891	,859	,15367	,253	23,275	1	10	,001

a. Predictors: (Constant), Qual_PPL

b. Predictors: (Constant), Qual_PPL, Flight simulation Experience [Type]

c. Predictors: (Constant), Qual_PPL, Flight simulation Experience [Type], Age (grouped)

d. Dependent Variable: Ln Mean of Jerkiness over All Five Flights [Inputs/s²]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,825	1	,825	7,321	,019[b]
	Residual	1,352	12	,113		
	Total	2,176	13			
2	Regression	1,390	2	,695	9,732	,004[c]
	Residual	,786	11	,071		
	Total	2,176	13			
3	Regression	1,940	3	,647	27,385	,000[d]
	Residual	,236	10	,024		
	Total	2,176	13			

a. Dependent Variable: Ln Mean of Jerkiness over All Five Flights [Inputs/s²]

b. Predictors: (Constant), Qual_PPL

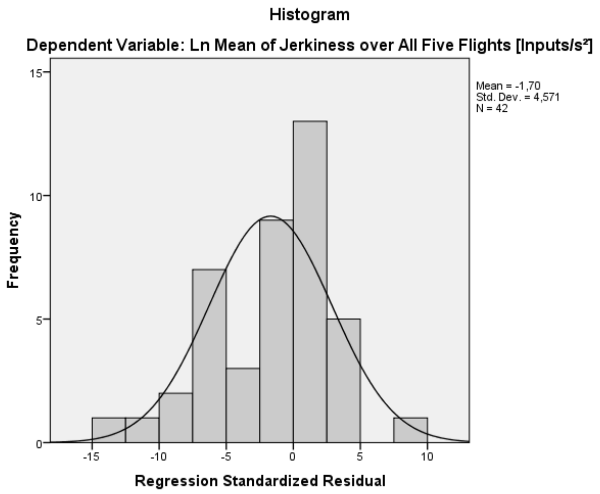
c. Predictors: (Constant), Qual_PPL, Flight simulation Experience [Type]

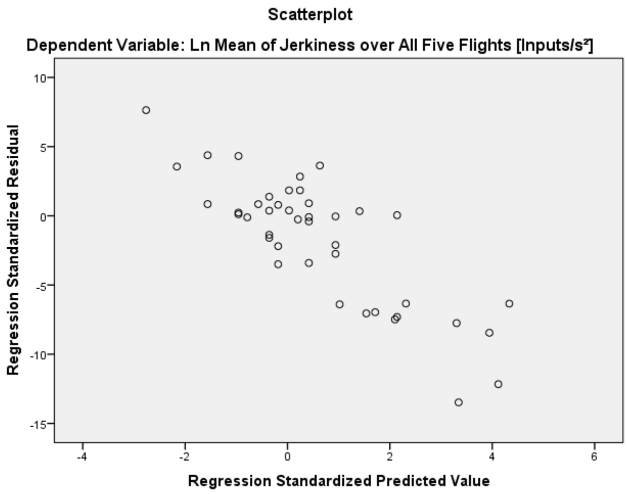
d. Predictors: (Constant), Qual_PPL, Flight simulation Experience [Type], Age (grouped)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	8,634	,237		36,382	,000	8,117	9,151		
	Qual_PPL	-,694	,256	-,616	-2,706	,019	-1,252	-,135	1,000	1,000
2	(Constant)	9,448	,345		27,348	,000	8,687	10,208		
	Qual_PPL	-,931	,221	-,826	-4,215	,001	-1,417	-,445	,854	1,171
	Flight simulation Experience [Type]	-,203	,072	-,552	-2,815	,017	-,363	-,044	,854	1,171
3	(Constant)	8,535	,274		31,123	,000	7,924	9,147		
	Qual_PPL	-1,197	,138	-1,063	-8,646	,000	-1,506	-,889	,718	1,392
	Flight simulation Experience [Type]	-,150	,043	-,406	-3,477	,006	-,246	-,054	,797	1,255
	Age (grouped)	,232	,048	,597	4,824	,001	,125	,340	,709	1,410

a. Dependent Variable: Ln Mean of Jerkiness over All Five Flights [Inputs/s²]





On SD Jerkiness

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Qual_CPL	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,537[a]	,288	,229	,51839	,288	4,865	1	12	,048

a. Predictors: (Constant), Qual_CPL

b. Dependent Variable: Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,307	1	1,307	4,865	,048[b]
	Residual	3,225	12	,269		
	Total	4,532	13			

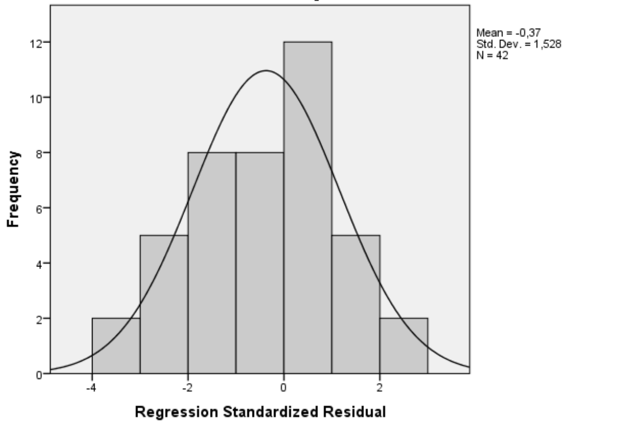
a. Dependent Variable: Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]

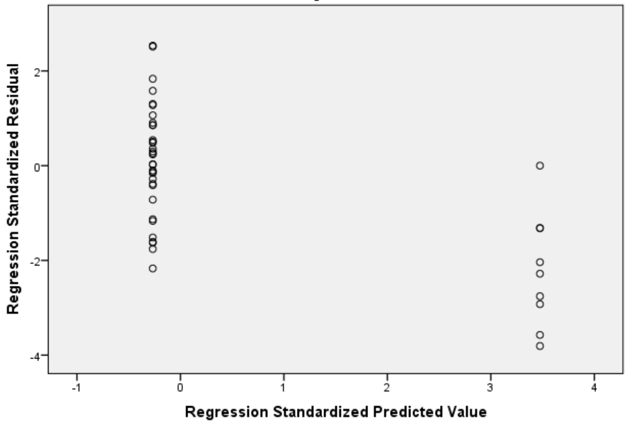
b. Predictors: (Constant), Qual_CPL

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	6,033	,144		41,958	,000	5,719	6,346		
	Qual_CPL	1,187	,538	,537	2,206	,048	,014	2,359	1,000	1,000

a. Dependent Variable: Ln Std. Deviation of Jerkiness over All Five Flights [Inputs/ s²]





Impact of Human Influencing Factors on Technical System

On Ln Mean Velocity

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Change of Fatigue over All Five Flights	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Level of Education [Type]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Age (grouped)	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,631[a]	,398	,348	,40495	,398	7,933	1	12	,016
2	,819[b]	,671	,611	,31288	,273	9,101	1	11	,012
3	,897[c]	,804	,746	,25296	,134	6,829	1	10	,026

a. Predictors: (Constant), Change of Fatigue over All Five Flights

b. Predictors: (Constant), Change of Fatigue over All Five Flights, Level of Education [Type]

c. Predictors: (Constant), Change of Fatigue over All Five Flights, Level of Education [Type], Age (grouped)

d. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,301	1	1,301	7,933	,016[b]
	Residual	1,968	12	,164		
	Total	3,269	13			
2	Regression	2,192	2	1,096	11,195	,002[c]
	Residual	1,077	11	,098		
	Total	3,269	13			
3	Regression	2,629	3	,876	13,694	,001[d]
	Residual	,640	10	,064		
	Total	3,269	13			

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]

b. Predictors: (Constant), Change of Fatigue over All Five Flights

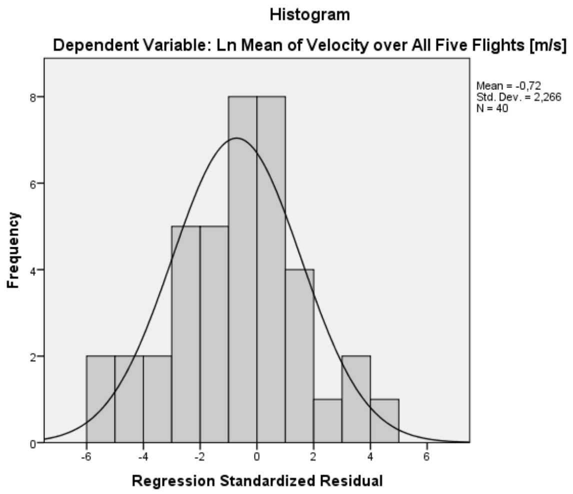
c. Predictors: (Constant), Change of Fatigue over All Five Flights, Level of Education [Type]

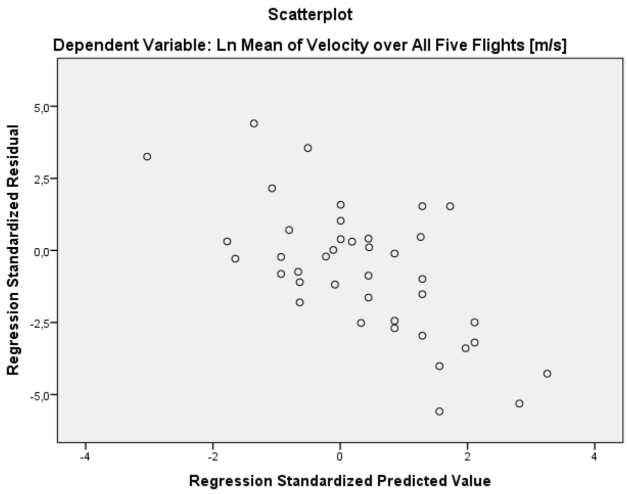
d. Predictors: (Constant), Change of Fatigue over All Five Flights, Level of Education [Type], Age (grouped)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1,603	,157		10,207	,000	1,261	1,945		
	Change of Fatigue over All Five Flights	-,345	,122	-,631	-2,817	,016	-,612	-,078	1,000	1,000
2	(Constant)	,584	,359		1,630	,131	-,205	1,374		
	Change of Fatigue over All Five Flights	-,344	,095	-,628	-3,631	,004	-,552	-,135	1,000	1,000
	Level of Education [Type]	,206	,068	,522	3,017	,012	,056	,357	1,000	1,000
3	(Constant)	-,367	,465		-,788	,449	-1,403	,670		
	Change of Fatigue over All Five Flights	-,381	,078	-,696	-4,893	,001	-,554	-,207	,967	1,035
	Level of Education [Type]	,248	,058	,629	4,313	,002	,120	,377	,922	1,085
	Age (grouped)	,185	,071	,387	2,613	,026	,027	,342	,893	1,120

a. Dependent Variable: Ln Mean of Velocity over All Five Flights [m/s]





On SD Velocity

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Cumulated Overall Flight Duration in Last Twelve Months [h]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	,565[a]	,319	,263	,53785	,319	5,630	1	12	,035

a. Predictors: (Constant), Cumulated Overall Flight Duration in Last Twelve Months [h]

b. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,629	1	1,629	5,630	,035[b]
	Residual	3,471	12	,289		
	Total	5,100	13			

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

b. Predictors: (Constant), Cumulated Overall Flight Duration in Last Twelve Months [h]

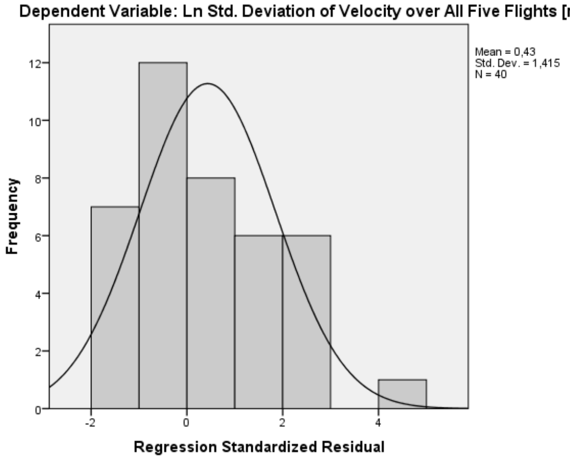
Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	,527	,204		2,580	,024	,082	,971		
	Cumulated Overall Flight Duration in Last Twelve Months [h]	-,014	,006	-,565	-2,373	,035	-,027	-,001	1,000	1,000

a. Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]

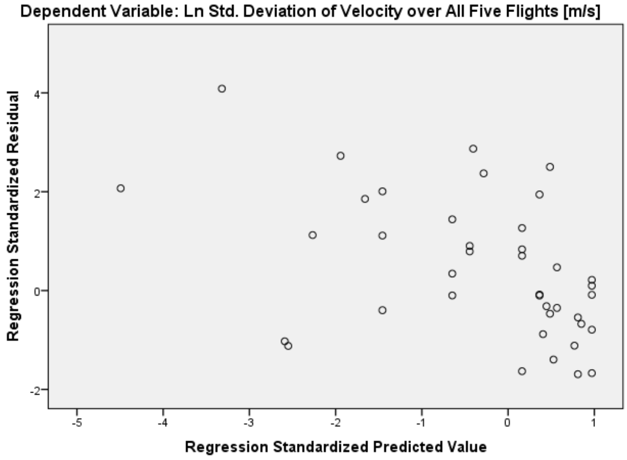
Histogram

Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]



Scatterplot

Dependent Variable: Ln Std. Deviation of Velocity over All Five Flights [m/s]



On RANKING

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Cumulated Overall Flight Duration in Last Twelve Months [h]	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	Change Statistics F Change	Change Statistics df1	Change Statistics df2	Change Statistics Sig. F Change
1	,541[a]	,293	,234	9,649	,293	4,969	1	12	,046

a. Predictors: (Constant), Cumulated Overall Flight Duration in Last Twelve Months [h]

b. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	462,583	1	462,583	4,969	,046[b]
	Residual	1117,132	12	93,094		
	Total	1579,714	13			

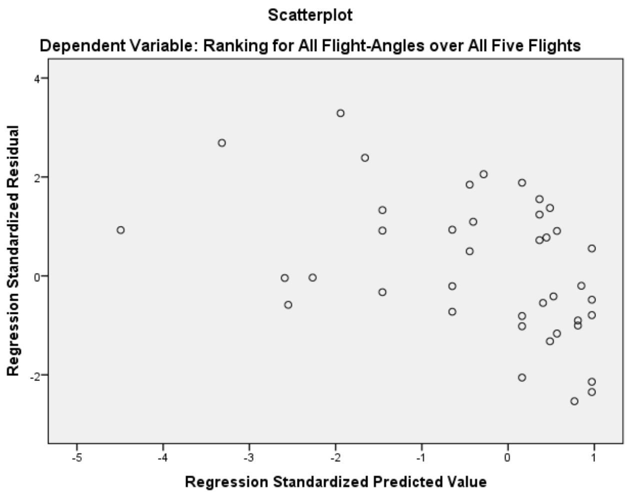
a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights

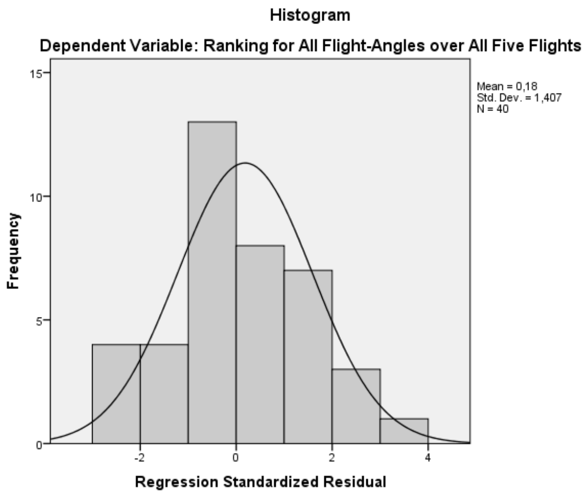
b. Predictors: (Constant), Cumulated Overall Flight Duration in Last Twelve Months [h]

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	27,651	3,661		7,552	,000	19,674	35,629		
	Cumulated Overall Flight Duration in Last Twelve Months [h]	-,241	,108	-,541	-2,229	,046	-,477	-,005	1,000	1,000

a. Dependent Variable: Ranking for All Flight-Angles over All Five Flights





J Questionnaire and Additional Material of Study Three

B.9: Fragebogen vor dem Versuch

TECHNISCHE UNIVERSITÄT DARMSTADT

Fragebogen vor dem Versuch

Probandencode

Um die beantworteten Fragen später den entsprechenden Messwerten aus dem Versuch zuordnen zu können, wird jedem Probanden ein individueller Probandencode zugewiesen. Des Weiteren kann dadurch in Zukunft festgestellt werden, ob der Proband an weiteren Versuchen am Dreibein teilnimmt. Durch den Probandencode kann nicht auf die Identität des Probanden geschlossen werden.

1. Bitte geben Sie die letzten beiden Buchstaben des Vornamens Ihrer Mutter an.
   Beispiel: Ihre Mutter heißt Sandra. Bitte geben Sie „ra" an.

   ____

2. Bitte geben Sie den Tag an, an dem Sie geboren wurden.
   Beispiel: Sie wurden am 08.12.1989 geboren. Bitte geben Sie „08" an.

   ____

3. Bitte geben Sie die ersten beiden Buchstaben Ihres Geburtsortes an.
   Beispiel: Sie wurden in Darmstadt geboren. Bitte geben sie „Da" an.

   ____

xxv

Müdigkeit

4. Bitte bewerten Sie Ihren momentanen Müdigkeitszustand durch Ankreuzen des zutreffenden Kästchens. Sie können auch die Zwischenstufen benutzen.
   Beispiel: Sie fühlen sich wacher als „wach", aber müder als „sehr wach". Kreuzen Sie dann das Kästchen „2" an:
   - ☐ 1 = sehr wach
   - ☒ 2
   - ☐ 3 = wach

- ☐ 1 = sehr wach
- ☐ 2
- ☐ 3 = wach
- ☐ 4
- ☐ 5 = weder wach noch müde
- ☐ 6
- ☐ 7 = müde, aber keine Probleme wach zu bleiben
- ☐ 8
- ☐ 9 = sehr müde, große Probleme wach zu bleiben, mit dem Schlaf kämpfend

Erfahrung mit Versuchsstand Dreibein

5. Haben Sie bereits Erfahrung mit dem Versuchsstand „Dreibein", z.B. in Zusammenhang mit einem anderen Versuch?
   - ☐ ja
   - ☐ nein

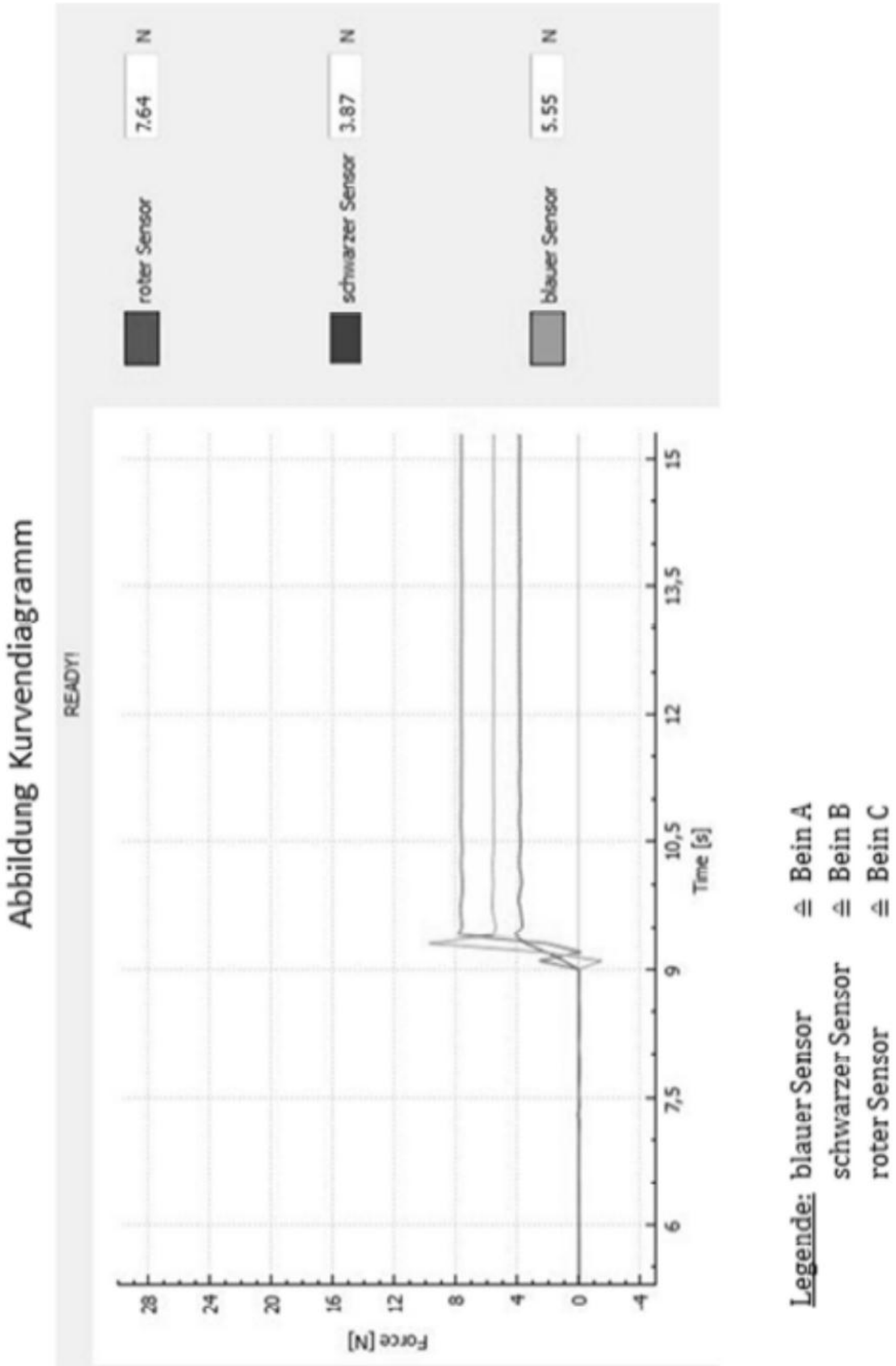
   Falls ja, wann und wobei haben Sie die Erfahrung gesammelt?

____

____

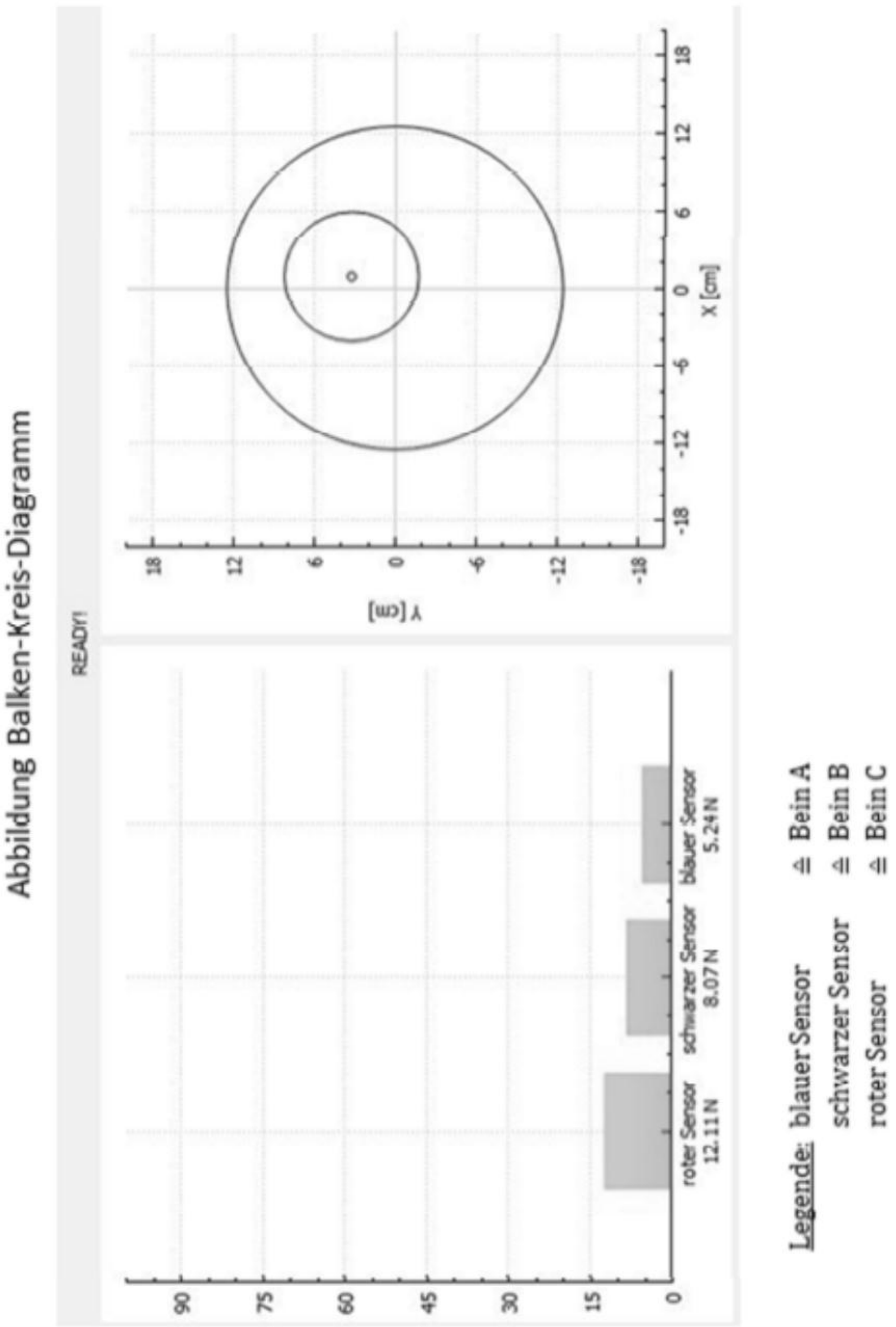
xxvi

B.10: Abbildung im Fragebogen nach dem Versuch für das Systemverständnis von VK



xxvii

B.11: Abbildung im Fragebogen nach dem Versuch für das Systemverständnis von VB



xxviii

B.12: Fragebogen nach dem Versuch

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SFB 805

Fragebogen nach dem Versuch

Vielen Dank, dass Sie an diesem Versuch zur Untersuchung von Feedbackvarianten teilnehmen.

Um die ermittelten Versuchsdaten korrekt auswerten zu können bedarf es noch der Beantwortung der folgenden Fragen. Dies wird etwa fünf Minuten Zeit in Anspruch nehmen. Durch die personenbezogenen Daten kann beispielsweise überprüft werden ob bestimmte Versuchswerte überwiegend von bestimmten Personengruppen stammen. Bitte beantworten Sie deshalb den Fragebogen **vollständig und gewissenhaft**.

Die Antworten sind **anonymisiert** und werden mit Hilfe einer Probanden-ID nur den ermittelten Versuchsdaten und nicht dem Probanden selbst zugeordnet. Alle ermittelten Daten werden **vertraulich** behandelt.

Sie können **jederzeit Verständnisfragen** stellen.

xxix

Müdigkeit

1. Bitte bewerten Sie Ihren momentanen Müdigkeitszustand durch Ankreuzen des zutreffenden Kästchens. Sie können auch die Zwischenstufen benutzen.

□ 1 = sehr wach

□ 2

□ 3 = wach

□ 4

□ 5 = weder wach noch müde

□ 6

□ 7 = müde, aber keine Probleme wach zu bleiben

□ 8

□ 9 = sehr müde, große Probleme wach zu bleiben, mit dem Schlaf kämpfend

Daten zu Ihrer Person

2. Alter: _______________

3. Studiengang: ______________________________________ im □ Bachelor □ Master

   am Fachbereich: ____________________________________

4. Haben Sie eine sonstige abgeschlossen Ausbildung? □ ja: _______________ □ nein

5. Leiden Sie unter Schwierigkeiten bei der Farbwahrnehmung? □ ja □ nein

xxx

Systemverständnis

Betrachten Sie die vor Ihnen liegende „**Abbildung Kurvendiagramm**" und beantworten Sie die Fragen 6 bis 7.

6. Welches Bein erfährt die **geringste Maximalkraft**?
   - ☐ Bein A (blau)
   - ☐ Bein B (schwarz)
   - ☐ Bein C (rot)
   - ☐ weiß nicht

7. Welches Bein hat bei der gegebenen **Zentrizität** den **geringsten** Abstand vom Schwerpunkt?
   - ☐ Bein A (blau)
   - ☐ Bein B (schwarz)
   - ☐ Bein C (rot)
   - ☐ weiß nicht

Betrachten Sie die vor Ihnen liegende „**Abbildung Balken-Kreis-Diagramm**" und beantworten Sie die Fragen 8 bis 9.

8. Welches Bein erfährt die **geringste Maximalkraft**?
   - ☐ Bein A (blau)
   - ☐ Bein B (schwarz)
   - ☐ Bein C (rot)
   - ☐ weiß nicht

9. Welches Bein hat bei der gegebenen **Zentrizität** den **geringsten** Abstand vom Schwerpunkt?
   - ☐ Bein A (blau)
   - ☐ Bein B (schwarz)
   - ☐ Bein C (rot)
   - ☐ weiß nicht

Bewertung der Feedbackvarianten

Bitte kreuzen Sie bei den Fragen 10 und 11 pro Spalte ein Feld an.

10. Bei welcher Feedbackvariante **ohne** Zeitdruck haben Sie Ihrer Meinung nach
    a. die geringste Maximalkraft
    b. die größte Maximalkraft
    c. die genaueste Zentrizität
    d. die ungenaueste Zentrizität erzielt?

		geringste Maximalkraft	größte Maximalkraft	genaueste Zentrizität	ungenaueste Zentrizität
ohne Zeitdruck	Variante „nicht computergestützt“				
	Variante „Kurvendiagramm“				
	Variante „Balken-Kreis-Diagramm“				

11. Bei welcher Feedbackvariante **mit** Zeitdruck haben Sie Ihrer Meinung nach
    a. die geringste Maximalkraft
    b. die größte Maximalkraft
    c. die genaueste Zentrizität
    d. die ungenaueste Zentrizität erzielt?

		geringste Maximalkraft	größte Maximalkraft	genaueste Zentrizität	ungenaueste Zentrizität
mit Zeitdruck	Variante „nicht computergestützt“				
	Variante „Kurvendiagramm“				
	Variante „Balken-Kreis-Diagramm“				

Blickrichtung

Bitte kreuzen Sie bei der Frage 12 pro Spalte ein Feld an

12. Was haben Sie bei den Varianten „Kurvendiagramm“ und „Balken-Kreis-Diagramm“ zur Analyse der Abstellvorgänge überwiegend betrachtet?

	Variante „Kurvendiagramm“	Variante „Balken-Kreis-Diagramm“
Feedback auf dem Monitor		
Gewicht auf dem Dreibein		
beides gleich		

Versuchsablauf

13. Wurden Sie während der Versuchsdurchführung durch etwas gestört, z.B. Lärm?

- ☐ ja
- ☐ nein

Falls ja, wodurch?

14. Haben Sie Anmerkungen und Kritik bezüglich des gesamten Versuchs?

xxxiii

Instructions on the Two Feedback Designs

B.7: Instruktion für VK

Instruktion
Variante „Kurvendiagramm"

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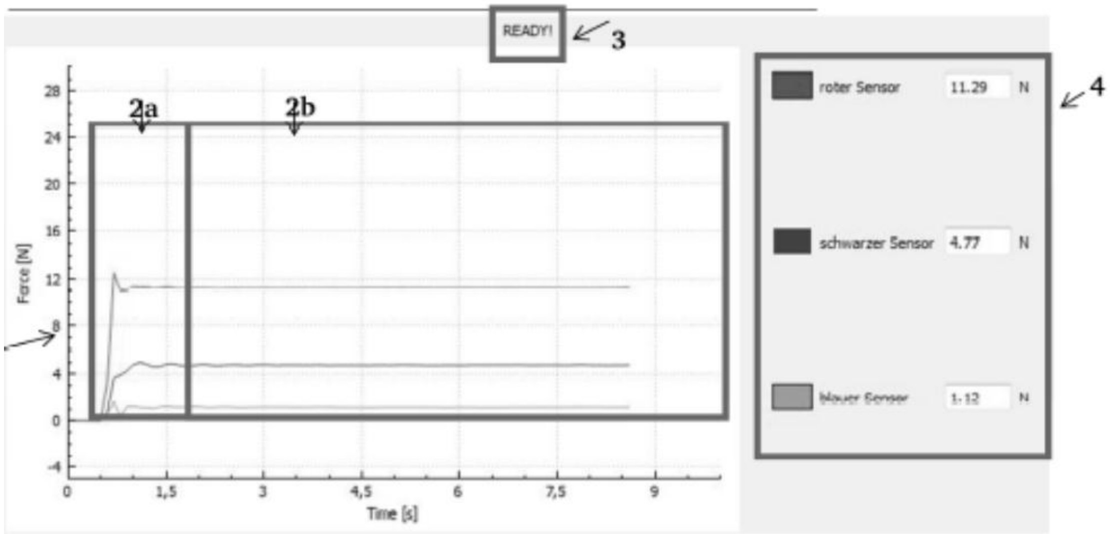

Das Kurvendiagramm besteht aus vier Teilen:

1. Die Koordinatenachsen:
   Auf der x-Achse ist die Zeit in Sekunden aufgetragen, auf der y-Achse die Kraft in Newton, welche von den Kraftmesssensoren der einzelnen Beine gemessen wird.
2. Der Graph:
   Wird das erste Gewicht abgestellt kommt es zu einer Einschwingungsphase (2a), wobei der größte Ausschlag der jeweiligen Linie die **Maximalkraft** angibt, welche auf dem jeweiligen Bein lastet.
   Im Graph entspricht blau Bein A, schwarz Bein B und rot Bein C. Die Farb- und Buchstabenverteilung haben keine Signalwirkung.
   Sind die Schwingungen abgeklungen wird die **Zentrizität** der Beine angezeigt (2b). Je geringer die Abstände zwischen den einzelnen Linien sind, desto zentraler liegt der Schwerpunkt der Gewichte auf dem Dreibein.
3. Statusmeldung der Software:
   Der Status „Ready!" gibt an, dass der Proband das nächste Gewicht auf das Dreibein stellen kann. Während der Einschwingungsphase zeigt „Please Wait!" an, dass das zweite Gewicht noch nicht hingestellt werden darf.
4. Messwerte:
   Beziffern die jeweilige aktuell gemessene Belastung der drei Beine in Newton.

xxiii

B.8: Instruktion für VB

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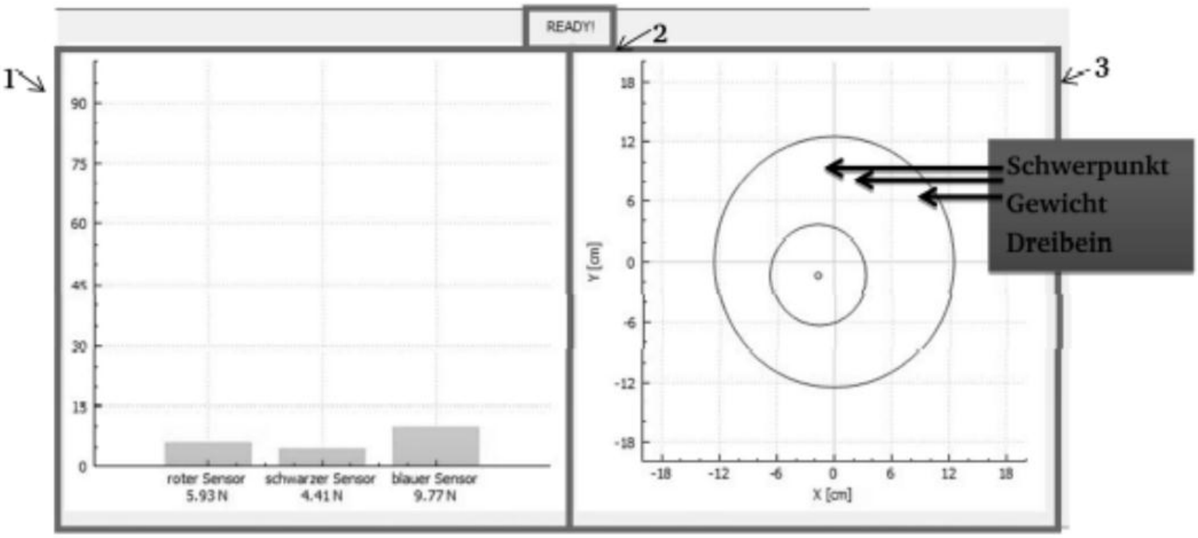
Instruktion
Variante „Balken-Kreis-Diagramm"



Das Balken-Kreis-Diagramm besteht aus drei Teilen:

1. Das Balkendiagramm:
   Auf der x-Achse sind die jeweiligen Sensoren der drei Beine genannt. Unter dem Namen steht der Wert der **Maximalkraft** in Newton, mit dem das jeweilige Bein belastet wurde. Dabei entspricht der blaue Sensor Bein A, der schwarze Sensor Bein B und der rote Sensor Bein C. Die Farb- und Buchstabenverteilung hat keine Signalwirkung. Auf der y-Achse befindet sich eine Kraftskala in Newton. Je stärker ein Bein maximal belastet wird, desto höher ist der Balken beim jeweiligen Sensor.
2. Statusmeldung der Software:
   Der Status „Ready!" gibt an, dass der Proband das nächste Gewicht auf das Dreibein stellen kann. Der Status „Please Wait!" sagt aus, dass die Software die Positionierung des Gewichts ermittelt und das zweite Gewicht noch nicht hingestellt werden darf.
3. Kreisdiagramm:
   Zeigt die **Zentrizität** des resultierenden Gewichtsschwerpunkts an.
   Auf den Koordinatenachsen sind die Entfernungen vom Mittelpunkt des Dreibeins in Zentimetern eingetragen. Wird das zweite Gewicht abgestellt, so wird die resultierende Position des Gewichts und Schwerpunktes angezeigt.