Junior Management Science 8(4) (2023) 887-925

Junior Management Science

journal homepage: www.jums.academy

Acceptance conditions of algorithmic decision support in management

Kiram Iqbal

Ruhr-Universität Bochum

Abstract

This thesis explores the acceptance of decision-aiding technologies in management, which is a challenging component in their use. To address the lack of research on algorithmic decision support at the managerial level, the thesis conducted a vignette study with two scenarios, varying the degree of anthropomorphizing features in the system interface. Results from the study, which included 281 participants randomly assigned to one of the scenarios, showed that the presence of anthropomorphized features did not significantly affect acceptance. However, results showed that trust in the system was a crucial factor for acceptance and that trust was influenced by users' understanding of the system. Participants blindly trusted the system when it was anthropomorphized, but the study emphasized that system design should not focus on the benefits of blind trust. Instead, comprehensibility of the system results is more effective in creating acceptance. This thesis provided practical implications for managers on system design and proposed a structural model to fill a research gap on acceptance at the managerial level. Overall, the findings may assist companies in developing decision support systems that are more acceptable to users.

Keywords: Decision support systems; Algorithmic management; Artificial intelligence; Anthropomorphizing; Technology acceptance.

1. Introduction and area of problem

Recent advances in technology enable aid for business in the context of problem-solving (J. R. Evans & Lindner, 2012). In practice, the usage of systems aiding decisions is low. Therefore it is necessary to research on acceptance conditions. This introduction outlines the practical and theoretical necessity of deriving acceptance conditions for research. Furthermore, the structure of the thesis is outlined.

1.1. Objective and research question

The scientific field of business analytics and business intelligence has gained high importance in strategic management. In this context, it is important to differentiate between these terms. Business analytics is defined as a process where data is converted to actions through an analysis of this data in the context of organizational problem solving or decision-making (J. R. Evans & Lindner, 2012). Business intelligence is defined as the use of various technologies like information technology to help managers to gain insights about their business and to improve decision-making (Gluchowski, 2016). Since analytic procedures are based on algorithms the term business analytics can be used as a synonym for algorithmic decision support.

Despite the rise of opportunities for algorithmic decision support, arising challenges should not be neglected. Challenges are legal issues like ownership and privacy of data and technical obstacles like analysis of complex data and scaling of algorithms (Mishra & Silakari, 2012).

One of the most challenging components due to the use of algorithmic decision support in business is the acceptance of these systems by users. From a user's perspective, one major problem is that precise algorithms generate the perception of authoritative correctness therefore human beings can feel inferior toward algorithms. Especially the introduction of deep learning algorithms in artificial intelligence (Linardatos, Papastefanopoulos, & Kotsiantis, 2020) and the scaling of algorithms (Mishra & Silakari, 2012) lead to higher accuracy and precision which in turn makes the human being feel inferior to algorithms. In this regard, it is necessary to do further research on the acceptance condition of algorithmic decision support.

Therefore, this paper conducts an analysis on the following research question: Which conditions lead to an accep-

DOI: https://doi.org/10.5282/jums/v8i4pp887-925

tance of algorithmic decision support in management?

1.2. Theoretical and practical research gap

To answer the research question, it is necessary to make an analysis of the state of the art in research and elucidate the research gap. Various studies do research on the topic of acceptance of artificial intelligence-based technologies. Hastenteufel and Ganster (2021) apply this topic to the digital transformation in banking. Therefore, they use the technology acceptance model by Davis, Bagozzi, and Warshaw (1989). Hastenteufel and Ganster (2021) identify the trustworthiness, perceived usability and social influence as acceptance conditions for algorithmic decision support. Gersch et al. (2021) do research about the challenges particular in trust in collaborative service delivery with artificial intelligence in the field of radiology. Therefore they conduct interviews with various stakeholders in radiology. They identify trust as an indicator to cope with uncertainties. Furthermore, they identify that cognitive trust is built in the first contact with the user. With repeated experience, the user develops affective trust. Understandability and comprehensibility are important for users. Further challenges are the change of own position in the workplace due to the introduction of support through artificial intelligence and arising of new duties and prerequisites in the design of the socio-technical system. Therefore, explainable artificial intelligence should take into account the perspective of different stakeholders. Rathje, Laschet, and Kenning (2021) do research about trust in banking. Therefore, they develop their own research model based on the models by Mayer, Davis, and Schoorman (1995), Gefen, Karahanna, and Straub (2003) and Davis (1989). They conducted a survey with 119 participants where the affinity to technology is high. Rathje et al. (2021) identify that trust has a relationship to the intention to use the technology. Pütz, Düppre, Roth, and Weiss (2021) do research on the topic of acceptance of voice and chatbots. They use the technology acceptance model (TAM) of Davis (1989) and the extended version of Venkatesh and Davis (2000) and Venkatesh and Bala (2008) to analyze the acceptance of this technology. The approach used by Pütz et al. (2021) is literature-based. They identify a relation between perceived usability and perceived user-friendliness. Further results are a relation between perceived user-friendliness and intention to use the technology.

Scheuer (2020) develops an acceptance model for the use of artificial intelligence. The model developed by Scheuer is called the KIAM model. The KIAM model is an extension of the TAM model and is considered the Artificial Intelligence Acceptance Model. Whereas KI is referred to as the german term for AI. The AI acceptance model (KIAM) consists of a holistic acceptance model that addresses the characteristics of the theoretical properties of an AI compared to a classical computer system. Scheuer (2020) assumes that an AI is accessible via a technology (e.g., a smartphone application) and enriching it with Narrow AI services (e.g., a chatbot integration, Speech-To-Text, or Text-To-Speech) through which a user can interact with the AI in natural language. Based on this, two essential components emerge first, the classical technology in the form of a software application, and second, the dialog component for interacting with the AI in the background. For the classical technology and the investigation of its acceptance, Scheuer uses the existing TAM model by Venkatesh and Bala (2008) TAM 3. However, for the dialog component and the resulting interaction between the AI and the user, Scheuer (2020) differentiates to what extent the user accepts the AI as a personality or even as a complete person. For this, he considers that psychological models for measuring sympathy and affection apply as personality acceptance takes precedence over pure technology acceptance. In this regard, Scheuer highlights that if the filter of the perception of the system as a personality is taken into account an AI is recognized as a personality. This relationship with technology can be described as interpersonal acceptance. According to inter-parental acceptance-rejection theory (IPART) (Rohner & Khaleque, 2002), interpersonal acceptance is generated by warmth and affection in the relationship and is based on sympathy. Sympathy, in turn, is dependent on reciprocity in human behavior of communication and sameness of character traits. Reciprocity of behavior is subsequently influenced by a perceived and radiated attractiveness of and to the other person and positive external perception. Interpersonal acceptance in decision support is a new component for analyzing acceptance conditions. Therefore this thesis considers interpersonal acceptance for deriving acceptance conditions. Due to a lack of research findings of algorithmic decision support on managerial-level, this thesis aims to identify acceptance conditions, in order to contribute to research and practice. This section aimed to emphasize the research gap and underline what has been already used in the context of academic literature. Summing up, the section shows that there is a need for investigating the conditions of accepting algorithmic decision support systems from a managerial perspective.

1.3. Outline of the thesis

This thesis aims to answer the following research question: which conditions lead to an acceptance of algorithmic decision support in management? In order to answer the research questions and derive the conditions that lead to an acceptance of algorithmic decision support in management, it is necessary to provide a better understanding of the theoretical foundation regarding algorithmic decision support in management and explain how this takes place in practice. This will be presented in section two where the relevance of algorithmic decision support is outlined. Hereby, the advantages of the integration of business analytics into business are examined. Necessary technological foundations are given in order to understand the underlying technology behind algorithmic decision support and understand the rapid development in performance of computing architecture.

Furthermore, acceptance conditions are derived from the literature. At first theories for an increase usage of technology are examined. In addition, the term acceptance plays an important role in the context of the research question, as the conditions that lead to an acceptance of algorithmic decision support in management are investigated. To further elaborate on the role of acceptance from a theoretical point of view, different acceptance models that exist in the literature are presented. Findings from literature from of non-managerial-levels are used to derive hypotheses for acceptance conditions.

Afterward, a structural equation model will be derived based on the thoughts of the TAM for conducting a quantitative study (vignette study) to provide empirical evidence to answer the research question. The target group for the empirical study will be managers and students in future management positions as the research question focuses on the acceptance of algorithmic decision support in management. The items are derived from Scheuer (2020) who introduced the KIAM model which contains the TAM of Venkatesh and Bala (2008). The items are used in a vignette study (Wason, Polonsky, & Hyman, 2002). The results are analyzed empirically and descriptive statistics are provided.

Before estimating the structural equation model, the quality indicators for the measurement models and structural models are examined.

In the next section, the survey data is analyzed by estimating a structural equation model. The results of the analysis are discussed in a further section and contextualized to findings in literature. This section puts emphasis on the interpretation of the results where the quantitative results are transferred into qualitative measures and reflected in the theoretical foundations. In addition to this, the findings will be applied and compared to the results of the state of the art in literature. Afterward, the theoretical and practical implications are presented along with the limitations of the study. The conclusion summarizes the findings of the thesis.

2. Understanding acceptance of algorithmic decision support

In order to answer the research question, it is necessary to outline theoretical foundations. The following section will emphasize the importance of algorithmic decision support for strategic management. At first, the relevance of algorithmic decision support is derived on a general level. Further, algorithmic decision support is applied to the business context where advantages of the application of this technology are outlined. Afterward, the underlying technological components or related technologies are addressed for a sufficient technological foundation.

2.1. Relevance of algorithmic decision support

In order to understand the relevance of algorithmic decision support, it is important to understand what decisions are and when they occur. According to Mallach (1994), decisions are part of the problem-solving process and are defined as a reasoned choice between available alternatives. The literature identifies two types of decision-making processes. The intuitive decision-making approach and the rational decision-making approach (Alvarez, Barney, & Young, 2010). These approaches are based on the two types of cognitive processes of Stanovich and West (2000) and are defined as System 1 (based on intuition) and System 2 (based on reasoning). An intuitive decision-making approach is defined as a decision based on biases and heuristics (Alvarez et al., 2010). Individuals tend to use various kinds of heuristics in judgmental decisions (Tversky & Kahneman, 1974).

Managers tend more toward the intuitive decision-making approach than the rational decision-making approach (Anderson, 2015). Anderson (2015) identified that only 29% of senior executives of 1135 surveyed base their decision on data and analysis, where 30 % of them use their intuition or experience and 28 % of them use advice or experience of others as a source of decision. The majority of the surveyed managers use availability heuristics to make decisions which implies that most managers tend to use the intuitive decision-making approach. The use of heuristics and biases may lead to efficient decision-making or to decreased decision quality. Various studies show that the occurrence of biases lowers the quality of decisions (Camerer & Lovallo, 1999; Carr & Blettner, 2010; Everett & Fairchild, 2015; Forbes, 2005; Kahneman & Tversky, 1996; Koellinger, Minniti, & Schade, 2007; La Hayward, Forster, Sarasvathy, & Fredrickson, 2010). According to Carr and Blettner (2010) especially the quality of *hot decisions*[1] is strongly related to the success or survival of companies. This literature shows those wrong decisions by an intuitive decision-making approach can lead to the failure of the company. On the other hand, the advantage of intuitive decision-making is that it may be faster than rational decision-making. Intuitive decision making is based on *System 1* which is faster than *System 2* (Kahneman, 2003). The rational decision-making approach is based on *System 2*.

In the literature, there is no mutual agreement on an exact description of the process of the rational decision-making approach. Bazerman and Moore (2012) specify the rational decision-making approach as a rational model of decision-making assuming that people follow a certain process. The rational decision-making process by them is segmented into six phases: (1) *perfectly define the problem* (2) *identify all criteria* (3) *accurately weigh all of the criteria according to preferences* (4) *know all relevant alternatives* (5) *accurately assess each alternative based on each criterion* (6) *accurately calculate and choose an alternative with the highest perceived value* (Bazerman & Moore, 2012).

The main problem by the rational decision-making approach is that human-beings do not have complete information (Biswas, 2015).

The Prospect Theory addresses the problem of bounded rationality and gives the advice to use biases and heuristics when rational decision-making is not applicable (Kahneman, Slovic, Slovic, & Tversky, 1982). Despite incomplete information, a manager may use the rational decision-making approach for problem-solving process. It is tautologic to imply

[1] Hot decisions are defined as decisions who are critical for companies' success Janis and Mann (1977)

that decisions based on incomplete information lead to a decreased decision quality because the use of incomplete information is referred to as the availability heuristic. The effects of heuristics and biases on decision quality are mentioned above.

To overcome this vicious cycle the literature suggests a different kind of decision aids. Decision support systems (DSS) are a particular technological form of a decision aid. First DSS help decision-makers by giving them more information and extending their decision-relevant knowledge (Mallach, 1994). Referring to previous thoughts extended information would increase decision quality. Huber (1990) identifies that managers using computer-assisted decision aiding would make better decisions. Mcafee, Brynjolfsson, Davenport, Patil, and Barton (2012) consider data-driven decisions better than intuitive decisions because they are based on evidence. Despite the dynamic development of technology computer-aided decision support is not new. In fact, it is more than 50 years old. The First DSS application was built in 1970 (Watson & Wixom, 2007). The usage of DSS has various advantages.

Carlson (1977) identifies that DSS can be used in all decision-making phases. DSS can help to make the rational decision-making process better by partially reducing previous incomplete information. Nevertheless, the past 50 years led to an increased computing power by the factor of approximately 67.41 Million[2] according to Moore's law (Moore, 1965). A better example to understand the increased computing power is given in the following. Assuming no change in algorithms, operations that needed approximately 2.13 years of calculation to give decision aid in 1970 can now be processed within one second. Considering the rise of new and better algorithms which differ in performance since they are evaluated by runtime (Güting & Dieker, 1992; Mcafee et al., 2012) the performance of algorithmic decision support is increased. In fact, new algorithmic technologies like artificial intelligence, big data analytics, neural network, etc., leverage the performance of decision support systems. This increase in the performance of decision support systems may lead theoretically to an extensive improvement of a rational decision-making process by reducing time and incomplete information in theory. At the practical level, necessary data for information processing should be available since information is processed out of data by analytics. The analysis of data to support decision-making is considered business analytics (Shanks & Bekmamedova, 2012). Besides supporting decisions, business analytics has a wide range of impacts on business. Therefore it is necessary to understand the impact of algorithmic decision support on business and the underlying technologies of algorithmic decision support.

[2]Meaning the computing power is doubled every second year due to constant costs of transistors. The necessary mathematical operation is 2^{26}. 52 years were passed. These years are divided by two results in the power of 26.

2.1.1. Advantage of business analytics in management

In order to understand the impact of business analytics on management, it is necessary to understand the role and tasks of management.

Management is defined as leadership in the efficient, informed, purposeful and planned conduct of complex organized activity (Andrews, 1980). The activity is characterized by high complexity and the desirability to increase the intuitive competence of the executing manager. Andrews (1980) suggests the need for a unitary concept for reducing the complexity of the manager's job and identifies strategy as a possible solution to reduce complexity. Therefore it is important to distinguish between operational and strategic activities. According to Porter (1996), operational activities are about performing similar activities. They differ only if they are performed in a more efficient way than rivals. Porter (1996) defines strategy as the creation of a unique and valuable position, involving various sets of actions. Therefore Andrews (1980) delivers the approach of a schematic development of an economic strategy. According to Andrews (1980), it is necessary to identify external opportunities and risks and get insights into the corporate capabilities and resources in terms of strengths and weaknesses and consider all combinations of internal and external analysis to evaluate and determine the best match for opportunity and resources. In the end, a choice is derived which is called an economic strategy. This schematic development of an economic strategy is relevant in theory and practice because the SWOT-Analysis is based on this scheme (Kotler, Berger, & Bickhoff, 2010). Andrews's (1980) approach shows that strategy is all about the evaluation and selection of choices – similar to the definition of making decisions. Porter (1996) confirms that strategy is the deliberate disregard of other alternatives by purposefully limiting what a company should do. Strategic management can be considered as the reasoned choice or decision between the combination of strategies from the internal and external analysis. As mentioned before there are two decision-making approaches.

The highest valuated companies in the world can be considered as successful in competition due to the financial indicator. The top five companies with the highest valuation in May 2022 are Apple, Saudi Aramco, Microsoft, Alphabet and Amazon (Companiesmarketcap, 2022). Except for Saudi Aramco, the highest valuated companies could establish their market position due to the use of algorithmic support, explicitly through the use of artificial intelligence (Rainsberger, 2021). Rainsberger (2021) shows four dimensions where algorithmic aid (artificial intelligence) revolutionizes business activities. The four dimensions are strategy, performance, effectiveness and competence. In the following, the wide range of impacts on business analytics is outlined. Especially strategic management is affected by business analytics.

The assumption that an alternative future can be derived from certain past events (Luhmann, 1990) is essential for algorithmic aid. This assumption is essential, since analytics is based on historical data (descriptive analytics), estimates future outcomes (predictive analytics) and determines actions for optimizing business outcomes (prescriptive analytics) (Apté, Dietrich, & Fleming, 2012). Descriptive analytics enable organizations to calibrate opportunities by providing insights into what happened previously in their internal and external environment (van Rijmenam, Erekhinskaya, Schweitzer, & Williams, 2019). Anticipating a possible future leads to a competitive advantage (Koch, 2015). Côrte-Real, Oliveira, and Ruivo (2017) specify that algorithmic aid allows effective internal and external knowledge management enhancing organizational agility. Côrte-Real et al. (2017) address the scheme of economic strategy by Andrews (1980) for sensing opportunities and threats and seizing possible chances.

The implementation of algorithmic aid in the internal and external analysis of a company can gain insights into the internal processes and external events (Benaben et al., 2019) with the possibility to analyze this data and make predictions of future internal processes and external events. Considering all combinations of internal and external analysis a more precise evaluation and determination for the best match of opportunity and resources is possible. The literature suggests that algorithmic aid (predictive analytics) leads to better decision-making by improving business value and competitive performance (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Shanks & Bekmamedova, 2012). A possible explanation for this relation is that predictive analytics helps companies to remain competitive by anticipating changing environments and adapting to these changes (Hajkowicz et al., 2016).

The distinction between strategic and operational activities was outlined. We showed that business analytics can enhance strategic activities. Other dimensions of Rainsberger (2021) address operational activities. In the following, a detailed description of enhanced operational activities is derived.

The second dimension of Rainsberger (2021) is performance. Operational activities can be enhanced by business analytics since we showed that algorithmic aid (Big Data Analytics) improves business performance (Mcafee et al., 2012). Furthermore, Chen, Preston, and Swink (2015) and Apté et al. (2012) show that algorithmic aid enhances operational efficiency. An example of operational efficiency is improved workforce planning and reduced need for new hires and a reduction in overtime (D. Barton & Court, 2012). Further benefits are decreased cost for IT-Infrastructure and efficient data delivery resulting in saving time (Watson & Wixom, 2007). An example of the reduction of costs is preventing and monitoring fraud in organizations. Analytics enable fraud detection at reasonable costs (Mishra & Silakari, 2012). All in all algorithmic aid helps to make effective decisions faster (Reid, McClean, Petley, Jones, & Ruck, 2015) even enabling to automate operational workflows (Iansiti & Lakhani, 2020) resulting in greater performance.

The third dimension of Rainsberger (2021) is competence. Gartz (2004) shows that business intelligence can enhance the representation and evaluation of companies' knowledge using knowledge-based systems. Therefore algorithmic aid can help to preserve knowledge within the company and make information flow more efficient (Watson & Wixom, 2007).

The fourth dimension of Rainsberger (2021) is effectiveness. The literature suggests explicit effectiveness of the use of algorithmic aid in sales and marketing (Halper, 2014; Mishra & Silakari, 2012; Rainsberger, 2021). The effectiveness is shown by the term pervasive business intelligence. Pervasive business intelligence is providing users with information for better job performance (Watson & Wixom, 2007). The advantage of pervasive business intelligence is that data is delivered to the certain user who needs the data to take an effective decision (Rainsberger, 2021). Furthermore, algorithmic aid can provide insights into customer habits & patterns by analyzing customer data (Hamilton & Koch, 2015). Therefore the use of algorithms enables personalized contextual interaction with customers (Brahm, Cheris, & Sherer, 2016). Customization to customers' needs is a very effective form of gaining competitive advantage at operational level since data-based customization to customers' needs brings value (Davenport, 2013). On the other hand customer prioritization by analyzing customer profitability through digital devices can increase effectiveness of business (Davenport, 2013). The effectiveness of a business can be measured by financial indicators. J. R. Evans and Lindner (2012) suggest that algorithmic aid can increase profitability, revenue and shareholder return. Furthermore, companies' goals can be reached faster with the use of analytics (Rainsberger, 2021).

2.1.2. Technological foundations for algorithmic decision support

The main goal of algorithmic decision support is to gain value-creating information (Mikalef, Pappas, Krogstie, & Pavlou, 2020). The information is derived from data (Azvine, Cui, Nauck, & Majeed, 2006; Benaben et al., 2019). The abstraction levels of data, information, decision and knowledge are shown in Figure 1.

According to Benaben et al. (2019) data is a formalized observation of the reality. Information is defined as the result of the interpretation of data through algorithmic methods (Benaben et al., 2019). The process of applying data analysis and discovery algorithms over the data is described as Data Mining (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). Benaben et al. (2019) define the exploitation of information generated by data mining as a decision. The definition of Benaben is not contradictory to the definition of Mallach (1994) mentioned earlier in this paper due to the fact that the information provides the ability for reasoning in choice-settings. The last distinction by Benaben et al. (2019) is knowledge.

Knowledge is a capitalized static information about extracted abstract concepts or previous experience (Benaben et al., 2019). As described earlier the interpretation of data is executed by algorithms. Therefore, it is necessary to define algorithms. The literature has a broad definition of algorithms. Moschovakis (2001) outlines the necessity to define algorithms precisely. According to Moaschavakis, a rigorous

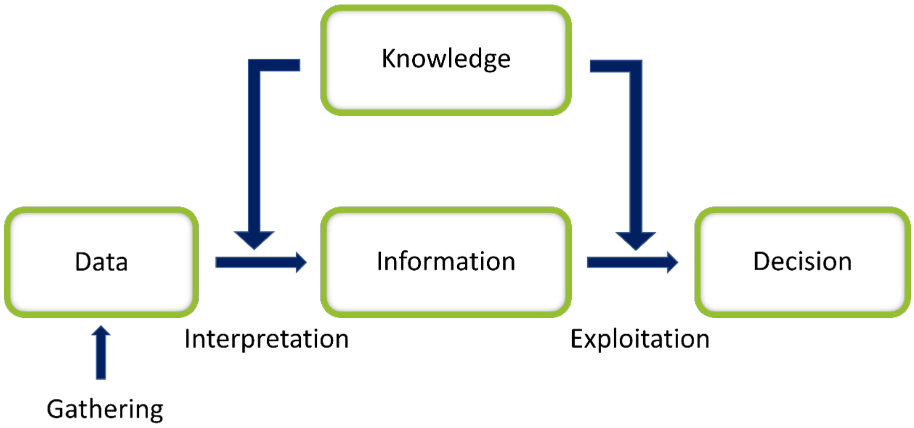

Figure 1: K-DID framework presenting the abstraction levels of data, information, decision and knowledge (Source: Benaben et al. (2019))

definition can lead to a wrong identification of abstract machines or mathematical models of computers.

According to Güting and Dieker (1992), an algorithm is defined as a specific process of tasks with a clear order of tasks run by mechanical or technical devices to receive an expected output for a task. Furthermore, they characterize that every task has to be described clearly and is executable with finite effort in finite time leading to a termination of an algorithm. Therefore algorithms can metaphorically be seen as a recipe for a problem-solving process. The recipes for the problem-solving process can vary in tasks. In the end the best performance of a recipe matters.

The implementation of a certain data type on algorithmic-level is characterized by data structures (Güting & Dieker, 1992). Algorithms differ in performance if they are used in other data structures than intended. Short runtimes are performance measures for algorithms. The selection of algorithms is based on a runtime analysis (Güting & Dieker, 1992; Knebl, 2019). The runtime analysis does not contain computing power of the underlying hardware run on algorithms. In the evaluation of algorithms, it is necessary to distinguish between runtime and computing time since the computing time involves the performance of hardware and algorithm combined. In practice, computing time is a desirable performance measure for algorithms. Computing time can be reduced by aiming for a low runtime of an algorithm or using performant hardware. Therefore decision support can perfectly aid in the decision-making process since the quality of algorithms is evaluated by time.

Recent advances in hardware show a leveraging effect on computing power. Besides Moore's law, other advances in hardware can be seen in Butters or Kryder's law. Butter's law indicates that the amount of data transmitted by fiberglass doubles every 9^{th} month (Rainsberger, 2021). Furthermore, Kryder's law states that storage capacity doubles every 13^{th} month proportional to one square-centimeters of a hard drive (Rainsberger, 2021). These technological advances have exponential growth by definition leading to radical advances of exploitation in the business context. Despite the rapid development of technology, the conception of computing hardware exhibits weakness in performance due to architectural issues. Computing architecture nowadays is divided into Central Processing Unit (CPU) and Random Access Memory (RAM) defined as Von-Neumann-architecture (Leimeister, 2019). The CPU interprets and executes commands in sequential order and the RAM saves necessary data for the necessary point of time for processing (Leimeister, 2019). Shi (2021) and Rosenberg (2017) show several problems in Von-Neumann architectures. Shi (2021) states that Moore's law will reach its physical limit in the coming 10 - 15 years. Furthermore, the sequential processing of commands leads to an inefficiency in comparison to the actual brain. The human brain has advances against the computer in coping with novelty, complexity and ambiguity (Furber, 2016). The calculating speed and precision of a computer is higher than that of human brains but the level of intelligence of computers is low (Furber, 2016; Shi, 2021). In fact, various research fields of computer science are inspired by the human brain. Therefore neuromorphic computer architecture is a solution toward the challenges faced by Von-Neumann architecture. Neuromorphic computing is inspired by the research findings of the structure and operation of the brain (Furber, 2016). Neuromorphic computing aims to extract the formidable complexity of the biological brain and apply this knowledge to practical engineering systems (Furber, 2016). An example of neuromorphic computer architecture is the product of the german startup from Bochum called GEMESYS Technologies. This startup develops a neuromorphic chip that substitutes Von-Neumann architectures (GEMESYS Technologies, 2022). Recent breakthroughs in neuromorphic computing research show that computing architecture can become intelligent. Kagan et al. (2021) introduce a new system architecture called DishBrain. The DishBrain integrates neurons into digital systems to leverage their innate intelligence. Kagan et al. create a synthetic biological intelligence by harnessing the computational power of living neurons. Therefore the DishBrain can exhibit natural intelligence and create a new computing architectures by potentially substituting Von-Neumann architectures (Kagan et al., 2021). Future developments in computing architecture are to use the human brain as a processing unit by creating an interface between the human brain and the computing system developing an interface to human brain (Kreutzer & Sirrenberg, 2019). These interfaces are called Brain Machine Interfaces (Kreutzer & Sirrenberg, 2019).

Since software is a leverage for enhancing computing performance (Rosenberg, 2017) it is necessary to put emphasis on recent advances in algorithmic developments.

AI is an expression of form of algorithms. The term AI has a wide range of definitions, and the selection of a specific definition results in path dependency for research (Wang, 2019). Considering the path dependency interpreted by Wang, a more general definition of AI is used. According to Rich (1985), AI is the science of enabling computers to do things that humans are currently better at. According to Kreutzer and Sirrenberg (2019), AI is the ability of a machine to perform cognitive tasks. This includes reasoning skills, learning, and finding solutions to problems independently. The idea of an AI is first introduced by Turing. Turing (1950) investigates the ability of machines to think. Therefore he argues that a successful imitation game by a computer can lead to the suggestion that machine can think. In the imitation game, the computer is programmed for doing realistic conversations. The imitation game is successful if a human being can differentiate whether the subject in the conversation is a computer or another human. According to Turing (1950), the perception of the interrogator plays a role in the evaluation of the question of whether machines can think or not. Therefore, if a machine is perceived as a human, Turing considers that this machine can think. The test for considering a system as intelligent according to Turing's definition of intelligence is defined as the Turing test.

Dellermann, Ebel, Söllner, and Leimeister (2019) define intelligence as the ability to achieve complex goals, reason, learn and adaptively perform effective activities within an environment. Moreover, they extend the concept of intelligence by dividing it into human intelligence and machine intelligence to gain complementary capabilities and augment each other (Dellermann et al., 2019). As mentioned before, computer architectures are in terms of performance in intelligence lower than human brains. Therefore computer architectures are inspired by the human. Dellermann et al. (2019) introduce the term of hybrid intelligence in terms to combine the advances of human brain and computer systems. The same applies to algorithms. The research field of computational intelligence aims to develop algorithms devised to imitate human information processing and reasoning mechanisms for processing complex and uncertain data sources (Iqbal, Doctor, More, Mahmud, & Yousuf, 2020). Further technologies inspired by humans are neural networks (Iqbal et al., 2020; Kreutzer & Sirrenberg, 2019).

A neural network is a computer system containing hardware and software inspired by human brain (Kreutzer & Sirrenberg, 2019). A neural network has multiple CPUs in order to approximate simultaneous information processing. In Figure 2 the structure of the neural network is shown. The first layer is the Input Layer where data is stored as input for further processing by the following Hidden Layer. Following layers are defined as Hidden Layer. A Hidden Layer can take the outputs of previous Hidden Layers and do further processing generating a new output which is processed by the following Hidden Layer. The last layer is defined as the Output Layer. The Output layer generates a new output of the previously generated outputs by the previous Hidden Layer. Each processing algorithm of a neural network can vary from the other. In Hidden Layers machine learning algorithms are also used (Kreutzer & Sirrenberg, 2019).

Machine learning (ML) on general level is defined as a set of methods that can automatically detect patterns in data and use uncovered patterns to predict future data or to support other kinds of decision-making under uncertainty (Murphy, 2012). Murphy (2012) states that ML provides automation in data analysis. Therefore he suggests three types of learning algorithms supervised learning, unsupervised learning and reinforcement learning (Murphy, 2012). Supervised learning is when results the machine should process are given a priori. The machine is trained to process the right results (Rainsberger, 2021). When results are not given a priori a ML algorithm is defined as unsupervised learning. Here the machine identifies automatically patterns in data and creates results (Rainsberger, 2021). Reinforcement learning is inspired by human learning the machine gets rewards for right results and punishments for wrong results (Buxmann & Schmidt, 2021; Murphy, 2012; Rainsberger, 2021). Punishments and rewards are normally associated with the teaching process (Turing, 1950). Reinforcement learning is inspired by the findings of Turing (1950) who suggests instead of programming a simulation of an adult mind programming a simulation of a child's brain can lead to a simulation of an adult brain in future. If ML is applied in neural networks the term Deep Learning is used in literature (Kreutzer & Sirrenberg, 2019).

As mentioned before data is necessary for data mining. Besides the technological advances in hardware and algorithms, data itself is developing in a broad way. It is necessary to define the term Big Data due to the fact that Big Data is essential for the previously mentioned technologies. Mashingaidze and Backhouse (2017) show various definitions of Big Data in literature and practice. Considering the broad range of definitions for Big Data, Mashingaidze and Backhouse (2017) synthesize all definitions into a new one. According to them, Big Data is data that is high in volume gathered from a variety of sources or data formats and is generated at high velocity. Conventional technologies are insufficient for the management of Big Data due to the high level of complexity of Big Data. Therefore new advanced technologies and techniques for storage and analysis of data are required (Mashingaidze & Backhouse, 2017). Data Ware-

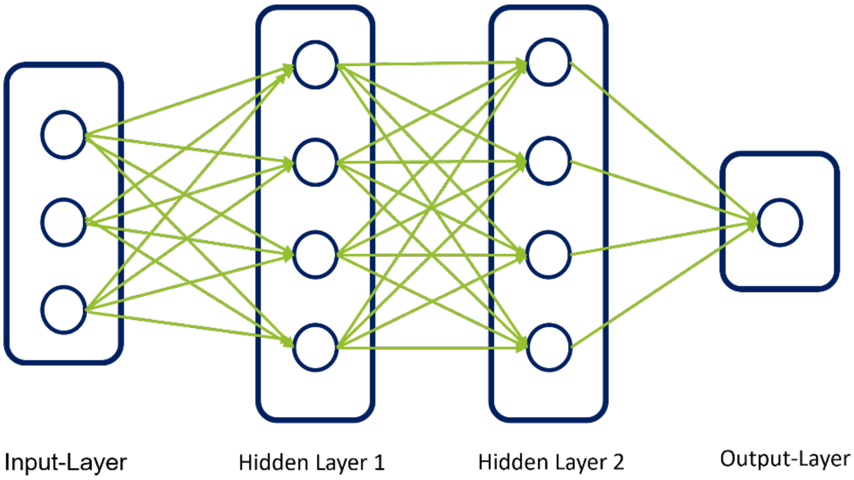

Figure 2: Structure of a neural network (Source: Own illustration according to Kreutzer and Sirrenberg (2019))

houses are the necessary technology for coping with the high level of complexity of Big Data (Leimeister, 2019). According to Leimeister (2019), Data Warehouses are a specialized technology for the storage of data and information. Furthermore, they are the underlying technology for business intelligence. Their function is to gather data and ensure data quality considering uniformity, consistency and freedom from error of data (Leimeister, 2019). They provide data for other systems using interfaces (Leimeister, 2019).The mentioned technologies can be used to assist humans in their work. The collaboration of technology and humans is called human-machine interface (Blutner et al., 2009). Human-machine interfaces are used to execute hybrid intelligence. Sheridan and Verplank (1978) develop ten automation levels for assisting human. In Figure 3 the ten automation levels are shown the terms used in the illustration are developed by Blutner et al. (2009).

The first level of automation is the manual control where the human executes tasks without the aid of the computer. In the second level (Action Support) the computer suggests choices for task execution. The Batch processing reduces the number of choices and takes a preselection of choices. The selection of the choices is done by the human. In the next level (Shared Control), the computer reduces the degree of choices and processes a result for one alternative which is suggested to the human. The human has the possibility to select the processed choice. The next level is Decision Support where the confirmation of the human is necessary for the computer-aided execution of the processed result. In the Blended Decision Making level, the human only has the right for interventions. The computer does the tasks automatically. The next level is Rigid system where the task execution is automated through computer aid. Human role here is to monitor task execution. At the Automated Decision Making level, the monitoring by human is only provided by request. The level of control by the computer is extended in the next level where the computer executes the tasks automatically. Monitoring possibility is only provided after a decision. Furthermore, the last level of automation is full automation where the computer has full control over the task and the human is ignored (Blutner et al., 2009; Sheridan & Verplank, 1978). Systems, where various technologies and concepts are combined to aid in management, are defined as business intelligence systems (Nedelcu, 2013). Therefore, a decision support system can be seen as an assistant system for management tasks. The use of various technologies to aid managers in decision-making is defined as business intelligence (Baars & Kemper, 2021; Gluchowski, 2016). In fact, the term business intelligence has no uniform definition. Furthermore, it is important to distinguish between business analytics and business intelligence. Mashingaidze and Backhouse (2017) show various definitions of business intelligence (BI) and business analytics (BA) in literature and practice. BI is defined as a set of integrated strategies, applications, technologies, architectures, processes and methodologies in order to gather, store, retrieve and analyze data to support decision-making (Mashingaidze & Backhouse, 2017). According to Mashingaidze and Backhouse (2017), BA is defined as a set of skills, applications, technologies, architectures, processes and methodologies used to collect, store and retrieve data for the purpose of data mining in order to support decision-making, inform business strategy and drive performance. The data mining techniques can be descriptive, predictive and prescriptive from scientific disciplines such as mathematics and statistics. Since this paper outlined the technological foundations and benefits of algorithmic decision support it is necessary for summarization to illustrate the components of decision support system. The figure 4 shows the framework of Delen and Demirkan (2013). Business processes create transaction data which are gathered in data warehouses. These data warehouses include various data sources for data mining. Interfaces with other systems process new data, information or knowledge. The processed findings are used for consultation of decision makers or to identify opportunities and risks (environmental monitoring).

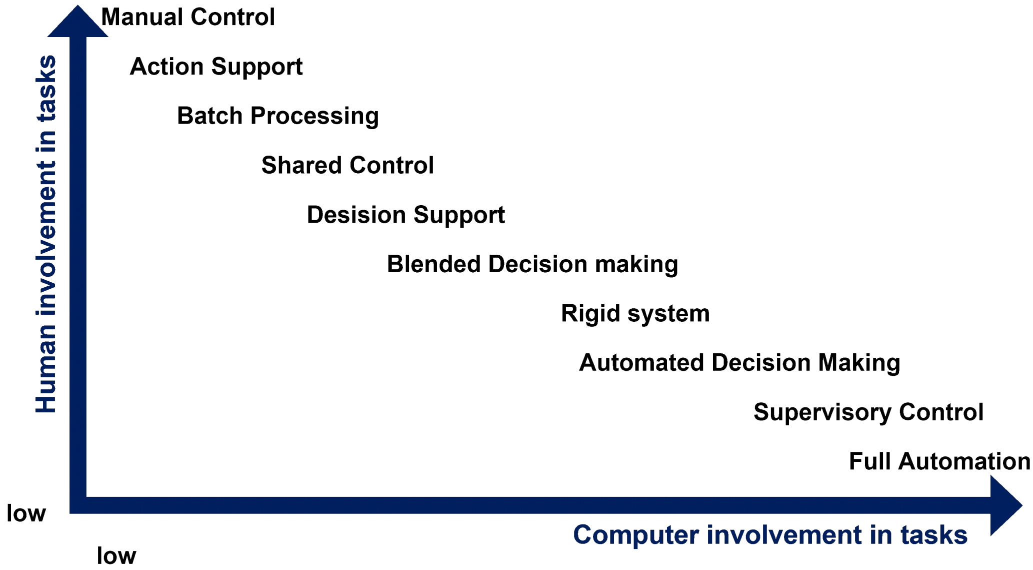

Figure 3: Illustration of ten automation levels for assisting humans (Source: Own illustration according to Sheridan and Verplank (1978) and Blutner et al. (2009))

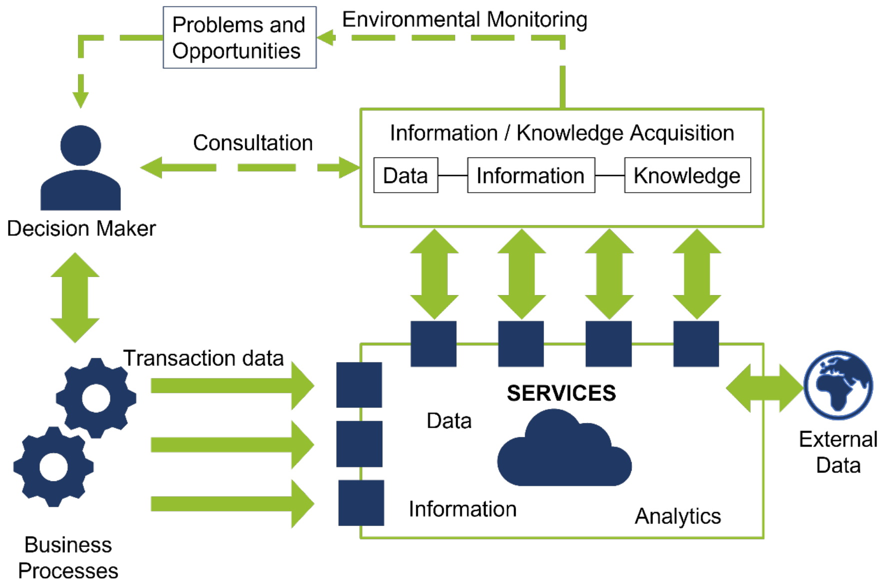

Figure 4: A conceptual framework for service-oriented decision support systems (Source: Delen and Demirkan (2013))

2.2. Deriving the need for acceptance conditions: technology acceptance models

Since this paper showed a wide range of benefits of algorithmic decision support on business activities, one can suggest to easily implement algorithmic aid to outperform the competition. In fact, the benefits of algorithmic aid are not from the application themselves. Moreover, the integration of algorithmic aid into business where business processes are transformed and redesigned deliver these kinds of benefits (Apté et al., 2012). Further literature shows that the application of algorithmic aid can even lead in a failure to realize expected performance gains (Mikalef, Boura, Lekakos, & Krogstie, 2019). Mikalef et al. (2019) outline that organizational aspects and managerial skills are more important in an uncertain environment than application of technology itself. Laudon, Laudon, and Schoder (2016) outline factors that determine the success or failure of an information system. They state that four factors influence the result of the implementation in terms of design, cost, usage and data. The factors of Laudon are the involvement of users and consideration of their influence which is also supported by (Korsgaard, Schweiger, & Sapienza, 1995). The next factor of Laudon et al. (2016) is the support from the management. Due to the fact that this paper focuses on decision support systems used by managers, managers and users are the same people. However, the need of support from management is a crucial factor for decision support systems (Mcafee et al., 2012; Rainsberger, 2021). A further factor of Laudon et al. (2016) is the degree of complexity and the risk of the implementation process. The next factor of Laudon et al. (2016) is the management of the implementation process. Laudon et al. (2016) refer here to the change management process.

In general, the technological change management process is related to challenges (Orlikowski, 1992). In specific, Larson and Chang (2016) show that the adoption of BI applications and services is challenging for organizations. According to Savolainen (2016), the commitment to a change process can be predicted by acceptance. Scheuer (2020) shows that the aim of acceptance research is the explaining of behavior of users in terms of rejection or affirmation due to the use of material or non-material (artificial) technologies. Therefore he defines acceptance as the willingness of someone to voluntarily accept, acknowledge, approve or agree with a subject. In fact, a decision suggested by system inhibits quality if the decision fulfills the goals and is accepted by users (Sharma, Mithas, & Kankanhalli, 2014).

Scheuer (2020) shows various kinds of acceptance models in the literature. Acceptance research varies in the point of technology usage. Various research fields focus on acceptance: information system research, marketing research, behavioral consumer research, psychology and philosophy (Königstorfer, 2008). The information system research is characterized by the technology acceptance model. The technology acceptance model (TAM) was first introduced by Davis (1989) and states that the attitude toward using a technology is influenced by the perceived usefulness or perceived ease of use. Furthermore, TAM by Davis (1989) was extended by social influence mechanisms and cognitive instrumental processes who influence decision making or an attitude towards using a technology (Venkatesh & Davis, 2000). This extension is defined as TAM 2 (Venkatesh & Davis, 2000). Moreover, a further extension of TAM 2 was introduced and defined as TAM 3 (Venkatesh & Bala, 2008). TAM 2 by Venkatesh and Davis (2000) is extended by determinants of perceived ease of use by Venkatesh (2000). The determinants of perceived ease of use are defined in the following. *Perceived Enjoyment* is defined as the perception of joy resulting from system use (Venkatesh, 2000). The second determinant of perceived ease of use is *Computer Self-Efficacy* which is defined as the subjective perception to have the necessary capabilities to perform a specific task using a computer. A further determinant by Venkatesh (2000) is the *Computer Playfulness* defined as the degree of cognitive spontaneity while interacting with the computer (Venkatesh & Bala, 2008). *Perception of External Control* is defined as the perception of support for the computer from organizational and technological resources. A further determinant is *Computer Anxiety* which stands for the perception of fear while using the computer. The last determinant of Venkatesh (2000) is the *Objective Usability* which is defined as a comparison of the system in terms of task completion.

Scheuer (2020) develops an acceptance model for the use of artificial intelligence. The model developed by Scheuer is called KIAM model (Scheuer, 2020). The KIAM model is an extension of the TAM model and is considered as the Artificial Intelligence Acceptance Model. Whereas KI is referred to the german term for AI. The AI acceptance model (KIAM) consists of a holistic acceptance model that addresses the characteristics of the theoretical properties of an AI compared to a classical computer system. Scheuer assumes that an AI is accessible via a technology (e.g., a smartphone application) and enriching it with Narrow AI services (e.g., a chatbot integration, Speech-To-Text, or Text-To-Speech) through which a user can interact with the AI in natural language. Based on this, two essential components emerge first, the classical technology in the form of a software application, and second, the dialog component for interacting with the AI in the background. For the classical technology and the investigation of its acceptance, Scheuer (2020) uses the existing TAM model by Venkatesh and Bala (2008) TAM 3. However, for the dialog component and the resulting interaction between the AI and the user, Scheuer (2020) differentiates to what extent the user accepts the AI as a personality and sees the system as a complete person or as a technology. Furthermore, he shows that the perception of the system as technology or as person determines suitability of acceptance models.

For this, he considers that psychological models for measuring sympathy and affection apply as personality acceptance takes precedence over pure technology acceptance if the system is seen as a person. In this regard, Scheuer (2020) highlights that if the filter of the perception of the system as a personality is considered and an AI is recognized as a personality. This relationship with the technology can be described by interpersonal acceptance models.

On the other hand, if a system is perceived as a technology TAM is suitable (Scheuer, 2020). He shows that the perception of a system as a technology has an influence on acceptance.

Since Scheuer (2020) shows that the perception of a system as a technology or a person determines how acceptance is created it is necessary to consider the perception of the system for acceptance conditions. Therefore it is necessary to derive further acceptance conditions for decision support systems.

Since decision support systems may influence the decision of the user it is important to understand the concept of persuasive technologies in order to derive acceptance conditions. A persuasive computer is an interactive technology that changes the attitude or behavior of the user (Fogg, 1998). The intention for technology usage is key here. If a person is using the interactive technology with the intent to extend or change his or her attitude or behavior the type of intent is defined as autogenous by Fogg (1998). The intent is defined as exogenous if the access to the interactive technology is given by others (Fogg, 1998). Furthermore, the intent of creation or production of interactive technology is defined as endogenous by Fogg. Additionally, Fogg (1998) differentiates three types of computer functions. Fogg (1998) sees the computer as a tool for reducing barriers, increasing self-efficacy, decision support and change of mental models. Moreover, the computer is seen as a medium for providing experience by insights and visualization, promoting understanding of causal relationships and motivating through experience. At least Fogg (1998) sees the computer as a social actor who creates relationships by establishing social norms, invoking social rules and dynamics and providing social support or sanction. Fogg (1998) demonstrates that it is important to see decision support systems as persuasive technologies with various kinds of functions for usage.

The structuration approach from DeSanctis and Poole (1994) focuses on the social structures for human activity provided by technology. Further, they differentiate between two social structures. Firstly the features of the technology called the structural and secondly the general experience towards the feature of the technology, defined as spirit. The adaptive structuration approach of DeSanctis and Poole (1994) can be seen as a structuration approach that highlights the user-centricity in terms of user experience (UX) and user interface (UI). The spirit of the social structure can be referred to UX due the definition by Hassenzahl and Tractinsky (2006). They define UX as a consequence of a user's internal state while interacting with the technology. UI is defined as including all aspects of system design that affect a user's participation in handling the system (Smith & Aucella, 1983). If the features of the system are not comprehensible a mismatch between system and user is given leading to a decreased effectiveness of the information system (Barbosa & Hirko, 1980).

UX and UI optimization may be a fundamental part of acceptance research for information technologies since Gong (2008) shows that an anthropomorphized interface leads to higher social responses from users. Scheuer (2020) identified that anthropomorphizing a system interface has a positive influence on the perception of the system as technology and as a person. **Therefore the hypothesis should be tested that an anthropomorphizing of a system leads to an acceptance of the system (H1)**.

In the following, the necessity of user-centricity due to the process of implementation of algorithmic decision support is outlined. Makarius, Mukherjee, Fox, and Fox (2020) research how to successfully integrate AI into an organization. They outline that comprehension of employees is crucial for a successful integration of AI. Furthermore, Makarius et al. (2020) formulate research necessity in the field of trust of decision-makers in the output of decision support systems, fostering team identification between AI systems and users. Scheuer (2020) identified a positive influence of trust on acceptance. Trust may be an acceptance condition for decision-support systems. **Therefore the hypothesis should be tested that trust leads to acceptance (H2)**.

Rainsberger (2021) identifies major challenges in the adoption of AI systems. According to Rainsberger insufficient knowledge about the benefits of the technology, lacking trust towards the technology and insufficient resources for technology implementation hinder AI adoption in an organization. He summarizes that these fallacies arise due to ignorance of the decision-makers. The TAM by Venkatesh and Bala (2008) considers the result demonstrability as the transparency of the information system in result processing. Since Scheuer identifies that trust is influenced by the transparency of the system **the hypothesis higher transparency/comprehensibility of a system leads to more trust is tested (H3)**.

Gartz (2004) also sees challenges in implementation of technologies for decision support due to missing awareness or lack of interest and motivation of management. It is necessary for senior leaders to recognize the importance of decision support (Grossman & Siegel, 2014; Mcafee et al., 2012). One major challenge here is the change in the decision-making culture. In important decisions companies often rely on "HIPPO" (highest paid person's opinion) (Mcafee et al., 2012). If a decision support system is introduced which is by definition a persuasive technology does the senior leader or decision maker allow themselves to be overruled by data (Mcafee et al., 2012)? Orlikowski and Robey (1991) assumes that more information in the decision-making process leads to a higher power of the decision maker**.** Does more information lead to a shift in the decision-making process from the HIPPO as an expert to HIPPO as an interrogator (Mcafee et al., 2012) leading to a decreased power? Does the senior leader accept a decision support system that may lead to a shift in their role in form of decreased power? **Therefore the hypothesis more transparency leads to higher perceived participation of the user in the decision-making process (H4) is tested**.

Participation in decision-making leads to a higher perception of fairness (Korsgaard et al., 1995). Newman, Fast, and Harmon (2020) show that participation possibilities in the decision-making process increase trust. Do participation possibilities in the decision-making process lead to an increased perception of trust if the output is not comprehensible due to the black box of algorithmic aid? In order to answer these questions, **the hypothesis the higher the perceived participation of the system-user in the decision-making process the higher the perceived trust towards the system (H5) is tested**.

The TAM model considers the perceived usefulness as an indicator for acceptance. Therefore it is necessary to consider the perceived intelligence of the system as an acceptance condition. Furthermore, Scheuer (2020) tests the effect of perceived intelligence and trust. Despite no evidence from Scheuer for a relationship between trust and the perceived intelligence, trust may be a mediator for the relationship between perceived intelligence and acceptance. **Therefore, the hypothesis the higher the perceived intelligence of the system is the higher the trust (H6) should be tested**.

As mentioned earlier Scheuer (2020) identifies that the perception of a system as a technology or as a person creates acceptance. The following hypotheses should be tested. **The higher the perception of the system as technology is, the higher acceptance (H7)**. **Furthermore the higher the perception of the system as a person, the higher acceptance**

(H8).

2.3. State of the art in literature: acceptance conditions of algorithmic decision support

In order to answer the research question, it is necessary to make an analysis of the state of the art in research. Various studies do research on the topic of acceptance of artificial intelligence-based technologies which is one of the technologies for algorithmic decision support.

Hastenteufel and Ganster (2021) apply this topic to the digital transformation in banking. They analyze the acceptance of Robo Advisors using a modified TAM model. Therefore they use the technology acceptance model by Davis et al. (1989) as a foundation. Hastenteufel and Ganster (2021) identify trustworthiness, perceived usability and social influence as acceptance conditions for algorithmic decision support. Similarly to Hastenteufel and Ganster (2021), Rathje et al. (2021) do research about trust in banking. Therefore they develop their own research model based on the models by Mayer et al. (1995), Gefen et al. (2003) and Davis (1989). They conducted a survey with 119 participants where the affinity to technology is high. Rathje et al. (2021) identify that trust has a relationship with the intention to use the technology. Despite relevant findings for this thesis, these papers analyze the acceptance on consumer-level.

Gersch et al. (2021) do research about the challenges particular in trust in a collaborative service delivery with artificial intelligence in the field of radiology. Therefore they conduct interviews with various stakeholders in the radiology. They identify trust as an indicator to cope with uncertainties. Furthermore, Gersch et al. (2021) identify that cognitive trust is built in the first contact with the user. With repeated experience, the user develops affective trust. Understandability and comprehensibility are important for users. Further challenges are the change of own position in the workplace due to the introduction of support through artificial intelligence and arising of new duties and prerequisites in the design of the socio-technical system (Gersch et al., 2021). Therefore they suggest that explainable artificial intelligence should consider the perspective of different stakeholders. Since the objective of research in this paper is applied to the health industry these results are partially applicable for this thesis.

Pütz et al. (2021) do research on the topic of acceptance of voice and chatbots. They use the technology acceptance model of Davis (1989) and the extended version of Venkatesh and Davis (2000) and Venkatesh and Bala (2008) to analyze the acceptance of this technology. The approach used by Pütz et al. (2021) is literature-based. They identify a relation between perceived usability and perceived user-friendliness. Further results are a relation between perceived user-friendliness and intention to use the technology. Since the research of Pütz et al. (2021) focuses on the acceptance of voice and chatbots these results are applicable to the research question of this thesis if these kinds of technology is considered.

Lee's (2018) study shows how people perceive decisions made by algorithms compared with decisions made by humans. He made an online experiment by using four managerial decisions that required human or mechanical skills. By manipulating the decision maker in terms of algorithm and human he measured the perceived fairness, trust and emotional response. In mechanical tasks, decisions made by algorithms and humans were perceived as equally in fairness, trustworthiness and evoked similar emotions. Decision made by humans for mechanical tasks differ in terms of trustworthiness due to the attribution to managers' authority. Decisions made by algorithms were perceived as fair and trustworthy due to attribution perceived efficiency and objectivity. In human tasks, decisions made by humans evoke positive emotions which can be attributed to social recognition. Further Lee (2018) identifies that human task made by algorithms are perceived as less fair and trustworthy. Furthermore, decision made by algorithms in human task evoke negative emotions due to the perception of a dehumanizing experience of being tracked and evaluated by machines. The perceived lack of intuition and subjective decision capabilities caused lower perception of fairness and trustworthiness. Newman et al. (2020) analyze the perceived fairness of decision-making by algorithms in human resource management. They assume that algorithms increase procedural fairness. Further they assume that decisions made by algorithms are less accurate than identical decisions made by humans. Newman et al. (2020) prove that individuals perceive decisions made by algorithms as less fair than comparable decisions made by humans. Further they outline that algorithms are perceived as reductionistic leading to a decreased perception of fairness. Newman et al. (2020) show that organizational commitment is affected in a negative way by decisions made by algorithms where the perception of fairness has a mediating effect. However, the negative effect of decisions made by algorithms is mitigated in decisions made by hybrid intelligence where the human has more involvement. Furthermore, high transparency in algorithmic decisions has a negative effect on perceived fairness and leads to decontextualization. On the other hand transparency in human decision leads to an increase in the perception of fairness and cause less decontextualization.

Lee (2018) shows that the perception of algorithms lies in the decision context and characteristics of the decision. Newman et al. (2020) show that the perception of fairness is human-centered. Despite the strong consideration of Lee (2018) on acceptance or Newman et al. (2020) on perceived fairness at worker-level, these results are applicable for this thesis. Newman et al. (2020) findings about the role of transparency will be considered for this thesis.

Panagiotarou, Stamatiou, Pierrakeas, and Kameas (2020) confirm Lee's (2018) results since they reveal that task characteristics matter in order to understand people's experiences with algorithmic technologies. Furthermore, they find to prove that participants with different levels of technical skills have statistical differences in perceived usefulness of the technology, perceived ease of use, intention to use the technology and actual use of the technology. Sagnier, Loup-Escande, Lourdeaux, Thouvenin, and Valléry (2020) analyzes the acceptance of Virtual Reality (VR). They identified an indirect effect of personal innovativeness on the intention to use due to the fact that people with high personal innovativeness have an interest in new technologies and are more likely to perceive a higher usefulness which leads to an intention to use Virtual Reality. Besides task characteristics, the literature suggests that the characteristics of the person who is going to use the technology matter. The results from (Panagiotarou et al., 2020; Sagnier et al., 2020) can be considered for further analysis.

Uysal, Alavi, and Bezençon (2022) analyze potential harmful and beneficial effects while using artificial intelligent assistants (AIA) such as Alexa. They identify that anthropomorphism of artificial intelligent agents increase consumer satisfaction through increased trust but also threatens user identity by undermining their comfort by a high degree of anthropomorphism of the technology. Further, the perception of threat to user-identity increases if the consumer relationship is closer and the relationship is longer (Uysal et al., 2021). The perception of threat to human identity can be mitigated when consumers are aware of data security solutions and adopt them in relationship with AIA. The hypothesis by Uysal et al. (2022) that higher anthropomorphism reduces consumer satisfaction and consumer well-being was not supported. Further findings of Uysal et al. (2022) indicate that higher threat to human identity reduces consumer comfort through decreasing consumer's AI empowerment. This effect is attenuated when consumers with a long relationship to AIA are aware of data issues of their usage (Uysal et al., 2022). Scheuer's (2020) findings imply a new acceptance model based on the dual-process theory (J. S. B. T. Evans & Stanovich, 2013; Kahneman & Schmidt, 2012). He distinguishes between acceptance based on System 1 (IPART) and System 2 (TAM). Scheuer (2020) identifies that the acceptance for AI systems is dependent on the acceptance of the specific technology medium, acceptance of AI as a technology and the interpersonal acceptance. If the degree of anthropomorphism is high the AI is considered as a personality. The use of AI systems which are considered as a personality is emotion-driven. Therefore Scheuer (2020) states that TAMs are not suitable to measure acceptance of an AI system if an AI system is considered as personality. Interpersonal acceptance models should be considered to describe acceptance of AI systems. On the other hand, TAMs are suitable if the user perceives the AI system as a technology (Scheuer, 2020). Furthermore, Scheuer identifies that users seek to use an AI system where the degree of machine learning is controllable and transparent. Since Panagiotarou et al. (2020) and Sagnier et al. (2020) showed the relevance of task characteristics, Uysal et al. (2022) and Scheuer (2020) put emphasis on the relevance of system features by anthropomorphizing the interface. The findings of Uysal et al. (2022) and Scheuer (2020) have a high applicability for this thesis. The specialty of Scheuer's research approach is that he refers to the Turing's idea of intelligence. Considering the computer developed to the point where it is perceived as a human being by the user (Turing, 1950). Since no literature except Scheuer (2020) focuses on interpersonal acceptance Scheuer's findings contribute to this thesis.

Bader and Kaiser (2019) research on the assessment of the role of artificial intelligence in workplace decisions. Bader and Kaiser (2019) outline the spatial and temporal detachment of decision-making. They explore how users deal with algorithmic decision-making and how user interfaces influence the involvement of decision-making. Bader and Kaiser (2019) argue due to sociomateriality the detachment to decision-making gets reduced. They outline that AI has a dual role in workplace decisions. On the one hand, AI creates human attachment due to emotion driven affective entanglement. On the other hand, AI facilitates detachment due to deferred decisions and manipulation in data. The dual role of AI results in high and low involvement in interactions with the interface. The involvement of interfaces in research will be necessary for this paper.

Merendino et al. (2018) explore whether Big Data has changed strategic decision-making processes on board-level. They identify a lack in cognitive capabilities in order to cope with Big Data. Furthermore, they outline a friction in group cohesion on board-level which has consequences on the decision-making process. Merendino et al. (2018) show that boards seek new ways of working in order to avoid information silos and relying on capabilities of third parties such as consultants in order to handle Big Data. Merendino et al. (2018) findings are applicable to this thesis due to the focus on managers. However, Merendino et al. (2018) results address decision making of managers in a group.

Abhari, Vomero, and Davidson (2020) analyze the psychological motivation behind the use of BI tools. Therefore they use the Needs-Affordances-Features framework by Karahanna, Xin Xu, Xu, and Zhang (2018). At first, they identify that the need for autonomy and competence in business environment motivates the use of BI tools where psychological affordance features of autonomy, collaboration and communication are addressed. Further, they outline that the need for relatedness, having a place and self-realization motivates the use of BI that afford the psychological features of collaboration and communication. Since Abhari et al. (2020) researches the adoption of BI on a voluntary user-level the findings of them are applicable for this thesis.

Meske, Bunde, Schneider, and Gersch (2022) show that explainability is a prerequisite for fair AI. Therefore Meske et al. define explainable AI (XAI) by distinguishing it from interpretable AI. If humans can directly make sense of a machine's decision without additional explanation interpretable AI is given (Guidotti et al., 2018). Giving additional information for an explanation as a proxy to comprehend the arguing process is defined as XAI (Adadi & Berrada, 2018).

The TAM by Venkatesh and Bala (2008) considers perceived comprehensibility of the system as an acceptance condition. An explanation as proxy tries to create acceptance by having a higher result demonstrability. XAI tries to overcome the boundary between artificial and material by approaching the cognitive System 2 of the human. By definition, it reduces simultaneously the amount of information approaching the cognitive system System 1 of the human by using availability heuristics. System 1 may lead to misinterpretation which can be reduced through a personalized XAI according to Meske et al. (2020). As the literature showed high lack in comprehensibility of the decision support systems, it may be challenging to create an acceptance through XAI.

The state of the art in literature shows that the research on acceptance in algorithmic decision support is new as the oldest literature is from 2018. Furthermore, few studies such as Merendino et al. (2018) analyze the acceptance of algorithmic decision support on managerial-level. However, they do not consider the acceptance of a single manager since they focus on board-level decision-making. Other studies show various results in the acceptance of algorithmic decision support. These studies do not focus on managerial-level. The study of Uysal et al. (2022) shows that anthropomorphism can lead to an increased consumer satisfaction and increase in trust. Since trust has a relationship to the intention to use the technology Rathje et al. (2021), it is necessary to consider anthropomorphizing of decision support systems for an analysis of acceptance. Therefore anthropomorphizing an interface can be seen as the structuration approach by DeSanctis and Poole (1994).

No literature except Scheuer (2020) and Uysal et al. (2022) focuses on the acceptance of anthropomorphized systems. Furthermore Scheuer (2020) showed that anthropomorphizing AI systems leads to an use that is emotion-driven. Since Bader and Kaiser (2019) show a dual role of AI in the workplace, it is necessary to analyze empirically whether anthropomorphizing the AI system may mitigate the detachment from AI system. The answer to this question may lead to conditions for an acceptance of algorithmic support on managerial level.

3. Analyzing acceptance conditions: methodological approach

This thesis aims to answer the following research question: which conditions lead to an acceptance of algorithmic decision support in management? To answer the research question two approaches are chosen. A vignette study is conducted along with a quantitative survey. The results are empirically analyzed and afterwards, a structural equation model is derived to illustrate the conditions that may lead to the acceptance of algorithmic decision support. In this regard, it is first important to explain why in the context of the research question it was important to select the innovative approach of a vignette study along with a quantitative survey. According to this, in the following section the rationale behind the methodological approach of this thesis will be presented.

3.1. Theoretical foundation of a vignette study

One of the most frequent tools to investigate the beliefs, attitudes and judgments of respondents is the combination of quantitative research and vignette study. Vignette studies are particularly helpful when research is designed to assess judgment from respondents about specific scenarios. In academic literature quantitative surveys along with vignette analysis were innovational breakthroughs as they allowed a new way of assessing public opinion in form of a survey while keeping the element of integrating contextual perception of specific situations. In the past, quantitative vignette studies have been used in different disciplines such as psychology by Barrera and Buskens (2007), Dülmer (2001) or Walster (1966) and marketing by Wason et al. (2002) or sociology by Alves and Rossi (1978), Beck and Opp (2001) or Jasso and Webster Jr (1999). Atzmüller and Steiner (2010) define a vignette as a "carefully constructed description of a person, object, or a situation representing a systematic combination of characteristics." (Atzmüller & Steiner, 2010). According to Dubinsky, Jolson, Kotabe, and Lim (1991), vignettes help identify management decisions. They especially outline that "Vignettes can be particularly illuminating with respect to managerial implications; an appropriately constructed and relevant [vignette] can help management discern where specific action is necessary" (Dubinsky et al., 1991). Another benefit of vignette studies is that the design of vignettes allows to simultaneously present several explanatory as well as context-dependent factors through which more realistic scenarios are possible (Atzmüller & Steiner, 2010). Moreover, vignettes can be presented in different forms such as text, dialog, cartoons, pictures, audios, or videos. Depending on the research setting and research question a vignette can inhibit an experimental design feature.

Several researchers argue that vignette surveys are superior to normal question-based surveys. In this regard, Wason and Cox (1996) support this statement by outlining that vignette surveys provide greater realism. Robertson (1993) underlines that vignette studies offer a greater range of situational and contextual factors. Similarly, Barnett, Bass, and Brown (1994) state that vignette studies "approximate real-life decision-making situations". Alexander and Becker (1978) further explain that vignette studies supply standardized stimuli to all respondents which makes a replication of the study easier and enhances the measurement reliability. On the other hand, Cavanagh and Fritzsche (1985) argue that vignette studies also improve construct validity (Wason et al., 2002). Furthermore, they outline that vignette studies increase the involvement of the respondents and decrease the potential of errors through not paying attention to questions or answering the same throughout the survey.

Researchers claim that in the context of vignette studies the target group plays an essential role and an appropriate population should be selected. Stevenson and Bodkin (1998) argue that with regard to the decision-making process vignette studies can be targeted toward students as the students are tomorrow's business professionals. Regarding the design of vignette studies, researchers suggest that vignettes should be designed adequately and not much detailed. Hyman and Steiner (1996) argue that vignettes should not be so detailed that they overburden respondents.

Grant and Wall (2009) highlight that especially in the context of management research it is important to understand causal relationships which in turn requires the use of experimental or quasi-experimental designs. Through vignette studies, exactly this aspect is addressed as this research design improves our knowledge about causal relationships (Aguinis & Bradley, 2014). The vignette survey methodology tackles participants with carefully constructed and realistic scenarios to assess dependent variables including intentions, attitudes, and behaviors. An example of providing insights on the causal relationships through vignette surveys is illustrated by McKelvie, Haynie, and Gustavsson (2011) where they addressed the impact of uncertainty in the decision-making process of entrepreneurs. In particular, they provided an evidence on which type of uncertainty had an effect on whether entrepreneurs choose to exploit or not to exploit opportunities (Aguinis & Bradley, 2014; McKelvie et al., 2011). Aguinis and Bradley (2014) conducted a review on 30 management journals from 1994 to 2003 and provided evidence that vignette surveys are a way to address the problem of internal and external validity.

In this regard, vignette surveys have been used in several contexts and formats. Cook (1979) investigate whether Americans support programs for social groups in need of aid or not. For this, they used text vignettes. On the other hand, Atzmüller, Kromer, and Elisabeth (2014) took a closer look at peer violence among adolescents. For their approach, they used short video vignettes. Also, audio vignettes have been used for example by Atzmüller et al. (2014) to investigate radio news on crimes. Several scholars claim that vignette surveys are flexible and have a wide range as they allow participants to come out of their comfort zone and perceiving different experimental settings in form of videos, audios, text etc. Moreover, vignette surveys allow participants to move away from socially desirable answers or politically correct answers which in turn reduces biases (Steiner, Atzmüller, & Su, 2016).

Based on the aforementioned aspects a vignette survey seems to be an appropriate tool to first, identify management decisions (Dubinsky et al., 1991). Secondly, to include different experimental settings in a survey such as videos, audios, text, etc. (Steiner et al., 2016). Thirdly, to construct realistic scenarios and consider context-dependent aspects (Atzmüller & Steiner, 2010). Because of this, the approach of a vignette survey was selected to answer the research question. In the next section it will be explained why structural equation modeling is relevant in the context of the research question and why is it used for the empirical approach in this thesis. In particular, why is structural equation modeling used to illustrate the results of the survey.

3.2. Structural equation modeling

With the method of structural equation modeling (SEM) it is possible to simultaneously model complex relationships among multiple dependent and independent variables (Hair Jr. et al., 2021). Moreover, there are two options in SEM which are common factor-based-SEM (CB-SEM) and partial least squares SEM (PLS-SEM). In this regard, the option of common factor-based SEM is mostly used in the context of accepting or rejecting hypotheses, which serves as an indicator to confirm or reject theories. In a practical manner, this approach of common factor-based-SEM investigates how closely a proposed theoretical model is able to reproduce a covariance matrix for the considered dataset. On the other hand, we have the PLS-SEM. For this thesis, a PLS-SEM was used. In the following, it will be explained why PLS-SEM is more appropriate than a common factor-based SEM for this thesis. PLS-SEM should be conducted if the objective of research is an exploratory research for theory development (Hair Jr. et al., 2021). The objective of research of this thesis is to identify acceptance conditions. Therefore, the approach of PLS-SEM fits to the objective of research of this thesis.

According to Jöreskog and Wold (1982), PLS-SEM is a "causal predictive" approach and aims at explaining the variance of the dependent variable. Basically, a partial least square (PLS) path consists of two essential elements.

One element is the inner model whereas the other one is the outer model. The inner model is referred as a structural model which links together constructs. The outer model, on the other hand, is referred as the measurement model. These measurement model shows the relationships between the constructs and the indicator variables as rectangles. The figure 5 demonstrates the inner and outer model. Another benefit of PLS-SEM is that there is a high efficiency in parameter estimation, and it is flexible in terms of its modeling properties. According to Hair Jr., Matthews, Matthews, and Sarstedt (2017), PLS-SEM is a prediction-oriented approach and is mostly used in exploratory research. PLS-SEM maximizes the amount of explained variance of endogenous constructs in a path model and provides a better understanding of the underlying causes and predictions (Shmueli et al., 2019).

In addition to this through PLS-SEM, it is also possible to include control variable to account for the target construct's variation. Furthermore, PLS-SEM allows the assessment of not only reflective but also formative measurement models along with single-item constructs, with no identification problems. Regarding the single items, it can be said that they have the advantage of being not complicated in terms of the scales and result in higher response rates where the questions are easily understood and answered (Fuchs & Diamantopoulos, 2009; Sarstedt & Wilczynski, 2009). Hair Jr. et al. (2021) further point out that a global single item is sufficient and captures the essence of the construct, especially in the context of executing a redundancy analysis.

As explained in the aforementioned section, the path model for PLS-SEM will be presented. This thesis aims to answer the following research question: which conditions lead to an acceptance of algorithmic decision support in management? In the theoretical foundation, acceptance conditions for algorithmic decision support were derived and formulated as hypotheses. The state-of-the-art shows that the degree of anthropomorphizing an AI system may lead to an acceptance. Therefore, a new model (figure 6) is derived

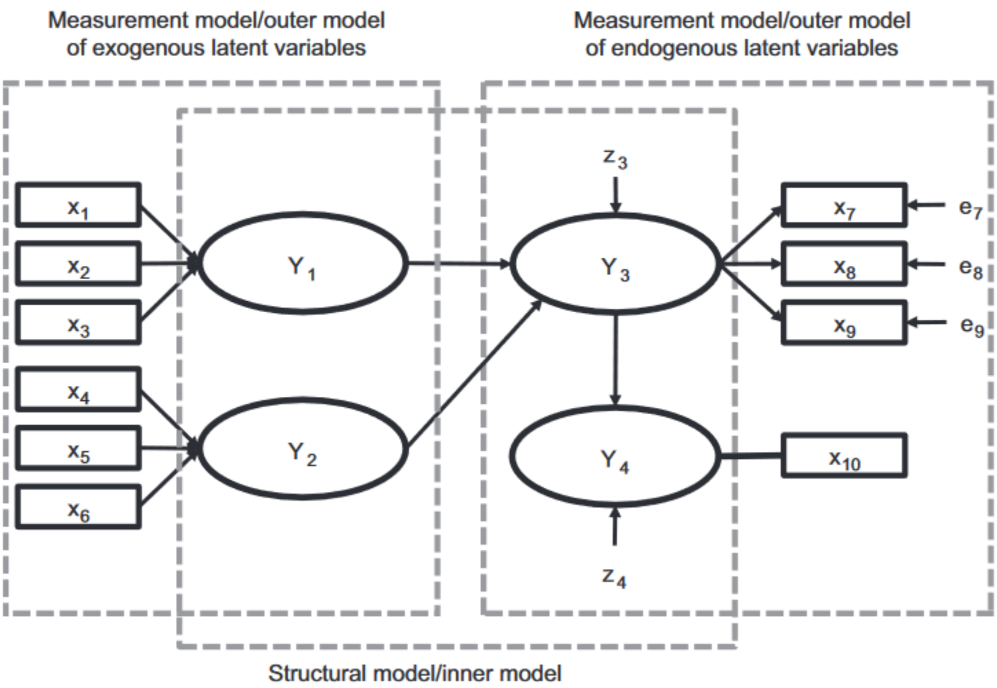

Figure 5: A simple path model (Source: Hair Jr. et al. (2021))

from the previously formulated hypotheses.

Due to hypotheses tests the path model is tested for validity using PLS-SEM. The hypotheses tests are executed in a two-step process according to Hair Jr. et al. (2021). Hair Jr. et al. (2021) suggest to first confirm reliability and validity of the measurement model and then testing the structural equation model for validity.

In order to create a measurement model, a survey is conducted where the degree of anthropomorphizing of the system-interface is manipulated. The items from the survey are used for creating a reflective measurement model.

The variables in the path model are measured as latent constructs in a reflective measurement model. The definition of constructs is described in table 1. In table 2 the hypotheses are summarized.

In an experimental setting, these hypotheses are tested for validity. These interactions with a system is simulated by a vignette study.

3.3. Design and parameters of the survey

A vignette study is conducted in german language where the scenario is described. In this scenario the survey participant is in the situation of a manager in a dynamic market environment where he has to make a hot decision according to Janis and Mann (1977). Furthermore, a decision support system aids in the decision-making. The decision support system is introduced in the scenario with high prediction capabilities. Moreover, the decision support system is implemented as an interface. The survey participants simulate an interaction with a decision support system. Due to the interaction, the survey participants are involved in the problem-finding process. Furthermore, the system suggests a solution to the problem without further explanation. The survey participants have to make the choice to accept the suggestion or to reject the suggestion and make their own decision. The structure of the survey is shown in figure 7.

There are two interfaces with a different degrees of anthropomorphizing features. The interface with low anthropomorphizing features is created by embedding HTML and javascript code into the survey tool. The interface is named Lisa, shown in figure 8.

Furthermore, the interface implemented as an interactive video with high anthropomorphizing features is named Maria, shown in figure 9.

The degree of anthropomorphizing features is relatively high due to the use of professional tools. In order to create the interface Maria, an AI actor is created with the tool Colossyan (Colossyan, 2022) and saved as a video. Furthermore, the tool Tolstoy (Tolstoy, 2022) is used to make the interface more interactive. Therefore the videos created by Colossyan (2022) are ordered through the use of various conditions leading to a high degree of anthropomorphizing features. The degree of anthropomorphizing could have been maximized through voice inputs. Despite the substitution of voice input for the interaction of the user via textual or button components, voice outputs could be implemented in the interface. Furthermore, the AI actress uses gestures while speaking.

The participants are randomly distributed to one interface. After the interaction with the interface, the participant has to make a decision, where he can approve the suggested decision by the system or reject the suggestion and choose an

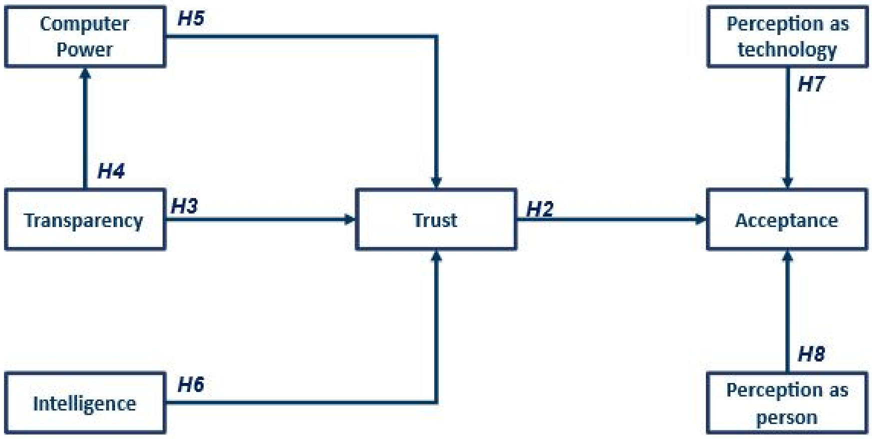

Figure 6: Path model for hypotheses testing (Source: Own illustration)

Table 1: Construct definition

Constructs	Description
Perception as technology is abbreviated as "TEC"	The extent to which the system-user perceives the anthropomorphized system as technology. A low value (1) for *perception as technology* indicates that the system is not perceived as a technology.
Perception as person is abbreviated as "PER"	The extent to which the system-user perceives the anthropomorphized system as a person. A low value (1) for *perception as person* indicates that the system is not perceived as a person.
Trust is abbreviated as "TRU"	The extent to which the user has trust towards the system. A low value (1) for *trust* indicates that the user does not trust the system.
Transparency is abbreviated as "TRAN"	The perceived comprehensibility of the system results. A low value (1) for *transparency* indicates that the results processed by the system were not perceived as transparent in terms of comprehensibility of the decision-making.
Computer Power is abbreviated as "CPOW"	The perceived control of the system within the decision-making process by the user. A low value (1) for *computer power* indicates that the system-user perceives his participation in decision-making process as high. A high value (5) indicates that the system-user perceives the participation of the system in decision-making process as high.
Intelligence is abbreviated as "INT"	The perceived intelligence of the system. A low value (1) for *intelligence* indicates that the user perceives the system as not intelligent.
Acceptance is abbreviated as "AIACC"	The willingness to voluntarily approve the system. A low value (1) for *Acceptance* indicates that the user is not willing to use the presented system in the future.
Decision is abbreviated as "ACC"	The final decision after receiving aid from the system. A low value (0) indicates that the user has rejected the suggested decision from the system. A high value (1) indicates that the user has accepted the suggested decision from the system.

Table 2: Formulation of hypothesis

Construct	No.	Hypothesis
Acceptance (ACC; AIACC)	H1	An anthropomorphizing of a system leads to an acceptance of the system.
Acceptance (ACC; AIACC)	H2	A higher trust in a system leads to higher acceptance.
Trust (TRU)	H3	A higher transparency/comprehensibility of a system has a positive effect on the trust towards the system.
Computer Power (CPOW)	H4	A higher comprehensibility of a system has a positive effect on the perceived participation of the user in the decision-making process.
Trust (TRU)	H5	The higher the perceived participation of the system-user in the decision-making process is, the higher the perceived trust towards the system.
Trust (TRU)	H6	The higher the perceived intelligence of the system is, the higher the trust.
Acceptance (ACC; AIACC)	H7	The higher the perception of the system as technology is, the higher the acceptance.
Acceptance (ACC; AIACC)	H8	The higher the perception of the system as person is, the higher the acceptance.

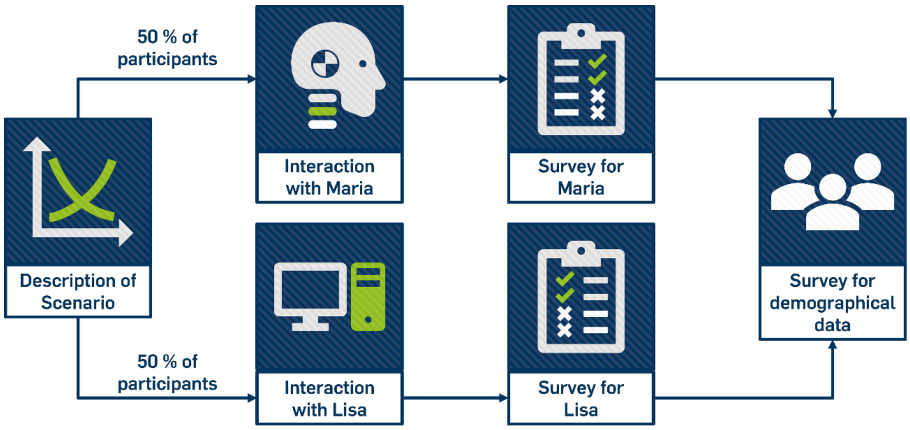

Figure 7: Structure of the survey (Source: Own illustration)

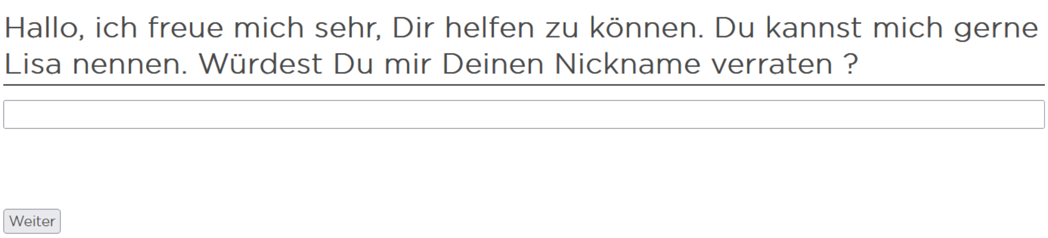

Figure 8: System interface of Lisa (Source: Own illustration)

alternative decision. Furthermore, the participants are surveyed for their experience while interacting with the system. In the end demographical data were surveyed.

The survey was created with the survey tool Unipark. This tool saves cookies on the devices of the participants and prevents multiple participations in the survey from the same user. The survey was online from 25.07.2022 to 07.08.2022 and distributed via various channels. Despite no specific target group, the target group was varied across the distribution channels. The survey was shared on social networks

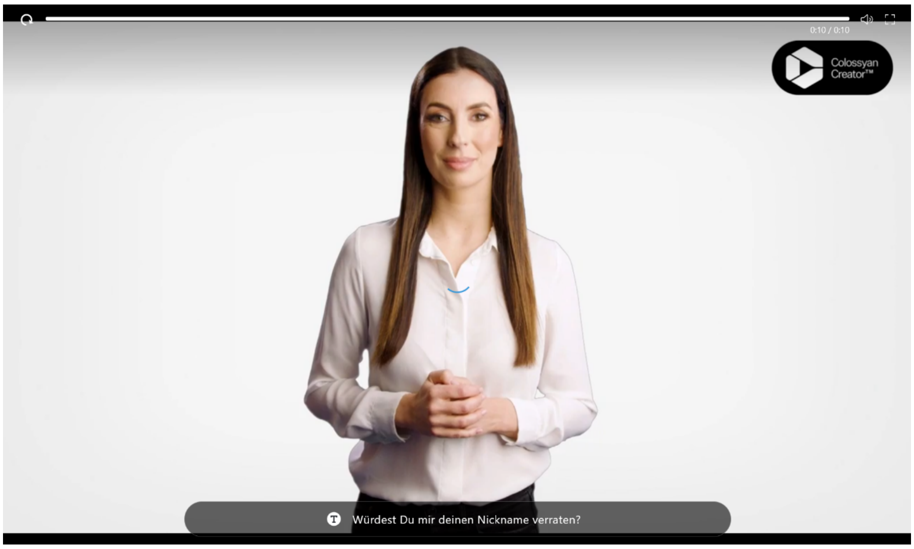

Figure 9: System interface of Maria (Source: Own illustration)

like Linkedin, Instagram and Whatsapp. The target group on Linkedin was specified as managers or people in leadership positions. The Linkedin post where the survey was shared had impressions of 6824 (07.08.2022) meaning the call for participation has reached 6824 people. Furthermore, students and researchers were targeted due to the distribution of flyers. 1000 Flyers were printed. People in the university were asked to participate in the survey while giving them the flyer. Furthermore, a flyer could be used multiple times meaning that minimum of 1000 students or researchers could be approached by flyers. The survey was shared multiple times on multiple Whatsapp and Instagram accounts with daily views of approximately 200 people. Leading to a distribution of approximately 3000 people as a non-specifiable target group. The sharing activities lead to a distribution of the survey to 11000 people who could be accounted multiple times.

746 people clicked on the survey and 253 people canceled their survey participation or did not give their consent to the survey leading to 493 people who started the survey. 212 people canceled their survey participation after starting the survey leading to 281 people who have fully participated in the survey. Due to the cancel activities, an equal distribution of the interfaces among the participants could not be guaranteed.

3.4. Assessment of measurement model

The latent constructs were measured by the previous described survey. The operationalization of constructs was derived from the study of the KIAM-Model by Scheuer (2020). Since Scheuer considers various items from TAM by Venkatesh and Bala (2008) in his research, the items from TAM are used for this study. The operationalization of the items is executed in german language since the target group of the study are german speaking students and employees. All operationalized items for the interface Lisa are shown in table 3. Items for the interface Maria are mostly identical to the interface Lisa. The items for Maria only differ from Lisa when the item consists the name of the interface. Similar to the study of Scheuer (2020) the measurement of items is executed on a 5-point-likert scale. Scheuer argues that the use of this scale minimizes time for the survey participants and delivers a higher precision than on a 7-point-likert scale due to more intuitive responses on perception.

On the 5-point-likert scale the rejection of the statement is coded as one and is increased by one each for a lower rejection or higher affirmation of the statement where the maximum affirmation of the statement is coded with a five.

The construct of acceptance was measured with a further construct defined as "ACC" where the variable is named as "acc" and is measured on a binary scale. The binary scale is used to assess the acceptance due the interaction with the system. A zero in this binary variable reflects rejection of the suggested decision. Moreover, one reflects an affirmation of the suggested decision.

The construct of acceptance could have been measured as a higher order construct, where the constructs "AIACC" and "ACC" are reflective measures for the higher order construct. This study composites the constructs "AIACC" and "ACC" as no single constructs because the estimation of the SEM is conducted partially for each acceptance construct leading to a higher accountability of acceptance conditions. A composition of both constructs to one higher order construct may distort the results due to the different scaling of both constructs. Therefore two SEM are estimated where the construct "ACC" is used to validate the results from the estimation with the construct "AIACC".

As shown previously Scheuer (2020) states that the perception of a system as a technology or a person determines how acceptance is created. Therefore it is necessary to separate the measurement of both systems into individual measurement models. A separation of measurement models in-

Table 3: Operationalization of items

Construct	Item	Question	Reference
INT	int_1	*“Das System wirkt intelligent”*	*“Das System wirkt intelligent”* (Scheuer, 2020)
TEC	tec_1	*“Ich habe das System als Technologie wahrgenommen”*	*“Ich habe das System als Technologie wahrgenommen“* (Scheuer, 2020)
TEC	tec_3	*“Ich habe Lisa als Technologie wahrgenommen”*	*“Ich habe das System als Technologie wahrgenommen“* (Scheuer, 2020)
PER	per_1	*“Ich habe das System als Persönlichkeit wahrgenommen“*	*“Ich habe das System als Persönlichkeit wahrgenommen“ (Scheuer, 2020)*
PER	per_2	*“Ich habe Lisa als Persönlichkeit wahrgenommen“*	*“Ich habe das System als Persönlichkeit wahrgenommen“ (Scheuer, 2020)*
PER	per_3	*“Ich habe in Lisa Menschlichkeit wahrgenommen“*	-
CPOW	part_1	*„Ich habe keine Kontrolle über die Nutzung des Systems“*	*“Ich habe Kontrolle über meine Nutzung des Systems”*–TAM *(Scheuer, 2020)*
TRAN	tran_1	*“Die Entscheidung des Systems ist transparent”*	-
TRAN	tran_2	*“Ich kann die Entscheidung des Systems nachvollziehen“*	-
TRAN	tran_3	*“Für mich ist hinreichend transparent, wie das System funktioniert“*	*“Für mich ist hinreichend transparent, wie das System funktioniert“(Scheuer, 2020)*
TRU	tru_1	*Ich vertraue dem System*	*“Ich vertraue dem System” (Scheuer, 2020)*
TRU	tru_2	*Das System wirkt vertrauensvoll*	-
TRU	tru_3	*„Ich vertraue auf die Ergebnisse des Systems“*	“Ich vertraue auf die Ergebnisse des Systems” (Scheuer, 2020)
AIACC	aiacc_1	*„Die zuvor vorgestellte künstlichen Intelligenz würde ich aktiv verwenden, wenn ich Zugriff auf dieses System habe und die Rahmenbedingungen gegeben sind“*	*“Eine künstliche Intelligenz wie dieses System würde ich aktiv verwenden, wenn ich Zugriff auf diese habe und die Rahmenbedingungen gegeben sind” (Scheuer, 2020)*
AIACC	aiacc_2	*„Angenommen ich hätte Zugriff auf das System, würde ich es nutzen wollen“*	*“Angenommen ich hätte Zugriff auf das System, würde ich es nutzen wollen”-TAM (Scheuer, 2020)*
AIACC	aiacc_3	*„Ich würde das System freiwillig nutzen, wenn die Rahmenbedingungen gegeben wären“*	*“Ich würde das System, wenn die Rahmenbedingungen gegeben wären, freiwillig nutzen”-TAM (Scheuer, 2020)*
ACC	acc	*Decision of the user*	-

creases the accountability of estimation for the certain interface. A separation of measurement leads to major challenges in the minimum sample size required.

For path coefficients of minimum 0.11 a minimum sample size of 113 is required to have significant path coefficients on a 10 % significance level. Furthermore, a sample size of minimum 155 is required to have significant path coefficients on a 5 % significance level (Hair Jr. et al., 2021).

Since the measurement model of Maria has a sample size of 127 and the measurement model of Lisa has a sample size of 154 the requirements for significant path coefficients on a 10 % significance level are fulfilled. The minimum sample size required for path coefficient with a minimum value of 0.21 is 112 with a significance level of 1% (Hair Jr. et al., 2021). Both measurement models exceed the minimum sample size required for significant path coefficients with a minimum value of 0.21.

In the following, the sample of the survey is described.

4. Analysis and findings of the survey

In the next section, the descriptive statistics of both measurement models are shown for describing the underlying sample. Furthermore, the data from the survey is analyzed according to Hair Jr. et al. (2021). At first, the quality indicators for both measurement models are assessed. Moreover, the quality indicators of the structural models are evaluated. At the end of the section, the results from the analysis are discussed.

4.1. Descriptive statistics: first findings

The sample size is 281, where eight people did not respond to sociodemographic questions. Furthermore, the average age of the participants is 25,66 years where the youngest participant being 18 years old and the oldest participant being 66 years. The distribution of ages is shown in the appendix. In addition to this 57.14 % of the participants were male and 41.03% were female. 1.47% of survey respondents were not specifiable and 0.37% of survey participants classified their gender as diverse.

More than 50% of the survey participants were students. The second largest group of the survey is classified as Managers. Further job descriptions of the survey participants are shown in figure 10.

Furthermore, 23.13% of survey participants stated that they have already gathered management or leadership experience with a duration of more than two years. Standard Industrial Classification (SIC) was used to determine the branch classifications of the companies of survey participants. The majority of branches were not specifiable. 62 survey respondents classified their branch in “Services”. The branch of “Agriculture, Forestry, Fishing” and “Mining” was not present in the sample. Furthermore, the survey participants were asked to classify their organization. 32.6% of survey participants responded that the classification is not specifiable. 17.95% of survey participants stated that they are working in public institutions. Further classifications of job institutions are shown in figure 11.

Since Panagiotarou et al. (2020) show the relevance of personal innovativeness on acceptance, it is necessary to have insights into the affinity to technologies or personal innovativeness of survey participants. At first, 91.21% of survey participants evaluated that they have the necessary capabilities for handling Office-software. Furthermore, 68,5% of survey participants responded that they have no experience in programming. 15.02% of participants stated that they have recently gathered experience in programming (less than years). 16.48% of participants reported that they have more than years of experience in programming. Since programming capabilities afford a high level of technical affinity 31.5% of survey participants can be classified as the minimum share of survey participant with a high level of technical affinity. People who spend time for gaming have the need to inform their self about the latest hardware. Therefore the survey measured the technical affinity by asking survey participants whether they like to spend their free time gaming. 40.66% of survey participants have answered with „Yes“ to this question. Besides the gaming experience, it is important to measure the experience with VR-technology for the assessment of personal innovativeness. Since Sagnier et al. (2020) argue that the use of new technologies like VR is related to personal innovativeness, the survey participants were questioned whether they have used VR-technology before. 51.28 % of survey participants have answered with „Yes“ to this question. Overall there is a high affinity to technology and personal innovativeness among the survey participants. The experience in handling Office-software may not be a measure for technical affinity because these are relevant job capabilities and are often expected as general knowledge in practice. The high share of participants who have Office-capabilities shows a representativeness of the sample since these capabilities are expected as general knowledge. Furthermore, 31.5% to 51.28% of survey participants can be classified as participants with a higher level of technical affinity leading to an overall high technical affinity of the sample.

4.1.1. Descriptive statistics: measurement model of Lisa

The summary of descriptive statistics of the measurement model Lisa are shown in table 4.

The maximum variance for a five-point likert scale on mathematical foundation is 2.00 [3]. Therefore the measurement model of Lisa shows a moderate to high variance within the variables. The acceptance variables show a low to moderate variance. As anticipated the Interface Lisa is perceived more as a technology (mean = 3.9870) than a person (mean = 2,4156).

Furthermore, the correlation matrix of constructs (table 5) shows that “CPOW” is negatively correlated to other constructs which is expected. The correlation of the perception of the system as technology is negatively correlated with the perception of the system as person. These negative correlations imply a validity of the measurement.

4.1.2. Descriptive statistics: measurement model of Maria

The descriptive statistics measurement model of Maria are shown in table 6. As shown previously the maximum variance for a five-point likert scale is 2.00. Therefore the measurement model of Maria shows a moderate to high variance within the variables. Similar to measurement model of Lisa, acceptance variables show a low to moderate variance.

Furthermore, the interface Maria is perceived more as a technology (mean = 4.1417) than a person (mean = 2,5669). Since Maria is an anthropomorphized interface the perception of the system as technology should be lower

[3]High dispersion on five-point likert scale means that every number should be distributed equally among the scale. Therefore a quantity of one number at each point of scale can be considered for further calculations due to the reduction of complexity. The average among the scale is equal to the median. The average is three. This average is considered for the variance calculation. The sum of squares of the difference between the observation and the mean is equal to 10. 10 is divided by the number of observations, leading to a variance of 2.

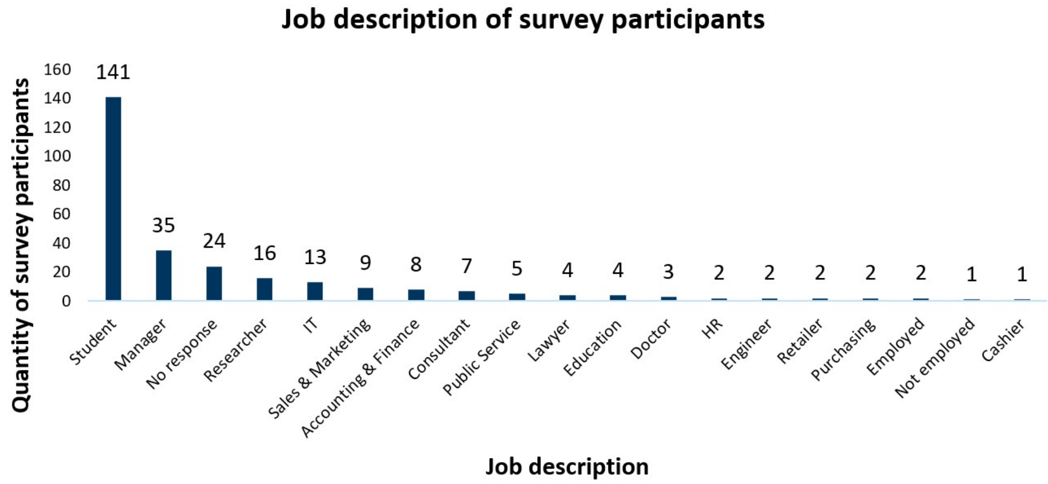

Figure 10: Job description of survey participants (Source: Own illustration)

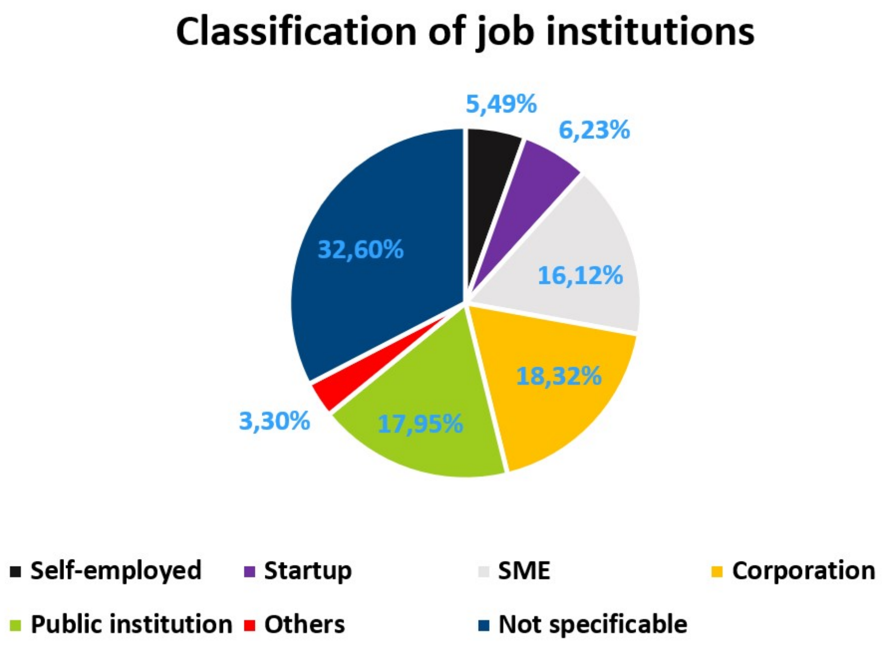

Figure 11: Classification of job institutions (Source: Own illustration)

than the perception of the system as technology. In fact, the system Lisa has a lower mean value for the perception as technology than the system Maria, which may indicate that the anthropomorphized system has failed the Turing test (Turing, 1950). Furthermore, the mean value for acceptance parameters of the system Lisa are slightly higher than the system Maria. The correlation matrix in table 7 shows that "CPOW" is no more negatively correlated to all other constructs which was not expected. Similar to the measurement model of Lisa the correlation of the perception of the system as technology with the perception of the system as person is negative which indicates a validity of the measurement.

4.2. Quality indicators for measurement and structural model

Hair Jr. et al. (2021) show that the first step in the assessment of measurement models is the examination of indicator reliability. Hair Jr., Risher, Sarstedt, and Ringle (2019) recommend indicator loadings, above 0.708 as reliable indicators. Indicators under this threshold should be considered for a removal. Indicator loading below 0.4 should always be eliminated from the measurement model (Hair Jr. et al., 2021).

Therefore, a factor analysis was conducted in R using the package "seminr" by (Hair Jr. et al., 2021). The results of the factor analysis are shown in the appendix. The measurement model was adjusted by deleting indicators with low values for indicator loadings. The final stage of the factor

Table 4: Descriptive summary of the measurement model of Lisa

Descriptive statistics

	n	min	q25	mean	median	q75	max	sd	var
l_per_1	154	1	2	2.4091	2	3	5	1.1411	1.3021
l_per_2	154	1	1	2.3312	2	3	5	1.1719	1.3733
l_per_3	154	1	2	2.4156	2	3	5	1.0646	1.1334
l_int_1	154	1	3	3.3766	4	4	5	1.1265	1.2690
l_tran_1	154	1	1	2.0974	2	3	5	1.1130	1.2388
l_tran_2	154	1	2	2.6299	3	4	5	1.1713	1.3719
l_tran_3	154	1	1	2.2338	2	3	5	1.2250	1.5006
l_part_1	154	1	2	2.9481	3	4	5	1.1013	1.2130
l_tru_1	154	1	2	2.9870	3	4	5	1.0846	1.1763
l_tru_2	154	1	2	3.1039	3	4	5	1.0427	1.0872
l_tru_3	154	1	2	3.1494	3	4	5	1.0833	1.1736
l_tec_1	154	1	4	3.9870	4	5	5	0.9768	0.9541
l_tec_3	154	1	3	3.8571	4	5	5	1.0125	1.0252
l_aiacc_1	154	1	3	3.5974	4	4	5	0.9533	0.9088
l_aiacc_2	154	1	3	3.5649	4	4	5	0.9283	0.8618
l_aiacc_3	154	1	3	3.5779	4	4	5	0.9754	0.9514
l_acc	154	0	1	0.7987	1	1	1	0.4023	0.1618

Table 5: Correlation matrix of Lisa

Correlations of constructs of Lisa

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
TEC	1	-0.312	0.109	0.064	-0.095	0.056	0.177
PER	-0.312	1	0.347	0.469	-0.169	0.381	0.258
TRAN	0.109	0.347	1	0.557	-0.274	0.536	0.268
INT	0.064	0.469	0.557	1	-0.353	0.581	0.414
CPOW	-0.095	-0.169	-0.274	-0.353	1	-0.492	-0.385
TRU	0.056	0.381	0.536	0.581	-0.492	1	0.514
AIACC	0.177	0.258	0.268	0.414	-0.385	0.514	1

analysis is shown in table 8. Indicator loadings from the initial measurement model are shown in the appendix. Due to low loadings the item “tran_4” and “part_2” had to be removed from the measurement model. Further measurement errors in construct validity were identified. Therefore “tec_2”, “int_2”,”int_3”,”part_4”, ”part_5” were eliminated in the measurement model.

After removing the previously stated indicators the measurement models were tested for final indicator loadings. The item “part_3” had an indicator loading of 0.589 for the measurement model of Maria. Therefore Hair Jr. et al. (2021) suggest to examine internal consistency. The necessary threshold for internal consistency could not be reached by both measurement models. Deleting an indicator should be considered when a removal leads to an increase in reliability (Hair Jr. et al., 2021). Therefore the item “part_3” was removed from the measurement model.

The second step for evaluating reflective measurement models according to Hair Jr. et al. (2021) is the examination of internal consistency reliability. Hair Jr. et al. state that the use of Cronbach’s alpha is a very conservative reliability measure. Further, they assume that composite reliability (rhoC) may be a too liberal measure. Therefore they suggest to use the reliability measure of rhoA. The reliability summary is shown in table 9.

The results from the reliability summary show high reliability of the measurement model. Since the rhoA-value for the construct of “TEC” in the measurement model of Maria is higher than 1, which may imply measurement errors. The correlation of items (Appendix 12) for measurement model of Maria show no anomalies since these items are correlated 0.716. The composite reliability shows reliability values exceeding the threshold of 0.7 to 0.9 suggested by Hair Jr. et al. (2021).

They state value above 0.9, especially above 0.95 imply a redundancy of indicators. As stated by Hair Jr. et al. (2021) the composite reliability measure may be too liberal measure for internal consistency. The results on the measure of Cronbach’s alpha, which is a conservative measure for reliability, show that the constructs “TEC”, “ PER” and “TRAN” can be

Table 6: Descriptive summary of measurement model of Maria

Descriptive statistics

	n	min	q25	mean	median	q75	max	sd	var
m_per_1	127	1	2	2.4961	2	3	5	1.0902	1.1885
m_per_2	127	1	2	2.5118	2	3	5	1.1117	1.2360
m_per_3	127	1	2	2.5669	3	3	5	1.1026	1.2157
m_int_1	127	1	3	3.4720	4	4	5	0.9048	0.8187
m_tran_1	127	1	1	2.3150	2	3	5	1.1866	1.4079
m_tran_2	127	1	2	2.8413	3	4	5	1.1298	1.2764
m_tran_3	127	1	1	2.2598	2	3	5	1.1071	1.2256
m_part_1	127	1	2	2.8898	3	4	5	1.0633	1.1306
m_tru_1	127	1	2.5	2.9921	3	4	5	0.9128	0.8333
m_tru_2	127	1	3	3.1969	3	4	5	0.9001	0.8101
m_tru_3	127	1	3	3.0709	3	4	5	0.9101	0.8283
m_tec_1	127	1	4	4.1417	4	5	5	0.8704	0.7575
m_tec_3	127	2	3.5	4	4	5	5	0.8909	0.7937
m_aiacc_1	127	1	3	3.3780	4	4	5	0.9994	0.9989
m_aiacc_2	127	1	3	3.4016	4	4	5	1.0333	1.0676
m_aiacc_3	127	1	3	3.4488	4	4	5	1.0213	1.0430
m_acc	127	0	1	0.7953	1	1	1	0.4051	0.1641

Table 7: Correlation matrix of Maria

Correlations of constructs of Maria

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
TEC	1	-0.386	-0.154	-0.049	0.028	-0.077	-0.128
PER	-0.386	1	0.311	0.373	-0.060	0.349	0.418
TRAN	-0.154	0.311	1	0.424	-0.185	0.428	0.276
INT	-0.049	0.373	0.424	1	-0.102	0.591	0.531
CPOW	0.028	-0.060	-0.185	-0.102	1	0.045	-0.057
TRU	-0.077	0.349	0.428	0.591	0.045	1	0.657
AIACC	-0.128	0.418	0.276	0.531	-0.057	0.657	1

considered as "good" in terms of reliability. Furthermore, the constructs of "TRU" and "AIACC" slightly exceed the threshold of 0.9. The constructs of "INT" and "CPOW" have a alpha-value of 1.0 because they are single item constructs.

The third step for the assessment of reflective measurement model according to Hair Jr. et al. (2021) is convergent validity. Therefore they suggest to examine the measure of average variance extracted (AVE). Furthermore, they state that the AVE should exceed the value of 0.5. The results from the examination of convergent validity are shown in table 9. All constructs exceed the threshold suggested by Hair Jr. et al. (2021).

In order to evaluate reflective measurement models, the fourth step of Hair Jr. et al. (2021) is the assessment of discriminant validity. They suggest to avoid the Fornell-Larcker Criterion by Fornell and Larcker (1981) due to an inability of the criterion to identify discriminant validities issues. Therefore Hair Jr. et al. recommend to examine the heterotrait-monotrait ratio of correlations (HTMT) (Henseler, Ringle, & Sarstedt, 2015). The results of the examination of the discriminant validity are shown in table 10.

Hair Jr. et al. (2021) suggest that the values for HTMT should be significantly lower than the threshold of 0.85. The values for HTMT shown in table 10 are below the suggested threshold. Furthermore, a significance test is conducted where the structural equation model is bootstrapped by 10000 samples for generating standard errors and confidence intervals. The significance test shows that the upper bound of the 95% confidence interval is significantly lower than the suggested threshold of 0.85 (Hair Jr. et al., 2021). The results of the bootstrapped values for HTMT are shown in the appendix. All bootstrapped paths are significantly lower than the suggested threshold leading to discriminant validity.

4.3. Analyzing acceptance conditions and robustness checks of study

Since the previous tests show that the measurement models fulfill reliability and validity measures, the structural model can be evaluated for testing the hypotheses. Before

Table 8: Loadings summary for Lisa and Maria

Loadings summary of Lisa

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
l_per_1	0	0.929	0	0	0	0	0
l_per_2	0	0.908	0	0	0	0	0
l_per_3	0	0.870	0	0	0	0	0
l_int_1	0	0	0	1	0	0	0
l_tran_1	0	0	0.890	0	0	0	0
l_tran_2	0	0	0.881	0	0	0	0
l_tran_3	0	0	0.880	0	0	0	0
l_part_1	0	0	0	0	1	0	0
l_tru_1	0	0	0	0	0	0.946	0
l_tru_2	0	0	0	0	0	0.883	0
l_tru_3	0	0	0	0	0	0.929	0
l_tec_1	0.946	0	0	0	0	0	0
l_tec_3	0.954	0	0	0	0	0	0
l_aiacc_1	0	0	0	0	0	0	0.919
l_aiacc_2	0	0	0	0	0	0	0.908
l_aiacc_3	0	0	0	0	0	0	0.916

Loadings summary of Maria

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
m_per_1	0	0.895	0	0	0	0	0
m_per_2	0	0.872	0	0	0	0	0
m_per_3	0	0.865	0	0	0	0	0
m_int_1	0	0	0	1	0	0	0
m_tran_1	0	0	0.902	0	0	0	0
m_tran_2	0	0	0.879	0	0	0	0
m_tran_3	0	0	0.918	0	0	0	0
m_part_1	0	0	0	0	1	0	0
m_tru_1	0	0	0	0	0	0.923	0
m_tru_2	0	0	0	0	0	0.888	0
m_tru_3	0	0	0	0	0	0.909	0
m_tec_1	0.851	0	0	0	0	0	0
m_tec_3	0.976	0	0	0	0	0	0
m_aiacc_1	0	0	0	0	0	0	0.934
m_aiacc_2	0	0	0	0	0	0	0.929
m_aiacc_3	0	0	0	0	0	0	0.954

Table 9: Internal consistency reliability and convergent validity

Summary of internal consistency reliability and convergent validity

Lisa	alpha	rhoC	AVE	rhoA	**Maria**	alpha	rhoC	AVE	rhoA
TEC	0.892	0.949	0.902	0.896	TEC	0.835	0.912	0.838	1.349
PER	0.890	0.930	0.815	0.967	PER	0.850	0.909	0.770	0.854
TRAN	0.863	0.914	0.781	0.892	TRAN	0.883	0.927	0.810	0.888
INT	1	1	1	1	INT	1	1	1	1
CPOW	1	1	1	1	CPOW	1	1	1	1
TRU	0.908	0.943	0.846	0.911	TRU	0.892	0.933	0.822	0.897
AIACC	0.902	0.938	0.835	0.902	AIACC	0.933	0.957	0.882	0.935

assessing the structural model, the hypothesis that an anthropomorphizing of a system leads to an acceptance of the system (H1) is tested for validity. Therefore the mean of the constructs of acceptance in the measurement model of Maria

Table 10: Summary of dicriminant validity

HTMT table of Lisa

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
TEC							
PER	0.365						
TRAN	0.125	0.392					
INT	0.069	0.490	0.592				
CPOW	0.101	0.176	0.278	0.353			
TRU	0.065	0.419	0.593	0.611	0.516		
AIACC	0.198	0.272	0.289	0.435	0.405	0.566	

HTMT table of Maria

	TEC	PER	TRAN	INT	CPOW	TRU	AIACC
TEC							
PER	0.464						
TRAN	0.183	0.366					
INT	0.043	0.403	0.446				
CPOW	0.025	0.067	0.191	0.102			
TRU	0.100	0.394	0.476	0.619	0.047		
AIACC	0.127	0.468	0.297	0.549	0.059	0.717	

has to be significantly higher than the mean of the constructs of acceptance in the measurement model of Lisa. Therefore a T-test is conducted in R (R Core Team, 2013), shown in table 11.

The T-test shows that the mean of the anthropomorphized system is not significantly higher than the mean of the textual interface. Therefore the hypothesis that an anthropomorphizing of a system leads to an acceptance of the system (H1) is not supported.

In fact, the mean-value of the textual interface for the construct of AIACC is higher than the mean-value of the anthropomorphized system. This difference in AIACC is not significant. Furthermore, the means of the constructs of ACC have equal means for both observation groups. Moreover, the mean-values for other constructs do not differ significantly, leading to the assumption that an anthropomorphizing of the system has no significant effect on acceptance measures. To confirm this assumption the structural models are assessed in order to understand how acceptance is created. Furthermore, equal findings in both structural models support the assumption that there is no significant effect of anthropomorphizing the system on acceptance.

In order to evaluate the structural model Hair Jr. et al. (2021) suggest to first examine potential collinearity issues in the constructs. Therefore the structural model is tested for variance inflation factors. According to Becker, Ringle, Sarstedt, and Völckner (2015) variance inflation factors above the threshold of 3.0 assume issues with collinearity. The results shown in table 12 indicate no issues for potential collinearity.

In the second step Hair Jr. et al. (2021) suggest to examine the significance of the structural model. Before evaluating the significance of the structural model it is important to outline the approach in order to estimate the model.

As mentioned earlier the dataset is divided into two measurement models. Furthermore, the construct of AIACC is considered as the main indicator for measuring acceptance. For confirming the results from PLS-SEM estimation, the construct of ACC is considered in a second structural model. The models only differ in the path coefficients from the predictors of acceptance to acceptance across both structural models. For reducing illustrative complexity the construct of ACC is added to the illustration of the SEM-estimation in figure 12 and figure 13. It is important to outline that both acceptance constructs were not estimated in a single SE. All in all two structural models with two measurement models were estimated by using R, specifically the "seminr"-package by (Hair Jr. et al., 2021), leading to four estimations of PLS-SEM.

In order to examine the significance of the path coefficients, it is necessary to perform bootstrapping standard errors for calculating confidence intervals (Hair Jr. et al., 2021). The summary of the bootstrapped paths is shown in the appendix. Figure 12 and figure 13 show the path coefficients after bootstrapping. Further green paths indicate positive path coefficients whereas red paths indicate negative path coefficients. The significance of paths is marked by stars. A p-value smaller than 0.01 is marked with three stars, p-value greater than 0.01 and smaller than 0,05 is marked with two stars and a p-value greater than 0.05 and smaller than 0.1 is marked with one star. The significance of paths aids to support the previously formulated hypothesis.

The path coefficients from Trust to Acceptance show a positive influence of trust on acceptance. This path is significant for both acceptance measures and by both measurement models. The SEM for Lisa shows a path coefficient of $\beta = 0.502$ ($p < 0.001$; 5% CI = 0.372; 95% CI = 0.625) for the construct Decision (ACC) and 0.445 ($p < 0.001$; 5%

Table 11: T-test summary for antropomorphizing interfaces

System	PER	INT	CPOW	TRAN	TRU	TEC	AIACC	ACC
Lisa	2.3852	3.3762	2.9480	2.3203	3.0800	3.3766	3.5800	0.7952
Maria	2.5249	3.4720	2.8897	2.4682	3.0866	3.4645	3.4094	0.7952
p-value	0.2407	0.4352	0.6531	0.2343	0.9518	0.4997	0.1223	1.0000

Table 12: VIF-values for structural model evaluation

Structural model of Lisa						
AIACC				**TRU**		**CPOW**
TEC	PER	TRU	TRAN	INT	CPOW	TRAN
1.153	1.344	1.217	1.464	1.546	1.154	.
Structural model of Maria						
AIACC				**TRU**		**CPOW**
TEC	PER	TRU	TRAN	INT	CPOW	TRAN
1.180	1.336	1.144	1.250	1.220	1.036	.

CI = 0.308; 95% CI = 0.571) for the construct Acceptance (AIACC).

Furthermore, the SEM for Maria shows a path coefficient of $\beta = 0.223$ (p = 0.008; 5% CI = 0.068; 95% CI = 0.371) for the construct Decision and 0.582 (p < 0.001; 5% CI = 0.372; 95% CI = 0.625) for the construct Acceptance (AIACC).

The path coefficients from Transparency to Trust show a positive influence of transparency on trust. This path is significant for both measurement models. The SEM for Lisa shows a path coefficient of $\beta = 0.277$ (p < 0.001; 5% CI = 0.155; 95% CI = 0.399). Furthermore, the SEM for Maria shows a path coefficient of $\beta = 0.237$ (p = 0.005; 5% CI = 0.084; 95% CI = 0.388).

The path coefficient from Transparency to Computer Power shows a negative influence of transparency on trust. This path is significant for both measurement models. The SEM for Lisa shows a path coefficient of β = - 0.277 (p < 0.001; 5% CI = - 0.396; 95% CI = - 0.149). Furthermore, the SEM for Maria shows a path coefficient of β = - 0.186 (p = 0.027; 5% CI = - 0.336; 95% CI = -0.028).

The path coefficient from Computer Power to Trust show different significant result of the trust towards the system. This path is significant for both measurement models. The SEM for Lisa shows a path coefficient of β = - 0.301 (p < 0.001; 5% CI = - 0.395; 95% CI = - 0.205). Furthermore, the SEM for Maria shows a path coefficient of $\beta = 0.142$ (p = 0.038; 5% CI = 0.011; 95% CI = 0.272).

The path coefficient from Intelligence to Trust shows a positive influence of Intelligence on Trust. This path is significant for both measurement models. The SEM for Lisa shows a path coefficient of $\beta = 0.321$ (p < 0.001; 5% CI = 0.172; 95% CI = 0.460). Furthermore, the SEM for Maria shows a path coefficient of $\beta = 0.504$ (p < 0.001; 5% CI = 0.374; 95% CI = 0.633).

The path coefficients from Perception as technology to Acceptance show a positive influence of trust on acceptance. The result on path significance differs for both measurement models. The SEM for Lisa shows a path coefficient of β = 0.096 (p = 0.160; 5% CI = - 0.004 ; 95% CI = 0.225) for the construct Decision (ACC) and 0.205 (p < 0.001; 5% CI = 0.073; 95% CI = 0.336) for the construct Acceptance (AIACC). Furthermore, the SEM for Maria shows a path coefficient of β = - 0.084 (p = 0.17; 5% CI = - 0.220; 95% CI = 0.057) for the construct Decision and 0.003 (p = 0.5; 5% CI = - 0.145; 95% CI = 0.175) for the construct Acceptance (AIACC).

The path coefficients from Perception as person to acceptance show a positive influence of trust on acceptance. This path is significant for both measurement models. Further, the path to the acceptance measure Decision (ACC) is not significant. The SEM for Lisa shows a path coefficient of β = - 0.069 (p = 0.160; 5% CI = - 0.239; 95% CI = 0.225) for the construct Decision (ACC) and 0.159 (p = 0.025; 5% CI = 0.033; 95% CI = 0.283). Furthermore, the SEM for Maria shows a path coefficient of β = - 0.091 (p = 0.170; 5% CI = - 0.035; 95% CI = 0.261) for the construct Decision and 0.214 (p = 0.003; 5% CI = 0.091; 95% CI = 0.339) for the construct Acceptance (AIACC).

After assessing the significance of the path coefficients it is necessary to evaluate the explanatory power of the model (Hair Jr. et al., 2021). Therefore the measure of R^2 explains how much of the variance of the construct is explained by the model. R^2-values of 0.75 indicate a substantial, R^2-values of 0.5 show a moderate and R^2 values of 0.25 state a low explanatory power (Hair Jr., Ringle, & Sarstedt, 2011). The measure of R^2 may increase by the number of explanatory variables. Therefore it is important to consider the measure of Adjusted R^2. The limitation of Adjusted R^2-measure is, that it may consider the number of explanatory variables but this measure is not a precise indicator as R^2 (Hair Jr. et al., 2021).

The results shown in table 13 state a moderate to low

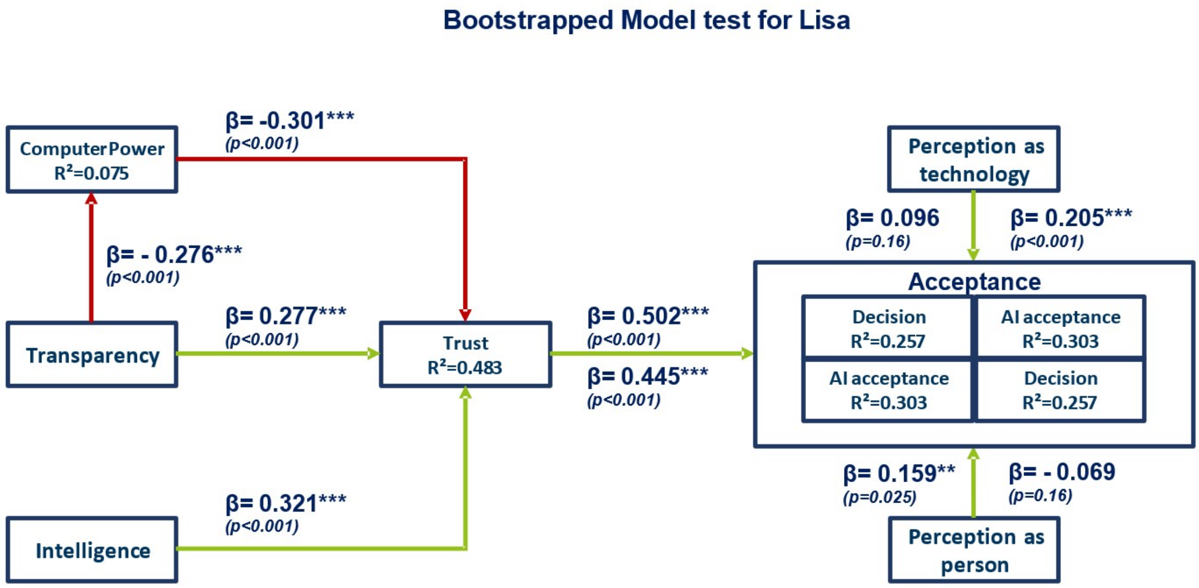

Figure 12: SEM for Lisa after Bootstrapping (Source: Own illustration)

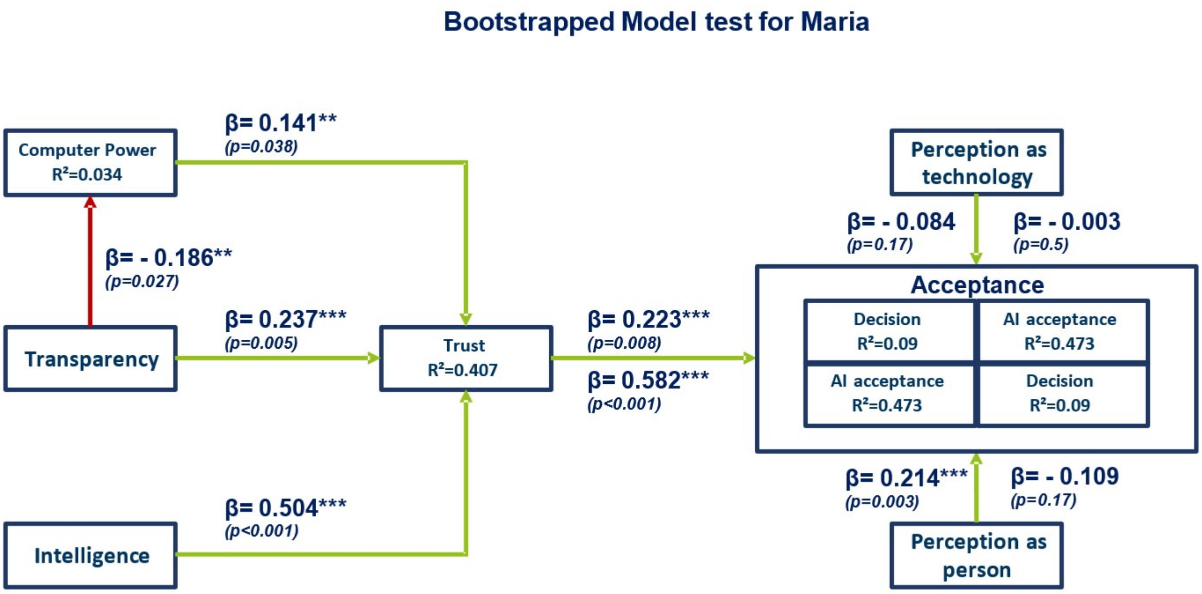

Figure 13: SEM for Maria after Bootstrapping (Source: Own illustration)

Table 13: Explanatory Power of model: R^2

			R-squared						
Lisa	AIACC	TRU	CPOW	ACC	**Maria**	AIACC	TRU	CPOW	ACC
R^2	0.303	0.483	0.075	0.257		0.473	0.407	0.034	0.090
Adj. R^2	0.289	0.473	0.069	0.242		0.460	0.393	0.027	0.068

explanatory power of both models. Furthermore, the model of Lisa and Maria only describes 7.5% and 3.4% of the variance of the construct of Computer Power. This may indicate that Computer Power is influenced by unobserved variables which are not measured by the model. The effect size f^2 may be a further measure to evaluate the explanatory power of the model (Hair Jr. et al., 2021). Results of f^2-measure are shown in the appendix.

Furthermore, the assessment of the predictive power of the model is the next step in order to evaluate the structural model (Hair Jr. et al., 2021). Predictive power is defined as the ability of a model to predict new observations (Hair Jr. et al., 2021). Therefore the sample is divided into a holdout and multiple training samples. The training sample are is estimated and evaluated by predicting performance while comparing the results to the holdout sample (Hair Jr. et al., 2021). In order to perform cross validation, this process is repeated by the number of subsamples where the holdout sample is changed to a training sample and a further training sample is changed to a holdout sample. Therefore the measure of root-mean-square error (RMSE) and mean absolute error (MAE) is calculated. Furthermore, prediction errors from a linear regression model for each indicator are calculated. The structural model needs to show lower prediction errors than the benchmark of prediction errors generated by the linear model.

In order to perform the prediction, the sample was divided into 10 subsamples. Furthermore the process calculation of prediction errors is repeated 10 times. The results generated by the "seminr"-package in R (Hair Jr. et al., 2021) are shown in table 14.

The results show that six out of seven indicators of the model Lisa have lower prediction errors (RMSE) than the benchmark of the linear model. Furthermore, five out of seven indicators of the model Maria have lower prediction errors than the benchmark of the linear model. According to Hair Jr. et al. (2021) a majority of indicators under the benchmark of the linear model imply medium predictive power.

The evaluation of the structural model showed no issues with collinearity in constructs, significant path coefficients, moderate explanatory power and medium predictive power for new observations.

4.4. Discussion of study results

After evaluating the structural model, the next section will interpret the results. Therefore the previously formulated hypotheses are evaluated for validity. Furthermore, the findings of the study are reflected in prior findings in research. Possible explanations for the findings are given, derived from previous research.

4.4.1. Interpreting study results

The hypothesis that an anthropomorphizing of a system leads to an acceptance (H1) is not supported by the study. The descriptive statistics show higher mean values for the perception of the system as technology for the anthropomorphized system than for the textual system. On the other hand, the perception of the system as a person has higher mean values of the anthropomorphized system than the textual system which may indicate appropriate system design in terms of anthropomorphizing. Furthermore, the results from the t-test indicate that there is no significant influence of anthropomorphizing the system on acceptance conditions. Despite these findings, this study shows significant differences in acceptance conditions which may be referred to an influence of anthropomorphizing features of the system on the acceptance. The results are shown in table 15.

Furthermore, the study shows empirical evidence that trust towards the system is the main indicator for creating acceptance by users since the path coefficients from Trust to AI acceptance are above 0.5. The hypothesis that higher trust in a system leads to higher acceptance (H2) is supported by this study. An anthropomorphizing of the system has higher path coefficients from Trust to AI acceptance which may indicate that higher trust towards the system has a higher influence on acceptance in more anthropomorphized systems.

The results show that trust towards the system is influenced by the transparency or the comprehensibility of the system. This study shows a significant influence of Transparency on Trust with a path coefficient of 0.277 for the textual system and a path coefficient of 0.237 for the anthropomorphized system. Therefore the hypothesis that higher transparency of a system has a positive effect on the trust towards the system (H3) is supported. Furthermore, the total effects shown in the appendix imply that the mediator variables which are influenced by transparency increase the influence of transparency of the system on trust towards the system for textual interface with a significant path coefficient of 0.362. The total effects statistic shows that transparency is a significant predictor for acceptance with a path coefficient of 0.161 and the total effects statistic for the anthropomorphized system implies that the mediating variable which is influenced by transparency decreases the influence of transparency on trust. The path from Transparency to Trust remains significant with a path coefficient of 0.123. Similar to the textual system, transparency is a significant predictor of acceptance with a path coefficient of 0.125 in anthropomorphized systems.

The tautologic relation between Transparency to Computer Power could be proven empirically. This study shows a significant effect of Transparency on Computer Power with a path coefficient of – 0.276 for the textual interface and a path coefficient of – 0.186 for the anthropomorphized system. Therefore the hypothesis that a higher comprehensibility of a system has a positive effect on the perceived participation of the user in the decision-making process (H4) is supported. Since the construct of Computer Power has low explanatory power the suggested predictor may not be sufficient and other unobserved variables would be more suitable for predictors. The anthropomorphized system has lower path coefficients than the textual interface which may indicate that anthropomorphizing features decrease the effect that transparency leads to a lower perception of a higher role in decision-making by the system (Computer Power).

Further findings of the study are that Computer Power has a significant effect on Trust with a path coefficient of -0.301 for the textual system and a path coefficient of 0.141 for the anthropomorphized system. Therefore the hypothesis that the higher the perceived participation of the system-user in the decision-making process is, the higher the perceived trust towards the system (H5), is supported partially. These findings were not expected since the literature showed that higher participation possibilities lead to an increase in trust. Similar to the literature the results suggest that a perception

Table 14: Summary of prediction errors

Prediction error measures for PLS of Lisa							
	l_aiacc_1	l_aiacc_2	l_aiacc_3	l_tru_1	l_tru_2	l_tru_3	l_part_1
RMSE	0.865	0.832	0.874	0.842	0.825	0.866	1.068
MAE	0.677	0.626	0.683	0.660	0.663	0.680	0.906
Prediction error measures for LM of Lisa							
	l_aiacc_1	l_aiacc_2	l_aiacc_3	l_tru_1	l_tru_2	l_tru_3	l_part_1
RMSE	0.913	0.863	0.930	0.847	0.856	0.885	1.027
MAE	0.696	0.632	0.720	0.651	0.657	0.709	0.866
Prediction error measures for PLS of Maria							
	m_aiacc_1	m_aiacc_2	m_aiacc_3	m_tru_1	m_tru_2	m_tru_3	m_part_1
RMSE	0.811	0.789	0.797	0.801	0.694	0.801	1.060
MAE	0.650	0.637	0.673	0.634	0.568	0.632	0.867
Prediction error measures for LM of Maria							
	m_aiacc_1	m_aiacc_2	m_aiacc_3	m_tru_1	m_tru_2	m_tru_3	m_part_1
RMSE	0.871	0.816	0.854	0.813	0.646	0.778	1.171
MAE	0.692	0.653	0.700	0.639	0.502	0.579	0.975

of higher participation of the system in decision-making decreases trust towards the system for the textual interface. For the anthropomorphized interface the perception of higher participation of the system in the decision-making process increases the trust in the system. This effect may be explained due a lower perception of high participation of the system in decision-making shown in the comparison of means in descriptive statistics. Furthermore, the total effects statistic shows that Computer Power is a significant predictor of acceptance with a path coefficient of – 0.082 for anthropomorphized interfaces. On the other hand, the path coefficient of – 0.135 is not significant for textual interfaces. This total effect statistics show that acceptance is increased if the system has higher power in decision making for anthropomorphized interfaces. On the other hand, there is no significant influence of the perceived power of the system in decision-making on acceptance for textual interfaces.

The results show that the perceived intelligence of the system has an influence on the trust in the system. This study shows a significant influence of Intelligence on Trust with a path coefficient of 0.321 for the textual interface and a path coefficient of 0.521 for the anthropomorphized interface. Therefore the hypothesis that the higher the perceived intelligence of the system is, the higher the trust (H6) is supported. The path coefficients of the anthropomorphized system show that the perceived intelligence has a greater role in predicting trust than the path coefficient of the textual interface. Furthermore, the total effects statistic shows that Intelligence is a significant predictor of acceptance with a path coefficient of 0.142 for the textual interface and a path coefficient of 0.294 for the anthropomorphized interface. This total effect statistic shows that a higher perceived intelligence of the system should be considered in order to create acceptance of the users.

The results show that the perception of the system as a technology has an influence on acceptance. This study shows a significant influence of the perception of the system as technology on the acceptance by users with a path coefficient of 0.205 for the textual interface. For anthropomorphized interfaces the path coefficient of – 0.003 is not significant. Therefore hypothesis that the higher the perception of the system as technology is, the higher the acceptance (H7), is supported partially.

Furthermore, the study results show that the perception of the system as a person has an influence on the acceptance of users. A Significant influence of the perception of the system as a person with a path coefficient of 0.159 for textual interface and path coefficient of 0.214 for an anthropomorphized system is identified. Therefore hypothesis that the higher the perception of the system as person is, the higher the acceptance (H8) is supported. The results may indicate that adding anthropomorphizing features for textual interfaces may not be necessary in order to create acceptance since the path coefficients for the perception of the system as a technology is higher than the path coefficient of the perception of the system as a person.

4.4.2. Theoretical relevance of study results

The acceptance research on the non-managerial level showed that trust is a major condition to create acceptance by users (Hastenteufel & Ganster, 2021; Rathje et al., 2021; Scheuer, 2020; Uysal et al., 2022). This study shows that findings from literature are applicable on the managerial level. Specifically, trust is identified as a major condition for creating acceptance by users. Furthermore, this study shows how trust is influenced. Since Makarius et al. (2020) iden-

Table 15: Results on acceptance conditions for algorithmic decision support

From	INT	CPOW	TRAN	TRAN	PER	TEC	TRU	CPOW	TRAN	INT
To	TRU	TRU	CPOW	TRU	AIACC	AIACC	AIACC	AIACC	AIACC	AIACC
Path coefficients: Lisa	0.321	-0.301	-0.276	0.277	0.159	0.205	0.445	-0.135	0.161	0.142
T-Statistics	3.678	-5.276	-3.606	3.691	1.973	2.490	5.574	-3.532	3.625	3.097
5 % CI	0.172	-0.395	-0.396	0.155	0.033	0.073	0.308	-0.201	0.094	0.094
95 % CI	0.460	-0.205	-0.149	0.399	0.283	0.336	0.571	-0.076	0.238	0.238
Significance	√	√	√	√	√	√	√	√	√	√
Path coefficients: Maria	0.504	0.142	-0.186	0.237	0.214	-0.003	0.582	0.082	0.123	0.294
T-Statistics	6.420	1.790	-1.985	2.607	2.834	-0.009	9.048	1.739	2.182	4.599
5 % CI	0.374	0.011	-0.336	0.084	0.091	-0.145	0.472	0.006	0.028	0.193
95 % CI	0.633	0.272	-0.028	0.388	0.339	0.175	0.683	0.161	0.217	0.402
Significance	√	√	√	√	√		√	√	√	√

tified cognitive issues in terms of strategic decision making where they identified the necessity to do further research in how decision-makers trust the output received from AI systems. This study shows how trust is influenced. Furthermore, Venkatesh and Davis (2000) show that perceived usefulness is an indicator of acceptance. The study results show that the perceived intelligence of the system is an acceptance condition for decision support. Furthermore, the results suggest that the system should be perceived as useful and exhibit a certain intelligence confirming the research on TAM by Venkatesh and Davis (2000). Despite no findings on the influence of perceived intelligence on trust by Scheuer (2020), this study showed empirical evidence that the perceived intelligence of system has an influence on trust. Research on acceptance states that it is necessary to have a transparent system in terms of the comprehensibility of a decision process (Gersch et al., 2021; Meske et al., 2022; Scheuer, 2020; Venkatesh & Davis, 2000). On the other hand, Newman et al. (2020) state that an increase in transparency may lead to a decontextualization of workers. Therefore the results of this study show that the findings from acceptance research are applicable on the managerial level, specifically that transparency of a result-generating process influences the trust in the system in a positive way. Transparency of the decision-making process of the system is identified as a necessary condition in order to create acceptance by users.

Further results of this study show evidence for the tautologic relationship between the transparency of result processing and the perceived participation of the system in decision-making. Orlikowski and Robey (1991) assume that more information in the decision-making process leads to a higher power of the decision-maker. Considering the manager as a decision-maker the study showed that more information for the manager increases his perceived power in decision-making. Furthermore, the perceived power of the system in decision-making decreases. This effect can be explained by the perception of authoritative correctness of algorithms. Precise algorithms may generate the perception of correctness therefore human beings can feel inferior to algorithms (Martini, 2019).

On the other hand, a higher perceived power of the system in the decision-making process may leads to an increase in trust towards the system if the system is anthropomorphized. Mcafee et al. (2012) questioned whether managers would accept a decision support system which may lead to a shift in their role in form of decreased power. The result showed that higher perceived power by the system in decision-making is an acceptance condition for anthropomorphized systems. These results are contradictory to prior research and to attribution theory by Kelley and Michela (1980).

Attribution theory states that individuals seek to understand the cause of their own behavior (Kelley & Michela, 1980). Since this study shows that the power of the system in decision-making process can be achieved by reducing the transparency of the system, it is assumable that users can have an increased trust in the system even if the system is not comprehensible. Furthermore, a low comprehensibility of a system may not lead to an understanding of the cause of own contribution on the success caused by the decision. Specifically, anthropomorphized systems cause blind trust. This assumption may be irrational in terms of research findings in the necessity of explainable systems regarding result processing (Gersch et al., 2021; Meske et al., 2022; Scheuer, 2020; Venkatesh & Bala, 2008). This irrational assumption may be explained by interpersonal acceptance. As mentioned before insufficient knowledge and a lack of trust hinder the adoption of decision support systems (Rainsberger, 2021). An anthropomorphizing of systems may build up a personal relationship by generating sympathy and affection towards the system which results in interpersonal acceptance (Rohner & Khaleque, 2002). Furthermore, an anthropomorphized system may lead to higher perception of effectiveness of the system causing automation bias. Anthropomorphized systems may be perceived as more effective leading to the tendency to over-rely on decisions made by algorithms (Meske et al., 2022). Goddard, Roudsari, and Wyatt (2012) shows that automation bias leads to a potential failure to detect mistakes made by algorithms. Expectancy theory by Isaac, Zerbe, and Pitt (2001) may explain this irrational assumption. Isaac et al. (2001) state that individuals choose a decision based on the expected outcome of a decision. Therefore a high perception of intelligence may lead to greater expectancy in the outcome of the decision. Further possible explanation for the positive effect of higher perceived power of the system on trust towards the system may be a perception of fairness. Korsgaard et al. (1995) show that participation possibilities as the consideration of an input brought for decision-making or the influence of the input brought for decision making on the outcome of a decision create procedural justice which is a prerequisite for fairness. As Lee (2018) and Newman et al. (2020) show the perception of a fair or trustworthy decision depends on whom the decision is made. Decisions made by the anthropomorphized system may be perceived fairer due to the anthropomorphizing features. Since the anthropomorphized system was more perceived as a technology than a person this explanation may be partially valid. Since the perception of the system as technology was higher in the anthropomorphized system than in the textual system, the Turing test (Turing, 1950) failed. The failure of the Turing test may purpose that the system was not perceived as intelligent by the users. In fact, the perceived intelligence of the system was higher in the anthropomorphized systems than in the textual system which may propose that Turing's definition of intelligence is outdated. Intelligence may be connected to the perception of anthropomorphizing features according to Waytz, Cacioppo, and Epley (2010) like cognition, emotions or interactivity. Furthermore, Lee (2018) shows that decisions made by humans evoke positive emotions due to the possibility of social recognition. Since anthropomorphized systems are characterized through the perception of cognitive capabilities in technology like emotions Waytz et al. (2010), users may see a psychological pleasure or social gain while interacting with the technology. Therefore, the social exchange theory

(Emerson, 1976) may be applicable in order to confirm findings on acceptance conditions. The social exchange theory states that the interaction between two humans is characterized by an exchange of costs and utilities. Utilities may be the effectiveness of the system (Goddard et al., 2012; Lee, 2018; Martini, 2019), psychological pleasure or the enjoyment of system usage (Waytz et al., 2010) and costs may be the perception of inferiority (Baumann-Habersack, 2021; Lee, 2018; Newman et al., 2020), possible detachment of decision making (Bader & Kaiser, 2019) in terms of involvement or the risk of failure due to data discrimination (Newman et al., 2020). Lawler and Thye (1999) show that emotion deepen the nature of the relationship between humans. Furthermore, they show that due to the rise of emotions, humans tend to focus on the decision rather than on the decision process in a group. Therefore social exchange theory may be a possible explanation for blind trust.

The theory of Uncanny Valley by Mori, MacDorman, and Kageki (2012) shows that anthropomorphizing features lead to an increase of acceptance influenced by trust (Scheuer, 2020). They state that an increase of anthropomorphizing features to a certain point lead to a radical reduction of acceptance. Furthermore, Mori et al. (2012) outline that after the critical point of reduction a certain high degree of anthropomorphizing leads to increasing effects on acceptance. Since the anthropomorphized system had high features of anthropomorphizing like gestures, human embodiment and voice output. The survey participants may felt an imperfection of anthropomorphizing leading to higher perception of the system as technology.

5. Acceptance conditions of algorithmic decision support for practice and research

Since the literature shows that research on acceptance conditions for management is critical in order to enhance the potential of algorithmic decision support (Grossman & Siegel, 2014; Laudon et al., 2016; Mcafee et al., 2012; Mikalef et al., 2019; Rainsberger, 2021; Reid et al., 2015). This paper identified plenty of acceptance conditions. Therefore it is necessary to categorize findings for practice and identify limitations for further research.

5.1. System design implications

This paper showed that an optimization of an interface in terms of anthropomorphizing has no effect on the acceptance. Despite no finding, the way acceptance is created differs in optimized interfaces. Therefore practitioners should first define their goal in terms of algorithmic decision support where they have to specify the role of the user. It is necessary to adjust the optimization of the interface to the intention to use the system. If a user should question the output of the decision support system, the decision-processing of the system should be transparent leading to a higher power of the user during the usage. Therefore anthropomorphized system would not be suitable.

On the other hand, if a user should rely on the output of the decision support system, the system should exhibit a higher perceived intelligence leading to a higher trust. Furthermore, the system should be perceived as a person in order to create acceptance. Therefore anthropomorphized systems would be suitable. The research showed that the expected outcomes of an anthropomorphizing is dependent on the system design. Therefore practitioners should pay attention to a suitable degree of an anthropomorphized system in order to avoid the Uncanny Valley proposed by Mori et al. (2012). Practitioners should examine which degree of anthropomorphized system is beneficial in order to fulfill their goals. The implications show that system design is key in order to optimize the interface to create acceptance.

Furthermore, the decision support system should be trustworthy since trust is identified as the main indicator for creating acceptance. In order to create trust according to Lemke, Monett, and Mikoleit (2021) ethical principles should be considered while designing the system. Specifically, beneficence, transparency, nonmaleficence, autonomy, justice, and privacy are principles for an ethical usage of AI according to M. C. Barton and Pöppelbuß (2022). The decision processing of the system should be transparent leading to a higher power of the user. Further performance measurement of the decision may lead to the realization of a positive impact of own contribution on the decision (attribution theory). Systems with high power in the decision making process should be avoided since they have a negative effect on trust. On the other hand anthropomorphized systems with high power in decision-making lead to an increase in trust (blind trust). Future technology advances in hardware like neuromorphic computer architecture, DishBrain and Brain Machine Interface or advances in algorithms like Computational Intelligence or Super Artificial Intelligence may lead to an affordance of blind trust. Since anthropomorphized systems should be introduced when a reliance on the system is afforded, practitioners have the possibility to avoid ethical principles by designing a system with low transparency leading to blind trust. They should carefully evaluate whether they want to benefit from blind trust. It may be beneficial in order to create acceptance. The research showed that the benefits (total effects) from blind trust are smaller than the benefits from trust created by comprehensibility (total effects). Therefore systems with high effectiveness due to technological advances should be transparent for the user because they lead to higher trust and make it possible to identify their own contribution to the outcome of the decision (attribution theory). Furthermore, advanced systems have to exhibit intelligence. The manager should rely on the system knowing that the system processes decision aid with high precision. Therefore the effectiveness of the system should be communicated properly in order to benefit from expectancy theory (Isaac et al., 2001).

This study showed that an anthropomorphizing may not have a direct effect on the acceptance. One of the first anthropomorphized system was introduced by Microsoft called Clippy (Swartz, 2003). The rejection of this assistant was high due to malfunction and a low effectiveness of the system (Swartz, 2003). Due to claims, Microsoft has removed the function of Clippy in Office (Swartz, 2003). Despite the failure of Clippy an interface with a similar degree of anthropomorphizing may be beneficial for advanced decision support systems in order to avoid the Uncanny Valley.

5.2. Limitations and future research

Further precise implications for practice could be derived if the study did not have limitations. The study results were based on an interaction of users with the system. Therefore vignettes have to be designed carefully which could imitate a realistic scenario. Vignettes may distort the perception of the user through the framing of information. This study carefully examined framing of information. The vignette was framed in terms of transparency of the system. The system used in the vignette was not comprehensible. Therefore the descriptive statistics confirm that on average the users do not understand the decision processing of the results of both systems. This distortion was necessary in order to examine whether users would accept the system even if it is not comprehensible. Therefore the vignette described an interaction with hybrid intelligence where the level can be classified as Decision Support System. Further levels of hybrid intelligence were not specified. Since this study showed that the participation of the user in the decision-making process is important for building a trustworthy system, further levels of hybrid intelligence should be considered for future research.

Due to measurement errors, constructs of the study contain single-items which may be not beneficial since exogenous variables are not measurable directly. Nevertheless, the literature shows that single item constructs are appropriate measures for an exploratory research. Since the research question focused on the exploration of acceptance conditions this study examined valid results through the use of PLS-SEM. In order to validate the constructs on theoretical level, a further study should be conducted where the data is analyzed by a common factor-based structural equation model (CB-SEM).

One major problem of the study is that the perception of the system as technology of the system of the anthropomorphized system was higher than that of the textual system. This may indicate that the system design of the vignette was affected by the Uncanny Valley by Mori et al. (2012). Since this study has aimed to maximize the level of anthropomorphizing a specific high degree of anthropomorphizing was reached. The degree of anthropomorphizing is not specifiable uniformly. Therefore the research has to develop a scale for identifying the degree of anthropomorphizing where features of system design are specified in order to derive the degree of anthropomorphizing. Due to the non-existence of a certain scale of anthropomorphizing the degree of anthropomorphizing was chosen arbitrarily, which may distort the results. Further research can focus on the acceptance of anthropomorphized systems with different scales of anthropomorphizing. The effect of Uncanny Valley is identified in the cancellation statistics of the survey. Most cancellations of the survey were done on the page of the introduction of the anthropomorphized system (75 survey participants). The results may be distorted since the users were annoyed by the presence of a human-like system which resulted in the cancellation of the survey. This group would have provided other results. Further research could examine whether a maximization of the anthropomorphizing features may lead to a perception of the system as a person and examine the effect of interpersonal acceptance on acceptance?

The T-test showed that anthropomorphizing has no effect on the acceptance or acceptance-creating variables. Furthermore, two PLS-SEM were estimated to identify how acceptance is created. This approach could be optimized by using anthropomorphizing as moderating variable. Since both models show similar effects except for the aspect of blind trust in anthropomorphized systems, a lack of explanatory power exists in the difference in the results of both systems. R^2 is low in the construct of system power for both SEM models highlighting the affordance of a research setting with moderating effect of anthropomorphizing. Furthermore, the method of PLS-SEM maximizes the explanatory power of the model R^2 (Hair Jr. et al., 2021). Low R^2 values indicate that variables were omitted in research, which may lead to a problem of causal identification (endogeneity). Since the research focuses on an exploration of acceptance conditions a validation of endogeneity was not necessary. Therefore future research should examine endogeneity to identify causalities for the acceptance conditions.

This study examined the acceptance conditions for a single decision-maker. In practice, decision situations may be more complex. Merendino et al. (2018) show that algorithmic decision support can create tension in boards. Therefore it is necessary to examine acceptance conditions for further decision scenarios. Future research should identify whether acceptance conditions for single managers are applicable for more complex decision scenarios, like group decisions.

6. Conclusion

The aim of this thesis was to investigate the conditions that lead to the acceptance of algorithmic decision support systems. In this study, it was especially important to consider the decision-making process of managers. According to this the target group of this study was german speaking students and employees including managers. To analyze different conditions, that may lead to the acceptance of algorithmic decision support systems it was necessary to choose a methodological approach that considers different scenarios but also provides insights on the perceptions, beliefs, and attitudes of the target group. Based on this, a vignette study along with a quantitative survey was used for the data collection for the thesis. In total 281 german speaking student and employees including managers participated in the study during the period from 25.07.22 -07.08.22.

Furthermore, to analyze the conditions of acceptance an estimation of a PLS-SEM model was conducted.

In the theoretical section, it was assumed that anthropomorphizing features may lead to a situation where the user perceives the system as a person and accordingly shows more trust and acceptance towards it. But the result show, an exact opposite behavior of the users. As in the vignette study, two scenarios were presented a textual scenario and a scenario considering anthropomorphizing features. The users perceive the anthropomorphized scenario as a technology and show more trust and acceptance towards a scenario that is not anthropomorphized. Accordingly, the results indicate that there is no significant influence of anthropomorphizing the system on acceptance.

On the other hand, this thesis shows how acceptance differs across both distinct system. This study confirms that higher trust in a system leads to higher acceptance. In addition to this, the results show that trust in the system is influenced by the transparency or the comprehensibility of the system. In this regard it might be interesting to investigate how a system can be designed to receive more trust. In other words, how can the variable transparency or comprehensibility be further elucidated to generate more trust which in the end leads to a situation where the user accepts a system? In this regard different vignette settings might be helpful to investigate scenarios that lead to more transparency and in turn to more trust and acceptance.

Moreover, this study presented several implications for managers and academics. It needs to be mentioned that exponential development in technology can help to aid strategic and operational decisions in management and can be crucial in order to be competitive in dynamic markets. Nevertheless, decision support systems are not used in practice which has many reasons. The literature shows that major challenges arise in the domain of management. Studies show that only few decision-makers understand data concepts well. Therefore the acceptance of algorithmic decision support is not given in the practice. Research on acceptance has identified many conditions in order to foster acceptance of information systems. Nevertheless, the research focuses on the acceptance on worker- or user-level. This study focuses on the gap in the existing literature on management-level. The research question is which conditions lead to an acceptance of algorithmic decision support in management.

Summing up, the literature on persuasive technology shows that an optimization of interfaces leads to more interaction with the technology. Anthropomorphizing is identified as an appropriate way to optimize interfaces. Therefore a vignette study design is conducted, where the survey participants simulate an interaction with a decision support system where the anthropomorphizing is manipulated due to two alternating degrees of anthropomorphizing (low and high). The data for both systems were measured on distinct measurement models. Initially, the results show that there is no effect of anthropomorphizing on acceptance, which may be biased by Uncanny Valley.

Practitioners should first define the level of hybrid intelligence in order to design the system. The system design should consider effects from the study. Benefits from blind trust are not recommendable since the creation through transparency has higher total effects than the total effect of the perceived power of the system in decision-making process. Furthermore, the system has to be effective which may be realized by technological advances. The effectiveness of the system has to be communicated in an appropriate level to enhance the perceived intelligence of the system.

This study showed which conditions lead to an acceptance of algorithmic decision support in management in an explorative study design. These conditions of acceptance could be confirmed by further research through a CB-SEM. All in all, it needs to be mentioned that this study firstly, provided a theoretical contribution by deriving a Structural model and based on the thoughts of the TAM. Secondly, this study provided an empirical contribution at a managerial level as 281 survey respondents participated in this study and shared their perceptions and attitudes towards two scenarios constituting two systems.

Finally, this study provided a practical contribution by showing how companies can use this model as an indicator to design systems and which conditions are necessary in order to create acceptance for users. All in all, this study contributes to the research gap on acceptance on managerial-level.

References

Abhari, K., Vomero, A., & Davidson, E. (2020). Psychology of Business Intelligence Tools: Needs-Affordances-Features Perspective. In *Proceedings of the Annual Hawaii International Conference on System Sciences.* Hawaii International Conference on System Sciences.

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138–52160.

Aguinis, H., & Bradley, K. J. (2014). Best Practice Recommendations for Designing and Implementing Experimental Vignette Methodology Studies. *Organizational Research Methods*, *17*(4), 351–371.

Alexander, C. S., & Becker, H. J. (1978). The Use of Vignettes in Survey Research. *Public Opinion Quarterly*, *42*(1), 93–104.

Alvarez, S. A., Barney, J. B., & Young, S. L. (2010). Debates in entrepreneurship: Opportunity formation and implications for the field of entrepreneurship. In *Handbook of entrepreneurship research* (pp. 23–45). Springer.

Alves, W. M., & Rossi, P. H. (1978). Who should get what? fairness judgments of the distribution of earnings. *American Journal of Sociology*, *84*(3), 541–564.

Anderson, C. (2015). *Creating a data-driven organization: Practical advice from the trenches* (1st ed.). O'Reilly Media Inc.

Andrews, K. R. (1980). The concept of corporate strategy.

Apté, C., Dietrich, B., & Fleming, M. (2012). Business leadership through analytics. *IBM Journal of Research and Development*, *56*(6), 7: 1–7: 5.

Atzmüller, C., Kromer, I., & Elisabeth, R. (2014). Peer Delinquency: Wahrnehmung und Bewertung typischer Jugenddelikte aus der Sicht Jugendlicher als Grundlage für Präventionsmaßnahmen. *Innovation und Technologie (BMVIT), Wien, Österreich*.

Atzmüller, C., & Steiner, P. M. (2010). Experimental Vignette Studies in Survey Research. *Methodology*, *6*(3), 128–138.

Azvine, B., Cui, Z., Nauck, D. D., & Majeed, B. (2006). Real Time Business Intelligence for the Adaptive Enterprise. In *The 8th IEEE International Conference on E-Commerce Technology and The 3rd IEEE International Conference on Enterprise Computing, E-Commerce, and E-Services (CEC/EEE'06)*. IEEE.

Baars, H., & Kemper, H.-G. (2021). Business Intelligence & Analytics–Grundlagen und praktische Anwendungen. *Aufl., Wiesbaden in Druck*. Retrieved from https://link.springer.com/content/pdf/10.1007/978-3-8348-2344-1.pdf

Bader, V., & Kaiser, S. (2019). Algorithmic decision-making? the user interface and its role for human involvement in decisions supported by artificial intelligence. *Organization*, *26*(5), 655–672.

Barbosa, L. C., & Hirko, R. G. (1980). Integration of Algorithmic Aids into Decision Support Systems. *MIS Quarterly*, *4*(1), 1.

Barnett, T., Bass, K., & Brown, G. (1994). Ethical ideology and ethical judgment regarding ethical issues in business. *Journal of Business Ethics*, *13*(6), 469–480.

Barrera, D., & Buskens, V. (2007). Imitation and learning under uncertainty: a vignette experiment. *International sociology*, *22*(3), 367–396.

Barton, D., & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review*, *90*(10), 78–83.

Barton, M. C., & Pöppelbuß, J. (2022). Prinzipien für die ethische Nutzung künstlicher Intelligenz. *HMD Praxis der Wirtschaftsinformatik*, *59*(2), 468–481.

Baumann-Habersack, F. H. (2021). Autorität, Algorithmen und Konflikte – Die digitalisierte Renaissance autoritärer Führungsprinzipien. In *Kooperation in der digitalen Arbeitswelt* (pp. 279–291). Wiesbaden, Springer Gabler.

Bazerman, M. H., & Moore, D. A. (2012). *Judgment in managerial decision making*. John Wiley & Sons.

Beck, M., & Opp, K. (2001). Der faktorielle Survey und die Messung von Normen. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, *53*(2), 283–306.

Becker, J.-M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing Letters*, *26*(4), 643–659.

Benaben, F., Lauras, M., Montreuil, B., Faugere, L., Gou, J., & Mu, W. (2019). Physics of Organization Dynamics: An AI Framework for opportunity and risk management. In *2019 International Conference on Industrial Engineering and Systems Management (IESM)*. IEEE.

Biswas, T. T. (Ed.). (2015). *Measuring Intrinsic Quality of Human Decisions* (Vol. 9346). Cham, Springer.

Blutner, D., Cramer, S., Krause, S., Mönks, T., Nagel, L., Reinholz, A., & Witthaut, M. (2009). Assistenzsysteme für die Entscheidungsunterstützung. In *Große Netze der Logistik* (pp. 241–270). Berlin, Heidelberg, Springer.

Brahm, C., Cheris, A., & Sherer, L. (2016). What Big Data Means for Customer Loyalty. *Brief, Bain and Company, August, 7*.

Buxmann, P., & Schmidt, H. (2021). Grundlagen der Künstlichen Intelligenz und des Maschinellen Lernens. In *Künstliche Intelligenz* (pp. 3–25). Berlin, Heidelberg, Springer Gabler.

Camerer, C., & Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *American economic review*, *89*(1), 306–318.

Carlson, E. D. (1977). Decision support systems: personal computing services for managers. *Management Review*, *66*(1), 4–11.

Carr, J. C., & Blettner, D. P. (2010). Cognitive control bias and decision-making in context: Implications for entrepreneurial founders of small firms. *Frontiers of Entrepreneurship Research*, *30*(6), 2.

Cavanagh, G. F., & Fritzsche, D. J. (1985). Using vignettes in business ethics research. *Research in Corporate Social Performance and Policy*, *7*, 279–293.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of management information systems*, *32*(4), 4–39.

Colossyan. (2022). *Create videos with AI actors, real easy.* https://www.colossyan.com/.

Companiesmarketcap. (2022). *Largest Companies by Market Cap.* https://companiesmarketcap.com/.

Cook, F. L. (1979). Who should be helped? Public support for social services: Public Support for Social Services.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*, *70*, 379–390.

Davenport, T. H. (2013). Analytics 3.0. *Harvard Business Review*, *91*(12), 64–72.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003.

Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support Systems*, *55*(1), 359–363.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid Intelligence. *Business & Information Systems Engineering*, *61*(5), 637–643.

DeSanctis, G., & Poole, M. S. (1994). Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory. *Organization Science*, *5*(2), 121–147.

Dubinsky, A. J., Jolson, M. A., Kotabe, M., & Lim, C. U. (1991). A Cross-National Investigation of Industrial Salespeople's Ethical Perceptions. *Journal of International Business Studies*, *22*(4), 651–670.

Dülmer, H. (2001). Bildung und der Einfluss von Argumenten auf das Moralische Urteil. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, *53*(1), 1–27.

Emerson, R. M. (1976). Social Exchange Theory. *Annual Review of Sociology*, *2*(1), 335–362.

Evans, J. R., & Lindner, C. H. (2012). Business Analytics: The Next Frontier for Decision Sciences. College of Business, University of Cincinnati. *Decision Science Institute*, *21*(12). Retrieved from http://www.cbpp.uaa.alaska.edu/afef/business{_}analytics.htm

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science*, *8*(3), 223–241.

Everett, C. R., & Fairchild, R. J. (2015). A theory of entrepreneurial overconfidence, effort, and firm outcomes. *Journal of Entrepreneurial Finance*, *17*(1), 1–27.

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI magazine*, *17*(3), 37–54.

Fogg, B. J. (1998). Persuasive computers: perspectives and research directions. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 225–232.

Forbes, D. P. (2005). Are some entrepreneurs more overconfident than others? *Journal of business venturing*, *20*(5), 623–640.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measure-ment error. *Journal of marketing research*, *18*(1), 39–50.

Fuchs, C., & Diamantopoulos, A. (2009). Using single-item measures for construct measurement in management research: Conceptual issues and application guidelines. *Die Betriebswirtschaft*, *69*(2), 195.

Furber, S. (2016). Large-scale neuromorphic computing systems. *Journal of Neural Engineering*, *13*(5), 051001.

Gartz, U. (2004). Enterprise information management. In *Business intelligence in the digital economy: opportunities, limitations and risks* (pp. 48–75). IGI Global.

Gefen, Karahanna, & Straub. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51.

GEMESYS Technologies. (2022). *Wir bauen einen vom menschlichen Gehirn inspirierten Computer.* https://gemesys.tech/.

Gersch, M., Meske, C., Bunde, E., Aldoj, N., Wesche, J. S., Wilkens, U., & Dewey, M. (2021). Vertrauen in KI-basierte Radiologie – Erste Erkenntnisse durch eine explorative Stakeholder-Konsultation. In *Künstliche intelligenz im dienstleistungsmanagement* (pp. 309–335). Wiesbaden, Springer Gabler.

Gluchowski, P. (2016). Business Analytics–Grundlagen, Methoden und Einsatzpotenziale. *HMD Praxis der Wirtschaftsinformatik*, *53*(3), 273–286.

Goddard, K., Roudsari, A., & Wyatt, J. C. (2012). Automation bias: a systematic review of frequency, effect mediators, and mitigators. *Journal of the American Medical Informatics Association*, *19*(1), 121–127.

Gong, L. (2008). How social is social responses to computers? the function of the degree of anthropomorphism in computer representations. *Computers in Human Behavior*, *24*(4), 1494–1509.

Grant, A. M., & Wall, T. D. (2009). The neglected science and art of quasi-experimentation: Why-to, when-to, and how-to advice for organizational researchers. *Organizational Research Methods*, *12*(4), 653–686.

Grossman, R., & Siegel, K. (2014). Organizational models for big data and analytics. *Journal of Organization Design*, *3*(1), 20–25.

Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. *ACM computing surveys (CSUR)*, *51*(5), 1–42.

Güting, R. H., & Dieker, S. (1992). *Datenstrukturen und Algorithmen*. Springer.

Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing AG.

Hair Jr., J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24.

Hair Jr., J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123.

Hair Jr., J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hajkowicz, S., Reeson, A., Rudd, L., Bratanova, A., Hodgers, L., Mason, C., & Boughen, N. (2016). Tomorrow's digitally enabled workforce: Megatrends and scenarios for jobs and employment in Australia over the coming twenty years.

Halper, F. (2014). Predictive analytics for business advantage. *TDWI Research*, 1–32.

Hamilton, B., & Koch, R. (2015). From predictive to prescriptive analytics. *Strategic Finance*, *96*(12), 62.

Hassenzahl, M., & Tractinsky, N. (2006). User experience - a research agenda. *Behaviour & Information Technology*, *25*(2), 91–97.

Hastenteufel, J., & Ganster, F. (2021). *Einflussfaktoren auf die Akzeptanz von Robo Advisors: Digitale Kommunikation in der Anlageberatung*. Springer Fachmedien Wiesbaden.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Huber, G. P. (1990). A theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. *Academy of Management Review*, *15*(1), 47–71.

Hyman, M. R., & Steiner, S. D. (1996). The vignette method in business ethics research: Current uses and recommendations. *Marketing: Moving Toward the 21st Century*, 261–265.

Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: How machine intelligence changes the rules of business. *Harvard Business Review*, *98*(1), 60–67.

Iqbal, R., Doctor, F., More, B., Mahmud, S., & Yousuf, U. (2020). Big Data analytics and Computational Intelligence for Cyber–Physical Systems: Recent trends and state of the art applications. *Future Generation Computer Systems*, *105*, 766–778.

Isaac, R. G., Zerbe, W. J., & Pitt, D. C. (2001). Leadership and motivation: The effective application of expectancy theory. *Journal of managerial issues*, 212–226.

Janis, I. L., & Mann, L. (1977). *Decision making: A psychological analysis of conflict, choice, and commitment*. Free press.

Jasso, G., & Webster Jr, M. (1999). Assessing the gender gap in just earnings and its underlying mechanisms. *Social Psychology Quarterly*, 367–380.

Jöreskog, K. G., & Wold, H. O. A. (1982). *Systems under indirect observation: Causality, structure, prediction*. North Holland.

Kagan, B. J., Kitchen, A. C., Tran, N. T., Parker, B. J., Bhat, A., Rollo, B., … Friston, K. J. (2021). In vitro neurons learn and exhibit sentience when embodied in a simulated game-world. *bioRxiv*. Retrieved from https://www.biorxiv.org/content/biorxiv/early/2021/12/03/2021.12.02.471005.full.pdf

Kahneman, D. (2003). A perspective on judgment and choice: mapping bounded rationality. *American psychologist*, *58*(9), 697.

Kahneman, D., & Schmidt, T. (2012). *Schnelles Denken, langsames Denken*. Siedler Verlag.

Kahneman, D., Slovic, S. P., Slovic, P., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge university press.

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions. *1939-1471*.

Karahanna, E., Xin Xu, S., Xu, Y., & Zhang, N. (2018). The Needs–Affordances–Features Perspective for the Use of Social Media. *MIS Quarterly*, *42*(3), 737–756.

Kelley, H. H., & Michela, J. L. (1980). Attribution theory and research. *Annual review of psychology*, *31*(1), 457–501.

Knebl, H. (2019). *Algorithmen und Datenstrukturen: Grundlagen und probabilistische Methoden für den Entwurf und die Analyse*. Springer Vieweg.

Koch, R. (2015). From business intelligence to predictive analytics. *Strategic Finance*, *96*(7), 56–58.

Koellinger, P., Minniti, M., & Schade, C. (2007). "I think I can, I think I can": Overconfidence and entrepreneurial behavior. *Journal of economic psychology*, *28*(4), 502–527.

Königstorfer, J. (2008). *Akzeptanz von technologischen Innovationen: Nutzungsentscheidungen von Konsumenten dargestellt am Beispiel von mobilen Internetdiensten*.

Korsgaard, M. A., Schweiger, D. M., & Sapienza, H. J. (1995). Building Commitment, Attachment, and Trust in Strategic Decision-Making Teams: The Role of Procedural Justice. *Academy of Management Journal*, *38*(1), 60–84.

Kotler, P., Berger, R., & Bickhoff, N. (2010). The quintessence of strategic management. *What You Really Need to Know to Survive in Business, Berlin*.

Kreutzer, R. T., & Sirrenberg, M. (2019). *Künstliche Intelligenz verstehen* ([1. Auflage] ed.). Wiesbaden, Springer Fachmedien.

La Hayward, M., Forster, W. R., Sarasvathy, S. D., & Fredrickson, B. L. (2010). Beyond hubris: How highly confident entrepreneurs rebound to venture again. *Journal of business venturing*, *25*(6), 569–578.

Larson, D., & Chang, V. (2016). A review and future direction of agile, business intelligence, analytics and data science. *International Journal of Information Management*, *36*(5), 700–710.

Laudon, K. C., Laudon, J. P., & Schoder, D. (2016). *Wirtschaftsinformatik: Eine Einführung* (3rd ed.). Pearson Studium.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT sloan management review*, *52*(2), 21–32.

Lawler, E. J., & Thye, S. R. (1999). Bringing Emotions into Social Exchange Theory. *Annual Review of Sociology*, *25*(1), 217–244.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, *5*(1), 205395171875668.

Leimeister, J. M. (2019). *Dienstleistungsengineering und-management: Data-driven service innovation*. Springer.

Lemke, C., Monett, D., & Mikoleit, M. (2021). Digitale Ethik in datengetriebenen Organisationen und deren Anwendung am Beispiel von KI-Ethik. In *Data Science anwenden* (pp. 33–52). Springer.

Linardatos, P., Papastefanopoulos, V., & Kotsiantis, S. (2020). Explainable AI: a review of machine learning interpretability methods. *Entropy*, *23*(1), 18.

Luhmann, N. (1990). Risiko und Gefahr. In *Soziologische aufklärung 5* (pp. 131–169). Springer.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273.

Mallach, E. G. (1994). Understanding Decision Support Systems and Expert Systems. Richard D. Irwin. *Inc., USA*.

Martini, M. (2019). Blackbox Algorithmus. *Grundfragen einer Regulierung künstlicher Intelligenz, Berlin*.

Mashingaidze, K., & Backhouse, J. (2017). The relationships between definitions of big data, business intelligence and business analytics: a literature review. *International Journal of Business Information Systems*, *26*(4), 488–505.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model Of Organizational Trust. *Academy of Management Review*, *20*(3), 709–734.

Mcafee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60–68.

McKelvie, A., Haynie, J. M., & Gustavsson, V. (2011). Unpacking the uncertainty construct: Implications for entrepreneurial action. *Journal of business venturing*, *26*(3), 273–292.

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, A. (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research*, *93*, 67–78.

Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable Artificial Intelligence: Objectives, Stakeholders, and Future Research Opportunities. *Information Systems Management*, *39*(1), 53–63.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, *98*, 261–276.

Mikalef, P., Pappas, I., Krogstie, J., & Pavlou, P. A. (2020). Big data and business analytics: A research agenda for realizing business value. *0378-7206*.

Mishra, N., & Silakari, S. (2012). Predictive analytics: a survey, trends, applications, oppurtunities & challenges. *International Journal of Computer Science and Information Technologies*, *3*(3), 4434–4438.

Moore, G. E. (1965). *Cramming more components onto integrated circuits*. McGraw-Hill New York.

Mori, M., MacDorman, K. F., & Kageki, N. (2012). The Uncanny Valley [From the Field]. *IEEE Robotics & Automation Magazine*, *19*(2), 98–100.

Moschovakis, Y. N. (2001). What Is an Algorithm? In *Mathematics unlimited — 2001 and beyond* (pp. 919–936). Berlin, Heidelberg, Springer.

Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT Press.

Nedelcu, B. (2013). Business intelligence systems. *Database Systems Journal*, *4*(4), 12–20.

Newman, D. T., Fast, N. J., & Harmon, D. J. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes*, *160*, 149–167.

Orlikowski, W. J., & Robey, D. (1991). Information Technology and the Structuring of Organizations. *Information Systems Research*, *2*(2), 143–169.

Panagiotarou, A., Stamatiou, Y. C., Pierrakeas, C., & Kameas, A. (2020). Gamification Acceptance for Learners with Different E-Skills. *International Journal of Learning, Teaching and Educational Research*, *19*(2), 263–278.

Porter, M. E. (1996). What is strategy? *Harvard Business Review*, *74*(6), 61–78.

Pütz, C., Düppre, S., Roth, S., & Weiss, W. (2021). Akzeptanz und Nutzung von Chat-/Voicebots. In *Künstliche intelligenz im dienstleistungsmanagement* (pp. 361–383). Wiesbaden, Springer Gabler.

R Core Team. (2013). *R: R: A language and environment for statistical computing : reference index*. http://www.R-project.org/. R Foundation for Statistical Computing.

Rainsberger, L. (2021). *KI–die neue Intelligenz im Vertrieb*. Springer Books.

Rathje, R., Laschet, F.-Y., & Kenning, P. (2021). Künstliche Intelligenz in der Finanzdienstleistungsbranche – Welche Bedeutung hat das Kundenvertrauen? In *Künstliche Intelligenz im Dienstleistungsmanagement* (pp. 265–286). Wiesbaden, Springer Gabler.

Reid, C., McClean, J., Petley, R., Jones, K., & Ruck, P. (2015). *Seizing the information advantage: How organisations can unlock value and insight from the information they hold: A PwC report in conjunction with Iron Mountain.* https://www.pwc.es/es/publicaciones/tecnologia/assets/Seizing-The-Information-Advantage.pdf.

Rich, E. (1985). Artificial intelligence and the humanities. *Computers and the Humanities*, *19*(2), 117–122.

Robertson, D. C. (1993). Empiricism in business ethics: Suggested research directions. *Journal of Business Ethics*, *12*(8), 585–599.

Rohner, R. P., & Khaleque, A. (2002). Parental acceptance-rejection and life-span development: A universalist perspective. *Online readings in psychology and culture*, *6*(1), 1–10.

Rosenberg, J. (2017). Security in embedded systems: Important Security Concepts, Security And Network Architecture, Software Vulnerability And Cyber Attacks, Security And Operating System Architecture. In A. Vega, P. Bose, & A. Buyuktosunoglu (Eds.), *Rugged Embedded Systems: Computing in Harsh Environments* (pp. 149–205). Elsevier/Morgan Kaufmann.

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User Acceptance of Virtual Reality: An Extended Technology Acceptance Model. *International Journal of Human–Computer Interaction*, *36*(11), 993–1007.

Sarstedt, M., & Wilczynski, P. (2009). More for less? a comparison of single-item and multi-item measures. *Die Betriebswirtschaft*, *69*(2), 211.

Savolainen, S. (2016). Could Acceptance Predict Commitment in Organisational Change? Impact of Changes Caused by Succession From the Viewpoint of Non-family Employees in Small Family Firms. *Management*, *4*(5), 197–215.

Scheuer, D. S. (2020). *Akzeptanz von Künstlicher Intelligenz*. Springer.

Shanks, G., & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: An evolutionary process perspective. *Journal of Decision Systems*, *21*(3), 231–244.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, *23*(4), 433–441.

Sheridan, T. B., & Verplank, W. L. (1978). *Human and Computer Control of Undersea Teleoperators*. Defense Technical Information Center.

Shi, Z. (2021). *Intelligence Science: Leading the Age of Intelligence*. Elsevier and Tsinghua University Press.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347.

Smith, S. L., & Aucella, A. F. (1983). *Design guidelines for the user interface to computer-based information systems*. MITRE CORP BEDFORD MA.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate? *Behavioral and brain sciences*, *23*(5), 645–665.

Steiner, P. M., Atzmüller, C., & Su, D. (2016). Designing valid and reliable vignette experiments for survey research: A case study on the fair gender income gap. *Journal of Methods and Measurement in the Social Sciences*, *7*(2), 52–94.

Stevenson, T. H., & Bodkin, C. D. (1998). A Cross-National Comparison of University Students' Perceptions Regarding the Ethics and Acceptability of Sales Practices. *Journal of Business Ethics*, *17*(1), 45–55.

Swartz, L. (2003). Why people hate the paperclip: Labels, appearance, behavior, and social re-sponses to user interface agents.

Tolstoy. (2022). *Tolstoy: A new way to communicate, with interactive video.* https://www.gotolstoy.com/.

Turing, A. M. (1950). Mind. *Mind*, *59*(236), 433–460.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, *185*(4157), 1124–1131.

Uysal, E., Alavi, S., & Bezençon, V. (2022). Trojan horse or useful helper? a relationship perspective on artificial intelligence assistants with humanlike features. *Journal of the Academy of Marketing Science*, 1–23. Retrieved from https://link.springer.com/article/10.1007/s11747-022-00856-9

van Rijmenam, M., Erekhinskaya, T., Schweitzer, J., & Williams, M.-A. (2019). Avoid being the Turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty. *Long Range Planning*, *52*(5), 101841.

Venkatesh, V. (2000). Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model. *Information Systems Research*, *11*(4), 342–365.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273–315.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204.

Walster, E. (1966). Assignment of responsibility for an accident. *Journal of personality and social psychology*, *3*(1), 73.

Wang, P. (2019). On Defining Artificial Intelligence. *Journal of Artificial General Intelligence*, *10*(2), 1–37.

Wason, K. D., & Cox, K. C. (1996). Scenario utilization in marketing research. *Advances in Marketing. Texas: Southwestern Marketing Association*, 155–162.

Wason, K. D., Polonsky, M. J., & Hyman, M. R. (2002). Designing vignette studies in marketing. *Australasian Marketing Journal*, *10*(3), 41–58.

Watson, H. J., & Wixom, B. H. (2007). The current state of business intelligence. *Computer*, *40*(9), 96–99.

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who Sees Human? The Stability and Importance of Individual Differences in Anthropomorphism. *Perspectives on psychological science : a journal of the Association for Psychological Science*, *5*(3), 219–232.