Balancing AI in SMEs: Overcoming Psychological Barriers and Preserving Critical Thinking

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Abstract: The rapid integration of artificial intelligence (AI) into various business sectors is transforming the operational landscape. This paper focuses on small and medium-sized enterprises (SMEs) and examines how they can achieve an optimal psychological balance when using AI. The goal is to encourage employees to adopt AI while maintaining critical thinking and autonomy. This research paper uses theoretical analysis as the research method, drawing on established psychological theories such as the Technology Acceptance Model and the Job Demands-Resources Model. The findings are used to propose a model for determining an optimal balance for SMEs. The analysis reveals several psychological barriers related to anxiety, which can lead to increased stress, lower motivation, and general resistance to the use of AI tools. Conversely, once the fear is overcome, there is a risk of over-reliance on AI. Therefore, it is important to provide training that helps employees recognize the benefits of AI and its impact on their tasks, critically evaluate AI recommendations, and find a balance between automated guidance with human judgement. Finding the optimal balance in the use of AI is critical. Fostering a culture of continuous learning, and adaptability, together with supportive leadership, can help maintain this balance. In summary, through a strategic application of psychological theories, SMEs can harness the potential of AI to improve work performance and mitigate labour shortages while developing motivated and critically thinking employees.

Keywords: Artificial intelligence, Technology acceptance, Psychological barriers, Critical thinking, Organisation, Model

1. Introduction

This paper examines how implementing artificial intelligence (AI) can succeed in organisations. Psychology as the science of human experiences and behaviour is embedded in the context of the digital working world. Specifically, the interaction between people and organisations in dealing with AI is examined. The key question is: How can organisations design a successful implementation so that AI is perceived as a relief rather than a burden and can contribute to an increase in productivity for the entire organisation?

Since the so-called "first industrial revolution" in the second half of the 18th century, people have been accompanied by technical achievements that generally cause discomfort at first. In Goethe's "Wilhelm Meisters Wanderjahre", textile machines threaten human activity, and Nietzsche speaks of the "idleness" triggered by the machine. Even today, in the so-called "digital age" or "age of artificial intelligence" (Castells 2010, Russel and Norvig 2022) people and organisations are grappling with the question of how to approach the new or avoid it.

Organisation is a multi-layered term, and the understanding of the term varies depending on the discipline. In organisational psychology, organisations are generally understood as social systems (Dorsch 2024, i.e. a complex network of technical and social structures. Technological developments influence the organisation of work and the social structure of employees and vice versa.

In the second chapter, findings and background information on technological progress and AI are presented to create an understanding of the organisational psychological spectrum of AI. Three relevant theories are then considered to present an integrative model based on their findings in the fourth chapter, which can contribute to the acceptance and successful introduction of AI by taking organisational, technological and psychological factors into account. Then, an interlinkage to preserving critical thinking is made before the main points of this work are summarised in the fifth chapter.

2. Background

Technological progress goes hand in hand with a reduction in the workload for people. The structural change from an agricultural to an industrial and service society to a digital society is one of the reasons for a high level of social mobility, both in the vertical direction of career advancement and relegation and in the horizontal direction of changing places of work and residence (Castells 2010; Ebeling et al. 2012). AI also provides support where it can relieve the burden on people (Langer et al. 2021). Since the introduction of machines, working hours have fallen from 72 hours to less than 40 hours per week without any major impoverishment, but on the contrary an increase in living standards and life expectancy (Statista 2024, 2024b). Technical innovations should therefore not cause any unease. But when something is difficult to understand, it tends to make people feel uneasy or indifferent (Tsao et al. 2013). Increasingly complex organisational structures, transnational production and distribution chains as well as AI software serve precisely this impenetrability. Technical progress with evershorter innovation cycles means that the goal of "being finished" can hardly be achieved, which brings with it a considerable degree of uncertainty. However, it is precisely the knowledge of recurring change that may facilitate the process and is made possible by human flexibility and adaptability.

The rapid technical progress of AI with its presumed productivity-enhancing potential, as well as the increasing shortage of skilled labour, have rekindled interest in AI in science and practice in recent years. For instance, the latest survey results in Germany from 2023 show that around 12% of German companies are already using at least one AI software, around 10% are planning to implement one and just over 35% are holding talks about potential AI use cases (OECD 2024). The main obstacles to the hesitant implementation of AI in the organisational context, especially among SMEs, include insufficient digitalisation - which is a prerequisite for the efficient use of AI, an insufficient amount of qualitatively prepared data, a poor understanding of the potential benefits of AI, uncertainty regarding data protection aspects and a lack of AI skills (OECD 2024).

A transformation towards AI-using organisations requires a rethink and a holistic approach, as AI has an impact on a variety of organisational areas. At the same time, care should be taken to ensure that employees perceive AI as increasingly attractive and remain loyal to the organisations.

Artificial Intelligence

"Intelligence" plays an important role in psychology and intelligence tests are one of the most successful diagnostic procedures. Although there are many views on what is meant by intelligence, which is reflected in the large number of intelligence models and correspondingly different intelligence tests, a relatively standardised understanding of what intelligence is has emerged. Intelligence represents both a personal characteristic and a procedural meaning, as it describes how something is done: quick comprehension, in-depth understanding, precise judgement, learning from experience, etc. (Schmidt-Atzert et al. 2021, Myers 2014).

AI goes beyond robotics and human-machine interaction and includes data science, affective computing, virtual realities (Hasenbein 2023, Langer et al. 2021). The definition of AI has changed over time. AI research began in the 1950s intending to simulate human-like thinking. Alan Turing introduced the Turing Test in the 1950s with the key question: Can a computer converse like a human? He assumed that a computer has intelligence on par with a human if a third party cannot distinguish who the human dialogue partner is (Turing 1950). As early as the 1960s, Joseph Weizenbaum's ELIZA program was one of the first computer programmes to conduct simple conversations with users, briefly giving the impression that a human was communicating (Weizenbaum 1966). Another founding father of AI is John McCarthy, who coined the English term "Artificial Intelligence" in civilian usage and surmised that any aspect of learning or any other characteristic of intelligence can in principle be described so precisely that a machine can simulate it (McCarthy et al. 2006). Today, the definition of AI focuses on the ability of machines to perform cognitive tasks efficiently and autonomously, reflecting advances in machine learning and neural networks (deep learning). An advanced subgroup is generative AI, which focuses on the creation of new content such as images, text, videos, music, etc. It aims to recognise and imitate patterns in existing data to generate new results (Kulkarni et al. 2023).

The rise of AI since the 2010s is mainly due to the availability of data, the further development of algorithms, the improvement of hardware and software and the increase in investment capital (Holdren et al. 2026, OECD 2024). Since the freely accessible publication of ChatGPT on 30 November 2022, AI has become a much more popular and becomes increasingly integrated into various sectors of daily working life, from decision-making to automating tasks.

The changing definition of AI reflects the growing capabilities and expectations of the technology. From an organisational psychology perspective, it is important to understand this development to promote the acceptance of AI in organisations. Employees must not only be trained in the use of AI but also develop an understanding of its potential. Successful integration of AI therefore requires both technological adjustments and a change in values towards greater openness and willingness to learn.

3. Theoretical Concepts

Research questions in the field of AI have traditionally been very technical and are increasingly becoming application oriented. AI applications, i.e. AI software, are a young business field and the acceptance of AI by users is still little researched. New theories and practical tools are needed for dealing with AI and its implementation in organisations. This article aims to develop a preliminary model that enables a holistic view, including technological, psychological and emotional factors, embedded in the organizational context. This is done based on three established scientific concepts, which are presented below.

3.1 7-S Model

The 7-S Model, developed in the 1980s by McKinsey consultants Waterman, Peters and Phillips, is a standard framework in business and management literature for analysing organisations that incorporates seven variables that interact with each other. The variables are divided into hard factors: 1. structure, 2. strategy, 3. systems and soft factors: 4. skills, 5. staff, 6. style and 7. superordinate goals (Waterman et al. 1980). A particular contribution of this model is the emphasis that structure alone is not enough, but that a holistic approach is necessary and an awareness that organisations adapt slowly to change (Waterman et al. 1980). This integrated approach enables organisations to understand and manage the complexity of organisational change, especially when it comes to implementing new technologies such as AI. The 7-S Model offers a top-down, strategic organisational perspective and framework that ensures that all aspects of the organisation are considered in the acceptance process.

3.2 Technology Acceptance Model

Fred D. Davis developed a technology acceptance model (TAM) with two variables that are fundamental determinants of user acceptance of information technology: 1) perceived usefulness and 2) perceived ease of use. The regression analyses indicate that perceived ease of use may be a causal precursor of usefulness. These findings are significant as they provide validated measures for predicting user acceptance of technology (Davis 1989). Davis and Venkatesh extended the TAM to include additional factors that influence perceived usefulness. Firstly, subjective norms and image from theories of social influence, and secondly, job relevance, output quality and result demonstrability from theories of cognitive instrumental processes (Venkatesh and Davis 2000). The resulting TAM2 also takes user experience and voluntariness into account, which allows the acceptance of new technologies in an organisational context to be better captured. In a further study, Venkatesh and Bala combine the TAM2 model and the determinants of perceived ease of use to form TAM3 (Venkatesh 2000). It is hypothesised that individuals develop an initial assessment of perceived ease of use through various anchors of their attitudes towards computers and their use. These anchors include computer self-efficiency, i.e. the belief in one's ability, the perception of external control, i.e. the belief in the availability of necessary structures and resources, computer anxiety and computer playfulness as an intrinsic motivation to try new things (Venkatesh and Bala 2008). When practical experience has been gained through actual use, perceived enjoyment and objective usability influence perceived ease of use.

The model provides the individual and experiential perspective as well as consistently explains about 40% of the variance in individuals' intention to use an IT and actual usage (Venkatesh and Bala 2008). The added value of TAM3 is that psychological and emotional factors are considered, allowing the model to better capture the diversity of human reactions to new technologies.

3.3 Job Demands-Resources Model

The Job-Demands-Resources model (JD-R) was introduced in 2001 and has since developed into a comprehensive theory for analysing and improving working conditions and employee well-being (Demerouti et al. 2001, Bakker and Demerouti 2017). The JD-R model provides organisations with a structured framework to understand the complex interactions between job demands and job resources and to analyse their impact on employee wellbeing and performance. Alongside stress models such as the Demand-Control Model and the Effort-Reward Imbalance Model, the JD-R Model is more flexible as it considers a broader range of working conditions and incorporates both negative and positive indicators of employee well-being (Bakker and Demerouti 2007). This flexibility is particularly valuable for the introduction of AI, as it brings completely new requirements and resources into the working environment.

The model divides all working conditions into two main categories: Job demands and job resources. While job demands encompass aspects of work that require sustained physical or mental effort and are therefore associated with certain physiological and psychological costs, job resources serve to achieve work goals, reduce work demands or promote personal growth and development (Bakker and Demerouti 2017). The JD-R model is based on two different processes. One is the health-impairing process, which can lead to exhaustion and health problems if work demands are high. The second is the motivational process, which can lead to increased commitment and better performance based on job resources. An important aspect is that job resources can buffer the negative impact of high job demands on stress (Bakker and Demerouti 2017). The JD-R model enables organisations to develop targeted interventions to minimise the negative effects of high demands and maximise the positive effects by providing appropriate resources.

This model bridges the individual and organisational levels by considering as it considers the balance between job demands and resources, which is crucial when introducing new technologies like AI. It helps in understanding how the introduction of AI might affect employee well-being and performance.

4. Integrative Model for AI Implementation

The integrative model for AI implementation shown in Figure 1 is a first attempt to analyse and implement the introduction of AI in organisations. It was developed based on elements of the TAM3, the JD-R model and the 7-S model and is discussed below. The combination of these three frameworks allows for a holistic approach to AI adoption and helps to overcome the limitations of using any single model. For instance, while TAM is excellent at predicting individual acceptance, it doesn't consider organisational factors. The 7-S Model fills this gap. Similarly, the JD-R model helps to understand the impact of AI adoption on employee well-being and performance, which neither TAM3 nor the 7-S Model directly addresses.

This integrative model considers technological as well as psychological and emotional aspects of AI adoption. It addresses individual factors such as fears and self-confidence, which are often barriers and embeds them in a broader organisational context. The model emphasises the need to align all factors, which is crucial for a successful implementation of AI.

Organisations are embedded in an *environment* with which they interact, e.g. AI developments affect them, but also organisations affect AI. Within the organisation, the organisational factors (cf. 7-S model) form the framework for the introduction of AI; they interact with each other as well as with individuals and groups, which in turn influence individual and organisational behaviour. An organisation's strategy should include the increased use of AI. The structure and the system should be flexibly adapted to the AI software, an appropriate IT infrastructure should be created, and employees should be trained to develop the necessary skills in dealing with AI.

Care should be taken to ensure that the style of management is characterised by greater flexibility to support new working methods. The role of AI should also be reflected in values such as willingness to learn, tolerance of mistakes and openness to new developments. As already made clear in the 7-S model, an organisation can only achieve its economic goals if it takes people seriously as human beings. While introducing AI, this is likely to be a particularly important point.

Good external conditions (external control), i.e. resources and support options made available to a person by the organisation, increase the likelihood that AI will be perceived as easy to handle. Provided resources can also support individual self-confidence and strengthen trust in one's abilities in dealing with AI software, e.g. through positive experiences. The strategy and working conditions can also inhibit or increase the fear of AI. An increased level of anxiety often leads to a perceived burden/stress and can result in the development of an aversion to AI. On the other hand, the playful element of AI can be emphasised, which should be possible through user-friendly tools on the market with appropriate guidance. By taking these soft factors into account, the model does better justice to the diversity of human reactions to new technologies. Targeted measures for understanding and promoting the acceptance of AI can overcome both technological and psychological barriers.

At the centre of this model is the perceived benefit, i.e. managers and employees must understand how AI can improve their work performance and productivity. In addition, the AI software used must be perceived as user-friendly and accessible to people with different levels of technical knowledge. Building on this, workshops and communication strategies can be developed that emphasise the usability of AI and demonstrate its user-friendliness to reduce resistance and increase the acceptance of AI.

AI software brings new tasks for the organisation and the employees at whose workplaces it is used, and in any case, those affected must adapt. This means that they must forget some of their old ways of working to learn new things. During AI implementation, new work requirements such as training, adaptation of the system to the AI software, etc. and new work resources through AI such as the automation of routine tasks, the generation of texts, images, ideas, etc. must be identified. This helps to understand how AI can be both stressful due to its increased opacity and motivating due to new possibilities and increased utility. Knowledge of the buffer effect of resources should be used to provide targeted resources such as clear communication, application-related support, etc. to minimise potential stress during the implementation of the AI strategy.

Particularly in the initial phase of implementing AI software, care should be taken to ensure that individuals are not overwhelmed by new tasks or an increased workload but are provided with resources such as practical assistance with relevant AI software that they can use effectively for their work. The challenge of our time lies in the fast pace of life, in the sensory overload, so care should be taken not to overburden individuals and to adapt the pace of the flood of information to their capacities. Collaboration and the exchange of experience among employees and in working groups should also be encouraged when adapting to AI technology.

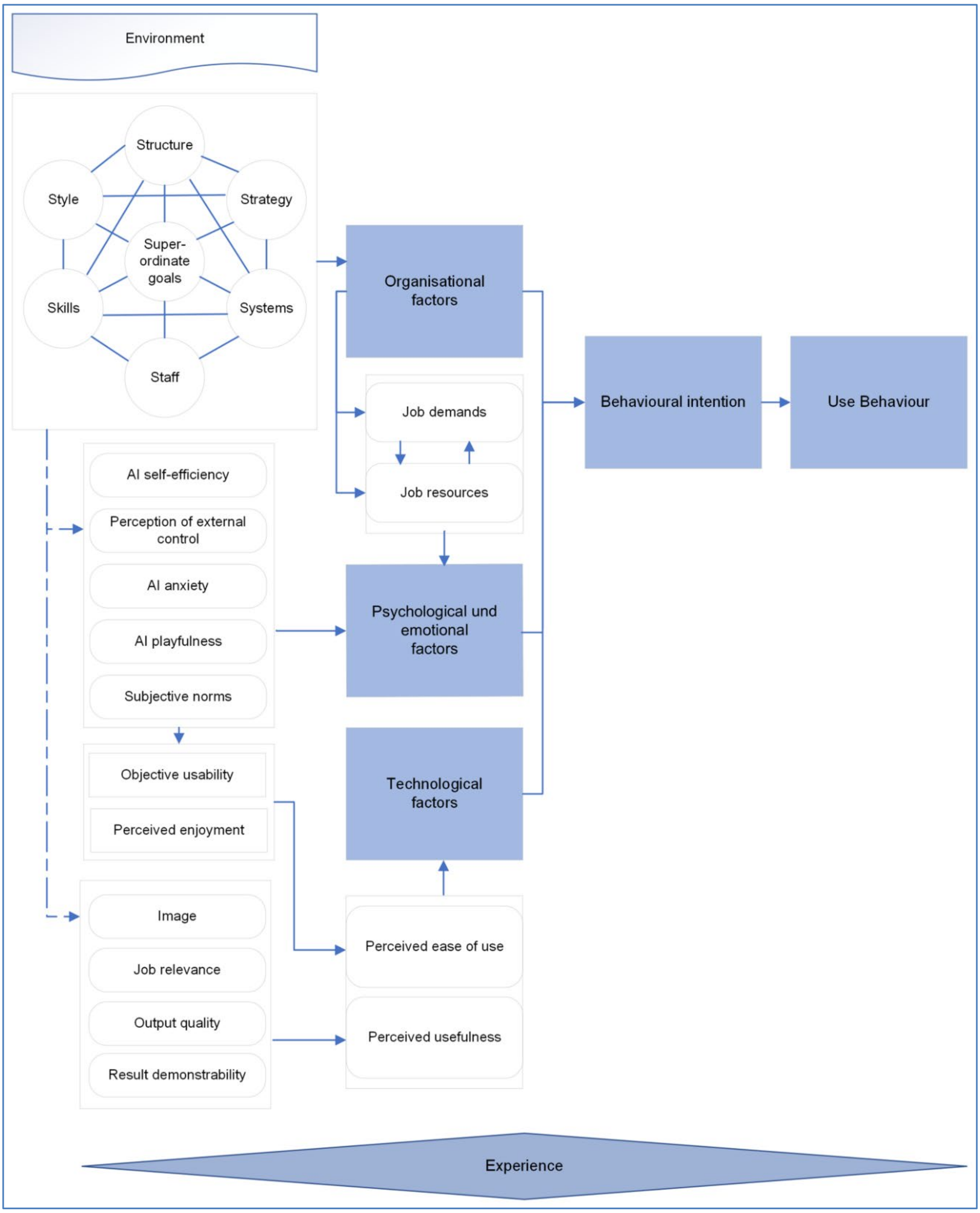

Figure 1: Integrative model for AI implementation

There are relationships between the factors and events in the model. These relationships cannot generally be fully recognised and predicted by humans; they are "probability relationships". During the changeover, work performance will generally drop initially and only gradually reach a new level of productivity. The critical moment is the changeover/adaptation to new environmental conditions, and management is well advised to make employees aware of initial difficulties, but also of the fact that successes can be expected subsequently, and to initiate the motivational process and overcome psychological barriers through positive experiences. As with all activities and technological innovations, human control is required. The results of AI should be critically scrutinised by the organisation and everyone. On the one hand, this serves to prevent errors and, on the other, it gives people meaning.

5. Preserving Critical Thinking

Assuming employees have accepted AI successfully, the user-friendliness and usefulness of the AI tools have been recognised, as they experience the benefits of AI in their daily work. This raises the question, can't it be that employees and humans are easily inclined to trust in the work of AI and no longer question it, to sit back and stop thinking?

Taken this idea further, means there is a growing concern about over-reliance on AI, leading to the "lay-back effect," where business leaders and employees become passive and uncritically accept AI-generated outputs. This dependence can in turn impede innovation, diminish problem-solving skills, and expose organisations to errors and biases inherent in AI systems. Exactly what should be increased. That's why maintaining critical thinking is inherently important.

Critical thinking begins with questioning assumptions and examining the evidence behind claims. Browne and Keeley (2015) argue that this skill is especially important in today's information-saturated world, where individuals are often bombarded with data, opinions, and conflicting viewpoints. A critical thinker actively engages with information by identifying biases, recognizing logical fallacies, and seeking out reliable sources. For instance, when evaluating news reports or online information, a critical thinker would not only consider the source but also question its motivations and underlying assumptions.

A significant risk associated with over-reliance on AI is the potential suppression of creativity and innovation. SMEs often thrive on their capacity for creative thinking, niche market identification, and rapid adaptation to change. However, when decision-making becomes overly dependent on AI tools, employee disengagement from the creative process may ensue, leading to a stagnation of innovative ideation. AI systems are designed to analyse existing data patterns but are not inherently equipped to engage in "out-of-the-box" thinking or generate entirely novel concepts (Tegmark, 2017). This creates a potential trap where businesses, instead of thriving on fresh ideas, settle into routines dictated by AI-driven patterns.

Although AI offers significant opportunities to enhance operational efficiency and competitiveness, it is crucial to avoid becoming overly dependent on these technologies. The "lay-back effect," where employees blindly trust AI recommendations, can erode critical thinking, limit creativity, and expose businesses to risks from biased or flawed AI outputs. To remain agile and competitive, SMEs must maintain a balance between leveraging AI for efficiency and fostering a culture that prioritizes human insight, critical thinking, and creative problem-solving.

How can employees in SMEs create this balance? It is essential to develop an awareness of the questioning of results, i.e. regularly review evaluations of AI-generated results. For example, a marketing expert can critically question the recommendations of an AI-driven targeting tool by incorporating their own market research data and customer feedback. This helps to identify potential errors or biases in the AI predictions and to develop alternative approaches. Another way is working together in interdisciplinary teams that include different departments such as marketing, sales and product development. This can also bring different perspectives to the table and encourages creative thinking, helping to develop innovative solutions that go beyond AI recommendations. Regular brainstorming sessions can be used to share ideas, test applications, and implement feedback mechanisms. A weekly or monthly exchange about the AI results and their impact on work can be helpful. These discussions allow employees to be more aware of the results and critically consider how to optimise the use of AI. One example would be internal meetings, in which employees show each other their experiences with AI in very specific use cases, sharing benefits and concerns. Such feedback can also help management improve AI tools and ensure that the human perspective is integrated into the decision-making process. Employees can learn to think of AI as another supportive employee and to treat him as such with all the advantages and disadvantages.

In doing so, SMEs ensure that AI remains a tool that complements human judgment, rather than replacing it.

6. Conclusion

In this paper, AI was examined from an organisational psychology perspective to better understand what AI is and how AI can be successfully implemented in organisations.

The starting point for the considerations was that organisations are social systems capable of learning. Section 2 looked at the period from industrialisation to the digital age in terms of technological developments. It was shown that the goal of making machines a reflection of humans and, in this sense, AI is not just a contemporary issue. Nor does today's knowledge point to a technical reconstruction of the human being. Nevertheless, generative AI has reached a milestone that is changing the world of work and organisations significantly. This presents organisations with major challenges in dealing with AI and the need to retrain. AI is giving job profiles new job characteristics and may also lead to job losses. Every cultural innovation, including AI, harbours opportunities in a positive sense, but also risks. It can be helpful to focus on the positive opportunities and familiarise oneself with the new so that it becomes more familiar, and organisations can learn to deal with or avert the risks. Section 3 introduced theoretical concepts that are useful to the research question and, building on this, Section 4 presents a first attempt at an AI implementation model. The model offers a holistic approach that takes organisational, technological and psychological factors into account and stimulates an iterative learning process based on gaining experience and experimenting with AI. It's an attempt to bridge the gap between different levels of analysis and provide a more complete picture of the AI implementation process in organisations. In the 5th section, an outlook was ventured and the question was raised of what happens when AI Tools are accepted and used by employees, the added value is experienced. In this context, the importance of maintaining critical thinking also concerning AI was emphasized.

The present work can only be a starting point for the exploration of organisational diagnoses and concrete design approaches for the implementation of AI in organisations (Hasenbein 2023). In further empirical research, the analysis of the individual factors of the model could be used to identify psychological and organisational barriers and to plan measures for targeted interventions to overcome identified barriers and to accompany the concrete implementation of AI, taking all model elements into account. During the process, the behavioural factors and production increases would be regularly evaluated and the strategy adjusted if necessary. Another interesting approach could be the inclusion of findings from stress theory, e.g. that the degree of aversiveness of a stimulus is not only defined by intensity, novelty and duration but also by the coping options and their prospects of success and failure (Lazarus and Folkman 2015). If organisations are aware of this, they can strengthen their own adaptability and that of individual employees by examining the environment to determine the extent to which aversive events are predictable and what options exist for influencing them or actively or passively avoiding them.

Research in the field of AI shows that the contribution of psychology could have a decisive influence in the future, both in counselling and in basic research, for example in the field of affective computing.

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