The Changing Nature of Work: Change Management for Applications of Artificial Intelligence

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AUTHOR ACCEPTED MANUSCRIPT. Unofficial translation[1]. Cite as:

Hüllmann, J. A. (2026). The Changing Nature of Work: Change Management for Applications of Artificial Intelligence. HMD Praxis der Wirtschaftsinformatik. https://doi.org/10.1365/s40702-026-01290-z

Abstract:
Introducing artificial intelligence (AI) in organizations raises questions about change management. For example, how can employees be trained to work with AI? Although there are scientific studies on change management in AI, practical recommendations from scientific theory are rarely presented in a concise manner. This article explains the scientific theories in an illustrative manner using three use cases and presents recommendations for action. The theories were selected based on a qualitative literature review. The recommendations for action address changes in tasks and roles, the identity and meaningfulness of work, the acceptance, trust, and use of AI, and finally, training. The use cases cover AI in agriculture, human resources, and surgery. Successful change management allows organizations to realize the positive effects of work transformed by AI.

Keywords: Change Management; Artificial Intelligence; Tasks and Roles; Job Identity; Technology Acceptance and Use

1 Introduction

Artificial intelligence (AI) was one of the key economic issues in Germany in 2025 (Engels et al. 2025). Applications range from waste management (Olawade et al. 2024) to industrial manufacturing (Sharp et al. 2018) to diagnostics and care in the healthcare sector (Jussupow et al. 2021).

The introduction of AI raises questions about changes in the workplace and the necessary change management. Employers are concerned about a lack of expertise and a shortage of skilled workers, fearing they will fall behind AI developments. Employees fear that AI could substitute their jobs (Ozgul et al. 2024). Not all employees will be replaced, but most will face fundamental changes in their work (Mayer et al. 2025). These changes in the workplace may lead to new tasks and roles involving AI or to different perceptions of work (Fischer et al. 2023).

[1] Maximilian Zieren translated this work with the help of GenAI tooling.

Information systems research provides practical insights into the opportunities and challenges of AI (Leible et al. 2024). Studies describe how AI is designed but do not focus on the subsequent changes in work and the necessary change management. AI challenges established change management theories because it differs from conventional information technology (IT) in characteristics such as non-deterministic outputs (Riemer et al. 2026). Initial findings on the topic of AI and change management document the collaboration between humans and AI (Fabri et al. 2023), predictors of the intention to use AI (Berger et al. 2021), and necessary AI competencies (Pinski and Benlian 2024).

Although these studies on AI and work exist, there is a need for practical knowledge about the changing nature of work and recommendations for managing change driven by AI (Ristau 2023). A synthesis of the existing academic literature on the topic would make such knowledge accessible to practitioners. The following article addresses this concern and answers the research question: *How can changes in work driven by AI be managed in practice?*

To answer this question, the literature on the changing nature of work and change management for AI is summarized in a practice-oriented manner through a qualitative literature review. Three case studies are used to illustrate how the theory derived from the literature review can be applied.

2 Background[2]

For up to 80% of U.S. workers, at least 10% of their daily work will change as a result of AI language models alone (Eloundou et al. 2024). These far-reaching impacts on work require a change management approach to AI. Without organizational support for these changes, the positive effects of AI will not be realized (Humlum and Vestergaard 2025). To inform change management for AI, this article examines established dimensions of work design: tasks and roles, meaningfulness, identity, adoption, and training.

Role theories explain how changes brought about by AI give rise to new conflicts. A lack of organizational structures, e.g., during the introduction of AI, or changing tasks lead to role conflicts and result in

[2] This article is not about change management process models, but rather about changes in work that must be managed *top-down* (i.e., work design theories). *Bottom-up* job crafting is also excluded from this article.

dissatisfaction, stress, and negative behavioral adjustments (Tubre and Collins 2000). AI shifts the balance between routine and non-routine tasks, as automation replaces some tasks and creates new ones (Raisch and Krawkowski 2021). The classic *job characteristics* model for analyzing tasks examines the effects of autonomy and feedback on motivation and performance (Hackman and Oldham 1976). *Work design* approaches emphasize the interdependencies between task structure, teamwork, and organizational context, and highlight how tasks must be redesigned in light of AI (Parker et al. 2001). Research on *meaningful work* links this structural level to individual experiences of the meaningfulness of work (Humphrey et al. 2007). A sense of meaning (*meaningfulness*) arises when work visibly contributes to an outcome (Hackman and Oldham 1976). Studies show that AI can both promote and undermine the perception of meaningfulness: on the one hand, AI enables a focus on value-adding activities, on the other hand, it triggers alienation from the job when core tasks are taken away (Selenko et al. 2022).

Changing roles affect the identity of job holders. Identity theories show that role changes are not only functional but also relevant to identity (Ibarra 1999). With AI, traditional definitions of expertise are coming under pressure, and established roles as experts are being challenged (Raisch and Krakowski 2021). Identity theories highlight that work structures not only tasks but also one’s self-understanding (e.g., values and self-perception). When work changes, individuals must adapt their professional identity (Ibarra 1999).

Changes in tasks and roles are accompanied by decisions regarding the adoption and use of AI. Technology acceptance models explain how employees adopt technological innovations (Venkatesh et al. 2003), with trust in AI increasingly coming into focus alongside usefulness and usability (Gille et al. 2020). AI requires additional measures to explain how the systems work to build this trust (Berger et al. 2021).

For the use of AI in new tasks and roles to be successful, users must be trained. The training perspective emphasizes the organization’s responsibility toward its employees. AI-based automation requires continuous learning and the skills to monitor algorithmic outcomes (Jarrahi 2018). Organizations must provide training for this purpose. In summary, the literature shows that the impact of AI on work must be managed.

3 Methods

The state of the art regarding change management and AI was determined by conducting a literature review and interpretive analysis (Paré et al. 2015). Based on this state of the art, practical recommendations for action were derived as examples for three use cases.

3.1 Identification and Analysis of Literature

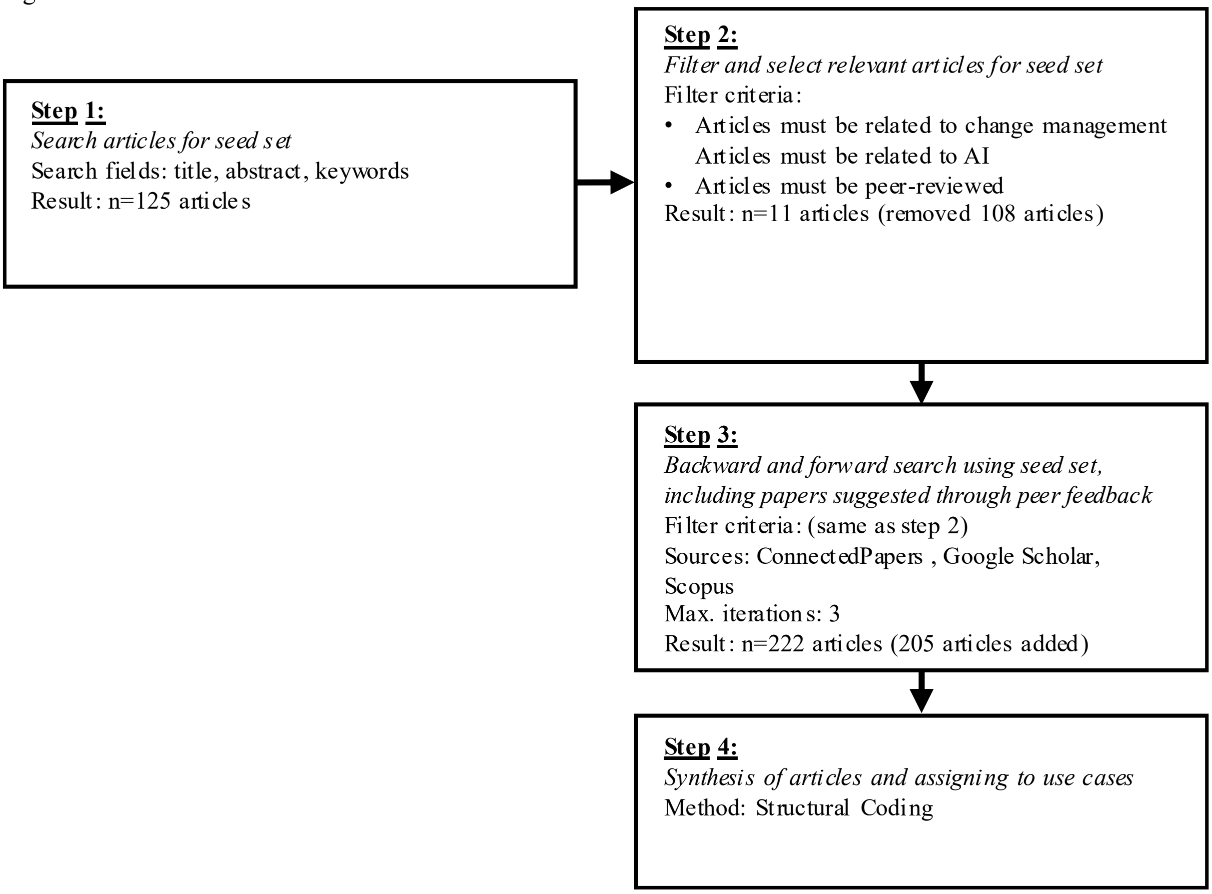
Deriving recommendations for action from scientific literature requires qualitative, systematic reviews (Paré et al. 2015). Therefore, a qualitative literature review was conducted following Schryen (2015). Reproducibility is ensured by documenting the selection process, which is illustrated in Figure 1. The review is representative and not exhaustive (Cooper 1988). It focuses on backward and forward searches, as relevant contributions can be found in related disciplines (e.g., organizational research, psychology). To this end, an initial selection of articles was identified from the "*Basket of Eight*" of information systems literature, as well as from practice-oriented and German journals (Table 1). The search query included the keywords "*adaptation management*," "*change leadership*," "*change management*," "*innovation management*," "*cultural change management*," "*organizational development*," "*transformation management*," "*transition management*," and the keyword "*artificial intelligence*." Variations of these terms were included in the query using OR operators (e.g., *adaptation management or adaptation-management*), including German & English variants and abbreviations (e.g., *Künstliche Intelligenz, KI)*

Table 1. Sources

Source	Justification	Access
Electronic Markets	German IS	Springer
Business Information Systems Engineering	German IS	Springer
Schmalenbach Journal of Business Research	German IS	Springer
HMD Praxis der Wirtschaftsinformatik	German IS	Springer
Wirtschaftsinformatik & Management	German IS	Springer
Harvard Business Review	Practice-oriented	SCOPUS
MIT Sloan Management Review	Practice-oriented	SCOPUS
California Management Review	Practice-oriented	SCOPUS
MIS Quarterly Executive	Practice-oriented	SCOPUS
Information Systems Research	Basket-of-Eight	SCOPUS
Journal of Strategic Information Systems	Basket-of-Eight	SCOPUS
MIS Quarterly	Basket-of-Eight	SCOPUS
Journal of Management Information Systems	Basket-of-Eight	SCOPUS
European Journal of Information Systems	Basket-of-Eight	SCOPUS
Information Systems Journal	Basket-of-Eight	SCOPUS
Journal of Information Technology	Basket-of-Eight	SCOPUS
Journal of the Association for Information Systems	Basket-of-Eight	SCOPUS

The search yielded an initial selection of n=125 articles. This initial selection was filtered through an analysis of the abstracts and full texts, leaving n=17 articles. The filtering criteria were that the articles contribute to change management related to AI and that they were peer-reviewed. Through forward and backward searching, this filtered initial selection was expanded by n=205 articles, resulting in a total of n=222 articles that were included in the analysis. Out of these, n=101 articles are cited in the final paper.

Figure 1. Method of Literature Search



Structural coding was used to organize the articles around key concepts (Saldana 2009). The coded segments containing similar statements were grouped together to form a coherent argument regarding change management for AI. In doing so, especially the practical implications of the selected articles were considered. From these arguments, the challenges and approaches to change management for AI were derived.

3.2 Identification of Use Cases

The use cases were selected to highlight various key aspects of the theory on change management in AI (Yin 2018). The aspects derived from the theory pertain to tasks and roles, job identity and meaningfulness, technology acceptance, trust, and use, as well as training. In addition to the theoretical substance, the focus was on the relevance, clarity, comprehensibility, and applicability of the case studies for AI change management (Eisenhardt 1989). Following the case study method (Yin 2018), I included diverse contexts (knowledge work vs. physical labor) and domains (agriculture, human resources management, medicine), as well as jobs undergoing change due to AI (Table 2).

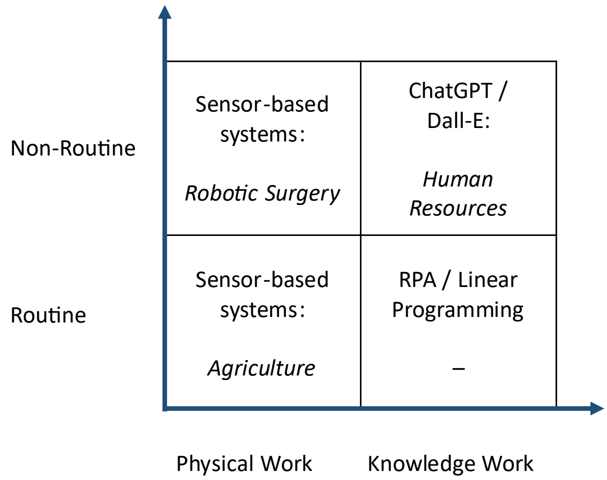
Table 2. Use Cases

Selection Criteria	**Agriculture**	**Human Resources Management**	**Robotic Surgery**
Content-theoretical	The use of AI in agriculture threatens professional identity when AI replaces experiential knowledge. Farmers must monitor complex decision-making and control systems and are subject to competence overload.	The use of AI in human resources leads to the elimination of several tasks and the emergence of new tasks and roles (e.g., HR analysts). These changes must be reflected in adjustments to business processes.	Robotic surgical systems support minimally autonomous surgical procedures. Extensive, long-term training to develop new skills and competencies, as well as corresponding strategic workforce planning, are necessary.
Relevance, clarity, comprehensibility, and applicability	This use case illustrates how AI is integrated into complex sequences of activities in various ways (e.g., support, augmentation, automation).	This use case illustrates a solution that is already common in the U.S. and has been widely discussed and criticized. The solution is explicitly cited as an example in the EU AI Act.	This use case illustrates the use of AI to support clinical decision-making: Physicians must weigh uncertain AI recommendations against their clinical judgment.
Various contexts and domains	This case study examines the use of computer vision-based AI to automate routine physical tasks. Small businesses, in particular, face challenges in this regard.	This use case focuses on traditional knowledge work in an office setting, such as in large human resources departments.	This case involves life-critical, non-routine care provided to patients in the context of public medical facilities.

3.3 Classification of Use Cases

These three use cases illustrate the diversity of changes in the workplace and the need for change management. They can be classified into four types of AI based on the degree of routine and the nature of the work (physical vs. knowledge work) (Figure 2) (Acemoglu and Autor 2011). Sensor-based systems are suitable for routine physical work. The use case from agriculture falls into this category.

Figure 2. AI by type of work (based on Acemoglu and Autor 2011). The use cases are shown in italics (own illustration)



For non-routine knowledge work, AI is used to process unstructured datasets with non-linear relationships. Unlike conventional optimization, these relationships change dynamically and are learned empirically and inductively through *training* with training data. In the case of human resources, this involves non-routine knowledge work performed on a computer. The medical use case addresses physical work with patients. This is non-routine work and is based on physical sensors and corresponding AI.

Robotic Process Automation (RPA) or conventional optimization methods are suitable for routine knowledge work. These methods are appropriate when there is a finite set of parameters that are related to one another through theoretically deducible relationships. Since these systems do not correspond to probabilistic AI as defined in this article, no use cases of this type will be discussed below.

4 Use Case Descriptions

The following section introduces the three use cases that demonstrate the need for change management in AI. Chapter 5 explores the scientific theory behind each use case and presents examples of recommended actions.

4.1 Computer Vision for Smart Farming

In crop farming, sensor-based AI enables yield predictions for crops and opens up opportunities for automation (Inoue 2020). Satellites generate high-resolution images of the cultivated area, which are used to estimate the plants' vegetation index (Van Klompenburg et al. 2020). Based on this estimate, a prediction is made regarding how much fertilizer should be applied to the field. A farmer can adjust this estimate based on their experience and contextual knowledge (e.g., fertilizer prices or weather conditions). The result is transmitted to a tractor for manual or (semi-)automated fertilizer application. During application, farmers decide in real time whether to adhere to the recommended fertilizer amount or deviate from it.

Before the introduction of AI, the focus was on physical support. Farmers make decisions based on their observations and operate machinery manually. AI enables augmented or automated decision-making and the operation of machinery based on sensor data. In addition to the ongoing physical support, cognitive support is now being introduced. There is a shift in the nature of work from decisions based on experience to decision-support systems. The role of farmers is evolving from caretakers of the fields to managers of machinery (Hüllmann et al. 2023).

4.2 People Analytics in Human Resource Management

People Analytics refers to data-driven analyses of employees (Hüllmann and Mattern 2020). It supports and automates workforce planning, recruitment, and development throughout the employee lifecycle (Hüllmann et al. 2021a). For long-term workforce planning, demand and supply forecasts are generated based on descriptive statistics and conventional optimization (Levenson and Pillans 2017; Hüllmann et al. 2021b). For recruitment, one-way interviews with AI-based evaluation are used to automatically screen job candidates (Hickman et al. 2025). Game-based assessments are evaluated using AI to assess a candidate's skills and fit (Landers and Sanchez 2022). In employee development, sentiment analysis is used to ensure employee satisfaction (Hüllmann and Kroll 2018) as well as to predict and prevent turnover (Isson and Harriott 2016; Rothmeier et al. 2021).

Before AI, HR professionals worked with human resources information systems (HRIS) that presented master data in a descriptive manner (Johnson et al. 2016). HR professionals were constantly engaged in interpersonal exchanges with employees. Data about employees was collected through traditional surveys and supplemented through conversations with employees. Decisions were made based on this data, supplemented by experiential knowledge. Modern HRIS offer complex inferential statistical AI methods. AI fully automates steps in the recruitment process and informs decision-making. The shift in tasks and roles affects the relationship between HR professionals and other employees, as HR professionals have fewer face-to-face interactions (Hüllmann 2022).

4.3 AI and Robotics in Surgery

Da Vinci is a robot-assisted surgical system designed for minimally invasive surgical procedures, particularly laparoscopy (Moglia et al. 2021). In this system, surgeons operate remotely. It promises gentle and highly precise procedures with reduced risk. *Da Vinci* features freely moving arms, three-dimensional high-resolution video technology, and is equipped with sensors (optical, haptic, spatial) to provide intraoperative support (Panesar et al. 2019). AI enables the automated detection, display, and magnified view of tissue for more precise work (Knudsen et al. 2024). Real-time guidance supports minimally invasive surgeries, and modern systems compensate for tremors and partially automate steps (Knudsen et al. 2024).

Conventional laparoscopic surgery is a manual procedure performed by surgeons using human expertise. There is no real-time assistance. The work takes place directly on the patient's body. In robot-assisted laparoscopy, surgeons control the robotic arms from a computer, away from the patient. AI provides data-driven support and automates certain steps. Trust in the technical solutions is a key factor given the life-critical nature of the procedure (Gille et al. 2020).

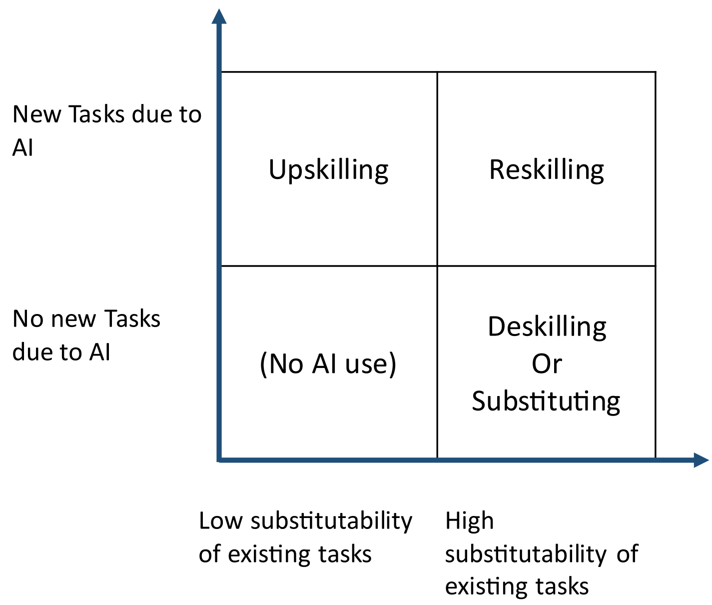
5 Change Management for AI

These three use cases demonstrate that implementing AI requires not only technical expertise but also change management. The *black-box* nature of AI is inherent to the technology. Although explainable AI exists, systems are gaining prominence in which neither the developers nor the users know how a specific output is generated, as these systems produce more accurate results. Conventional IT typically produces deterministic outputs, meaning that users obtain the same result when performing the same action. With non-deterministic AI, similar inputs can generate drastically different outputs. There is no guarantee of a correct output (Riemer et al. 2026). On the contrary, these systems contain systematic biases based on the training data from which the system was constructed (Venkatesh 2022). The technical characteristics of AI give rise to specific aspects of change management. Trust in AI differs from trust in humans and conventional IT (Thiebes et al. 2021). There are new requirements for data, algorithm, and skill management, as well as for training staff. Increasing automation affects tasks, roles, and job identity.

5.1 Tasks and Roles

Based on the two dimensions the *number of new tasks created by AI* and the *extent to which existing tasks can be replaced by AI* change management measures for various job functions can be derived (Figure 3).

Figure 3. Employee Training Approaches (based on Dornelles et al. 2023) (own illustration)



When existing tasks remain unchanged but new tasks are added, this is referred to as upskilling. In upskilling, existing skills remain important, but the performance of a task is enhanced through additional methods or technologies (Dornelles et al. 2023). A company can implement continuing education programs for upskilling by expanding existing knowledge to include AI expertise. In reskilling, new tasks are introduced through AI, replacing existing ones. Old tasks become obsolete, so affected employees must learn new roles and tasks. The need for reskilling becomes apparent as automation advances. Continuing education programs aid in reskilling by imparting new skills to meet changing professional requirements. If the introduction of AI eliminates existing tasks but does not create new ones, this constitutes deskilling or substitution. For workers, the resulting redundancy of their own jobs is the worst possible outcome of AI implementation. Companies must take measures to preserve skills, such as documenting tacit knowledge, to reduce reliance on individual expertise. A gradual introduction of AI minimizes risks and allows for the adaptation of business processes (Doppler and Lauterburg 2008).

When developing social plans for a reorganization, communication should take place early on and involve the employees or worker representatives. If AI is not implemented, there will be no AI-induced changes to existing tasks and no new tasks will be created.

Figure 4. Degree of integration (based on Möllers et al. 2024) (own illustration)

The impact on work and tasks can also be measured by the degree of integration (Figure 4). This ranges from no impact to support, augmentation, and finally automation of tasks (Brynjolfsson and Mitchell 2017). In the case of supportive AI, the AI provides decision recommendations, but the actions remain the responsibility of humans. Here, clarity must be established regarding how the AI functions, e.g., how AI decisions are made and how they should be interpreted. Augmenting AI describes partial automation, in which AI takes over some parts of a task while humans retain responsibility for the remaining parts. Measures are needed to clarify the understanding of roles, specifically, which tasks the AI takes on and where human judgment remains necessary (Möllers et al. 2024). Measures to clarify roles build the skills needed to collaborate with AI. Since automation leads to deskilling, measures similar to those used for deskilling or substitution should be applied.

It is not always possible to upskill employees or expand their roles. Changes in responsibilities do not necessarily have to occur within an existing role; instead, new roles may emerge, such as those of AI intermediaries (Waardenburg et al. 2022). New roles must be designed and may involve hiring new staff (Table 3).

In the **agricultural use case**, decisions are no longer made solely on the basis of experiential knowledge, but rather through a combination of experience and data analysis, extending all the way to fully automated decisions (Ingram and Maye 2020). The need for physical labor is decreasing (Rotz et al. 2019), and the combination of physical and cognitive skills is coming to the forefront (Burton and Riley 2018). This includes new tasks in the management of systems and data (Smith 2020). Accordingly, upskilling measures are needed. Traditional skills remain necessary, and agricultural operations must retain knowledge of mechanical engineering, technology, and plant biology. In addition, new knowledge of quantitative methods, statistics, and software is required to use AI in a value-adding way. Given the competence overload faced by farmers, with burnout being the second most common cause of reduced work capacity in agriculture (Buhne 2019), it is advisable to engage agricultural consultants (Eastwood et al. 2019a). A high level of AI product maturity reduces the competence overload experienced by farmers. Depending on individual circumstances, AI supports, augments, or automates farmers' tasks, as farmers themselves decide how to integrate AI into their work.

Therefore, training on how AI works is important (Hüllmann et al. 2023) so that farmers can decide what level of integration is right for them. As the level of automation increases, reskilling becomes important.

In the **human resources use case**, deskilling resulting from augmentation and automation is evident. Reduced human contact is changing the way decisions are made (Weiskopf and Hansen 2023). Discretionary decisions and empathy are giving way to automation through quantitative-statistical methods. AI processes information about applicants and employees and provides recommendations or makes decisions. In one-way interviews, humans are excluded from the first round of the application process. Accordingly, HR decision-makers must be trained to handle the AI's recommendations and automated processes. HR staff must be retrained or reassigned. It must be clarified at which process steps human intervention is necessary, particularly when it comes to interpersonal relationships (Huang et al. 2019). Finally, new roles are emerging, such as HR analysts (Kashive and Khanna 2023). HR staff must be trained in this new understanding of their roles, as AI increasingly takes over their responsibilities.

In the **medical use case**, reskilling is necessary because robotic and traditional laparoscopic surgery require different skill sets. Both skill sets require long-term qualifications that call for strategic workforce planning. Intraoperative AI is currently low-autonomous. The focus is on detection, segmentation, alerting, and training support (Rivas-Blanco et al. 2021). AI labels tissue types and automatically highlights bleeding or high-risk structures (Ebigbo et al. 2022). Surgeons remain responsible for the robot's actions but receive support through the recognition and evaluation of surgical actions (Atroshchenko et al. 2025). As automation increases, surgeons are becoming integrators rather than "craftsmen" (Hashemi et al. 2025). For the implementation of AI, it is important that training programs address the uncertainties that arise regarding AI-provided support and feedback, as well as how AI is integrated into the surgical process. The routine use of AI can lead to deskilling effects that must be managed over the long term (Natali et al. 2025).

Table 3. Tasks and Roles (own Table)

Use Case	Exemplary Measures
Agriculture	Upskilling is necessary. Due to competence overload, external consultants are brought in. Training is needed to help farmers determine in which cases they should rely on support, augmentation, or automation provided by AI.
Human Resources	Deskilling is necessary. HR staff need to be retrained or reassigned. HR decision-makers should be made aware of the need to integrate AI into HR business processes (e.g., governance).
Surgery	Reskilling is necessary. In AI-based robotic surgery, surgeons must undergo reskilling. This requires specialized, long-term training, which must be supported by strategic workforce planning.

5.2 Identity and Meaningfulness

Changes in tasks and roles affect job identity (Mirbabaie et al. 2022). On the one hand, people feel empowered because AI enables them to perform new tasks or carry out processes more effectively (Richter and Schaller 2025). AI increases perceived control and autonomy by allowing people to use their skills and knowledge more effectively (Ackerkhans et al. 2024). On the other hand, a job threatened by AI leads to fear of losing one's identity, status, or job, and resistance to the introduction of AI (Jussupow et al. 2022). The use of AI reduces emotional attachment to work (Mei et al. 2025). In particular, the reduction in interpersonal relationships, for example, in human resources or medical applications, is viewed critically (Ackerhans et al. 2024).

To address these perceptions, expectation management is advisable. Companies should demonstrate that AI is a supportive tool that makes work easier and improves results (Jussupow et al. 2022). They can foster a positive identification with AI by supporting employees through transparency and training as they navigate this change (Mirbabaie et al. 2022). In doing so, it helps to convey an understanding of how AI works (Cao et al. 2023). AI that has little impact on employees' core tasks and responsibilities poses a lesser threat to their job identity (Richter and Schaller 2025). Similarly, a strong sense of professional identity mitigates the effects of AI (Richter and Schaller 2025). Finally, employees can be rotated among different tasks so that they do not work with AI for extended periods (Cao et al. 2023).

Changes in job duties affect the meaning of work, the perception of which depends on five factors:

- **Integrity of tasks**: Are there complete tasks, rather than just small, repetitive steps?
- **Skill development and utilization**: Are different skills required to complete the tasks?
- **Importance of tasks**: Do the tasks contribute to the company's success or even to society?
- **Autonomy**: How much responsibility does the employee have?
- **Sense of belonging**: Does the employee feel a sense of belonging to the organization?

When new tasks are challenging, this has a positive effect on the perceived significance of work (Bankins and Formosa 2023). AI serves the employee and is subordinate (*Managing the Machine*). In contrast, the emergence of repetitive and low-skill tasks has negative effects on the perceived significance of work (Bankins and Formosa 2023). AI takes over the exciting tasks, while employees merely ensure that the AI runs smoothly (*Minding the Machine*).

Companies can take steps to ensure that work transformed by AI meets the criteria for meaningful work (Table 4). For example, tasks transformed by AI are reorganized into roles in such a way that the criteria continue to be met (Pratt and Ashforth 2003). The new roles should create complex, important tasks and enhance existing ones to maintain meaningful work. According to Hackman & Oldham (1975, 1976) and Humphrey et al. (2007), employees should be responsible for their own decisions and tasks. People retain their autonomy when they are allowed to manage their own use of AI, for example, when and how they use and configure AI (Zhou et al. 2025). People perceive their work as more meaningful when they interact directly with AI and are integrated into processes (Sadeghian et al. 2024). Partial AI decision support promotes autonomy (Passalacqua et al. 2025), whereas fully automated AI reduces autonomy over time. A balance between AI support and human control is therefore advisable. This is reinforced by the ability to critically question AI (Zhou et al. 2025). Finally, meaningful work is characterized by a sense of belonging (Pratt and Ashforth 2003). It helps to proactively involve employees in the change process and to demonstrate how individual tasks contribute to the overall business results (Carton 2018).

While farmers in the **agricultural use case** welcome automation and the reduction of labor, change management becomes important when AI supports or augments decision-making. Decisions that were once made based on experience, sometimes influenced by emotion and a connection to the field, are now driven by data. On the one hand, the very nature of agriculture is changing (Butler and Holloway 2016). This change is perceived as self-fulfilling and value-adding when modern agriculture is understood as evidence-based farming (Klerkx et al. 2019). On the other hand, the change leads to less autonomy when it restricts farmers' familiar workflows, e.g., through algorithmic barriers (Miles 2019). The reduction of farmers to knowledge workers results in a less value-creating and autonomous identity (Rotz et al. 2019). Transparency and explainability clarify the role of AI and maintain the emotional connection to the job (Mei et al. 2025). Furthermore, farmers' strong trust in their professional identity mitigates the negative effects of AI (Richter and Schaller 2025). Empowering farmers to decide when and how to use and configure AI, including in terms of whether it provides support, augmentation, or automation, protects against a loss of identity (Zhou et al. 2025). Given the cognitive overload faced by farmers, AI does not threaten the integrity or importance of their tasks. Measures are limited to training for new tasks and roles.

While HR staff in the **Human Resources use case** previously conducted face-to-face conversations to foster relationships with candidates and employees, screen-based work and the analysis of data are becoming increasingly important. This leads to less autonomy and a reduced sense of belonging, as HR staff no longer decide for themselves when and with whom to make contact, instead, AI makes those decisions (Schafheitle et al. 2020). Individual HR staff members bear less responsibility for operational decisions. On the one hand, the HR department can evolve from a support function to a strategic business function (Gierlich-Joas and Zimmer 2023). On the other hand, AI can negatively impact the status of HR staff, as the importance of their work in operational activities declines (Hüllmann et al. 2025). These changes fuel a fear that AI will take over creative tasks, while humans perform piecework. Proactive work design during AI implementation is crucial (Bailey et al. 2019), including transparency regarding the integration of AI into business processes (Mirbabaie et al. 2022), in order to manage these fears. It must be demonstrated where interpersonal relationships remain relevant (Passalacqua et al. 2025).

In the **medical use case**, systems remain low-autonomous for the time being, and surgeons remain responsible. However, the systems are increasingly performing core tasks, and as automation increases, the distance from patients grows, which undermines the medical identity. Surgeons see potential in AI support but express concerns about a loss of autonomy when AI makes assessments and monitors work steps (Voskens et al. 2022). AI recommendations create pressure to act, even though the decision to act ultimately remains with humans. Although surgical outcomes are improving, clinical intuition can be devalued by AI. While the identity as a surgeon is not fundamentally called into question, a new identity as a human-machine collaborator is emerging (Merdin-Uygur et al. 2025). Accordingly, organizations should foster a strong sense of professional identity among affected physicians (Richter and Schaller 2025) and demonstrate how their decisions and tasks will continue to contribute to patient well-being in the future (Pratt and Ashforth 2003). Surgeons must be trained in how to manage AI, such as when and how to use AI during a surgical procedure and when direct contact with patients remains important (Zhou et al. 2025).

Table 4. Identity and Meaning (own table)

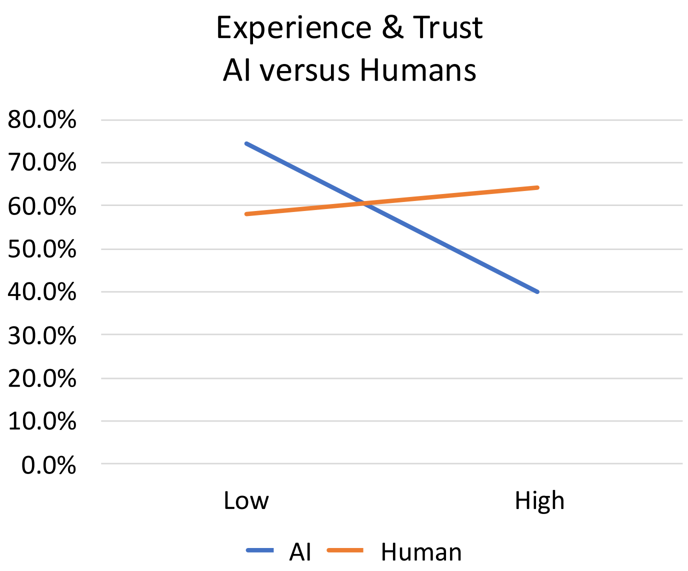
Use Case	Exemplary Measures
Agriculture	Farmers' long-term professional identity is reinforced by educational initiatives that dispel misconceptions about AI (e.g., that a direct view of the field and experiential knowledge remains important).
Human Resources	Training programs should highlight the areas in which AI supports or automates HR business processes, as well as the areas in which human empathy and contextual understanding remain irreplaceable.
Surgery	Training should be provided on how physicians can use AI while maintaining their clinical responsibility, in order to make a significant contribution to patient well-being. These measures must combine technical competence with ethical reflection and clinical judgment.

5.3 Acceptance, Trust, and Use

For users to adopt AI, its usefulness and usability must be demonstrated to each individual concerned (Venkatesh et al. 2003). To this end, training measures increase the individual usability of AI (Chapter 5.4). Clear communication about the use of AI is important because users discuss the technology among each other.

The differences between AI and conventional IT give rise to new requirements for change management. Because AI does not operate deterministically, errors are inevitable. This is a sensitive issue, as people are less tolerant of errors made by technology than of errors made by other people (Berger et al. 2021). While human errors are forgiven, IT errors tend to linger in people's minds. As a result, the longer people use AI and thus experience more errors the more resistant they become to the system (Figure 5). An organization can counteract this effect by fostering a better understanding of how AI works (Table 5). As users' understanding of AI increases, they no longer interpret any errors made by the AI as being so negative (Berger et al. 2021). Explaining that these are *learning systems* increases acceptance and sets expectations regarding the AI's capabilities (Kocielnik et al. 2019). The ability to critically question AI and its outputs is a prerequisite for users to assess the risks and potential and to evaluate the fairness of an AI system (Thiebes et al. 2021). Furthermore, trust is built when the provider of an AI system is perceived as trustworthy (Saffarizadeh et al. 2024).

Figure 5. Knowledge of and Trust in AI versus Humans (based on Berger et al. 2021) (own illustration)



In the **agricultural use case**, the focus is on the effectiveness of AI, particularly for small farms (Hüllmann et al. 2023). AI must not be a gimmick; rather, it must deliver added value, coupled with appropriate performance expectations (Klerkx et al. 2019). Farmers generally view the future of AI in agriculture positively but cite a lack of understanding as a barrier to assessing its effectiveness (Knierim et al. 2019). The more transparent the functioning of AI is, the more accurately farmers can assess its effectiveness and the risks to their operations, which fosters trust and acceptance of AI (Knierim et al. 2019). This transparency also conveys a sense of autonomy and helps counter reservations about AI and changing work practices (Higgins et al. 2017).

In the **human resources use case**, it is important for employees to understand the assumptions about people that underlie AI algorithms. People should not be reduced entirely to numbers through quantitative measurements. Organizations must clarify which aspects of a person AI can validly assess and where interpersonal relationships remain important (Hüllmann et al. 2026). Training is needed to explain the technical capabilities and limitations of AI. HR staff should be trained to understand AI inputs and outputs (McCartney and Fu 2024) to enable trustworthy use. A balance must be struck between transparency and decision-making authority (Gierlich-Joas et al. 2024).

In the **medical use case**, particular emphasis should be placed on training surgeons to recognize the non-deterministic uncertainty inherent in AI and how to manage it. Building trust in the system and fostering acceptance is challenging, as surgical errors can have serious consequences. A precise understanding is essential (Cobianchi et al. 2023). The transparency of statistical uncertainties or biases builds trust in the use of AI during surgical procedures. Clarifying which tasks AI will take on and which will remain the responsibility of surgeons creates the necessary balance to integrate AI while keeping the focus on patients (Anichini et al. 2024).

Table 5. Acceptance, Trust, and Usage (own table)

Use Case	Exemplary Measures
Agriculture	Measures should explain how AI works and how effective it is, as well as identify its potential and limitations, in order to build trust and foster acceptance of the technology.
Human Resources	Measures should highlight which aspects of a person are quantifiable and which are not. The limitations of AI in this context should be explained to foster reflection and awareness.
Surgery	Surgeons should be educated on how to deal with statistical uncertainty and AI biases in order to foster safety and trust, as even the smallest errors can have serious consequences.

5.4 Training

To implement the measures mentioned, employees need to be trained:

a) *Knowledge* (theoretical understanding) and *skills* (technical abilities) related to the fundamentals of computer science, as well as the types, development, and functioning of AI models;

b) *Competence* (applying skills to achieve the company's purpose) in the management, analysis, interpretation, and visualization of data;

c) *Understanding* the extent to which data reflects reality, and *awareness* of useful AI use cases and interfaces to existing value creation;

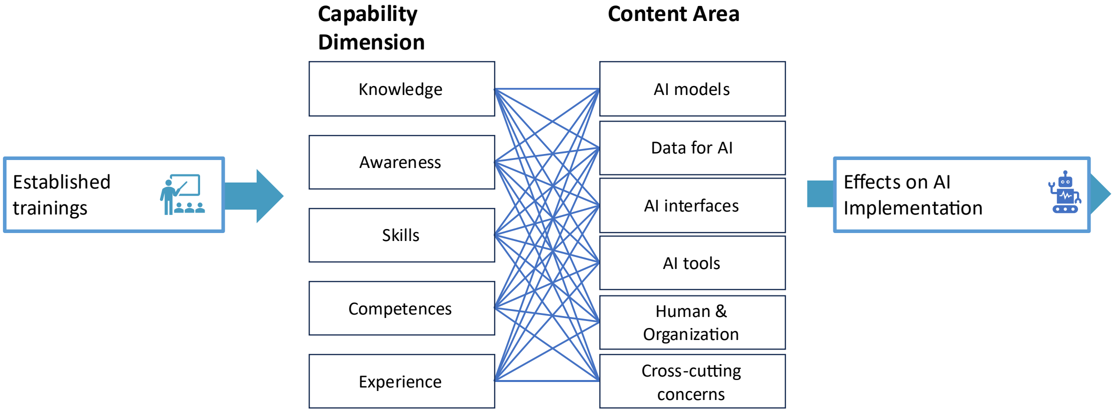
d) *Awareness*, *skills*, and *competencies* regarding the types of AI solutions available and how to use them effectively;

e) *Experience* (implicit knowledge gained through trial and error) and *competence* in managing AI projects, the role of humans, and the implications for business, employees, and society;

f) *critically evaluating* the implementation of AI and the resulting ethical implications.

Employees' capability in the six areas influences their intention to use AI, their trust in and attitudes toward AI, their professional adaptability, and, ultimately, their productivity when using AI (Pinski et al. 2024). Established learning formats can be used to develop the five dimensions of capability (Figure 6).

Figure 6. AI-Capabilities (based on Pinski and Benlian 2024) (Own illustration)



In the **agricultural use case,** farmers need knowledge and skills to understand how AI works (Lundström and Lindblom 2018). When they seek external help due to a lack of expertise, they need to be aware of what AI can do in order to integrate that external help in a meaningful way (Eastwood et al. 2019b). Farmers have a high degree of freedom in deciding which tasks to use AI for, which requires awareness. Selecting the appropriate level of integration for each task, whether to support, augment, or automate, requires farm-specific expertise in AI use. Positive experiences with AI contribute to strengthening professional identity and a sense of significance.

In the **human resources use case,** staff must understand AI's recommendations and automated processes and require the appropriate skills. Reorganizing processes and structures requires skills that integrate AI into the organization. Determining the extent to which specific AI applications reduce people to numbers and whether this is acceptable requires theoretical knowledge and awareness of AI. In addition, HR professionals must develop the knowledge and awareness needed to assess where AI cannot replace human interaction and where empathy remains essential.

In the **medical use case,** surgeons need theoretical knowledge to accurately assess statistical uncertainties and biases in AI-assisted surgical procedures. Integrating AI into the surgical process despite these uncertainties requires profession-specific AI competencies. Through skills such as evaluating holistic patient processes while taking into account contextual information that cannot be quantified, AI contributes to patient well-being, while physicians simultaneously maintain close contact with their patients (Aslam and Hoyle 2022).

For these three use cases, the topics of AI tools and AI interfaces are particularly relevant. The required level of technical expertise regarding AI models and data remains an open question in research (Table 6).

Table 6. Competency (own table)

Use Case	Exemplary Measures
Agriculture	Given the high degree of flexibility, it is helpful to train awareness: What solutions are available, and which ones are effective for one's own operation?
Human Resources	Theoretical knowledge should be taught regarding the extent to which people can be quantified and where human involvement must remain in the process. Competencies enable integration into processes.
Surgery	Theoretical knowledge should be taught to identify statistical uncertainties and biases. In addition, skills and competencies help to successfully work with AI on patients in real time.

6 Limitations and Future Work

The selection of use cases was based on theoretical and content-related aspects, as well as relevance, clarity, comprehensibility, applicability, and diversity. The analysis shows that there are commonalities among the use case regarding change management approaches. Practitioners can learn from the analysis and apply the findings to their own contexts. At the same time, this article highlights only exemplary measures that represent a snapshot in time. Each use case is unique, and measures must be implemented on a case-by-case basis. Furthermore, the measures were not empirically tested in their respective contexts but were derived from the literature.

Just like AI, change management is a field that has been extensively researched. It is a topic that is evolving dynamically due to rapid technological progress. Nevertheless, social systems remain characterized by inertia (Hüllmann et al. 2025). Established change management measures remain useful, but they must be reevaluated in light of new technology and research findings.

This article discusses organizational (*top-down*) change management measures aimed at transforming work. Job crafting activities (*bottom-up*) are not addressed in this article. Job crafting refers to changes in one's own work initiated by employees themselves in order to adapt it to their needs, skills, values, and identity (Lazazzara et al. 2020).

Finally, change management is not only necessary for the implementation of AI, but is itself supported by AI. AI enables data-driven decisions and supports the management of change processes (Kanitz and Gonzalez 2021)—a perspective that goes beyond the scope of this article.

7 Conclusion

AI will transform work in many ways. Compared to conventional IT, AI presents new challenges for change management. This article has used three use cases to demonstrate how change management approaches related to tasks and roles, identity and meaning, acceptance, trust and adoption, and training are connected to AI implementations. We need managers who take responsibility for change processes, develop a vision and a plan, and lead the way through the change.

Despite the challenges for change management, AI offers great potential for reaping productivity gains. Therefore, companies will be forced in the future to grapple with the changing nature of work and change management for AI applications. The aspects highlighted here are important but must be adapted to the specific business context. This will require applied research to determine which change management measures are effective in which business contexts. Those who successfully overcome the multitude of change management challenges will sustain more productive and satisfying work with AI.

8 Conflicts of Interest

The author declares that there are no conflicts of interest.

9 Acknowledgements

Many thanks to the editor, Dr. Sara D'Onofrio, who played a key role in ensuring the quality of the manuscript, as well as to the anonymous reviewers for their helpful comments.

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