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HUMAN-CENTRED AI IN SMEs: A MATURITY MODEL FOR CHANGE AND TRANSFORMATION

Julia Bosbach, Maximilian Helms and Christoph Lattemann
Constructor University, Bremen, Germany

ABSTRACT

This paper presents design science research on the development of a human-centred maturity model for change management in digital transformation (DT) and its empirically validating. The model is specifically designed for skilled trades enterprises (SMEs). Three newly specified maturity model dimensions are introduced and validated through qualitative focus groups with 39 skilled trades experts: (1) Change Competence in the Company, (2) Leadership Regarding Change Initiatives, and (3) Dealing with Change and Artificial Intelligence. Drawing on Dynamic Capabilities theory, the study conceptualises these dimensions as interconnected organisational capabilities that mutually reinforce each other in AI-enabled DT and innovation projects. Further, this paper introduces a refined six-step implementation framework and deepens the discussion of AI's dual role - as both an object and a tool of change - in project management and innovation. Additional attention is given to societal implications, cross-sectoral transferability, and integration with established change frameworks such as Kotter's 8-step model and ADKAR. The findings contribute to an emerging body of research connecting AI governance, human-centred project management, and organisational maturity in SME and skilled-trades contexts.

KEYWORDS

Digital Transformation, Maturity Model, Change Management, Artificial Intelligence, SMEs, Dynamic Capabilities, Employee Well-Being, Leadership, Project Management, Innovation

1. INTRODUCTION

Digital Transformation (DT) has fundamentally changed the world of work, significantly influencing working methods, processes, and ultimately the needs of employees in companies (Burr, Taddeo and Floridi, 2020). Small and medium-sized enterprises (SMEs), especially in skilled trades, are particularly affected by these changes (Brockhaus et al., 2020). Recent studies show that these transformations have differentiated effects on employee well-being across life stages and business sectors, underlining the societal relevance of DT beyond purely economic outcomes (Helms et al., 2024). To help organizations navigate these transformational challenges, maturity models provide a structured framework for assessing the level of

development in various areas, including DT (Herget, 2020). These models enable companies to identify their strengths and weaknesses regarding DT and to systematically drive improvements (Herget, 2020).

In many organizations, DT materializes through concrete projects - such as the introduction of new digital services, AI-supported tools, or data platforms - so that maturity models increasingly become decision-support instruments for project portfolios and individual transformation projects in which AI is used both as an object and as a tool of project management (Nenni et al., 2025; Hashfi and Raharjo, 2023; Salimimoghadam et al., 2025). Yet, a persistent gap remains: most existing DT maturity models focus predominantly on technical and organizational dimensions, while systematically neglecting the human-centred aspects of change management - specifically, employee needs, leadership behaviour, and the responsible integration of AI in change processes.

The skilled trades sector presents unique characteristics that make it particularly suitable for investigating change management in DT contexts. Unlike large corporations with dedicated IT departments and change management specialists, craft enterprises typically operate with limited resources, smaller teams, and flatter organizational structures (Helms et al., 2024). These enterprises often rely on traditional, hands-on approaches and have historically been slower to adopt digital technologies compared to other sectors (Helms et al., 2024). We selected the skilled trades sector as our research context because it represents a particularly challenging environment for DT due to its complex change management requirements, traditional structures, and employee-centric nature.

This paper builds on and extends former research (blinded for review) by (1) providing a deeper theoretical grounding of the three maturity model dimensions within Dynamic Capabilities theory, (2) introducing a refined six-step implementation framework for practitioners, (3) broadening the discussion of AI's dual role in DT projects, (4) addressing cross-sectoral transferability, and (5) situating the model within the landscape of established change management frameworks such as Kotter's 8-step model and ADKAR. The central research question remains: how can individual employee needs and organizational factors in change management be integrated into a DT maturity model for craft enterprises - and how does such a model support the planning and governance of AI-enabled innovation projects?

The remainder of this paper is structured as follows: Section 2 presents the review of relevant literature; Section 3 describes the methodology; Section 4 presents the results; Section 5 discusses implications; and Section 6 offers conclusions, limitations, and future research directions.

2. LITERATURE REVIEW

The following literature review analyses the current state of research on maturity models in DT, with a particular focus on the human-centred dimension. Starting with research on maturity models as assessment tools, the review explores current findings on employee needs, the role of leaders, and the potentials of AI in change management. The literature analysis reveals a research gap regarding comprehensive maturity models that integrate technical, human-centred, and leadership aspects. This section also links the discussion to project management and innovation by examining how maturity models and change frameworks inform the design and implementation of DT projects and AI-enabled innovation initiatives.

2.1 Maturity Models as Assessment Tools

Maturity models serve as strategic measurement instruments that help organizations analyse their current state, identify potential improvements, and create roadmaps for further development (Doelfs, 2021; Hock et al., 2023; Hofmann, 2021). These models typically consist of different dimensions and maturity levels, where dimensions represent relevant aspects to be evaluated, while maturity levels indicate different stages of development (Christiansen and Gausemeier, 2010). In the context of DT, maturity models are particularly valuable as they provide structured frameworks for assessing and developing an organization's digital capabilities and transformation readiness (Herget, 2020).

However, the successful implementation of maturity models faces several challenges. Felch et al. (2019) highlight that maturity models often fail due to a lack of clarity and practical applicability. Their research emphasises that effective implementation requires sufficient training for users and clear instructions tailored to the specific needs of the target audience. This is particularly relevant for SMEs with limited resources for implementing complex assessment tools. Furthermore, existing maturity models often focus predominantly on technical aspects and organisational structures, while neglecting crucial human-centred and corporate culture dimensions that are essential for successful DT (Aras and Büyüközkan, 2023; Schumacher et al., 2016).

In the context of DT projects and innovation initiatives, this technological and structural focus means that many maturity models provide only limited guidance for project managers who must align digital investments with employee needs, leadership readiness and AI usage. Recent work on AI in project management shows that AI tools increasingly support planning, monitoring and learning in projects (Nenni et al., 2025), while systematic reviews in open innovation project management highlight the role of AI technologies in enabling collaborative, data-driven innovation processes (Prasetyo et al., 2025). Yet, these streams of research rarely connect back to human-centred maturity models that capture how ready organisations and their project teams actually are to deal with AI-enabled change.

The maturity model dimensions developed in this study are theoretically anchored in research on dynamic capabilities (Teece et al., 1997; Teece, 2007). Dynamic capabilities describe an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece et al., 1997). This theoretical lens is particularly appropriate for DT contexts, as it emphasises the importance of organisational adaptability and continuous evolution in response to technological and market changes. Building on research on dynamic capabilities, this study proposes an integrated theoretical model that positions leadership behaviour, change management competence, and AI integration as interconnected dynamic capabilities that mutually reinforce each other in DT contexts.

The theoretical foundation rests on three core propositions:

- Leadership as the Catalyst: Leadership behaviour serves as the primary dynamic capability that enables organisational sensing and seizing of opportunities (Teece, 2007). In the context of digital transformation and innovation projects, leaders' ability to communicate vision, build trust, and demonstrate openness to innovation creates the psychological safety required for project team members to actively engage in transformation initiatives (Edmondson, 2019).

- Change Management as the Process: Organisational change competence represents the transformation capability, understood as the systematic ability to reconfigure resources and processes (Teece, 2007). This competence becomes particularly salient in project management contexts, where it translates leadership vision into structured project phases, interventions, and governance mechanisms, thereby ensuring that transformation initiatives are implemented in a sustainable and employee-centred manner (Kotter, 2014).
- AI as the Amplifier: AI integration functions as an enabling and amplifying mechanism that enhances both leadership effectiveness and the efficiency of change and project management processes. AI technologies support data-driven decision-making, project planning, scheduling, risk management, and personalised employee support, enabling a more predictive approach to project-based change and thereby amplifying the impact of leadership behaviours and change processes (Brynjolfsson and McAfee, 2017).

The interconnectedness of these three capabilities suggests that successful DT requires not just technical capabilities, but the orchestrated development of all three dynamic capabilities. Leadership without structured change management leads to vision without execution. Change management without AI support remains reactive rather than predictive. AI without human-centred leadership becomes technocratic and risks employee resistance.

2.2 Employee Needs in Digital Transformation

While technical aspects are crucial, the human dimension of DT has proven to be a critical success factor for the sustainable implementation and acceptance of digital technologies within organizations. Studies by Aras and Büyüközkan (2023) and Schumacher et al. (2016) reveal that traditional change management models often fail to adequately consider employee needs. However, as Bosbach et al. (2024) emphasise, employee acceptance, motivation, and competence are key factors for successfully implementing digitalisation initiatives. Open and transparent communication, a trusting approach, and consideration for individual needs and life stages are essential to minimise employees' resistance and increase acceptance of change (Schwarzmüller et al., 2018; Helms et al., 2024).

Classic research on resistance to change by Coch and French (1948) already demonstrated that participation and involvement in decision-making can significantly reduce resistance and improve the outcomes of change programs. Subsequent work has confirmed that resistance is often rooted less in individual characteristics than in contextual factors such as perceived fairness, communication, and involvement (Burnes, 2015). In the context of DT and AI-enabled innovation projects, this implies that maturity models must not only measure technical readiness, but also capture the extent to which organisations provide participatory structures and support mechanisms that foster employee engagement and reduce resistance to new technologies.

Against this backdrop, the present study builds on the concept of 'change competence' which represents one particularly critical dimension within our research. Change competence, as we define it, draws on Teece's concept of 'reconfiguration capability' (Teece, 2007) and builds on the work of Helfat and Peteraf (2015) on 'dynamic managerial capability'. We define change competence as the ability of an organization to initiate and sustainably implement transformative initiatives with particular attention to the well-being and satisfaction of employees. This competence represents a specific dynamic capability, with human-centredness as the central resource.

2.3 Leadership Role in Transformation Processes

The success of transformation processes is intrinsically linked to leadership behaviour and organizational culture. Corporate cultures that foster openness, flexibility, and a willingness to learn create an environment conducive to implementing new technologies and processes (Sen and Gandhi, 2023). Leaders play a pivotal role in shaping such cultures (Kim and Kim, 2022) through demonstrating openness for innovation and actively involving their teams in change processes. Trust and empowerment are particularly crucial, as leaders need to signal confidence in their employees' ability to take responsibility and make independent decisions (Blanka et al., 2022).

A participative leadership style, characterised by active team involvement in decision-making processes, creates ownership and promotes change acceptance (Hagström and Backström, 2017). Regular communication is of central importance - leaders should continuously inform their employees about transformation progress, seek feedback, and address concerns (Schwarzmüller et al., 2018). Through open dialogue and constructive feedback, employees not only feel taken seriously but are also encouraged to actively contribute to the success of the changes.

These findings resonate with established change leadership frameworks such as Kotter's 8-step model (Kotter, 1996, 2014), which emphasises the creation of a sense of urgency, building coalitions, and communicating a compelling vision, as well as with participation-oriented perspectives rooted in Coch and French's work on overcoming resistance to change (Coch and French, 1948). While these frameworks provide rich guidance on how leaders should steer change processes, they do not offer a structured assessment of an organisation's maturity regarding leadership behaviour in digital and AI-related transformation contexts. Our maturity model addresses this gap by translating leadership-related insights into concrete maturity levels.

2.4 Change Management, Artificial Intelligence, and Project Management

Change management describes the systematic process of planning, implementing, and executing organisational changes (Mento et al., 2002). Various models, such as the McKinsey 7S Model, the ADKAR Model, or the Kübler-Ross Model, offer structured frameworks to effectively manage change processes (Bosbach et al., 2024). In the context of DT, change management's importance is particularly emphasised as it helps prepare organisations and their members for new circumstances while increasing change acceptance (Carayannis et al., 2017).

Modern change management approaches increasingly incorporate AI technologies, offering new opportunities for optimisation and acceleration of transformation processes (Sen and Gandhi, 2023). AI can analyse large amounts of data to identify patterns and trends relevant for planning and implementing change, create personalised learning opportunities, and improve communication through chatbots (La Torre, 2021; Rukadikar and Khandelwal, 2023; Dutta et al., 2023). However, it is important to emphasise that AI should be viewed as a supportive tool rather than a replacement for human interaction and empathy in change management processes (Bosbach et al., 2024).

AI's role in DT is dual in nature: it functions simultaneously as an object of change (organizations must manage the introduction of AI tools and AI-driven processes) and as a tool that enables more effective change management (AI can identify resistance patterns, personalise communication, and support data-driven decision-making). This duality makes the integration of AI into change management maturity models particularly complex and important. From a project management perspective, recent systematic literature reviews show that AI applications increasingly support project planning, scheduling, risk management, and performance monitoring (Nenni et al., 2025), while in open innovation project management AI is used to identify partners, evaluate ideas and orchestrate innovation ecosystems (Prasetyo et al., 2025).

Current maturity models in the context of DT often treat technical, leadership, and human factors as separate dimensions, failing to recognise their interdependent nature (Aras and Büyüközkan, 2023). Our integrated framework addresses this gap by conceptualising leadership behaviour, change management competence, and AI integration as mutually reinforcing dynamic capabilities. This perspective recognises that effective DT requires not the isolated development of individual capabilities, but their orchestrated evolution as an integrated system that places employee well-being at its centre while leveraging technological opportunities for enhanced change management effectiveness.

2.5 Positioning the Maturity Model within Established Change Frameworks

A distinctive contribution of this study is the explicit positioning of the proposed maturity model within the broader landscape of established change management frameworks. Process-oriented models such as Kotter's 8-step model, ADKAR (Hiatt, 2006), and McKinsey's 7S framework (Waterman et al., 1980) have become foundational references for practitioners managing organizational change. These frameworks provide rich, step-by-step guidance on how to sequence change activities, communicate with stakeholders, and align organizational elements. However, they are fundamentally process models, not diagnostic maturity instruments, and they do not address the progressive development of AI-related organizational capabilities across multiple projects over time.

The maturity model proposed in this study complements these approaches rather than replacing them. Where Kotter's model tells practitioners what to do in a specific change initiative, the maturity model tells them how capable their organization currently is of doing it - and what they need to develop to do it more effectively in the future. Similarly, ADKAR focuses on individual transitions through change (Awareness, Desire, Knowledge, Ability, Reinforcement), while the maturity model captures the organizational-level infrastructure needed to support these individual transitions systematically and at scale.

This complementary relationship has direct implications for practitioners. Organisations can use the maturity model diagnostically - before initiating a DT project - to assess whether their leadership practices, change competences and AI capabilities are sufficient for the planned initiative. They can then use a process model such as Kotter's 8-step model to guide the actual execution. After project completion, the maturity model can be used again to assess what capabilities have been built and what gaps remain for future projects. This iterative, project-spanning use of the maturity model is consistent with the dynamic capabilities perspective and represents a key practical innovation of this study.

3. METHODOLOGY

Building on the central research question, a collaborative, qualitative approach was chosen to design and evaluate the practicability and applicability of the enhanced maturity model. This approach was particularly suitable because it allows participants to reflect collectively on concrete DT and innovation projects and to articulate implicit assumptions about change management, leadership and AI usage.

This research follows the echeloned Design Science Research (eDSR) approach by Tuunanen et al. (2024), which structures design research into five distinct echelons: (1) Problem Identification, (2) Objective Definition, (3) Design and Development, (4) Demonstration, and (5) Evaluation. This paper specifically focuses on Echelon 4 (Demonstration) and prepares for Echelon 5 (Evaluation), while Echelons 1–3 were completed in prior studies.

The maturity model encompasses nine dimensions and five maturity levels (ranging from Level 1 'Infancy' to Level 5 'Ultimate Maturity'). This study concentrates on the practical validation of three employee-affecting dimensions: Change Competence in the Company, Leadership Regarding Change Initiatives, and Dealing with Change and Artificial Intelligence. These three dimensions were selected because they directly impact employees and are often conflated when considered together.

3.1 Focus Group Design and Participant Selection

To evaluate the practical application of the three dimensions, focus group discussions with experts from various fields of the skilled trades sector were conducted. This qualitative method was chosen to ensure a comprehensive and diverse perspective on the new dimensions in the context of DT, facilitating the explanation of underlying motivations and thought processes, enhancing the richness of insights, and providing a practical and efficient way to gather qualitative data from multiple individuals simultaneously.

The focus group composition was strategically designed to capture diverse perspectives from the skilled trades sector. Using purposive sampling, 39 experts were recruited and divided into four focus groups. The sample consisted of 32 male and 7 female participants, with an age distribution of: 5 participants under 30 years, 14 participants between 30–40 years, 12 participants between 41–50 years, and 8 participants over 50 years. Participants were selected based on their professional roles, industry experience, and involvement with digitalisation initiatives.

Table 1. Demographic characteristics of participants

Stakeholder group	Female	Male	Sum	Experience distribution
Craft research	6	10	16	2×>1y, 3×>2y, 8×>3y, 1×>5y, 1×>10y, 1×>20y
DT enabler	5	1	6	4×>2y, 1×>4y, 1×>25y
End-users	–	8	8	3×>2y, 2×>7y, 1×>10y, 2×>20y
Suppliers & manufacturers	1	8	9	1×>1y, 6×>3y, 1×>5y, 1×>20y
Total	**12**	**27**	**39**	**–**

3.2 Structured Four-Step Focus Group Process

The focus group process comprised multiple structured steps and aimed to develop and validate the practical application of the three dimensions for the craft sector. The workshops took place in October 2024 and were conducted by four trained facilitators following a standardized agenda. A methodological feature was the consensual selection of use cases within each focus group, ensuring that the evaluation was grounded in relevant, real-world applications familiar to the participants.

The structured four-step process comprised:

- Step 1 – Action Assignment: Participants were asked to assign specific actions to the dimensions and maturity levels of the developed model. After a brief introduction, participants faced difficulties in determining an appropriate starting point. A practical recommendation that emerged was to use existing regulatory requirements as an initial benchmark defining maturity level 1.
- Step 2 – Use Cases and Supplements: After the initial discussion, each group selected a relevant use case that all members could meaningfully engage with. Selected use cases included: implementation of exoskeletons in craft operations, transition from private to commercial clients, integration of Building Information Modeling (BIM), and application of virtual reality in customer consultations.
- Step 3 – Maturity Level Assessment: Participants assessed the current maturity levels of their organisations concerning the three dimensions. They also defined target maturity levels they aspired to achieve within a five-year period.
- Step 4 – Action Definition: Participants developed targeted action plans based on the previously assigned actions and the requirements of their selected use cases. These action plans frequently took the form of project roadmaps, training concepts, or change communication plans.

Each workshop lasted approximately two hours. The structured, hands-on approach ensured that the maturity model was thoroughly tested and validated in a practice-oriented environment.

4. RESULTS

The empirical study focused on two central research questions: (1) the clarity and applicability of the validated dimensions of the maturity model and (2) the possibility of deriving directly actionable recommendations from the model.

4.1 The Change Maturity Model: Three Dimensions

The maturity model encompasses five levels across three dimensions, as shown in Table 2. Level 1 (Infancy) represents the starting point where organisations have minimal competence or structure, while Level 5 (Highest Maturity) represents a state of systematic, embedded, and continuously improving capability.

Table 2. Change maturity model – three dimensions and five levels

Level	Leadership Regarding Change Initiatives	Dealing with Change & Artificial Intelligence	Change Competence in the Company
5 – Highest maturity	Change management is seen as a priority. Regular support and communication occur at all levels of the organization.	AI is automatically integrated into many business areas. Leaders derive AI-supported decisions; employees supported on a personal level.	Change competence is evident at all levels and is part of organizational intellectual property and competitive advantage.
4 – Optimized	Support and communication from all leaders. Managing change is starting to be seen as a priority.	AI integrated into strategy and implemented in several processes. Data foundation allows conclusions for new systems.	Organization-wide standards and methods used to manage changes. Change management considered from the start in almost all projects.
3 – Transforming	Support from some leaders. Benefits recognised, but implementation out of necessity rather than priority.	AI implemented in at least one process (e.g. chatbots).	Comprehensive approach to managing change in all areas. Regularly applied in most projects, though neglected under time pressure.
2 – Developing	Change management applied reactively. Communication methods used when employees resist change.	Experiments and pilots with AI launched. Data foundation being created.	Some elements/models for managing change present in certain areas.
1 – Infancy	Little or no communication about change initiatives from leaders.	Basic interest in AI. A fundamental understanding of what AI is exists.	Little or no competence in managing change within the organization.

4.2 Clarity and Applicability of the Model

After the introduction of the maturity model, participants generally found the model to be useful and adaptable. However, the initial response across all four focus groups indicated that, without appropriate guidance, the model was perceived as complex. A recurring challenge in all groups was defining a starting point or 'baseline'. A practical solution proposed in several groups was to use regulatory requirements as an initial benchmark, defining them as maturity level 1.

The facilitation role was critical to the participants' success in engaging with the model. Once the baseline was established, participants found the task of assigning additional activities significantly easier. In several groups, the model was applied directly to concrete DT and innovation projects in the skilled trades, such as the introduction of exoskeletons in craft operations, the integration of Building Information Modeling (BIM) into construction processes, or the use of virtual reality in customer consultations.

As participants continued to engage with the model, their comprehension markedly improved. One participant noted: 'I've never paid much attention to maturity models because they seem overly theoretical, but linking them to specific activities makes them much easier to grasp.' Another remarked: 'Now I understand what's meant. Organisational culture impacts openness to change, which explains why DT is embraced differently across various contexts.'

Table 3 presents a representative example of the actions assigned by one focus group to the three dimensions and maturity levels.

Table 3. Collected actions for change activities based on the maturity model

Level	Leadership Regarding Change Initiatives	Dealing with Change & Artificial Intelligence	Change Competence in the Company
5	Leaders aware of how to manage changes individually. Leaders view continuous improvement as their responsibility.	Leaders access data analysis and make decisions based on it. Data-driven decisions recognised as more objective.	Employees have internalised continuous improvement. Change management methodologies conveyed through regular training.
4	Leaders and employees see mutual support in adopting changes as part of their responsibilities.	Employees open to data-driven management; do not feel controlled by it.	Employees have time and know-how to consider change management when introducing tools/systems.
3	Leaders apply change methods because they have experienced that employees do not revert to old behaviours.	Regular AI training sessions attended by all employees. Space and time to experiment with AI.	Employees familiar with models describing how each person reacts differently to change. Central platform or contact person for questions about new tools.
2	Leaders apply communication methods because they have seen employees accept new tools better this way.	Employees already successfully using AI in a tool or process.	Regular formats support acceptance of changes. Employees informed about new tools at the last minute.
1	Emphasis on soft skills alongside hard skills.	Employees educate themselves privately about AI and use tools like ChatGPT.	Employees involved only when they revert to old behaviour patterns or show resistance.

4.3 Derivation of Actionable Recommendations

Of the four focus groups in total, two groups were able to fully document their current and target maturity levels. The results showed that none of the groups had yet reached the highest maturity level, although all aimed for it as a long-term goal. Table 4 illustrates the results of one of these groups as an example.

Table 4. Actual and target maturity based on the work of one focus group

Level	Leadership regarding Change Initiatives	Dealing with Change & Artificial Intelligence	Change Competence in the Company
5 – Highest maturity	Target Maturity Level	Target Maturity Level	Target Maturity Level
4 – Optimized	Current Maturity Level	Target Maturity Level	
3 – Transforming		Current Maturity Level	Target Maturity Level
2 – Developing			
1 – Infancy			Current Maturity Level

In the final phase, the groups that reached this stage selected specific activities from the previously defined actions to move their organisation to the next maturity level within five years. The participants explicitly stated that they found the process valuable, as it provided them with concrete, actionable recommendations. These recommendations typically included: establishing regular communication formats, developing training concepts, clarifying responsibilities, and creating time and space for experimentation with AI-supported tools. Overall, the results indicate that once the current and target maturity levels have been defined, the model can be used to derive clear development paths for organisations and their DT projects.

5. DISCUSSION

The aim of the study was to answer the question: how can individual employee needs and organisational factors in change management be integrated into a DT maturity model for skilled trades? The research results show that considering the three dimensions – leadership behaviour in the context of change initiatives, dealing with change and AI, and change competence within the company – is of significant practical importance, yet has not been sufficiently addressed in existing maturity models.

5.1 Understandability and Applicability

The first sub-research question, which focuses on the understandability and applicability of the three dimensions of the maturity model, is answered positively by the results of the focus groups. The model proved to be easily understandable and applicable, particularly after a concise introduction. The integration of practical examples was especially valuable for understanding the model. This confirms the importance of open and transparent communication, as well as a trusting approach, as emphasised by Schwarzmüller et al. (2018).

Without a moderator with adequate knowledge in change management and maturity models, misinterpretations and difficulties in application can occur. A moderator can provide a more impartial perspective, which aligns with the importance of organisational cultures that promote openness, flexibility, and willingness to learn, as emphasised by Sen and Gandhi (2023).

Comprehensive documentation and training materials that are accessible without a moderator should be developed to support independent use.

5.2 Derivation of Actionable Recommendations

The second sub-research question, which addresses the derivation of actionable recommendations, highlights the practical applicability of the model. The focus groups successfully identified concrete actions for each dimension and level. Clearly defined maturity levels are necessary, as described by Christiansen and Gausemeier (2010) as an essential element of maturity models. Furthermore, the proposed actions should be practical and actionable to increase user acceptance, which aligns with the criticism expressed by Aras and Büyüközkan (2023) regarding traditional change management models.

5.3 A Refined Six-Step Implementation Framework

Based on the empirical validation and the feedback regarding usability, and extending the earlier conference paper, this study proposes a refined structured six-step implementation approach for practitioners seeking to apply this maturity model in their organisations and in their AI-enabled DT and innovation projects:

- Step 1 – Model Introduction: Present the overall maturity model framework and explain dimensions, levels and workshop structure to all relevant stakeholders in the organisation and/or project team.
- Step 2 – Action Development: Facilitate company- and project-specific action collection for each dimension and maturity level, ensuring that activities reflect the concrete context of ongoing or planned DT and innovation projects.
- Step 3 – Use Case Analysis: Apply and refine actions through concrete real-world scenarios relevant to the organisation, ideally by selecting one or more DT or AI-enabled innovation projects as use cases.
- Step 4 – Current State Assessment: Conduct a collaborative evaluation of the organisation's present maturity level for the three employee-centred dimensions, using the selected projects as reference points.
- Step 5 – Target Definition: Establish desired maturity levels with clear justification and organisational commitment, including explicit implications for future DT and innovation projects (e.g. required leadership behaviours, communication formats, AI-support tools).
- Step 6 – Implementation Planning: Develop concrete steps, timelines, responsibilities and required resources for achieving the target maturity levels, translating them into project roadmaps, work packages and supporting change interventions.

This structured approach addresses the challenges identified in the focus groups (need for facilitation, difficulty in defining baselines, risk of staying on an abstract level) and connects the maturity assessment directly with the planning and steering of DT and innovation projects in the skilled trades.

5.4 Interdependence of Dimensions and Dynamic Capabilities

The focus group findings underline the interdependence of the three dimensions. Higher self-assessed maturity in 'Leadership regarding change initiatives' was often associated with

more systematic approaches to 'Change competence in the company' and more advanced practices in 'Dealing with change and artificial intelligence'. Participants from organisations with a history of structured DT projects described more established routines for involving employees, using data and experimenting with AI-supported tools, whereas less mature organisations relied more on ad-hoc communication and informal learning.

This pattern is consistent with the dynamic capabilities perspective underlying the model, in which leadership, change competence and AI use reinforce one another over time (Teece et al., 1997). It directly reflects the theoretical propositions that leadership acts as the primary sensing and seizing capability, change competence represents the transformation capability, and AI functions as an amplifier that enhances both leadership effectiveness and change processes. The observed maturity patterns therefore provide empirical support for conceptualising these three elements as interconnected dynamic capabilities in AI-enabled DT projects (Teece, 2007; Warner and Wäger, 2019).

5.5 Implications for Project Management, Innovation, and Society

An important implication of the findings concerns the role of the maturity model in project management and innovation contexts. Many of the focus group use cases – such as the introduction of exoskeletons, the integration of Building Information Modeling or the deployment of virtual reality in customer consultations – were structured as projects with clear goals, time frames and stakeholder constellations. In these settings, the maturity model served as a steering and reflection tool that helped project teams clarify expectations, identify risks and plan interventions related to leadership, employee involvement and the use of AI.

The results support recent work on AI in project management, which emphasises that AI is increasingly used to support planning, scheduling, risk management and performance monitoring in projects (Nenni et al., 2025; Hashfi and Raharjo, 2023). At the same time, our findings show that the effective use of such AI tools in DT and innovation projects depends strongly on organisational and human factors: employees' willingness to experiment with AI, leaders' communication behaviour and the availability of change competences. By making these factors visible and assessable, the maturity model provides project managers and innovation leaders with a structured way to connect AI-enabled project practices with human-centred change capabilities.

Beyond project management, the model has broader societal implications. The skilled trades context is characterised by physically demanding work, strong person-to-person interactions and, in many cases, concerns about job security and changing skill requirements. The results show that organisations with higher maturity levels are more likely to provide transparent communication, opportunities for participation and targeted support for employees, which can mitigate fears, reduce resistance and foster a more positive attitude towards AI and digital technologies in the workplace. From a societal perspective, the maturity model can therefore be understood as a tool that encourages organisations to treat AI-enabled DT not only as a technical or economic challenge, but also as a question of social sustainability and employee well-being.

5.6 Cross-Sectoral Transferability

While the model was developed and validated in the skilled trades context, its theoretical foundations - Dynamic Capabilities theory, participation-based change management, and human-centred AI integration - are not sector-specific. The three dimensions of Leadership, Change Competence, and AI Integration are relevant to any organisation undergoing DT.

The skilled trades context served as a deliberately demanding test environment: resource constraints, traditional cultures, and limited prior exposure to DT created conditions under which the model had to prove its robustness.

Organisations in sectors with greater prior DT experience - such as financial services, manufacturing, or healthcare - may find that they can progress more quickly through the lower maturity levels and benefit most from the higher levels that address systematic AI integration and data-driven decision-making. Conversely, sectors with similar human-centric and resource-constrained characteristics - such as social care, artisanal food production, or small-scale professional services - may find the model directly applicable with minimal adaptation.

Future research should investigate which elements of the model are context-specific and which are more universal, through comparative studies across sectors and countries. Particular attention should be paid to cultural differences in employee participation norms, attitudes towards AI, and leadership styles, as these may moderate the relationships between maturity levels and outcomes.

6. CONCLUSION

This paper extends earlier conference work by developing and empirically validating a human-centred maturity model for change management in digital transformation, specifically designed for skilled trades enterprises. Three new maturity model dimensions - Change Competence in the Company, Leadership Regarding Change Initiatives, and Dealing with Change and Artificial Intelligence - were validated through qualitative focus groups with 39 skilled trades experts.

The research findings show that the developed maturity model dimensions are generally understandable and applicable but require a structured introduction. Linking the abstract maturity levels to concrete activities and examples proved crucial for acceptance and usability. The ability to derive concrete and actionable recommendations represents a key value-added feature of the model. Drawing on Dynamic Capabilities theory, the study demonstrates that leadership behaviour, change competence and AI usage can be meaningfully operationalised as interconnected capabilities that evolve across maturity levels and can be actively shaped through targeted interventions.

As key extensions beyond the conference paper, this study (1) introduced a refined six-step implementation framework; (2) deepened the discussion of AI's dual role as both object and enabler of change; (3) explicitly positioned the model within the landscape of established frameworks (Kotter, ADKAR, McKinsey 7S); (4) addressed cross-sectoral transferability; and (5) broadened the discussion of societal implications for AI governance and employee well-being in SME contexts.

Limitations include: the demonstration sessions were conducted by researchers familiar with the model, introducing potential researcher bias; the predominantly qualitative nature limits statistical generalisability; the sample mainly included organisations with some prior DT experience; and the focus group format may have favoured consensus-oriented views. Future research should develop self-explanatory accompanying materials, investigate how maturity levels develop over time across multiple projects, conduct quantitative validation, and pursue comparative studies across sectors and countries.

The practical implications are diverse. For craft businesses, the maturity model provides a structured tool to assess and improve change management capabilities in the context of DT. For project managers and innovation leaders, it serves as a steering and reflection instrument in AI-enabled DT and innovation projects. For chambers, associations and policy-makers, it offers a common reference framework for designing support programmes and training offers that aim to foster responsible, employee-centred AI adoption in SMEs and the skilled trades.

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