How manufacturing leaders shape employee attitude towards AI adoption: A retrospective analysis from change management literature

Author: Quinten van Schuppen
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT,

Artificial Intelligence (AI) constitutes the most recent advancement in Digital Transformation (DT), with growing prevalence across societal domains. Within the field of business, its unparalleled capabilities and implications are becoming more evident at a rapid pace. This development has generated employee concerns regarding job security and their ability to remain competitive in an AI-integrated workplace. This shift in 'employee attitude' has been proven to produce negative outcomes for organizations and people alike, though research indicates that employee attitudes toward technological change are malleable through targeted intervention. Organizational leaders have been shown to hold a certain influence over their subordinates' cognitive and behavioral reactions in such periods of fundamental change. This results in the following *research question: How can manufacturing leaders tailor their change management strategies to address different employee attitudes toward AI adoption, as identified through historical and theoretical models?* This research performs an analysis by meticulously following a systematic literature review (SLR) process, carefully selecting and analyzing twenty articles. By using a coding method, a well-documented shortcoming of the highly relevant Technology Acceptance Model (TAM) was identified. Leveraging yet another theory on employee attitude, Solberg's digital mindsets, and combining the two theories in a single model, led to a novel contribution to existing literature. By incorporating an additional leadership dimension, this study develops a four-quadrant framework aimed at proposing fitting leadership approaches for particular employee digital mindsets in face of technological change.

Graduation Committee members:
dr. P. Weritz
dr. L. Carminati
ms. A. Devi

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1. INTRODUCTION

1.1 Topic

Global organizations have faced a trend of digital transformation for some time now (Ghobakhloo & Ching, 2019; Omol, 2024), and with the rapid development and implementation of Artificial Intelligence (AI), organizations will encounter yet another significant technological disruption. As an increasing amount of businesses start to understand the capabilities of AI and how it can improve their job efficiency, its applications in business environments have increased substantially (Manresa et al., 2024; Mishra & Tripathi, 2021). This has, however, impacted a substantial range of people, not all of whom are certain about their response to this change. Operational employees in particular frequently exhibit uncertainty regarding AI collaboration and potential job displacement (Burhan, 2025; Presbitero & Teng-Calleja, 2022). Leaders within organizations play a considerable role in shaping this sentiment, as subordinates commonly look up to them to provide information and clarity (Jiatong et al., 2022; Parke & Seo, 2017). The significant scope of this transformation presents organizations with a challenge. The nature of this transformation provides a ground for existing literature on similar scenarios to be valuable in mitigating adverse outcomes. This research does so by carefully examining and combining twenty studies on this topic. Most notably, it leverages two commonly utilized theories on employee attitude into tangible insights and a framework to match, following a sentiment that negative employee attitudes pose issues for themselves as well as organization. By understanding their 'digital mindsets' as proposed by Solberg's model, using the Technology Acceptance Model's (TAM) dimensions of Perceived Usefulness (PU) and Perceived Ease-of-Use (PEOU), this research proposes unique recommendations for leaders to act on.

1.2 Problem Statement

Although some employees have shown behaviors of acceptance and willingness towards working alongside AI, exhibiting signs of increased efficiency and confidence (Bhatt & Shah, 2023; Presbitero & Teng-Calleja, 2022), literature suggests there is still a vast majority of people who perceive it as a threat (Kim & Kim, 2024; Pericleous et al., 2025). They show signs of anxiety, rationalizing how AI will undoubtedly be able to do everything they do, for cheaper (Biswas et al., 2024). Irrespective of perceived AI capabilities, negative sentiments produce undesirable outcomes as these emotional responses often result in a decrease in job performance (Xu et al., 2023). Additionally, certain literature shows an increase in turnover as a consequence of AI-induced fear (Kang et al., 2024; Presbitero & Teng-Calleja, 2022; Teng et al., 2024). Whether the outcome is decreased performance or a higher turnover, they present suboptimal outcomes for organizations. These issues therefore demand organizational interventions that address general resistance but adopt personalized courses of action based on specific employee attitudes, laying the groundwork for a targeted leadership framework presented in this study.

1.3 Content of this Research

This research focuses predominantly on the human aspect of change in an organizational setting. It studies employee attitude, looking at leadership as a mitigating factor. It does so in light of the most recent and prevalent instance of technological change: AI. Suffering from the novelty of the phenomenon, as well as a large potential for bias, this research avoids traditional narrative data collection methods and instead performs an academically supported systematic literature review (SLR). It examines similar occurrences in recent years, in the manufacturing industry specifically, and leverages them into recommendations for future directions. It does this through a careful process of selecting and coding a series of studies, yielding twenty articles to be used for the final analysis. Specifically focusing on the dimensions of employee attitude and leadership, their contributions where synthesized in a theoretical sense. The insights as presented, whether theoretical or practical, were built around the following research question:

RQ: *How can manufacturing leaders tailor their change management strategies to address different employee attitudes toward AI adoption, as identified through historical and theoretical models?*

1.4 Contribution of this Research

By carefully studying relevant contributions in existing literature, this research aims to craft a novel framework combining two theories on employee attitude, being the Technology Acceptance Model (TAM) and Solberg's digital mindsets. Having recognized a lack of an organizational aspect in this model, a dimension of leadership was added. This has resulted in a novel four-quadrant framework aimed at gauging employees' digital mindsets and recommend corresponding leadership styles. It follows up on this framework with managerial applications, turning the theoretical into practical recommendations. These can serve as a valuable addition to existing literature, as they are tailored to the manufacturing industry and are highly applicable to the groundbreaking implications of AI introduction in said industry. Additionally, by analyzing twenty significantly relevant studies pertaining to this particular topic, their findings can serve as a foundation for leaders and scholars alike trying to develop their understanding of 'employee attitude' and 'leadership' as standalone concepts.

2. LITERATURE REVIEW

2.1 Digital Transformation

Given the comprehensive scope of Digital Transformation (DT), scholars have not established a unified definition. However, some key concepts can be found in many of their definitions, allowing for combining them into a clear conceptualization which will be used throughout this research: ‘a process of transforming business activities, processes, competencies, and models by leveraging the changes and opportunities of digital technologies, with the ultimate goal of value creation’ (Marks & Al-Ali, 2022, p. 61; Reis et al., 2018, p. 412; Verhoef et al., 2021, p. 889). As previously mentioned, DT is an impossibly vast construct. It is therefore unsuited to be researched as a whole, which is why this paper will aim to provide recommendations towards the latest and most prevalent DT trend: Artificial Intelligence.

2.2 Artificial Intelligence

Artificial Intelligence (AI) is an overarching concept. Although still broad, scholars have approached consensus of what is meant by the term. This paper combines their definitions into a definition of its own: ‘the ability of machines and/or computer systems to mimic human-like intelligence’ (Bajwa et al., 2021, p. 189; Booyse & Scheepers, 2024, pp. 64-65; Passmore et al., 2025, p. 2; Xu et al., 2021, p. 1). Human-like intelligence is often described as possessing features such as reasoning, self-learning, and problem-solving capabilities (Bajwa et al., 2021; Xu et al., 2021). These characteristics are found in nature only in humans and other animals. Through the development of systems and machines that possess these characteristics, engineers effectively replicate intelligence.

Manufacturing companies often use a multitude of AI systems to run their operations. One example is that of a phenomenon known as a ‘digital twin’. A digital twin is a virtual counterpart to a physical system, commonly powered by AI to transfer data to one another and make informed decisions and/or recommendations (Kritzinger et al., 2018; Onaji et al., 2022). A main value creating property of the digital twin is that of predictive capability, being able to analyze usage and behaviors of machines to predict whether they might break down or when they are due for maintenance. This reduces the amount of downtime, and if proven trustworthy, eliminates the need for human inspection of machine condition (Aivaliotis et al., 2019; Luo et al., 2020). Furthermore, AI is increasingly being integrated into the automation of today’s manufacturing factory floors. It can check up on and control entire systems. It can do so to assure quality, predict energy consumption, and even manage output by cross-referencing with the demand it has predicted (Nelson et al., 2023; Plathottam et al., 2023). Lastly, having its roots in what was simply an aid in the 1970s, AI has revolutionized the process of research & development (R&D) and similarly product development for many manufacturers. It has allowed manufacturers to shorten R&D cycles, whilst maintaining quality (Rout et al., 2024). Also, it has been shown to be able to predict certain outcomes, such as surface roughness (Omar & Lahcen, 2024).

2.3 Employee Attitude

Employee attitude can refer to a large number of definitions and is also not widely regarded as the term to use when speaking of how employees feel about something work-related. However, for this research, it becomes easier to attribute a definition to, as it will only be spoken of in the context of technological change. Therefore, employee attitude in this research will refer to: ‘an employee’s cognitive and behavioral reaction to change’ (Khaw et al., 2023, p. 19137; Vakola et al., 2013, p. 97). These reactions are not nearly always positive or supportive, but rather reluctant or even hostile. Existing literature has extensively researched this interaction, and many papers attribute it to humans’ innate resistance to change (Mathews & Linski, 2016; Sweers & Desouza, 2010). This negative sentiment is often associated with the uncertainty that comes with change (Zhu et al., 2023). However, employee attitude is not as straightforward as it seems and is able to be swayed by a number of factors, whether internal or external.

Employee attitude on organizational change is in large supply within the existing literature, often being described as being able to make-or-break organizational change altogether. Employees being reluctant or hostile to change affects both themselves as well as their leaders, ultimately harming the organization. Change resistance is often paired with psychological strains for employees, with common symptoms such as anxiety, distress, and insecurity (Al-Ghazali & Afsar, 2022; Bryson et al., 2013; Coupaud, 2023). In most cases, these feelings result in a decrease in work performance and/or engagement (Edwards & Clinton, 2023). At long last, the fall in job satisfaction causes some employees to showcase signs of “absenteeism and intentions to quit, which predict voluntary turnover” (Fugate et al., 2012, p. 890). These types of behaviors often lead to strain on leaders, resulting in similar outcomes, while also affecting their subordinates even more than they already were (Groulx et al., 2024).

2.4 Leadership

Leadership, and the concept of leaders and followers, is one that manifests in all parts of society. However, to give a more fitting definition for this research, leadership will only be explored in a business context. It is important to understand that leadership is a concept that has known many definitions over time and is constantly changing. Merely using the most recent adaptations of the concept, this research defines 'leadership' in a business context as: 'the ability of a leader to combine domain expertise with human engagement, showing understanding that organizational success stems from employees, whilst also keeping the organization's core values in mind' (Buribaevich et al., 2022; Olkowicz & Jarosik-Michalak, 2022, p. 55; Vorina et al., 2023).

Leaders within organizations play a big part in shaping employee attitudes and consequently behaviors. Especially during phases of transformative change, when employee attitude is often under high scrutiny, it becomes vital for leaders to steady the proverbial ship. Although important at all times, the strain on employees during times of change specifically requires effective leadership to guide them through as smoothly as possible. It is therefore advisable for leaders to look at ways in which they can positively influence employee attitude and act on them in accordance with the situation they find themselves in.

3. METHODOLOGY

3.1 Research Approach

As for the serious concerns regarding primary data collection in the context of this research, a systematic literature review (SLR) approach was chosen to best fit. An SLR is an approach that uses existing data with the specific aim of reducing bias and increasing reproducibility (Sauer & Seuring, 2023; Snyder, 2019; Varsha et al., 2024). Since AI implementation remains in early stages across manufacturing companies, stakeholders lack sufficient knowledge and robust evidence on effective leadership approaches for managing such technological shifts (Abdelaal, 2024; Lopez-Garcia & Rojas, 2024). Additionally, employee attitudes toward technological change are often intangible and personal, making direct data collection from both leaders and employees problematic. By conducting an SLR, this research set out to provide comparisons between the implementation of AI and similar technological change in recent years of digital transformation across the manufacturing industry. By drawing from existing data and well-documented sentiments and leadership to be proven effective, it attempted to provide actionable insight for manufacturing leaders. This lined up with scholarly insights, which describe how SLR can be an excellent way of doing research, especially when traditional narrative analysis lacks a solid foundation and/or might be subject to bias (Grant & Booth, 2009; Price, 2022; Tranfield et al., 2003).

This paper meticulously followed the steps for a SLR as provided by Wolfswinkel et al. (2013). Additionally, the approach and flow model as presented were based on the 2020 PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines, accounting for an academically recognized way of conducting such research (Page et al., 2021). Whereas the initial literature review gave a general idea of what the concepts important to this research entail, the data collection went more in-depth in an attempt to come to general advice for leaders within manufacturing branches. In the following section, an approach for "defining, searching, and selecting" was developed, with "inclusion/exclusion criteria, field of research, and appropriate sources" being accounted for (Wolfswinkel et al., 2013, p. 47).

3.2 Literature Used

As for the 'define' phase of the methodology, a set of inclusion/exclusion criteria was developed. These criteria were based on insight from various scholarly sources (Clarke & Braun, 2014; Meline, 2006; Vollstedt & Rezat, 2019), in combination with the researcher's own rationale and purpose. The full list of criteria can be found in Appendix 1.

Two extensive bibliographic databases, being Web of Science and Scopus because of their accessibility and search algorithms, were selected for the literature search. They were combined to ensure comprehensive coverage and to reduce the risk of missing relevant studies. Both of them were hosts to the same search prompt, having its roots in the introduction and chapter 2, targeting articles that had a focus on AI implementation or similar technological shifts, dimensions of employee attitude and leadership, within a manufacturing context. Both prompts are provided in Appendix 1.

Lastly, for the 'selection' phase, the articles that were analyzed from the search were first screened to test their eligibility. This initial screening phase was done solely on the premise of an article's title and abstract. If an industry, or the content, or both was unfitting, they were eliminated from contention. Additionally, duplicates between the Web of Science and Scopus results were also eliminated at this stage.

After the initial screening, the remaining articles were analyzed based on their full text and cross-referenced for eligibility based on the inclusion/exclusion criteria as presented in the 'define' phase. If an article positively contributed to answering the queries in the inclusion criteria and thus the RQ, without meeting the exclusion criteria, they were picked as sources for the final analysis. To test the validity of the claims made in such research, they were cross-referenced with other papers and their data, as to ensure that what is said holds true. In line with the PRISMA guidelines, this process yielded the following flow chart:

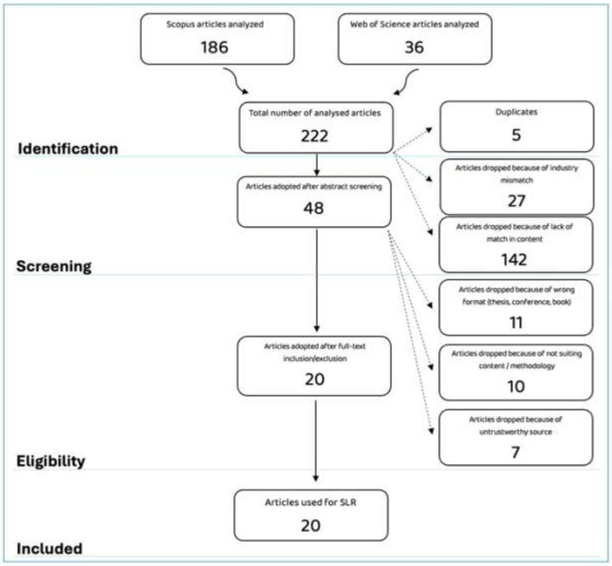

Figure 1. PRISMA flow chart

3.3 Method

This research performed an SLR following the method of ‘thematic analysis’. According to Clarke and Braun (2017, p. 297), “the aim of TA is not simply to summarize the data content, but to identify, and interpret, key, but not necessarily all, features of the data, guided by the research question. The emphasis is on producing rigorous and high-quality analysis.” This method fitted this research, as the SLR leveraged qualitative articles and case studies to delve into their narratives to come up with more generalized managerial implications.

In line with the set of analysis principles as provided by Wolfswinkel et al. (2013), this research followed a coding principle. Firstly, the articles which made it through the initial define, search and select phase were analyzed more carefully using an ‘open coding’ principle. Open coding is a process in which articles are dissected into distinct sections whilst giving these sections a particular label, and subsequently, categories (Khandkar, 2009). The individual codes per article, along with a list of the twenty articles which were used in the SLR, can be found in Appendix 2. These labels and categories could then help to see certain themes throughout singular articles, but also very much through multiple articles, deepening the understanding of the literature. Finding these links is the second step in the analysis and is called ‘axial coding’ (Vollstedt & Rezat, 2019). In the final step, these relations are leveraged to build towards a certain conclusion. This phase is highly dependent on a researcher’s ability to cognitively recognize certain patterns and shape them into a narrative that fits the research question (Wolfswinkel et al., 2013). This is called ‘selective coding’ and ultimately determines how applicable the outcomes will be.

4. RESULTS

First-order codes	Second-order themes	Aggregated dimensions
Transparent leadership (papers 1, 6, 18, 19)	Transformational leadership	Leadership
Leading by example (paper 2, 3, 18)		
Individualized attention (paper 7)		
Transformational leadership (papers 8, 11)		
Empowering leadership (paper 9)		
Transparent communication (papers 1,6)	Strategic communication	
Leadership communication strategies (papers 2, 7, 16)		
Effective communication (paper 12)		
Framing of communication (paper 15)		
Aligning organizational and individual interests (papers 1, 12)	Support systems	
Micro- and meso-level support (paper 2)		
Autonomy vs development support (paper 9)		
Perceived usefulness (papers 1, 2, 9, 10, 12, 13, 17)	Technology Acceptance Model (TAM)	Employee attitude
Perceived ease-of-use (paper 2, 9, 10, 12, 13, 17)		
DT/AI-induced anxiety (papers 2, 11, 14, 15, 17, 18, 20)	Technostress	
Job insecurity (papers 4, 5, 7, 12, 14, 16, 18, 19)		
Psychological contract (papers 5, 8)		
Growth vs fixed mindset (papers 9, 15)	Solberg’s digital mindsets model	
Zero-sum vs expandable-sum mindsets (paper 15)		

Table 1. Data Structure

4.1 Leadership

4.1.1 Transformational leadership

Evidence exists that transformational leadership significantly reduces turnover intentions ($\beta = -0.192$, $p = 0.002$), more so than transactional leadership ($\beta = -0.131$, $p = 0.019$)(Ru & Ibrahim, 2024). In the context of digital change in the manufacturing industry, this seems to especially hold true. According to Klein et al. (2024), 87,5% of DT attempts ultimately fail. As a reason they point out leadership, or better yet, a lack thereof. They suggest that leadership is still too focused on managerial capabilities and processes, lacking the detrimental factor of employee attitude. In the context of technological change, specific attention should be on transformational leadership with practices such as leading by example, individualized attention and proper communication and transparency (Bauer, 1991; Mukhuty et al., 2022; Schriesheim et al., 2006). This more personal leadership approach is in response to the tensions that employees often experience during times of change, inevitably looking for support and ease-of-mind from their superiors (Höyng & Lau, 2023; Hwang & Seo, 2025; Kelm & Johann, 2025; Klein et al., 2024; van Dun & Kumar, 2023). Nonetheless, leaders should also maintain an organizational point-of-view, providing clear guidelines and a rigid structure to guide employees and leaders alike during periods of change. A combination of a clearly defined path forward, whilst also addressing employee concerns and mental issues, is described as the most likely indicator for success.

4.1.2 Strategic communication

To address tensions among employees, strategic communication is vital. According to Klein et al. (2024) leaders should try to understand where employees are coming from. They should acknowledge their concerns and engage in meaningful conversation, rather than downplaying their employee's emotions. The aim should be to foster an environment where a mindset of "both/and thinking" replaces one of "either/or". By stimulating the former, leaders can create a setting in which "individuals feel comfortable with and are energized by tensions" (Kelm & Johann, 2025; Klein et al., 2024, p. 1005; Solberg et al., 2020). Strategic communication, in the context of technological change such as the implementation of AI, is often an ongoing process instead of a radical change. That is why leaders should provide continuous information flows to keep employees posted. Additionally, leaders should try to tailor these flows based on the particular mindset an employee possesses. If they have showcased such "both/and thinking", leaders can expect a more willing attitude. If they are stuck in an "either/or" pattern of thinking, leaders might have to expect resistance (Klein et al., 2024, p. 1005). Ultimately, effective communication should be focused on aligning individual values and expectation patterns with those of the organization (Hwang & Seo, 2025). Communication has the ability to make or break the process of implementing new technology. If employees believe their superiors have broken their promises, or in general, feel left in the dust, even the most willing can turn into skeptics. Conversely, open and personalized, yet structured and goal-oriented communication, can sway employees towards positivity (Meissner et al., 2020; Picado Argüello & González-Prida, 2024).

4.1.3 Support systems

Organizations are able to put support systems in place to make the introduction of new technology as pleasant as possible for employees. According to Kelm and Johann (2025), at an individual level, first impression last. They suggest that organizations and leaders should aim to make the first exposure as comfortable as possible, as this is likely to become the pillar that shapes the digital mindset of that particular employee. At the organizational level, support systems should build on the extensively covered leadership styles and strategic communication. Essentially, organizational support in the context of technological change boils down to three distinct dimensions: 'shared goals, visibility, and communication (Hwang & Seo, 2025, p. 420; Molino et al., 2021)'. By carefully crafting these dimensions to fit the scenario an organization finds itself in, they are able to influence employees' value perception of the imposed technological change (Molino et al., 2021).

4.2 Employee attitude

Whilst a lot has been said about humans' innate resistance to the uncertainty that comes with (organizational) change, certain studies have examined the particular psychology of this interaction even more carefully. Focusing solely on technological shifts in a manufacturing setting, they were able to explain it in more detail, having to rely less on generalization.

4.2.1 Technology Acceptance Model

Many studies on technological change throughout the years are grounded in the TAM-model (Technology Acceptance Model), originally developed by Fred Davis in 1985. It was built upon two distinct dimensions, which are used to predict how well employees would react to technological change. These are "Perceived Usefulness (PU)" and "Perceived Ease-of-Use (PEOU)". Since then, TAM has evolved into TAM2 and even TAM3, including factors such as social influence, cognitive processes and trust (Kelm & Johann, 2025).

The TAM model has also been applied to the rapidly successive innovations across industries in recent years, commonly referred to as DT. TAM is commonly combined with outside factors or other models, stemming from the perceptions of the author or the characteristics of the particular shift they wanted to analyze. As an example, (Höyng & Lau, 2023) combined the TAM model with a dimension of personal and job resources, ultimately trying to determine digital readiness more carefully. They found that both PU and PEOU are positively related to digital readiness. Additionally, the positive relationship between PEOU and digital readiness is mediated through PU, underlining that the latter ($\beta = 0.33$) holds even more of an influence than the former ($\beta = 0.19$). Having analyzed the TAM model in a setting undergoing DT, four distinct factors were identified: a system's design features, cognitive response, affective response, and behavioral response. The cognitive response is directly formed by PU and PEOU and shapes the affective response. The affective response then leads to a behavioral response (Höyng & Lau, 2023; Kelm & Johann, 2025).

PU is about whether an employee believes that the proposed technology will enhance their job performance. Although PU and PEOU are cognitive reactions to an imposed technology, often determined by an employee's personality and mindset, there are ways in which it can be steered either positively or negatively. Most notably, empowering leadership and trust in management were found to play a big part in shaping PU (Höyng & Lau, 2023; Molino et al., 2021). Additionally, well-formulated and transparent communication is vital to convince an employee of a technology's worth. Pertaining to an individual's specific situation, explaining how an innovation can make their lives easier is the best way to improve PU retroactively (Chatterjee et al., 2021).

PEOU is about how much time and/or effort employees believe the technology will take for them to master. It has two functions. First, it directly influences an employee's digital readiness. Second, it serves as an antecedent to PU. A low PEOU is likely to also decrease one's PU of a new technology (Höyng & Lau, 2023; Kelm & Johann, 2025). Whereas PU is therefore the more ultimate indicator of digital readiness, a lack of PEOU should not be downplayed and should be effectively managed by leaders. Firstly, they should foster a proactive mindset in their employees. This increases PEOU regardless of the innovation (Höyng & Lau, 2023). Secondly, leaders should lead by example. Employees are reported to look up to their superiors. If they see them use a certain technology with success and supposedly without much effort and mental strain, they are more likely to give it a try themselves (Kelm & Johann, 2025). Lastly, organizations should provide an abundance of training and education. With proper information and by building the skills required to learn a new technology, employees are expected to change their stance on PEOU (Kelm & Johann, 2025). However, merely convincing an employee of a technology's ease of use is often not enough. PEOU is closely linked to an employee's sense of self-worth. According to Chatterjee et al. (2021, p. 5) "PEOU includes the concepts of self-efficacy, perception of external control, anxiety, playfulness, and enjoyment". It is therefore also recommended that leaders engage in more personalized approaches, such as meaningful conversation, to distinguish where such uncertainty might stem from.

4.2.2 Technostress

The effect uncertainty has on people has been underlined once more, this time in a context of technological shifts within organizations. Terms such as 'technological anxiety' and 'technostress' have become more prevalent and generally accepted over the last couple of years. In the manufacturing industry specifically, evidence is starting to surface that many employees have started to suffer from such concepts (Meissner et al., 2020; Raj et al., 2024; van Dun & Kumar, 2023). This has only been fueled more so ever since the positive impacts of industry 4.0 and 5.0 have increasingly come to light. "This has fascinated some, but has scared most, as there is uncertainty around job security and further implications for people and organizations alike" (Butt, 2020, p. 2). AI implementation has left an impact beyond traditional job insecurity, causing severe workplace anxiety (Kelm & Johann, 2025). According to Kim et al. (2024), this is because of the unique characteristics associated with this technological change. These include, but are not limited to, the rapid pace at which it has developed and is developing, the range of applications which does not leave any department safe, and its complexity making it hard for employees to gauge. Anxiety is closely linked to a decrease in work performance. It has been associated with higher stress and lower job satisfaction, causing resistance and a lower willingness to perform tasks efficiently (Kim et al., 2024; van Dun & Kumar, 2023). Moreover, research performed in the manufacturing industry as well as other industries has shown an increase in turnover intention as a direct result of AI implementation (Gandía et al., 2025; Mukhuty et al., 2022; Raj et al., 2024), making AI-induced anxiety the biggest risk to successful implementation of such a new technology.

The connection between AI-induced anxiety and turnover intentions is often not linear. It was found that psychological contracts play a major moderating role. Psychological contracts refer to unwritten agreements that determine perceptions and expectations between employer and employee (Kim et al., 2024; Ru & Ibrahim, 2024). If a psychological contract is perceived as strong by an employee, they are less likely to follow up on AI-induced anxiety with quitting their job. Conversely, if an employee felt unimpressed by their psychological contract with their employer, they were more likely to engage in turnover intentions following such an inconvenience (Ru & Ibrahim, 2024). Understanding this, leaders who demonstrated ethical leadership and effective, transparent communications, suffered less from organizational turnover by successfully leveraging the concept of psychological contracts (Kim et al., 2024). Similarly, another moderating factor in the relationship between AI-induced anxiety and employee behavior is an employee's trust in their management. By building trusting relationships with their employees, leaders found their employees to be more accepting of new technologies, embracing them rather than running away. Trusting relationships also showed to reduce change induced anxiety altogether, underlining the role leaders have on employee attitude (Höyng & Lau, 2023; Meissner et al., 2020; Ru & Ibrahim, 2024).

4.2.3 Solberg's digital mindsets

Another widely accepted theory on employee attitudes towards technological shifts was provided by Solberg et al. (2020). By leveraging two dimensions, Solberg created a matrix with four quadrants. The dimensions were growth vs fixed mindsets, and zero-sum vs expandable sum beliefs. By determining an employee's stance on both these dimensions, the author was able to predict what 'digital mindset' this employee was likely to possess (Solberg et al., 2020). This model became well-regarded because of its ability to look solely at employees themselves, not the imposed technology at hand. It is therefore different in nature from the TAM model yet shares some similarities. The dimension of fixed vs growth mindsets shares the belief that some employees are more malleable than others. Those with fixed mindsets do not believe their (technological) abilities can be improved in any way and will avoid trying as much as they can. Those with growth mindsets, however, are open to the possibility of learning new skills and improving themselves along the way. The former are likely to have a lower PEOU, regardless of the imposed technology. They simply do not have faith in themselves to master such new skills. The second dimension of Solberg's model is more resource-focused. Employees with a zero-sum belief are convinced that technological change comes with finite opportunities that have to be competed for. They do not belief in win-win situations. They are therefore easily threatened by technological change and are commonly associated with feelings of anxiety and job insecurity. On the other hand, are the employees with an expandable-sum set of beliefs. They are convinced that technological change can serve the greater good and can ultimately create opportunity and growth for employees and organizations alike. Whereas the growth vs fixed mindset is more connected to PEOU, zero-sum vs expandable-sum mindsets are more in line with PU. The employees who see technological change as threatening, providing limited chances, are more likely to have a lower sense of PU (Höyng & Lau, 2023; Solberg et al., 2020).

5. DISCUSSION

5.1 Theoretical contribution

Drawing from multiple studies, this research extends the TAM model through integration with a complementary theoretical framework, as well as an organizational dimension. Several researchers have successfully adopted similar approaches: Höyng and Lau (2023) combined TAM with the Personal Resource Adaptation Model, while Kelm and Johann (2025) incorporated managerial support, ethics, governance, culture and commitment factors. Molino et al. (2021) enhanced TAM's core dimensions with Worker-Centric Design and Job-Demands-Resource theories, and La Torre et al. (2021) added peer influence as a social component. These studies collectively demonstrate that while TAM is effective, it benefits from organizational context integration (Bryan & Zuva, 2021; Höyng & Lau, 2023; Kelm & Johann, 2025; La Torre et al., 2021; Molino et al., 2021; Prikshat et al., 2025).

Combining existing models into a more comprehensive and applicable model has been recognized as academically justifiable, being able to create novel applications and improve explanatory power (Marzi et al., 2025; Whittemore & Knafl, 2005). The specific approach adopted in the framework as presented in this study closely follows established guidelines on integration patterns (Na et al., 2022; Prikshat et al., 2025).

The proposed framework combines TAM with Solberg's digital mindset matrix, enabling leaders to predict employee reactions to technological changes and rationalize behaviors retroactively. This integration provides manufacturing-specific leadership approaches based on employee positioning within the framework quadrants. As shown in Figure 2, the model merges TAM's dimensions of PU and PEOU with Solberg's proposed quadrants of digital mindsets. Whereas these theories are different in nature, TAM being about cognitive reactions to imposed change and Solberg focusing more on innate employee psychology, quadrant typologies were renamed to maintain academic soundness.

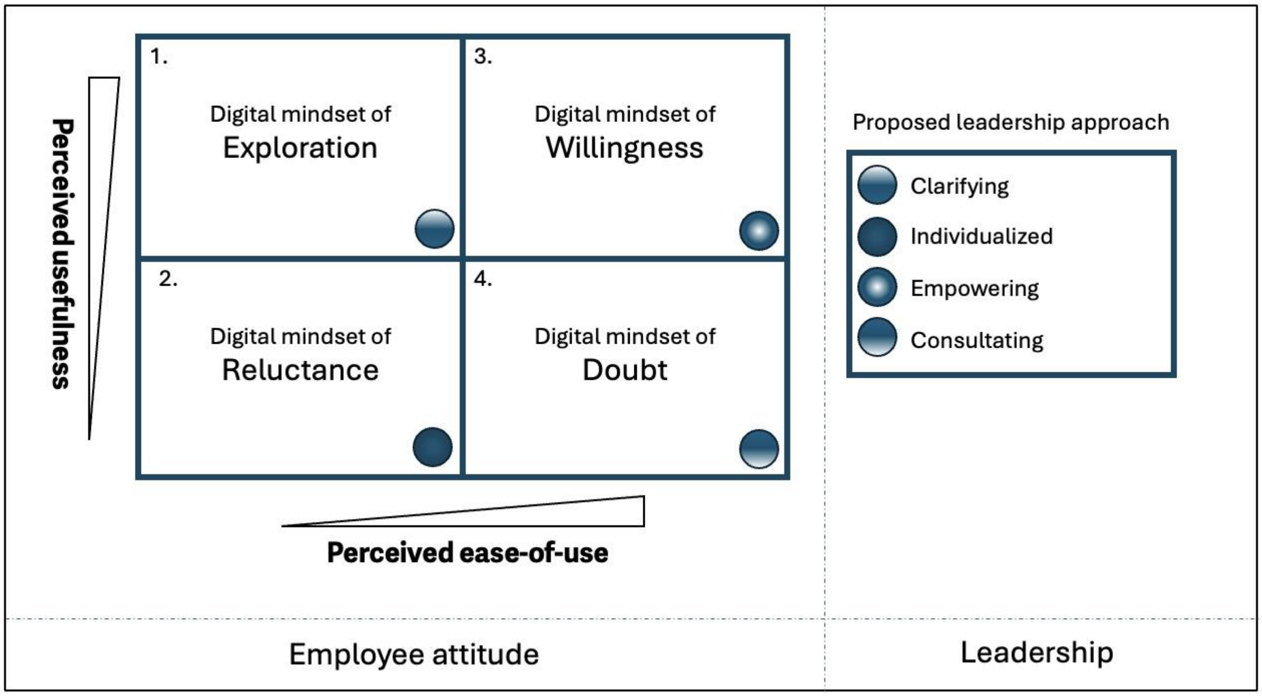

Figure 2. Employee Attitude quadrants with fitted leadership styles

5.1.1 Digital mindset of 'Exploration'

This digital mindset is characterized by employees who recognize technology's value despite their belief that it will require significant learning effort on their end to successfully implement it. Ultimately, their adoption depends on whether the perceived benefits outweigh the perceived cognitive costs (Hwang & Seo, 2025). In a manufacturing context, this digital mindset can manifest as maintenance employees struggling with the usage of a digital twin system yet attempting it anyways because of their understanding of its worth.

5.1.2 Digital mindset of 'Reluctance'

This digital mindset is found in individuals who perceive an imposed technological shift as having a low ease-of-use and low usefulness. Following this sentiment, they are expected to become reluctant to the change, possibly even hostile. Additionally, these individuals can prove problematic in team projects involving AI by passively or actively sabotaging their implementation. This can create tensions and slow down digital transformation efforts, therefore causing issues for both employees and the organization (La Torre et al., 2021). In a manufacturing setting, this particular digital mindset has manifested itself in various ways. Employees are reported to showcase a reluctance to use new systems and technologies, even when the old systems are demonstrably less efficient. They are also often unwilling to undergo training to learn such new innovations, stubbornly holding on to the familiar way of doing things. A more tangible example in the manufacturing industry was provided by (Chatterjee et al., 2021, p. 9): "They believe in the existing system, and this has been perceived when attempts were made to convert the legacy system to an ERP system".

5.1.3 Digital mindset of 'Willingness'

This digital mindset represents the most desirable adoption state, characterized by both high PU as well as PEOU. These types of individuals commonly become the 'early adopters' of new innovations, often providing them with opportunities of growth within companies. They are able to evolve into "mediators, moderators and fact checkers, quality checkers, or AI moderators" (Kelm & Johann, 2025, p. 132). In manufacturing settings, they demonstrate enthusiasm and curiosity towards innovations such as digital twin models or AI-powered R&D. They are also likely to actively influence peer adoption processes, making these individuals imperative to organizational implementation success.

5.1.4 Digital mindset of 'Doubt'

This digital mindset occurs when an individual believes an innovation has high ease-of-use yet fails to understand its usefulness to them and/or the organization. Research confirms that PEOU's positive relationship with digital readiness is mediated through PU, making leadership intervention crucial for adoption success (Höyng & Lau, 2023). In manufacturing settings, these employees often engage in selective technology usage. They might embrace

AI for everyday queries yet refuse to use it for more complex tasks, such as predictive maintenance, if they fail to see its added value.

5.2 Managerial Implications

5.2.1 Digital mindset of 'Exploration'

Although situation dependent, this research proposes a leadership style of *'clarifying'* to effectively manage individuals with this digital mindset. Individuals within this quadrant are usually willing to engage in new technologies but are unclear or hesitant about how much time and effort it is going to cost them, worrying about the mental strain it might have on them. Leaders should therefore focus on ensuring clarity and transparency about what is expected of them, and potentially providing training and information sessions, showcasing that adoption might not be as challenging as subconsciously thought by these particular individuals. Alternatively, if it really is a challenging route, leaders should try to make these individuals feel supported and provide them with the space they need to master such new skills (Wesche & Sonderegger, 2019). This can be done most effectively by carefully examining each employee's strengths and weaknesses to create targeted skill development programs instead of very generalized workforce upskilling. This works well for both parties, as the employee will have more faith that they can master this new technology with the skills they already believe to have mastered, but also for leaders and the organization as the employee will likely be more motivated and cut out to effectively carry out this development (Chatterjee et al., 2021; Höyng & Lau, 2023). As uncertainty can have feelings such as anxiety as a result, leaders are wise to engage in transformative leadership. In times of change, when employees often already feel hesitancy, and are also doubtful about the ease-of-use of said change, they are more likely to respond to personalized, informal and/or charismatic leadership.

5.2.2 Digital mindset of 'Reluctance'

To match this problematic digital mindset, this research proposes a leadership approach focused on *'individualization'*. These individuals are expected to take up much of a leader's time because they not only resist engaging in such a change but they can also negatively affect the people around them by showcasing poor behavior or through informal communication channels. It is therefore vital for leaders to steer them towards a more willing attitude as much as possible. The recommendation for the digital mindset of 'exploration' can largely also be applied to the mindset of 'reluctancy', as they are designed to achieve a higher sense of PEOU. However, leaders should invest more in convincing employees within this quadrant that the innovation actually holds value, as PU has a larger impact on digital readiness than PEOU. Additionally, employees who persistently maintain a reluctant mindset, often have underlying issues such as insecurity or anger. It might therefore be valuable for leaders to carefully examine the situation and have an individualized conversation rather than solely trying to convince the individual in question of a technology's worth. These employees may require additional support and demonstrate greater sensibility to organizational change. One strategy to employ with these types of individuals is to make them feel valued by celebrating the small wins they experience regarding change in organizations (Kelm & Johann, 2025; Molino et al., 2021). Additionally, pairing them with peers who have adopted a digital mindset of 'willingness' can positively influence them. However, leaders need to be careful that this doesn't end up working counterproductively. Lastly, these individuals should be constantly monitored to ensure that their behavior doesn't become destructive and hostile (La Torre et al., 2021). These measures should be focused on increasing one's trust in management, as this was identified as a critical indicator for digital readiness in this type of individual.

Nonetheless, if leaders believe it to be fully about the proposed technology, there are certain strategies to improve PU in employees. Firstly, sharing tangible stories regarding the technologies' worth often proves valuable. These might be stories of how they successfully used it themselves, or how competing organizations have used it to gain a competitive edge. Alternatively, a leader can invite an expert on technology to explain what it can do for individuals and organizations alike.

For low PEOU, low PU individuals it might also be beneficial to break the process of implementation down into small steps. This way, they are able to view it as easier to overcome since they can shift their focus to a small step at a time, increasing PEOU. Additionally, by explaining what each step achieves for them, their PU can rise simultaneously (Chatterjee et al., 2021; Molino et al., 2021).

5.2.3 Digital mindset of 'Willingness'

Following the aforementioned rationale, these individuals are expected to benefit most from a leadership style of *'empowerment'*. As they already view new technologies as useful and worthwhile, these individuals are highly desired by leaders. Nonetheless, they still require attention to maintain such an attitude and to cherish all positive outcomes that come with it. These people benefit from autonomy over development. They thrive in situations where they feel trusted by their superiors, in an environment where they are allowed to play around with new technology. More generalized development programs commonly work counterproductive on these types of individuals (Höyng &

Lau, 2023; Wesche & Sonderegger, 2019). However, it is still recommended to involve these individuals in processes of planning, training and education to solidify their role in the implementation and build even more of a trusting relationship. Additionally, individuals who display behaviors of not only willingness, but also proactiveness, are often the ones who are able to become 'digital transformation champions' of organizations. These are the early adopters who are also able to encourage their peers of a technology's usefulness. These individuals should therefore be placed into scenarios where they can be mentors to others, although leaders should closely monitor this dynamic so as not to accidentally create a bigger divot between enthusiasts and skeptics (Chatterjee et al., 2021).

5.2.4 Digital mindset of 'Doubt'

The leadership style that fits this digital mindset is one of '*consultation'*. As PU is the most significant contributor to digital readiness, a high PEOU but low PU commonly leads to a lack of motivation to engage in a new technology. These people, therefore, need to be convinced of an innovation's worth, similar to how the digital mindset of 'reluctancy' had to be. The ways in which this can be done remain similar. Tangible examples of use cases for new technology, especially those tailored to the individual who has to be convinced have the highest chance of succeeding in their intended aim.

5.3 Limitations

While posing valuable insights, this study has several limitations that should be taken into account when attempting to utilize its data. Firstly, a singular author performing an SLR can create interpretation bias, as well as bias in how the data was coded. Additionally, by only using two bibliographic databases, valuable contributions or contradictions may have been left out. Secondly, however novel, the specific combination of the TAM model and Solberg's matrix lacks practical validation, raising questions about its applicability in real-life contexts. Thirdly, by relying extensively on data on similar technological shifts compared to AI, the validity of the claims made in this research can be questioned as they are likely to suffer from unjust generalization between events. Lastly, although tailored to the manufacturing industry in a scope of technological change, the recommendations and framework remain highly generalized. Whilst it can serve as an effective set of guidelines for leaders, it is important to note that they should always critically look at the situation they find themselves in and use the implications accordingly.

5.4 Future research

As for the lack of practical validation of the proposed framework as such, future research can provide a valuable contribution to this study by performing primary data collection in the manufacturing industry, examining the model's worth. Similarly, as predicting PEOU and PU in employees is often very challenging for leaders, future research could focus on developing specialized ways in which this can be done. As an example, a tailored set of survey questions could prove to be an aid to determine the digital mindsets of employees, making it easier to use the framework as proposed in this study.

As previously stated, the set of recommendations this study offers remains very general. Future research can build on this research' proposed framework and make it more specific to certain cultures and/or particular characteristics of manufacturing firms. Moreover, since the implementation of AI in a business setting is not something unique to the manufacturing industry, future research can leverage this study's approach and apply it to a different industry, potentially developing a framework that is different from the one developed here.

6. CONCLUSION

This research addresses a critical challenge facing manufacturing leaders today: how to successfully navigate employee attitudes during AI implementation. Whereas AI is developing rapidly, and implementation within manufacturing contexts becomes more common, the human dimension remains the predominant determinant of success or failure, as underlined by an 87.5% failure rate of DT initiatives.

By combining the Technology Acceptance Model with Solberg's digital matrix, this study provides leaders with a tool that moves beyond a simple sentiment of acceptance or reluctance. Facilitating a four-quadrant model, consisting of novel digital mindset typologies being willingness, exploration, doubt, and reluctance, a theoretical advancement was made by combining a sense of reaction to imposed innovation with employees' innate psychology. These quadrants were coupled with actionable leadership approaches, being empowering, clarifying, consultating, and individualized, respectively. Consequently, accounting for a well-documented shortcoming of the TAM model, this research has turned the theoretical into practical insights.

Although aimed towards AI implementation, the framework, as proposed, can provide a foundation for future technological introduction as well, posing potentially limitless implications.

However useful, this study does have its limitations in interpretation bias, a lack of practical validation, comparison ambiguity and a very broad scope. It therefore encourages future research to build on the phenomenon as investigated, providing a more secure and targeted basis to build upon.

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Appendix 1

Search prompts

Scopus:

((TITLE-ABS-KEY("assembly line" OR "technological disruption" OR "digital transform*" OR "industry 4.0" OR "smart manufactur*" OR automation) AND TITLE-ABS-KEY("employee attitude*" OR "change resist*" OR "change reluctan*" OR anxiet* OR acceptan* OR turnover) AND TITLE-ABS-KEY(leader* OR "change management" OR "organizational change")) AND PUBYEAR > 1989 AND PUBYEAR < 2026)

Web of science:

TS=("assembly line" OR "technological disruption" OR "digital transform*" OR "industry 4.0" OR "smart manufactur*" OR automation)AND TS=("employee attitude*" OR "change resist*" OR "change reluctan*" OR anxiet* OR acceptan* OR turnover)AND TS=(leader* OR "change management" OR "organizational change") AND PY=(1990-2025)

Inclusion/exclusion criteria

Inclusion

Characteristics

- Articles available in full, potentially through the researcher's institution

Content

- Articles with a focus on a technological shift comparable to the adoption of AI
- Articles which do not merely discuss the technological implications, but also the human aspect of it (i.e. employee attitude)
- Articles which discuss leadership's influence during such shifts
- Articles which discuss a historical series of events in light of organizational change (management)

Exclusion

Characteristics

- Theses
- Nonacademic articles (i.e. blogs, websites, etc.)
- Conferences
- Books
- Journals from little recognized sources

Content

- Articles with a questionable methodology and/or non-supported claims
- Articles which specifically focus on an industry other than manufacturing

Appendix 2

Article	Code
1) *Organizational support for digital transformation in the metaverse: a contingent pathway from user experience to digitalization resistance*	DT shift comparable to AI
	Digitalization resistance
	Perceived usefulness
	Psychological barriers
	Aligning organizational and individual interests
	Transparent communication / leadership

Article	Code
2) *Artificial intelligence in corporate communications: determinants of acceptance and transformative processes*	Perceived usefulness
	Perceived ease-of-use
	AI integration challenges
	AI anxiety
	Leading by example
	Leadership communication strategies
	Micro- and meso-level support

Article	Code
3) *An investigation into the effect of path-goal clarifying behavior on employee role performance in crisis situation*	Leading by example
	Leader contingent reward behavior
	Job satisfaction
	Leading by example

Article	Code
4) *Towards sustainable business in the automation era: Exploring its transformative impact from top management and employee perspective*	AI / automation perception
	Job insecurity
	Owners vs employees

Article	Code
5) *Code green: ethical leadership's role in reconciling AI-induced job insecurity with pro-environmental behavior in the digital workplace*	Job insecurity
	Psychological contract
	Trust in management
	Leadership role in change
	Workforce adaptation

Article	Code
6) *Employee acceptance of digital transformation strategies: A paradox perspective*	DT shift comparable to AI
	Employee acceptance
	Strategic communication
	Leadership perspective limitations
	Transparent leadership

Article	Code
7) *Integrating Change Management with a Knowledge Management Framework: A Methodological Proposal*	Human-centric approach
	Individualized attention
	Leadership communication strategies
	Knowledge retention
	Job insecurity

Article	Code
8) *RELATIONSHIPS BETWEEN LEADERSHIP STYLE, CAREER DEVELOPMENT, WORK STRESS, AND TURNOVER INTENTION IN A HIGH-TECH INDUSTRY: MODERATING ROLE OF PSYCHOLOGICAL CONTRACT*	Transformational vs transactional leadership
	Psychological contract
	Turnover intention
	HRM strategies
	Managing employee expectations

Article	Code
9) *Being ready for digital transformation: How to enhance employees' intentional digital readiness*	DT shift comparable to AI
	Perceived usefulness
	Perceived ease-of-use
	Growth vs fixed mindset
	Autonomy vs development support
	Trust in management
	Empowering leadership

Article	Code
10) *Team Formation for Human-Artificial Intelligence Collaboration in the Workplace: A Goal Programming Model to Foster Organizational Change*	AI implementation
	Perceived usefulness
	Perceived ease-of-use
	Organizational change management

Article	Code
11) *Social enablers of Industry 4.0 technology adoption: transformational leadership and emotional intelligence*	DT induced anxiety
	Transformational leadership
	Emotional intelligence

Article	Code
12) *Technology acceptance and leadership 4.0: A quali-quantitative study*	Perceived usefulness
	Perceived ease-of-use
	Job insecurity
	Demographics on acceptance
	Effective communication
	Aligning organizational and individual interests

Article	Code
13) *Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model*	Perceived usefulness
	Perceived ease-of-use
	Technology-Organization-Environment (TOE)
	Organizational change (management)
	Digital readiness

Article	Code
14) *A conceptual framework to support digital transformation in manufacturing using an integrated business process management approach*	DT induced anxiety
	Job insecurity
	Leadership role in change
	Continuous improvement

Article	Code
15) *Digital Mindsets: Recognizing and Leveraging Individual Beliefs for Digital Transformation*	Inherent uncertainty of change
	Growth vs fixed mindsets
	Zero-sum vs expandable-sum mindsets
	DT induced anxiety
	Framing of communication
	Leader's self awareness

Article	Code
16) *Friend or Foe Understanding Assembly Workers' Acceptance of Human-robot Collaboration*	Job insecurity
	Human-robot collaboration positivity
	Trust in management
	Strategic communication
	Acceptance over time

Article	Code
17) *When computers take the lead: The automation of leadership*	Computers as leaders
	Leadership-TAM (LTAM)
	Perceived usefulness
	Perceived ease-of-use
	Skepticism / anxiety

Article	Code
18) *Resistance to change-A monitor of new technology*	DT induced anxiety
	From skepticism to careful acceptance
	Job insecurity
	Leadership role on change

Article	Code
19) *Strategic sustainable development of Industry 4.0 through the lens of social responsibility: The role of human resource practices*	Change resistance
	Digital skill gap
	HRM strategies
	Leadership role on change

Article	Code
20) *A moderated mediation approach to deciphering the effects of leader knowledge hiding behavior in industry 4.0*	Knowledge sharing
	Intrinsic motivation
	Turnover intentions
	DT induced anxiety
	Leader knowledge hiding behavior (LKHB)