Agile Mindset Leader as the Leader of the Future: Collective Human and Artificial Intelligence Broker

Wioleta Kucharska[1], Jari Jussila[2] and Maciej Kucharski[1]
[1]Gdańsk University of Technology, Gdansk TECH, Fahrenheit Universities Association, Poland
[2]Häme University of Applied Sciences, HAMK Design Factory, Finland

wioleta.kucharska@pg.edu.pl
jari.jussila@hamk.fi
maciej.kucharski@pg.edu.pl

Abstract: As artificial intelligence (AI) takes on a larger role in knowledge work, understanding the psychological and collective factors that enable successful human-AI collaboration becomes critical. This study examines how agile versus non-agile mindsets, conceptualized as cognitive-motivational orientations towards change, experimentation, and iterative learning, relate to collective human intelligence and to employees' adoption of AI at work. Also investigating how these factors jointly contribute to organizational intelligence. The study involves 3871 knowledge workers: 1871 (initial study) and 2000 (replication) from Poland and Finland, across the IT and OTHER-than-IT sectors. Using structural equation modeling, we found that collective human intelligence strongly predicts organizational intelligence and that AI adoption adds explanatory value by strengthening this relationship. Results suggest the need for inclusive practices that support both change-oriented and stability-oriented employees when designing human-AI work systems. This study contributes to followership theory and to technology-mediated collaboration by specifying mindset-based boundary conditions for collective intelligence in AI-enabled workplaces. Artificial intelligence, agile mindset, collective human intelligence, agile organization.

Keywords: Leader, Agile mindset, Agile mindset leader, Organizational intelligence, AI adoption

1. Introduction

Artificial intelligence (AI) is increasingly embedded in everyday work practices, reshaping how individuals and groups make decisions, coordinate tasks, and learn (Akkaya and Sever, 2022; Luthia, 2023). In organizational settings, AI refers to tools, agents, and technologies that emulate aspects of human cognition and can augment work processes through data-driven inference and prediction (Russell and Norvig, 2021; Sheikh et al., 2023). While AI-enabled collaboration can improve productivity and support continuous improvement in knowledge-intensive tasks (Atolagbe-Olaoye, 2025), realized benefits depend on human factors such as employees' willingness to experiment, redesign routines, and integrate AI into collective work practices, rather than on technological capability alone (Mehta et al., 2025). This makes mindset differences a relevant boundary condition for technology-mediated collaboration (Chew and Mohamed Zainal, 2024). Moreover, AI also brings significant changes to leadership practices oriented toward knowledge, learning, and collaboration cultures, shifting employees toward building collective intelligence to adopt AI and make the best use of it to develop an organizationally intelligent, comprehensive, adaptive system, as agile organizations are (Kucharska, 2026; Kucharska and Kucharski, 2026). In this context, agile leadership involves integrating human and artificial intelligence, where AI reduces routine managerial tasks and enables leaders to focus on higher-level decision-making (Tominc et al., 2023). However, this transformation also presents significant challenges. Leadership competencies in the era of artificial intelligence are more complex and demanding than ever before (Bock and von der Oelsnitz, 2025; Zaidi et al., 2025).

Agile mindset leaders seem to be precisely the kind of leadership that a currently challenging, volatile, uncertain, complex, and ambiguous world needs (Akkaya and Sever, 2022). However, leadership quality is always reflected in followers' outcomes (Udin, 2025). Although prior work highlights the role of agile leadership (Akkaya and Sever, 2022) and the evolving competency demands of AI-era leadership (Bock and von der Oelsnitz, 2025; Zaidi et al., 2025), less is known about how agile- and non-agile mindset employees, together with agile mindset leaders, differentially contribute to collective human intelligence and to AI adoption in knowledge-driven organizations oriented toward intelligence building. Following followership theory, which emphasizes leadership as a co-created process that involves followers' contributions (Uhl-Bien et al., 2014), we examine how leaders' and followers' mindsets relate to collective human intelligence, AI adoption, and organizational intelligence in AI-enabled workplaces.

2. Conceptual Framework

Followership theory (Uhl-Bien et al., 2014) states that leadership fundamentally relies on followers. Specifically, it shifts the focus from leader-centered models to a co-created process in which leaders and followers jointly

contribute to value creation. It suggests that modern leadership requires today's active, engaged, committed, and critical followers. This study then explores how organizational intelligence advances through the insights of agile- and non-agile-mindset followers who thrive under an agile-mindset leader. This study aims to expand this theory by empirically demonstrating the critical importance of leaders' and followers' agile mindsets in fostering collective human intelligence, embracing AI adaptability, and driving overall organizational intelligence.

2.1 Agile Mindset Leaders and Their Agile and Non-agile Followers

Agile organizations thrive on a dynamic culture of agility, strong leadership, and active employee engagement (Kucharska et al., 2026b; Nold and Michel, 2016). Research by Eilers et al. (2022) and Ozkan et al. (2023) powerfully illustrates the pivotal role that employees' mindsets play in cultivating agility. Furthermore, Kucharska et al. (2026a, 2026c) emphasize that agile leaders are not just important—they are essential to the success of agile organizations—by providing compelling evidence of their impact on both agile and non-agile teams. Moreover, social interactions between leaders and their followers directly shape organizational performance (Lehmann-Willenbrock, 2024). So, studying these relations matters. Finally, leadership is defined as "the process through which an individual becomes influential to relevant others in a manner that involves the implicit or explicit granting of the leader role" (Badura et al., 2022, p. 2070), clearly suggesting the need to consider the leader's impact on their followers when exploring any kind of organizational performance, including intelligence building, as this study focuses on. Building on these insights, we propose the following hypotheses:

H1a Agile mindset leader impacts directly and positively agile mindset followers.

H1b Agile mindset leader impacts directly and positively non-agile mindset followers.

2.2 Agile Mindset Leaders and Their Followers' Impact on Collective Human Intelligence

Collective intelligence, broadly conceived, refers to the adaptive behavior groups achieve through interactions among members (Falandays et al., 2023; Leimeister, 2010; Secundo et al., 2016). Importantly, this adaptive capacity emerges at the macro level and can exceed what any individual member could achieve alone (Cui and Yasseri, 2024; Falandays et al., 2023). Since an organization exists as a collective body, its agility relies heavily on cultivating such collective intelligence. Collective human intelligence (CHI) thus embodies the shared ability to take smart action as a whole, going beyond a simple aggregation of individual capabilities and emphasizing what people can accomplish together (Kucharska, 2025). Although research shows that many organizational competencies are shaped through collective, interaction-based processes and that collectivistic orientations can strengthen key team capabilities, their importance varies depending on the competence and context (Bablo et al., 2023; Hagemann and Kluge, 2017). Therefore, the following hypotheses are formulated:

H2a Agile mindset employees impact CHI directly and positively.

H2b Non-agile mindset employees have a direct and negative impact on CHI.

2.3 AI Adoption (AIa)

Technological innovations support organizational intelligence processes (Volberda et al., 2021), and AI technologies do as well. However, Ardichvili (2022) argues that AI systems pose a significant threat to organizational intelligence by undermining the expertise of veteran members. In his opinion, this decline in expertise arises from diminished opportunities for collaborative learning and reduced engagement with complex tasks that foster skill development and deliberate practice. Recently, Kucharski et al. (2025) demonstrated that collective higher-level learning skills, known as organizational dynamic capabilities (Winter, 2003), are strongly dependent on leaders' agile mindsets. Taken together, these findings suggest that the risks identified by Ardichvili (2022) are more strongly associated with characteristics of a non-agile mindset than with those of an agile orientation. Furthermore, as is often the case, AI's adaptability is influenced by individual personality traits (Riedl, 2022). Although many enthusiasts argue that interactions with machines can surpass those with humans in areas such as efficiency, trustworthiness, impartiality, and even altruistic behavior (Sundar and Kim, 2019), empirical evidence remains mixed and highly context-dependent (Ishowo-Oloko et al., 2019). Algorithms can outperform humans on certain structured tasks, particularly in terms of consistency, objectivity, or efficiency, but these advantages often depend on task characteristics and may involve trade-offs with transparency, fairness, or human values (Ishowo-Oloko et al., 2019). Likewise, trust in AI is not uniformly higher: people frequently exhibit initial skepticism or algorithm aversion (Burton et al., 2020), especially when ethical considerations are salient. Thus, these optimistic claims should be understood as reflecting a particular strand of enthusiasm rather than a universal empirical reality.

This perspective helps explain why some individuals embrace AI readily. Interpreting machine logic as consistent and unbiased can foster a positive relationship with AI and enhance willingness to adapt to its capabilities. However, cognitive complacency may arise when human decision-makers fail to question the reasoning behind algorithmic outputs (Araujo et al., 2020). Conversely, distrust may emerge when AI systems are perceived as opaque or uncontrollable, particularly among individuals with low tolerance for ambiguity or high need for predictability. Prior research shows that personality traits such as low openness and higher anxiety are associated with reduced trust in algorithmic systems, especially under conditions of uncertainty and limited transparency (De Freitas et al., 2023). These tendencies align with stability-oriented cognitive styles, suggesting that individual differences can significantly shape attitudes toward AI acceptance. At a deeper level, AI directly and indirectly reshapes working routines (Del Giudice et al., 2023). Regarding the impact of non-agile mindsets on AI adaptability, we assume that such employees may initially respond with skepticism that is consistent with their broader resistance to change, but may eventually become enthusiastic adopters when AI demonstrably simplifies their work. Based on all the above, the following hypotheses are formulated:

H3a Agile mindset employees impact AIa directly and positively.

H3b Non-agile mindset employees' impact AIa directly and positively.

Moreover, Jarrahi et al. (2023) suggest that organizations should foster human–AI partnerships grounded in people, technological infrastructures, and processes to optimize integrity. Zirar et al. (2023) further emphasize that effective AI–human coexistence requires higher-level technical, social, cognitive, and conceptual skills. Importantly, machines cannot recognize broader contextual cues; tacit knowledge emerges from a combination of contextual signals, experience, and expertise. This makes the superiority of human intelligence, particularly that associated with agile mindsets, logical in tasks requiring flexible, context-sensitive judgment (Kucharska, 2025). From this perspective, collective human intelligence must upshift and evolve continually to maximize the benefits of AI technologies. At the same time, humanity must collectively adapt to the new working realities AI creates, as the relationship between artificial and human intelligence is inherently bidirectional. Since this study examines how employees with agile and non-agile mindsets contribute to organizational intelligence development through AI adaptability, the following hypotheses are formulated:

H3c: CHI directly and positively impacts AIa.

2.4 Organizational Intelligence (OI)

The combination of human and artificial intelligence (named augmented intelligence) plays a crucial role in driving organizational performance (French and Shim, 2025). AI supports performance and enhances employees' cognitive skills, whereas skilled employees foster AI adoption. In this way, augmented intelligence constitutes organizational intelligence. Augmentation, considered 'weak', focuses on automating tasks performed by a human worker (human replacement). It impacts business by improving efficiency and reducing costs. 'Strong augmentation' combines AI with human input (e.g., assessment) to change business processes (Hurwitz et al., 2019). Successful AI adoption and 'strong augmentation' are related (Neumann et al., 2026). Organizational intelligence is defined as the effective use of relevant knowledge in a business context, and the best effects are achieved when human collective and artificial intelligence synergize (Kucharska, 2025, p. 1), as Kucharska and Kucharski (2026) empirically confirm. Therefore, based on this perspective, the following hypotheses are proposed:

H4: CHI impacts OI directly and positively.

H5: AIa directly and positively impacts OI.

2.5 Expected Mediations

Apart from the above direct relations, the following indirect relations are expected:

- AML impact on CHI is expected to be mediated by agile and non-agile mindset employees.
- The impact of agile and non-agile mindset employees on AIa is expected to be mediated by CHI.
- CHI's impact on AI is expected to be mediated by AIa.

3. Methodology

The models presented reflect the perceptions of knowledge workers, specialists, and managers from Poland and Finland. The data were collected in March 2025 (N=1871 initial study) and in March 2026 (N=2000 replication), applying the CAWI (Computer-Assisted Web Interview) method. The total sample size is 3871 cases (country

input, position, mindset view, and gender balance secured). We selected initial and replication sample participants from the same research panel each year. However, we did not verify whether the same individuals gave informed consent to participate in the survey every year.

The study was designed to compare agile (AM) and non-agile (nAM) mindsets; therefore, the sample was balanced to include individuals with both mindsets, facilitating this comparison and supporting the study's goals. One of the 'qualification questions' asked respondents to self-assess their agility. We asked: *Which statement describes you better (a or b)? a) I like changes and intellectual challenges; I usually adapt quickly to new situations; I am eager to find and implement new solutions (AM); b) I don't like changes; I prefer quiet work in predictable conditions over chasing challenges; I rely on proven solutions instead of trying new things (nAM).* Consequently, we split the general sample (N=1871/2000 initial/replication) into two subsamples: first, those who described their attitudes as closer to agile (N=932/1000), and second, those who described their attitudes as closer to non-agile mindset characteristics (N=939/1000). It is worth stressing that such a balanced structure is purposeful for the study's aims (50/50) and is a consequence of the entire study aim. Models always simplify reality, just as ours do, within the purpose and scope of the study, allowing us to focus more deeply on the impact of agile and non-agile mindsets on collective human intelligence, embracing AI adaptability, and driving overall organizational intelligence. That's exactly why we designed the sample to be mindset-balanced (Dataset availability, Kucharska, 2026b).

Supplementary materials (SM), Appendix 1 provides details on the measurement scales used, their sources, and their reliabilities. The cross-loading matrix (SM, Appendix 2) proves the sound quality of all measures (loadings exceed 0,5 and scales do not overlap). Moreover, the KMO (Kaiser-Meyer-Olkin) test of sample adequacy (0.965/0.976), the total variance explained (66%/66%), and Harman's single-factor test (39%/35%) are all acceptable (Byrne, 2016). The common method bias (CMB) common latent factor test result was (0.29/0.40), allowing us to proceed with further analysis. Because our sample includes responses from participants in two distinct countries and focuses on two opposing mindsets, we applied a measurement invariance procedure to ensure respondents across groups interpreted the measurement instrument similarly, thereby supporting its quality. In short, we ran two invariance procedures (SM, Appendix 3): Poland-Finland and agile and non-agile mindset (self-assessment). This robust analysis enables us to proceed to the next step: validity analysis, which highlights the perspectives of participants with agile and non-agile mindsets. Next, validity analysis (SM, Appendix 4) showed that, across all examined samples from the initial study for agile leader mindset (AML) and agile mindset employees (AMe), as well as for collective human intelligence (CHI) and organizational intelligence (OI), the Fornell-Larcker criterion was not met. In the replication samples, the same issue was only observed between the CHI and OI variables. Therefore, Heterotrait-Monotrait (HTMT) analysis, which is considered more reliable than the widely used Fornell-Larcker criterion, was performed to assess discriminant validity (Henseler et al., 2015). This analysis yielded very good results for the initial sample (SM, Appendix 5), indicating that the observed correlations are likely due to genuine strong interdependence rather than poor measures. Regarding replication samples, the HTMT analysis shows that, among non-agile mindset participants, the discriminant validity of the CHI and OI variables is indeed liberal. This suggests that in the non-agile-minded respondents sample, these constructs (variables) are statistically close. Since the meanings of the two constructs are clearly distinct (SM, Appendix 1), we view this as a result of a strong natural dependence between collective human and organizational intelligence. If so, it underscores how critical the development of collective human intelligence is. This conclusion is supported by the previous analysis of CMB, cross-loading, and invariance results, all of which indicate good measurement quality. The other replication samples (the total sample and the agile mindset participants sample) demonstrate excellent discriminant validity (SM, Appendix 5).

So far, the initial and replication samples confirm the strong discriminant validity of the measures and suggest a close, natural link between collective human and organizational intelligence, highlighting the importance of developing collective human intelligence. To verify this assumption, the SEM models will be run on both the initial and replication samples, with the aim of building a strong evidence base. A replication study is considered the best way to assess the reliability of any empirical evidence (Freese and Peterson, 2017).

4. Results

Overall, the findings (initial and replicated) emphasize the crucial role of collective human intelligence (CHI) in developing organizational intelligence (OI) and demonstrate that AI adoption (AIa) significantly enhances the development of organizational intelligence. Therefore, as expected, the synergy of CHI and AIa best serves OI. Furthermore, the initial and replicated results indicate that leaders with an agile mindset, along with their agile-minded followers, contribute most to the creation of collective human intelligence. The impact of non-agile

employees (nAMe) on human collective intelligence is not significant (based on the initial sample), nor is the impact of agile-minded leaders (AML) on non-agile employees (nAMe) - the replication shows opposite results for all samples in this matter. However, the results for agile-minded participants in the replication are close to those observed in the initial sample, indicating a weak impact of AML on them. The AML impact on nAMe is noted as significant, but weak (H1b replication β=0.08*). Also, the nAMe impact on collective human intelligence is significant relative to the initial sample, and this is confirmed by all replication sample results. It suggests that the attitude of non-agile staff toward agility and AI adoption improves over time, and it is positive, but agile mindset employees are still much more involved in building collective human intelligence. Regarding AI adoption in the initial sample, the direct impact of AME is significant for both the TOTAL and agile mindset (AM) samples. The views of non-agile mindset respondents suggest that AMe has an indirect impact on AIa, with CHI fully mediating this effect. In the replication, CHI fully mediates the relationship between AMe and AIa, except in the non-agile mindset sample, where complementary mediation is observed. In fact, it is the opposite of what we observed at the initial study stage. But since all the obtained significant results between AMe and AIa are weak (*), this suggests that collective human intelligence strongly mediates this relation. Findings are detailed in Table 1, a) initial, b) replication, and illustrated in Figure 1.

Table 1: Hypotheses verification

a) initial sample

Hypothesis	TOTAL SAMPLE *n=1871; χ^2=2084.47(518) Cmin/df=4.02* *CFI=.963 TLI=.966* *RMSEA=.040(.038-.042)*		AGILE MINDSETS view *n=932; χ^2=1369.58(518) Cmin/df=2.64* *CFI=.965 TLI=.962* *RMSEA=.042(.039-.045)*		non-AGILE MINDSETS view *n=939; χ^2=1564.48(518) Cmin/df=3.20* *CFI=.954 TLI=.950* *RMSEA=.046(.044-.049)*	
	β	VERIFICATION	β	VERIFICATION	β	VERIFICATION
H1a (+)	.80***	*sustained*	.80***	*sustained*	.79***	*sustained*
H1b (+)	ns	rejected	ns	rejected	ns	rejected
H2a (+)	.65***	*sustained*	.70***	*sustained*	.60***	*sustained*
H2b (+)	ns	rejected	ns	rejected	ns	rejected
H3a (+)	.09*	*sustained*	.13*	*sustained*	ns	*rejected*
H3b (+)	.07**	*sustained*	.ns	*rejected*	.14***	*sustained*
H3c (+)	.48***	*sustained*	.48***	*sustained*	.47***	*sustained*
H4 (+)	.70***	*sustained*	.77***	*sustained*	.67***	*sustained*
H5 (+)	.21***	*sustained*	.14***	*sustained*	.25***	*sustained*
MEDIATIONS ANALYSIS*						
Mediation expected	INDIRECT EFFECT	Mediation detected	DIRECT/INDIRECT IMPACT	Mediation detected	DIRECT/INDIRECT IMPACT	Mediation detected
AML->AMe->CHI	.491(***)	complementary	.61(***)	complementary	.40(***)	complementary
AML->nAMe->CHI	.000(.824)	no mediation	-.001(.563)	no mediation	.000(.760)	no mediation
AMe->CHI->AIa	.310(***)	complementary	.329(***)	complementary	.282(***)	full mediation
nAMe->CHI->AIa	-.002(.747)	no mediation	-.006(.282)	no mediation	.003(.747)	no mediation
CHI->AIa->OI	.117(***)	complementary	.07(*)	complementary	.15(***)	complementary

b) replication sample

Hypothesis	TOTAL SAMPLE *n=2000; χ^2=3198.4(964)* *Cmin/df=3.31* *CFI=.970 TLI=.968* *RMSEA=.034(.033-.035)*		AGILE MINDSETS view *n=1000; χ^2=2703.47(1013)* *Cmin/df=2.66* *CFI=.956 TLI=.953* *RMSEA=.041(.039-.043)*		non-AGILE MINDSETS view *n=1000; χ^2=2666.43(1013)* *Cmin/df=2.63* *CFI=.957 TLI=.954* *RMSEA=.040(.039-.042)*	
	β	VERIFICATION	β	VERIFICATION	β	VERIFICATION
H1a (+)	.73***	*sustained*	.72***	*sustained*	.74***	*sustained*
H1b (+)	.18***	*sustained*	.07*	*sustained*	.30***	*sustained*
H2a (+)	.73***	*sustained*	.74***	*sustained*	.73***	*sustained*
H2b (+)	.18***	*sustained*	.19***	*sustained*	.16***	*sustained*
H3a (+)	ns	*rejected*	ns	*rejected*	.09*	*sustained*
H3b (+)	.28***	*sustained*	.24***	*sustained*	.28***	*sustained*
H3c (+)	.38***	*sustained*	.39***	*sustained*	.42***	*sustained*
H4 (+)	.82***	*sustained*	.84***	*sustained*	.78***	*sustained*
H5 (+)	.10***	*sustained*	.07*	*sustained*	.18***	*sustained*
MEDIATIONS ANALYSIS*						
Mediation expected	INDIRECT EFFECT	Mediation detected	DIRECT/INDIRECT IMPACT	Mediation detected	DIRECT/INDIRECT IMPACT	Mediation detected
AML->AMe->CHI	.522(***)	complementary	.515(***)	complementary	.517(***)	complementary
AML->nAMe->CHI	.032(***)	complementary	.013(.059)	no mediation	.046(***)	complementary
AMe->CHI->AIa	.435(***)	full mediation	.441(***)	full mediation	.477(***)	complementary
nAMe->CHI->AIa	.071(***)	complementary	.077(***)	complementary	.068(***)	complementary
CHI->AIa->OI	.037(***)	complementary	.02(*)	complementary	.069(***)	complementary

Note: ML – maximum likelihood, standardized results; *p< 0.05, **p<0.01, ***p<0.001; ns- not significant result; mediation effects were measured by 2000 bootstrap samples, 90 confidence intervals, two-tailed significance effects

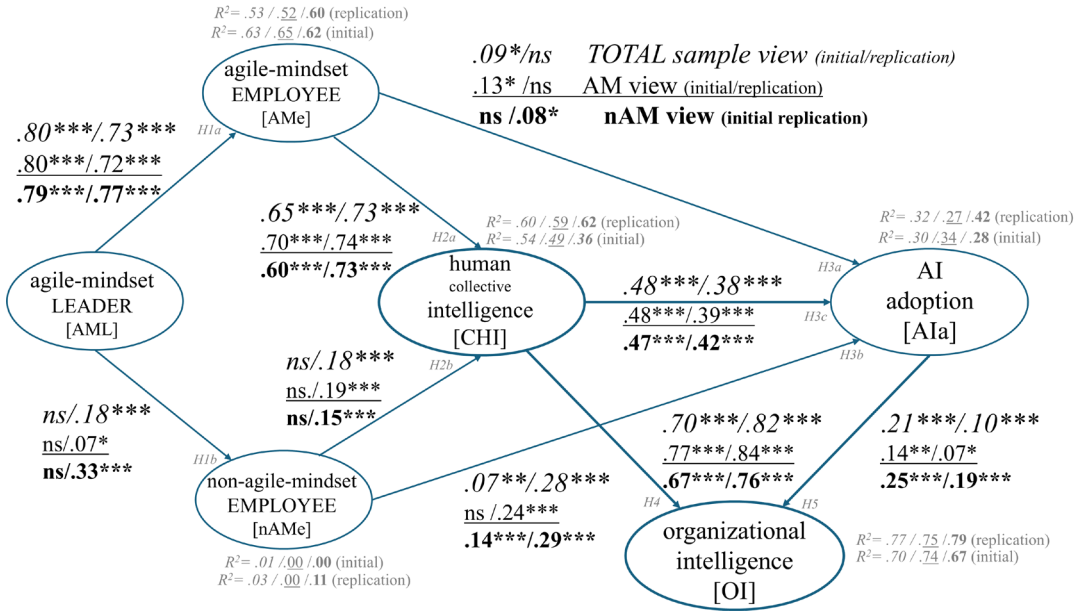


Figure 1: Results

Note: AML- agile minded leader; AME-agile minded employee; nAMe – non-agile minded employee; CHI – collective human intelligence; AIa – artificial intelligence adoption; OI- organizational intelligence ML – maximum likelihood, standardized results; *p< 0.05, **p<0.01, ***p<0.001; ns- not significant result

INITIAL STUDY

a) TOTAL SAMPLE *n=1871; χ^2=2084.47(518) Cmin/df=4.02 CFI=.963 TLI=.966 RMSEA=.040(.038-.042)*

b) AGILE MINDSETS view *n=932; χ^2=1369.58(518) Cmin/df=2.64 CFI=.965 TLI=.962 RMSEA=.042(.039-.045)*

c) non-AGILE MINDSETS view *n=939; χ^2=1564.48(518) Cmin/df=3.02 CFI=.954 TLI=.950 RMSEA=.046(.044-.049)*

REPLICATION STUDY

a) TOTAL SAMPLE *n=2000; χ^2=3198.4(964) Cmin/df=3.31 CFI=.970 TLI=.968 RMSEA=.034(.033-.035)*

b) AGILE MINDSETS view *n=1000; χ^2=2703.47(1013) Cmin/df=2.66 CFI=.956 TLI=.953 RMSEA=.041(.039-.043)*

c) non-AGILE MINDSETS view *n=1000; χ^2=2666.43(1013) Cmin/df=2.63 CFI=.957 TLI=.954 RMSEA=.040(.039-.042)*

5. Discussion

The given empirical models showed that leaders with an agile mindset serve as brokers of organizational intelligence. Their increasing positive influence over time on agile and non-agile mindset staff and collective intelligence leads us to conclude that agile mindset leaders are the leaders of the future. What warrants a more in-depth discussion is their impact on non-agile-minded staff changing over time. From the initial study results perspective, agile mindset leaders may be experienced as stressors by employees who have a stronger preference for stability and predictability, and such a collision of mindsets can cause serious tension, which Kucharska et al. (2026a) named an 'agile mindset leader paradox.' Thus, the initial study's results confirm its existence and justify the need to find a way to mitigate it. However, the replication shows that the positive impact of the agile mindset leader on both agile and non-agile staff increases over time, which we see as confirmation of the agile mindset leader's exceptional abilities, as stressed earlier by these authors.

The other findings related to non-agile staff also require comment. Specifically, the impact of nAMe on CHI, which was initially not significant, became positive over time. Taken together, these patterns suggest that, in organizational contexts strongly oriented toward rapid change and intelligence development, employees who prefer stability and predictability may experience a weaker fit with prevailing norms and practices, which can limit (or complicate) collective intelligence building, but replication results suggest they can adopt. In such a context, the collective intelligence-building effort seems even more pressing but, at the same time, more challenging than expected at the theoretical assumption stage. This is because, going back to the 'agile mindset leader paradox' (Kucharska et al., 2026a) essence, employees who prefer stability and predictability are often in the majority in organizations, and, if they feel excluded, may be less willing to engage with or support change initiatives to protect their sense of psychological safety and well-being – both of which support performance (Aubouin-Bonnaventure et al., 2024). Moreover, Ambituuni et al. (2021) suggested that some people are naturally more comfortable with agile work practices, whereas others may be less inclined toward such practices. This suggests that agile and non-agile employees may benefit from differentiated managerial approaches and virtuous organizational practices to mitigate tension, which is critical for building collective intelligence. Kucharska et al. (2026a) suggested that an AML leader can be an antidote to this, and the given results seem to confirm it.

Importantly, employees who prefer stability and predictability can also offer complementary strengths that organizations may need alongside agility. Individuals with a stronger stability orientation may play essential roles in maintaining organizational memory, ensuring operational reliability, and providing the consistency needed for long-term performance. Thus, leading employees wisely requires mastery of ambidexterity – agile mindset leaders master it (Kucharska et al., 2026a, 2026b; Lewis et al., 2014). Nevertheless, further qualitative studies are needed to better understand relations between agile and non-agile staff and to propose more detailed solutions.

5.1 Limitations and Implications

Trust, critical thinking skills, company culture type: adhocracy, market, clan, hierarchy (Cameron and Freeman, 1991), knowledge, learning, and collaboration functional cultures, and the overall technological advancement of the organizations are elements included in Kucharska's (2025) organizational intelligence building framework,

and those factors are omitted in this study. So, the observed positive change in the impact of non-agile staff on CHI over time may actually be due to another overlooked factor. We do not know what it is, and it is worth further clarification. Further studies would provide more insight into the relationships examined. Additionally, the study samples are drawn from the IT sector and also include a mix of other sectors. However, more specific sectoral research would help us better understand the relationship between leaders' agility and organizational intelligence. Agility competencies are clearly most developed in IT. However, this approach is increasingly applied across other sectors.

The study resulted in the following practical conclusions:

- Leaders with an agile mindset have a strong positive impact on other agile mindset staff and help build collective intelligence within organizations.
- The significant positive impact on agile and non-agile mindset staff and on collective intelligence leads us to conclude that agile mindset leaders are leaders of the future; therefore, organizations should search for and employ agile mindset leaders.
- The "agile mindset leader paradox" highlights that non-agile staff, often being the majority, can feel excluded and may resist changes to protect their psychological well-being, which can hinder organizational development. So, leaders should pay special attention to securing smooth cooperation between agile and non-agile staff.
- To address this, organizations should:
- *Recognize that agile and non-agile staff require different management approaches and organizational practices.*
- *Develop strategies to mitigate tensions between these groups, as this is crucial for building collective intelligence.*
- *Value the strengths of non-agile staff, such as their roles in maintaining stability, organizational memory, and operational reliability.*
- *Aim for managerial ambidexterity—balancing agility with stability—to lead all employees efficiently.*

5.2 Conclusion

This study shows that in a business world increasingly driven by artificial intelligence, an agile mindset leader can be important in helping individuals and organizations adapt effectively to AI-enabled work. The research emphasizes that leaders with such a mindset play a vital role in nurturing organizational intelligence (augmentative). Moreover, they can implement new managerial approaches and adopt best practices to support both employees who readily embrace change and those who prefer greater stability and predictability, while respecting the strengths and trade-offs of both orientations. An agile mindset leader's paradox, rooted in the collision of mindsets, is one of the key challenges to address in an AI-driven world, and agile mindset leaders are best suited to manage it.

Supplementary materials and dataset access: https://doi.org/10.34808/vmmm-xe55

Funder: National Science Center (NCN), Poland **NCN UMO-2022/47/B/HS4/00597**

Ethics Declaration: Gdansk University of Technology Ethics Committee approval: KEBNzUCz 01_2026.

AI usage declaration: Gemini Notebook (reference checking), Grammarly (language)

References:

Akkaya, B. and Sever, E. (2022), "Agile leadership and organization performance in the perspective of VUCA", *Post-Pandemic Talent Management Models in Knowledge Organizations*. https://doi.org/10.4018/978-1-6684-3894-7.ch010

Ambituuni, A., Azizsafaei, F. and Keegan, A. (2021), "HRM operational models and practices to enable strategic agility in PBOs: Managing paradoxical tensions", *Journal of Business Research*, Vol. 133, pp. 170-182. https://doi.org/10.1016/j.jbusres.2021.04.048

Araujo, T., Helberger, N., Kruikemeier, S. and De Vreese, C.H. (2020), "In AI we trust? Perceptions about automated decision-making by artificial intelligence", *AI & Society*, Vol. 35 No. 3. https://doi.org/10.1007/s00146-019-00931-w

Ardichvili, A. (2022), "The impact of artificial intelligence on expertise development: Implications for HRD", *Advances in Developing Human Resources*, Vol. 24 No. 2, pp. 78–98. https://doi.org/10.1177/15234223221077304

Atolagbe-Olaoye, A. (2025), "Collaborative information behavior and human-ai context in group work: The perspectives of agile practitioners", *International Journal of Library and Information Services* (IJLIS), Vol. 13 No.1, pp. 1-16. https://doi.org/10.4018/IJLIS.366590

Aubouin-Bonnaventure, J., Chevalier, S., Lahiani, F.J. and Fouquereau, E. (2024), "Well-being and performance at work: a new approach favourable to the optimal functioning of workers through virtuous organisational practices", *International Journal of Organizational Analysis*, Vol. 32 No. 4, pp. 608-623. https://doi.org/10.1108/IJOA-01-2023-3584

Bablo, J., Marcinkowski, B. and Przybylek, A. (2023), "Overcoming challenges of virtual Scrum teams: Lessons learned through an action research study", *Agile Processes in Software Engineering and Extreme Programming. XP 2023. Lecture Notes in Business Information Processing*. Springer, Cham. https://doi.org/10.1007/978-3-031-33976-9_3

Badura, K.L., Galvin, B.M. and Lee, M.Y. (2022), "Leadership emergence: An integrative review", Journal of Applied Psychology, Vol. 107 No. 11, 2069-2100. https://doi.org/10.1037/apl0000997

Bock, T. and von der Oelsnitz, D. (2025), "Leadership-competences in the era of artificial intelligence – a structured review", *Strategy and Leadership*, Vol. 53 No. 3, pp. 235-255. https://doi.org/10.1108/SL-09-2024-0100

Burton, J.W., Stein, M.K. and Jensen, T.B. (2020), "A systematic review of algorithm aversion in augmented decision making", *Journal of Behavioral Decision Making*, Vol. *33* No. 2, pp. 220-239. https://doi.org/10.1002/bdm.2155

Byrne, B.M. (2016), *Structural Equation Modeling with Amos*, Routledge.

Cameron, K.S. and Freeman, S.J. (1991), "Cultural congruence, strength and type: relationships to effectiveness", *Research in Organizational Change and Development*, Vol. 5, pp. 23-58.

Chew, Y.C. and Mohamed Zainal, S.R. (2024), "A sustainable collaborative talent management through collaborative intelligence mindset theory: A systematic review," *Sage Open*, Vol. *14 No.* 2, 21582440241261851.

Cui, H., and Yasseri, T. (2024), "AI-enhanced collective intelligence", *Patterns*, Vol. *5* No. 11. https://doi.org/10.1016/j.patter.2024.101074

De Freitas, J., Agarwal, S., Schmitt, B. and Haslam, N. (2023), "Psychological factors underlying attitudes toward AI tools", *Nature Human Behaviour*, Vol. *7* No. 11, pp. 1845-1854. https://doi.org/10.1038/s41562-023-01734-2

Del Giudice, M., Scuotto, V., Ballestra, L.V. and Pironti, M. (2023), "Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines", in *Artificial Intelligence and International HRM* (pp. 33-59). Routledge.

Eilers, K., Peters, C. and Leimeister, J.M. (2022), "Why the agile mindset matters", *Technological Forecasting and Social Change*, Vol. 179, 121650. https://doi.org/10.1016/j.techfore.2022.121650

Falandays, J.B., Kaaronen, R.O., Moser, C., Rorot, W., Tan, J., Varma, V., ... and Youngblood, M. (2023), "All intelligence is collective intelligence," Journal of Multiscale Neuroscience, Vol. 2 No. 1, pp. 169-191. https://doi.org/10.56280/1564736810

Freese, J. and Peterson, D. (2017), "Replication in social science", *Annual Review of Sociology*, Vol. 43, pp. 147-165. https://doi.org/10.1146/annurev-soc-060116-053450

French, A.M. and Shim, J.P. (2025), "From artificial intelligence to augmented intelligence: a shift in perspective, application, and conceptualization of AI", *Information Systems Frontiers*, Vol. 27 No. 4, pp. 1345-1366. https://doi.org/10.1007/s10796-024-10562-2

Hagemann, V. and Kluge, A. (2017), "Complex problem solving in teams: the impact of collective orientation on team process demands", *Frontiers in Psychology*, Vol. 8, 1730. https://doi.org/10.3389/fpsyg.2017.01730

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling", *Journal of the Academy of Marketing Science*, Vol. *43 No.* 1, pp. 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hurwitz, J., Morris, H., Sidner, C. and Kirsch, D. (2019), *Augmented intelligence: the business power of human–machine collaboration*. Auerbach Publications.

Ishowo-Oloko, F., Bonnefon, J.F., Soroye, Z., Crandall, J., Rahwan, I. and Rahwan, T. (2019), "Behavioural evidence for a transparency–efficiency tradeoff in human–machine cooperation", *Nature Machine Intelligence*, Vol. 1 No. 11, 517-521. https://doi.org/10.1038/s42256-019-0113-5

Jarrahi, M.H., Askay, D., Eshraghi, A., and Smith, P. (2023), "Artificial intelligence and knowledge management: A partnership between human and AI", *Business Horizons*, Vol. 66 No. 1, pp. 87–99. https://doi.org/10.1016/j.bushor.2022.03.002

Kucharska, W. (2025), *Organizational Intelligence for Change Adaptability: The Knowledge, Learning, and Collaboration Cultures Approach.* Routledge.

Kucharska, W. (2026a), "How do the internal dynamics of agile and non-agile mindset employees, influenced by agile culture, impact organizational change management?", *Journal of Organizational Change Management*, Vol. 39 No. 8, pp. 216-232. https://doi.org/10.1108/JOCM-12-2025-1093

Kucharska, W. (2026b). Agile mindset and collective human and artificial intelligence [Data set]. Gdańsk University of Technology. https://doi.org/10.34808/vmmm-xe55

Kucharska, W. and Kucharski, M. (2026), "Agile culture, collective human intelligence and AI adoption: Gender and sectoral perspectives on augmented intelligence in Europe", *International Journal of Information Management Data Insights*, Vol. 6 No. 1, Article 100406. https://doi.org/10.1016/j.jjimei.2026.100406

Kucharska, W., Balcerowski, T., Kucharski, M., Jussila, J. and Laanti, M. (2026a), "Why does the agile leader mindset matter the most? The agile-mindset leadership paradox", *Heliyon*, Vol. 12 No. 4, Article 44638. https://doi.org/10.1016/j.heliyon.2026.e44638

Kucharska, W., Kucharski, M. and Jussila, J. (2026b), "When agile and non-agile mindsets collide: mastering paradox management to navigate the VUCA", *Strategy & Leadership*. https://doi.org/10.1108/SL-04-2026-0201

Kucharska, W., Kucharski, M. and Jussila, J. (2026c), "Agile-minded leadership as agile-cultural practice. Leaders' and followers' views per gender", *Gender in Management*. https://doi.org/10.1108/GM-05-2025-0253

Kucharski, M., Kucharska, W. and Jussila, J. (2025), "Impact of Agile Software Development Team Leader's Mindset on Dynamic Capabilities for Achieving Organizational Agility", in Proceedings of the 33rd International Conference on Information Systems Development *(ISD 2025)*, Belgrade, Serbia.

Lehmann-Willenbrock, N. (2024), "Dynamic interpersonal processes at work: Taking social interactions seriously," *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 12.

Leimeister, J.M. (2010), "Collective intelligence", *Business Information Systems Engineering*, Vol. 24, pp. 245–248. https://doi.org/10.1007/s12599-010-0114-8

Lewis, M.W., Andriopoulos, C. and Smith, W.K. (2014), "Paradoxical leadership to enable strategic agility", *California Management Review*, Vol. *56* No. 3, pp. 58-77. https://doi.org/10.1525/cmr.2014.56.3.58

Luthia, M. (2023), "Agile leadership in managing human capital in Industry 4.0", *Agile Leadership for Industry 40: An Indispensable Approach for the Digital Era*, pp. 79–95.

Mehta, P., Chakraborty, D., Rana, N.P., Mishra, A., Khorana, S. and Kooli, K. (2025), "AI-driven competitive advantage: the role of personality traits and organizational culture in key account management", *Journal of Business & Industrial Marketing*, Vol. 40 No. 2, pp. 543–569. https://doi.org/10.1108/JBIM-03-2024-0205

Neumann, M., Bischof, L., Hinz, N.E. … and Przybyłek, A. (2026), "Between Policy and Practice: GenAI Adoption in Agile Software Development Teams", in: Goldman, A. et al. Agile Processes in Software Engineering and Extreme Programming. XP 2026. Lecture Notes in Business Information Processing, vol 578. Springer, Cham. https://doi.org/10.1007/978-3-032-22375-3_18.

Nold, H. and Michel, L. (2016), "The performance triangle: a model for corporate agility", *Leadership and Organization Development Journal*, Vol. 37 No. 3, pp. 341-356. https://doi.org/10.1108/LODJ-07-2014-0123

Ozkan, N., Eilers, K. and Gök, M.S. (2023), "Back to the essential: A literature-based review on agile mindset", in *Proceedings of the 18th Conference on Computer Science and Intelligence Systems*, Vol. 35, pp. 201–211. https://doi.org/10.15439/2023F6360

Riedl, R. (2022), "Is trust in artificial intelligence systems related to user personality? Review of empirical evidence and future research directions", *Electronic Markets*, Vol. 32 No. 4, pp. 2021-2051. https://doi.org/10.1007/s12525-022-00594-4

Russell, S. and Norvig, P. (2021), *Artificial Intelligence: A modern approach*. Pearson.

Secundo, G., Dumay, J., Schiuma, G. and Passiante, G. (2016), "Managing intellectual capital through a collective intelligence approach: An integrated framework for universities", *Journal of Intellectual Capital*, Vol. 17 No. 2, pp. 298–319. https://doi.org/10.1108/JIC-05-2015-0046

Sheikh, H., Prins, C. and Schrijvers, E. (2023), "Artificial Intelligence: Definition and Background", in: *Mission AI. Research for Policy*, Springer, Cham. https://doi.org/10.1007/978-3-031-21448-6_2

Sundar, S.S. and Kim, J. (2019). *Machine heuristic: When we trust computers more than humans with our personal information. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, Paper no. 538, pp. 1–9. https://doi.org/10.1145/3290605.3300768

Tominc, P., Oreški, D. and Rožman, M. (2023), "Artificial Intelligence and Agility-Based Model for Successful Project Implementation and Company Competitiveness," *Information*, Vol. 14 No. 6. https://doi.org/10.3390/info14060337

Udin, U. (2025), "Agile leadership and employee outcomes: A bibliometric analysis for future research agenda", *Human Systems Management*, Vol. 44 No. 2, pp. 237-248. https://doi.org/10.3233/HSM-240093

Uhl-Bien, M., Riggio, R.E., Lowe, K.B. and Carsten, M.K. (2014), "Followership theory: A review and research agenda", *Leadership Quarterly*, Vol. 25, pp. 83–104. https://doi.org/10.1016/j.leaqua.2013.11.007

Volberda, H., Khanagha, S., Baden-Fuller, C., Mihalache, O.R. and Birkinshaw, J. (2021), "Strategizing in a digital world: Overcoming cognitive barriers, reconfiguring routines and introducing new organizational forms", *Long Range Planning*, Vol. 54 No. 5, 102110. https://doi.org/10.1016/j.lrp.2021.102110

Winter, S.G. (2003), "Understanding dynamic capabilities", *Strategic Management Journal,* Vol. 24, No. 10, pp. 991-995. https://doi.org/10.1002/smj.318

Zaidi, S.Y.A., Aslam, M.F., Mahmood, F., Ahmad, B. and Raza, S.B. (2025), "How Will Artificial Intelligence (AI) Evolve Organizational Leadership? Understanding the Perspectives of Technopreneurs", *Global Business and Organizational Excellence*, Vol. 44 No. 3, pp. 66-83. https://doi.org/10.1002/joe.22275

Zirar, A., Ali, S.I. and Islam, N. (2023), "Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda", *Technovation*, Vol. 124, Article 102747. https://doi.org/10.1016/j.technovation.2023.102747