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# Educating Tomorrow's Leaders: Human-AI Collaboration Patterns for Professional Military Education

**Abstract:** We educate tomorrow's military leaders for operations involving tools we cannot access, doctrine not yet codified, and threats evolving faster than curricula. This article presents empirical findings from systematic exploration of human-AI collaboration in military education involving thirteen Baltic-Nordic defence organisations. Through AI-assisted facilitated workshops, three empirically grounded patterns of human-AI collaboration emerged alongside a command-control distinction derived from practitioner wisdom. The probe-sense-respond methodology enabled pattern discovery where traditional planning approaches fail. Findings offer transferable frameworks for professional military education institutions navigating AI integration while maintaining human primacy in command authority. Regional collaboration achieved what no single institution could accomplish independently.

**Keywords:** Human-AI Collaboration; Professional Military Education; Complexity Theory; Command-and-Control; Baltic Defence Cooperation

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## Introduction

We educate tomorrow's leaders to fight with tools we cannot show them, in ways we have not mastered, against threats we do not fully understand. This represents professional military education's defining challenge in an era where artificial intelligence has moved from strategic planning documents to operational reality. The North Atlantic Treaty Organisation (NATO)'s Artificial Intelligence (AI) Strategy (NATO, 2021) marked a strategic inflection point that recognised AI's military potential, while committing to systematic integration across Alliance operations. The 2022 Strategic Concept (NATO, 2022) reinforced this trajectory, emphasising AI as essential to maintaining technological edge in an era of strategic competition. By 2024, the question shifted from whether to integrate AI to how quickly institutions could develop capabilities and prepare leaders for AI-enabled warfare.

This acceleration matters profoundly for professional military education: the timeline for institutional adaptation has collapsed from decades to years, even as regional security pressures demand immediate capability development. Baltic and Nordic defence institutions operate in environments characterised by AI-accelerated volatility, uncertainty, complexity, and ambiguity (VUCA) where strategic urgency meets institutional complexity, where operational deployment outpaces organisational preparation, and where traditional approaches to technology integration prove inadequate for the challenge we face. This introduces a paradox for professional military education (PME).

This paradox manifests across three dimensions. Classification: operational AI systems remain inaccessible for educational use. Cost: equivalent capabilities exceed institutional budgets. Evolution: AI advances monthly while curricula update annually. We cannot train on classified systems, afford operational equivalents, or keep pace with technological change. This forces a fundamental shift from teaching specific systems to developing adaptive competencies for unknown AI capabilities.

Recognising AI integration as a complex challenge requiring systematic exploration rather than traditional planning, Baltic Defence College convened thirteen organisations in February 2025 – PME institutions, ministries of defence, and NATO headquarters elements from Baltic and Nordic countries. Through three structured sessions employing question-storming before solution-finding, practitioners explored rather than prescribed: identifying AI threats, examining human-AI decision-making patterns, and developing institutional requirements. This probe-sense-respond approach enabled wisdom emergence from those confronting these challenges daily.

This methodology reflects complexity theory's core insight: in complex domains, cause-effect relationships become clear only retrospectively, and patterns emerge through experimentation rather than analysis. Question-storming before solution-finding created conditions where practitioners could surface assumptions, articulate tacit knowledge, and recognise patterns in their own experience. The approach respected that those navigating AI integration challenges daily possess essential wisdom academic literature has yet to capture – validating Snowden's observation that in complex domains, practice often precedes theory. Workshop exploration necessarily engaged questions at the intersection of human-AI collaboration research (how do humans develop appropriate trust and maintain accountability when partnering with AI?) and institutional transformation (how do PME organisations integrate AI systematically when individual faculty adoption differs fundamentally from coordinated change across curricula, faculty development, and organisational capabilities?).

This article makes three interconnected contributions to scholarship and practice in professional military education and human-AI collaboration. Primarily, it presents three empirically grounded patterns of effective human-AI collaboration illustrated through operational examples from Ukraine and Israel. These patterns, Strategic Sense-Making (AI recognising patterns across sources while humans provide contextual judgment and meaning); Ethical Responsibility (AI rapidly generating options while humans conduct ethical and strategic evaluation); and Adaptive Command (humans setting objectives and direction while AI performs environmental sensing), offer PME institutions concrete guidance that transcends specific technologies. The accompanying command-control framework distinguishing essentially human functions from those amenable to AI augmentation provides additional clarity for doctrine developers and institutional leaders (see Table 1).

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| **KEY FINDINGS AT A GLANCE** |
| **Three Patterns of Human-AI Collaboration:** |
| • Pattern 1 - Strategic Sense-Making:<br>AI identifies patterns in data; humans judge operational significance |
| • Pattern 2 - Ethical Responsibility:<br>AI generates options rapidly; humans evaluate ethical implications |
| • Pattern 3 – Adaptive Command:<br>Humans set objectives; AI monitors environmental changes |
| **Command-Control Framework:** |
| • Command remains essentially human (leadership, authority, responsibility) |
| • AI augments control functions (information processing, option generation) |
| **Operational Evidence:** |
| • Ukrainian operations demonstrate successful pattern implementation |
| • Israeli cases illustrate risks if patterns break down |
| **Implementation Guidance:** |
| • Seven focal points for PME transformation identified |
| • Eight obstacles with emerging mitigation strategies documented |
| • Regional cooperation accelerates institutional learning |

*Table 1: Key Findings at a Glance*

Second, it documents a methodology for navigating AI integration as a complex challenge requiring approaches fundamentally different from traditional technology adoption. The three-session workshop structure, question-storming technique, and facilitation approach that enabled pattern emergence represent transferable practices applicable beyond AI integration to any complex challenge where best practices remain emergent.

Third, this work contributes to complexity theory's application in educational contexts by demonstrating how probe-sense-respond principles can be operationalised through concrete facilitation techniques. While complexity theory has been applied extensively to strategic planning and crisis response, its application to systematic facilitation of practitioner learning about emerging technologies remains underexplored. The workshop methodology validates that enabling emergence rather than constraining solutions yields actionable frameworks when facing genuine uncertainty.

These contributions position within a broader research trajectory. An earlier article established digital transformation as strategic imperative for professional military education and outlined a human-centric approach to AI integration. This article provides empirical grounding for that approach through documented practitioner exploration. Future work will examine how these collaboration patterns and complexity insights inform the design of AI systems themselves to enhance rather than replace human judgment in complex operational environments.

## Article Structure

This article proceeds through the following sections: The literature review examines complexity theory, human-AI collaboration research, and PME technology integration bodies of literature to identify where each reveals critical gaps our workshop findings address. After which, the methodology section documents the workshop methodology and implementation, demonstrating how probe-sense-respond principles translated into concrete facilitation practice. The findings portion presents the three collaboration patterns and command-control framework with supporting evidence. Next, the analysis section analyses why this approach worked through complexity theory's explanatory lens. The implications and implementation section explores implications for operational practice, leadership development, and institutional change. Finally, the conclusion synthesises contributions and issues a call for collaborative action on this shared challenge. Practitioners seeking immediate command-control framework implementation guidance should focus on the Findings and Implications portions; researchers interested in the methodological innovation will find the Methodology section, Complexity Theory Analysis section, and Appendix A most relevant.

## Literature Review and Theoretical Framework

Navigating AI integration in professional military education requires drawing on three distinct but interconnected bodies of scholarship. Complexity theory provides the conceptual foundation for understanding why traditional technology adoption approaches prove inadequate and what methodologies work when cause-effect relationships remain unclear. Human-AI collaboration research reveals the competencies that matter for effective partnership between humans and AI systems, while exposing gaps in how institutions prepare leaders for these partnerships. Professional military education scholarship offers frameworks for critical thinking and regional cooperation models yet lacks systematic methodologies for technology integration under genuine uncertainty. This section examines each body of literature to identify the specific gaps the February 2025 workshop addressed.

### *Complexity Theory and the Cynefin Framework*

Artificial intelligence integration in professional military education represents a fundamentally different challenge from traditional technology adoption. Snowden's Cynefin framework provides essential conceptual clarity through its categorisation of decision-making contexts: clear, complicated, complex, chaotic, and confused domains distinguished by their cause-effect relationships (Snowden and Boone, 2007). The complex domain proves particularly relevant for AI integration challenges, where cause-effect relationships exist but remain discernible only in retrospect, solutions emerge through experimentation rather than planning and enabling constraints matter more than governing rules (Kurtz and Snowden, 2003).

Complex domains require probe-sense-respond methodology: conduct safe-to-fail experiments, identify emerging patterns, and amplify productive approaches while dampening unproductive ones (Snowden and Boone, 2007). NATO's Sentinel Vanguard 2044 and UK Defence exercises validate safe-to-fail environments for complexity exploration (NATO ACT, 2024; Ministry of Defence, UK, 2023).

Professional military education institutions increasingly apply complexity frameworks to curriculum design. The U.S. Command and General Staff College implemented Cynefin-based reforms teaching officers to distinguish complex from complicated challenges and apply appropriate methodologies (McConnell, Kaluzny, and Whitaker, 2024), while Baltic Defence College integrated complexity thinking into defence management education (Toci, 2024).

The literature gap persists: how do facilitators operationalise probe-sense-respond principles when the subject matter itself – AI integration – represents a moving target? What conditions enable diverse practitioners to collaboratively develop frameworks when expert knowledge proves insufficient (Kurtz and Snowden, 2003)? Recent PME initiatives demonstrate growing complexity awareness (McConnell, Kaluzny, and Whitaker, 2024; Toci, 2024) yet lack systematic methodology for facilitating collective exploration of emerging technologies. The workshop methodology documented in this article addresses this gap, demonstrating how probe-sense-respond principles translate into concrete facilitation techniques when the subject matter itself remains emergent.

### *Human-AI Collaboration in Military Contexts*

The challenge of human-AI collaboration in military operations centres on what researchers term the trust-reliance-accountability nexus: how operators develop appropriate trust in AI systems, calibrate reliance to match capability and context, and maintain accountability for decisions with life-and-death consequences (Lee and See, 2004; Hancock et al., 2011). Lee and See's framework for appropriate reliance demonstrated that trust guides dependence on automation when complexity makes complete understanding impractical, an insight profoundly relevant as AI systems grow more sophisticated and opaque (Lee and See, 2004).

Recent developments reveal critical extensions to this foundation. Trust calibration in military contexts exhibits non-linear dynamics: trust builds gradually through consistent performance but collapses rapidly after failures, with early malfunctions having disproportionately larger negative impacts (Wischnewski et al., 2023). Military environments introduce adversarial dimensions largely absent from civilian research – opponents actively exploit automation vulnerabilities, requiring trust frameworks accounting for potential system compromise. Additionally, AI compression of decision timelines from hours to minutes creates what researchers term the "experience bypass problem": when AI accelerates decision cycles, how do commanders maintain the pattern recognition expertise that normally develops through accumulated operational experience (Smith, 2025)?

Mollick's concept of co-intelligence offers productive framing, emphasising complementary capabilities where AI processes vast information at speeds humans cannot match while humans apply contextual judgment, ethical reasoning, and strategic thinking algorithms cannot replicate (Mollick, 2024). Daugherty and Wilson's research reinforces this perspective, demonstrating highest performance emerges when humans and AI each contribute distinctive strengths rather than AI simply automating human tasks (Daugherty and Wilson, 2018). NATO doctrine increasingly operationalises this through meaningful human control principles: humans maintain command authority – leadership, decision-making, responsibility – while AI enables control functions including communication, information processing, and coordination (Van Rijn et al., 2025).

However, a critical implementation gap persists: existing research addresses operator trust in specific AI systems (Hancock et al., 2011; Lee and See, 2004) or task-level human-AI collaboration (Mollick, 2024), yet PME institutions face fundamentally different challenges. Professional military education must develop institutional frameworks preparing leaders to work effectively with AI capabilities they have never encountered, in operational contexts not yet fully defined, applying doctrine still under development (Smith, 2025; Biggs, 2025). The collaboration patterns emerging from the February 2025 workshop address this gap by providing competency-level guidance that transcends specific technologies – preparing leaders institutionally for AI capabilities they cannot yet access individually.

*Professional Military Education and Technology Integration*

Professional military education institutions face what might be termed the implementation gap: broad recognition that AI literacy matters for military leadership coexists with limited systematic guidance on institutional integration across curricula, faculty development, and organisational capabilities. Fischer and Gerras's foundational research establishes that effective military leaders require metacognitive skills – recognising when situations exceed expertise, questioning assumptions, considering alternatives, and evaluating evidence quality – competencies proving particularly crucial when algorithms process information at speeds exceeding human verification capacity (Fischer and Gerras, 2008; Gerras, 2006). Parenteau's analysis demonstrates that military officers benefit from structured frameworks for challenging assumptions when facing novel operational challenges, precisely the context AI integration represents (Parenteau, 2021).

Regional collaboration models offer promising approaches. Nordic-Baltic defence cooperation demonstrates how smaller PME institutions achieve capabilities impossible independently through systematic knowledge sharing and coordinated experimentation. Swedish Defence University research exemplifies this collaborative approach: Bovet's analysis of decision advantages in military targeting found that AI-enabled systems enhance speed, precision, and efficiency while requiring careful human oversight of ethical boundaries (Bovet, 2025), while Comprehensive Shield 2025 exercises validated that AI decision support systems generate multiple courses of action three times faster than traditional planning while human commanders maintain evaluative authority over strategic choices (Bovet et al., 2025). The

Nordic Council of Ministers' 2025 establishment of the Nordic-Baltic AI Centre with €4 million funding creates infrastructure for such collaborative research, shared curriculum development, and joint capability testing across national boundaries. Estonia's digital-first approach to defence systems as articulated in its Defence Artificial Intelligence Strategy and Finland's defence research emphasis on drones, sensor technology, and international cooperation provide complementary models for technology integration at different scales (Republic of Estonia Ministry of Defence, 2024; Finnish Defence Forces, 2025).

However, educational AI research focuses predominantly on student learning outcomes – tutoring system effectiveness, automated assessment accuracy, pedagogical technology adoption – rather than institutional capability development: how PME organisations systematically integrate AI across curriculum design, faculty development, research functions, and operational support simultaneously. This distinction proves critical. Individual faculty adopting AI tools for lesson planning differs fundamentally from institutional transformation where AI integration spans multiple organisational functions, requires coordinated change management, and necessitates cultural adaptation alongside technical implementation (Combes, 2025). The frameworks emerging from the February 2025 workshop address this institutional-level challenge, identifying both where capabilities must develop and what barriers predictably emerge during systematic AI integration in professional military education contexts.

These three bodies of literature converge on a shared insight: AI integration in military education represents a complex challenge requiring approaches fundamentally different from traditional technology adoption. Complexity theory explains why traditional planning fails and probe-sense-respond succeeds. Human-AI collaboration research reveals what competencies matter but shows gaps in institutional preparation approaches. PME scholarship identifies critical thinking frameworks and regional collaboration models but lacks systematic methodologies for technology integration under genuine uncertainty.

The workshop methodology and findings presented in subsequent sections address these gaps by demonstrating how complexity principles can be operationalised through systematic facilitation, how practitioner wisdom can generate transferable collaboration patterns, and how institutional frameworks can emerge from collective exploration when best practices do not yet exist. The literature establishes that the challenge we face is real, substantial, and inadequately addressed; the workshop demonstrates that systematic approaches to navigating this complexity yield actionable results. Critically, the workshop demonstrated that practitioners navigating these challenges daily possess insights that academic literature has yet to capture – validating Snowden’s observation that in complex domains, practice often precedes theory.

## Methodology and Workshop Implementation

How do military education institutions systematically navigate AI integration when traditional planning approaches prove inadequate? Established technology adoption frameworks function well for complicated problems where cause-effect relationships can be determined through analysis (Snowden, 2005). AI integration represents a different category of challenge where relationships between actions and outcomes emerge only through exploration and experimentation (Stacey, 2011). The February 2025 workshop at Baltic Defence College operationalised complexity-informed methodology through systematic facilitation, drawing on action research traditions (Reason and Bradbury, 2008), soft systems methodology (Checkland and Scholes, 1990), and AI augmentation reflecting human-centred design principles (Shneiderman, 2022). This section documents both design rationale and implementation, demonstrating how probe-sense-respond principles translated into concrete facilitation practice.

*Design Philosophy and Context*

The workshop convened at Baltic Defence College on 18-19 February 2025, in Tartu, Estonia – the "City of Good Thoughts" during the city's tenure as European Capital of Culture. The timing carried strategic weight: NATO's AI strategy was moving from policy documents to operational implementation, regional tensions demanded accelerated capability development, and PME institutions faced mounting pressure to prepare leaders for AI-enabled warfare they might not fully understand themselves.

BALTDEFCOL positioned the workshop as a stepping stone in its broader digital transformation journey, building on progress with AI tool integration, staff development initiatives, and establishment of clear use policies aligned with NATO's responsible AI principles. The opening session framed the challenge: preparing students to succeed with NATO AI concepts and systems not yet fully implemented, or when deployed, inaccessible to educational institutions for security and budgetary reasons.

The two-day format alternated between expert presentations establishing shared context and collaborative working sessions enabling pattern identification (Kaner et al., 2014). Operating under Chatham House Rule enabled frank discussion of institutional challenges without attribution concerns. We employed AI augmentation throughout, using ALEX (Admired Leadership's Claude-based assistant) to refine facilitation questions and test framing effects during preparation (Gregersen, 2018). During sessions, AI-assisted synthesis enhanced pattern recognition across participant contributions without imposing algorithmic categorisation, reflecting emerging best practices in human-AI interaction for knowledge work (Amershi et al., 2019). This reflexive approach – where methodology becomes part of findings – demonstrated the collaboration patterns the workshop itself would identify (Herr and Anderson, 2014). See Appendix A for detailed AI methodology.

*Participant Selection and Structure*

Effective exploration of complex challenges requires carefully curated diversity enabling productive dialogue across institutional boundaries (Brown and Isaacs, 2005). We convened thirteen organisations representing three essential perspectives: educational institutions, policy authorities, and operational stakeholders.

Six PME institutions participated: Baltic Defence College, Estonian Military Academy, Lithuanian Military Academy, Finnish National Defence University, Swedish Defence University, and Royal Danish Defence College – institutions operating under different governance structures and resource constraints while facing similar AI integration imperatives. Ministries of Defence from Latvia, Lithuania, and Estonia provided policy and resourcing perspectives, bringing understanding of strategic drivers, budgetary realities, and political constraints. Four NATO entities contributed alliance-level perspectives: Supreme Headquarters Allied Powers Europe (SHAPE), NATO Strategic Communications Centre of Excellence, NATO Hybrid Centre of Excellence, and NATO Allied Command Transformation Quality Assurance. SHAPE's participation ensured alignment with NATO's AI-enabled digital warfighting system priorities.

The three-session structure operationalised probe-sense-respond methodology. Session One explored the threat landscape, Session Two examined decision-making patterns, and Session Three developed PME requirements – each building on insights from the previous. Two parallel working groups employed different facilitation approaches: one evolved toward fluid question exploration allowing patterns to emerge organically, while the other maintained structured analytical frameworks throughout. This methodological variation strengthened findings through triangulation.

*Day One: Threat Landscape and Decision-Making*

Each session followed deliberate structure: expert presentations establishing shared context, followed by question-storming before solution-finding. This sequence created cognitive space for divergent thinking, with natural saturation points indicating transition from exploration to synthesis.

Session One began with presentations establishing the threat context. NATO Strategic Communications Centre of Excellence detailed AI's role in information warfare – malicious large language models enabling sophisticated phishing, malware development, and coordinated disinformation campaigns that amplify frequency, speed, and scope while lowering skill barriers. The European Centre of Excellence for Countering Hybrid Threats framed hybrid warfare as coordinated multi-domain actions exploiting systemic vulnerabilities, targeting democratic foundations through military and non-military means.

Following presentations, working groups engaged question-storming: 'What should we be asking about AI threats facing military operations and PME?' Eight high-impact threats emerged: disinformation campaigns, lawfare enabled by AI-generated legal arguments, AI analysis feeding malicious applications, sophisticated phishing, denial of service attacks, malicious AI training corrupting defensive systems, OODA loop manipulation, and deception operations. Discussion pivoted when participants recognised these same capabilities represent educational requirements when employed within legal and ethical frameworks – transforming defensive concerns into curriculum opportunities.

Session Two opened with presentations on operational decision-making. SHAPE outlined NATO's commitment to AI-enabled digital warfighting, emphasising PME's role in technology awareness and bias mitigation. Swedish Defence University questioned whether traditional control paradigms may hinder future warfare effectiveness. Estonia's Ministry of Defence presented their draft Defence AI strategy emphasising human oversight in targeting decisions and practical value-addition.

Working groups then explored: 'How does AI support operational decision-making given identified threats?' During discussion, participants organically distinguished between command functions such as leadership, authority, responsibility, and decision-making, and control functions including communication networks, information processing, and logistics planning and coordination. This framework emerged from practitioners wrestling with operational experience, not facilitator introduction. Consensus was immediate: command remains essentially human; control functions are where AI augments capability.

Trust emerged as Session Two's second theme. Participants emphasised AI systems must earn trust through training, exercises, and certification – like human teammates. The group expressed strong preference for rules-based AI over black-box approaches in critical functions, reflecting professional judgment that understanding system reasoning matters for appropriate reliance.

*Day Two: Educational Requirements and Validation*

Day Two shifted from exploration to synthesis, demonstrating organisational ambidexterity – simultaneous capacity for exploration and exploitation essential when navigating complex challenges (Warner and Wäger, 2019). The safe-to-fail environment established on Day One enabled participants to move from identifying patterns to constructing actionable frameworks (Snowden and Rancati, 2021).

Session Three opened with presentations on practical AI integration experiences. NATO Allied Command Transformation's Quality Assurance section demonstrated AI chatbot integration into NATO education courses, emphasising human validation to maintain quality. The Lithuanian Military Academy presented their policy framework: over 75% of students use AI tools, but outputs must be verified against academic sources, use declared, and critical evaluation mandatory. Estonian Military Academy showcased AI-enabled wargaming initiatives, while Finnish National Defence University demonstrated autonomous systems research. The University of Tartu presented sobering findings: AI allows novices to complete university assignments achieving passing grades in approximately 20% of expected time, with instructors detecting AI use only 64% of the time – no current assignment format is AI-resilient.

Working groups then synthesised findings into comprehensive PME requirements. Seven focal points emerged: future-ready leadership competencies, command-control understanding, trust-building, ethical and legal dimensions, wargaming integration, staff productivity, and innovation management.

The most valuable discussion addressed obstacles directly. Rather than producing aspirational frameworks divorced from implementation realities, participants candidly identified eight barriers: institutional conservatism spanning excessive scepticism to uncritical over-trust; cultural resistance captured in one participant's observation that institutions face a choice – 'either you help us win, or watch us win'; bureaucratic rigidity; data availability issues; rapid AI advancement outpacing curriculum cycles; tool availability concerns; technical skill requirements; and student mindset challenges. This honest assessment reflected the workshop's philosophy: frameworks grounded in actual implementation requirements; not idealised solutions disconnected from resource constraints and institutional realities.

SHAPE's endorsement of the collaborative approach provided strategic significance beyond immediate outcomes. Their participation suggested that frameworks emerging from practitioner exploration offer operational value that complements expert-prescribed solutions, validating the systematic exploration methodology. The workshop concluded with commitments to share implementation experiences, coordinate faculty development, and reconvene in 2026 to refine frameworks based on application experience.

## Findings: Three Patterns of Effective Human-AI Collaboration

The workshop's collaborative exploration surfaced three distinct patterns of effective human-AI collaboration, each demonstrating how practitioners instinctively navigate the division between command-and-control functions.

These patterns emerged not from theoretical frameworks but from participants wrestling with operational realities: how AI actually works in complex environments, where human judgment proves essential, and what this means for preparing future military leaders. Each pattern reflects the command-control distinction Session Two identified: AI augments control functions while humans retain command authority. The three patterns can be understood as Strategic Sense-Making, Ethical Responsibility, and Adaptive Command, each representing a distinct mode of human-AI collaboration essential for military operations.

*Pattern 1 – Strategic Sense-Making: AI Pattern Recognition with Human Contextual Judgment*

The threat analysis session revealed this pattern most clearly. As participants explored adversary AI capabilities, they recognised AI's superiority in processing multiple information streams simultaneously, identifying patterns across disparate data sources, and flagging anomalies humans might miss entirely. A participant observed that AI systems could detect subtle shifts in adversary communication patterns (frequency changes, vocabulary shifts, network topology alterations) that would escape human analysts reviewing the same raw data. This represented AI's control function: continuous sensing, pattern recognition, data correlation.

However, every participant recognised that detecting patterns differs fundamentally from understanding their significance. The same communication pattern shift might indicate operational preparation, deception, technical malfunction, or routine activity. Distinguishing among these possibilities requires operational context, strategic awareness, and professional judgment that algorithms cannot replicate. As participants framed it, AI excels at showing what changed; humans must determine what it means. This represents command: applying context, making meaning, assessing operational significance.

Ukrainian operations demonstrate this pattern under combat conditions. The Avengers targeting system processes sensor data from multiple sources, identifying equipment positions and generating over 12,000 target locations weekly through AI pattern recognition (UNN, 2024). However, Ukrainian operational doctrine requires human verification before actionable intelligence use (Pardo de Santayana, 2024; Bondar, 2025). Human teams assess the tactical significance of identified positions, their relationship to broader operational objectives, the reliability of AI classification through confidence intervals, and the strategic context and implications. Ukrainian commanders have learned through operational experience that AI detection capabilities (control functions) require human judgment (command authority) to maintain both effectiveness and ethical accountability (Pardo de Santayana, 2024; Bondar, 2025). As the International Centre for Defence and Security observed: 'AI-powered solutions are no longer optional for Ukraine but are crucial for safeguarding Ukrainian lives and national security. However, maintaining human judgment in final decision-making preserves both operational effectiveness and ethical accountability' (Goncharuk, 2024).

Research on trust in human-AI teams explains why this pattern, Strategic Sense-Making, works. Appropriate trust develops when humans understand AI capabilities and limitations, calibrating reliance based on task characteristics and system reliability (Hancock et al., 2011; Lee and See, 2004). Pattern recognition tasks suit AI strengths while contextual interpretation leverages human expertise. The challenge for PME institutions lies in developing both competencies: helping future leaders understand what AI pattern recognition can reveal while cultivating the contextual judgment essential for command decisions.

*Pattern 2 – Ethical Responsibility: AI Rapid Option Generation with Human Ethical Evaluation*

Session Two's exploration of operational decision-making revealed a second pattern. Participants recognised AI's capability to generate multiple courses of action rapidly, modelling potential outcomes, and accelerating planning cycles beyond human capacity. Several participants suggested AI-assisted planning teams could produce significantly more option variants than traditional approaches. Subsequent AI-assisted exercise demonstrated AI-assisted teams producing three times more course of action variants in the same timeframe compared to conventional planning methods, though human planners evaluated each for feasibility, risk tolerance, and alignment with commander's intent (Bovet et al, 2025). This effectively augments the control function of translating commander's intent into executable options.

Yet this capability generated immediate ethical concerns. More options do not automatically produce better decisions; they create evaluation challenges. Participants insisted that human commanders must evaluate each AI-generated option against ethical frameworks, legal constraints, proportionality requirements, and strategic intent. Speed cannot supersede responsibility. The sentiment of one participant could be expressed as: 'AI can show us what we could do much faster than before. The question that keeps me awake is whether we are equally fast at evaluating what we should do'.

Reports regarding Israel's experience with the Lavender system provide a cautionary illustration of why human ethical evaluation remains essential (Levy, 2024). The system generated potential targets rapidly through AI analysis, identifying tens of thousands of suspected affiliates for airstrikes (Levy, 2024). However, investigative reporting indicates that human analysts often reduced approval to seconds per target, with final review sometimes degraded to perfunctory approval rather than genuine evaluation (Levy, 2024; Sarig, 2025). The targeting accuracy threshold for junior operatives was reportedly set to accept significant risk of civilian casualties (Sarig, 2025; Sylvia, 2024). According to these published analyses, this represents Pattern 2's failure mode: when option generation (control) outpaces ethical evaluation (command), the pattern breaks down with potential tragic consequences. The lesson is not that AI should not generate options; it's that PME institutions must develop leaders whose ethical evaluation capabilities match AI's option generation speed.

Ukrainian battle management systems demonstrate Pattern 2's successful implementation. AI rapidly models multiple targeting approaches with different weapon combinations, timings, and attack vectors – control functions that accelerate planning (Bondar, 2025). However, commanders evaluate each option against international humanitarian law constraints, proportionality calculations considering civilian harm, strategic objectives beyond immediate targeting, and operational risk to friendly forces (Bondar, 2025; Mysyshyn, 2025; Pardo de Santayana, 2024). As the Mysyshyn (2025) documented: 'Ukrainian developers emphasise "human-in-the-loop" architecture, particularly when it comes to lethal targeting. AI supports decision-making, but humans retain control – a principle rooted in both military pragmatism and ethical caution' (Mysyshyn, 2025). Ukrainian doctrine explicitly rejects automated approval, maintaining human command authority over lethal decisions; reflecting both operational experience with AI misidentification risks and ethical commitment to human responsibility (Mysyshyn, 2025; Bondar, 2025; Pardo de Santayana, 2024).

Ethical Responsibility requires PME curricula that develop speed-compatible ethical reasoning. Future leaders need frameworks for rapid yet rigorous evaluation, understanding that AI-enabled operations compress decision timelines without diminishing ethical obligations. This represents a fundamental shift from traditional sequential planning toward parallel evaluation where AI generates options while humans simultaneously assess ethical implications.

*Pattern 3 – Adaptive Command: Human Primacy in Objectives with AI Environmental Sensing*

The third pattern emerged during Session Three's focus on PME requirements. Participants consistently emphasised human primacy in setting objectives (defining mission intent, establishing success criteria, determining acceptable risk) while recognising AI's superiority in continuous environmental monitoring. This distinction maps directly to command versus control: humans exercise command through objective-setting; AI enables control through persistent sensing and adaptation alerting.

A captured reflection from discussion of mission command doctrine: 'We tell AI what we want to achieve and what boundaries constrain us. AI tells us what is changing in the environment that might affect our approach. But we decide what those changes mean for our objectives – whether to persist, adapt, or reassess entirely'. This reflects Pattern 3's essential dynamic: human intent guides action while AI-enhanced situational awareness informs execution.

Ukrainian brigade operations demonstrate this pattern operationally. Defence Ministry and General Staff set campaign objectives (territorial defence, air defence degradation, force sustainability) representing command functions (Liang, 2025; Bondar, 2025). AI systems continuously monitor battlefield sensor data, environmental conditions, signals intelligence, and logistics status; control functions enabling environmental sensing (Bondar, 2025; Mysyshyn, 2025). When AI detects changes (Russian force repositioning, supply line vulnerabilities, weather impacts) humans evaluate significance relative to original objectives, adjusting tactics while maintaining command authority over mission-level decisions (Liang, 2025; Bondar, 2025; Mysyshyn, 2025). As the Geneva Centre for Security Policy (2025) documented: 'By 2024, the Ukrainian Defence Ministry had supplied approximately 1.2 million UAVs, enabling deep strikes and reducing frontline casualties...' (Liang, 2025).

This pattern directly challenges assumptions about autonomous warfare. Ukrainian experience demonstrates that sophisticated AI integration does not require surrendering human command – it actually enhances mission command by providing commanders with environmental awareness previously unattainable. Leaders maintain objective-setting authority while AI systems function as persistent, tireless observers reporting changes requiring command attention.

For PME institutions, Pattern 3 suggests curricula must develop objective-setting competencies alongside AI literacy. Future leaders need skills in translating strategic intent into AI-monitorable parameters, interpreting AI environmental reports within operational context, and maintaining objective clarity amid AI-generated information streams. The challenge lies not in teaching leaders to rely on AI for objectives (participants unanimously rejected this) but in preparing them to leverage AI environmental sensing while exercising human command.

*Command-Control Framework as Organising Principle*

These three patterns share an underlying structure that participants themselves articulated during Session Two: the distinction between command-and-control functions in AI-enabled operations. As the methodology section documented, command encompasses functions requiring human judgment (leadership, authority, responsibility, decision-making) while control encompasses functions where AI augmentation enhances speed and scale without assuming decision authority. This framework emerged organically from practitioner wisdom rather than theoretical imposition: participants recognised from operational experience that effective AI integration requires clarity about which functions AI augments versus which remain essentially human. The distinction provides conceptual clarity for technology adoption decisions, training program design, and leader development priorities.

The framework carries significant implications for mission command doctrine. Traditional mission command emphasises decentralised execution within commander's intent, assuming human subordinates execute with understanding and initiative. AI-enabled operations extend this model: AI systems execute control functions within parameters established by human command authority. The doctrine's fundamental premise (clear intent enables effective decentralised action) remains valid whether subordinates are human, AI-assisted humans, or AI systems operating under human oversight. As the NATO Command and Control Centre of Excellence's analysis has stated: 'In the overall C2-cycle, there are no plans to delegate the deciding phase to such systems' (Van Rijn et al., 2025). This NATO doctrinal position confirms what workshop participants recognised: AI supports decision-making through enhanced control functions, but command authority remains human.

Workshop participants demonstrated this framework across all three patterns. Pattern 1 (Strategic Sense-Making) demonstrates AI control (pattern recognition) requiring human command (contextual judgment). Pattern 2 (Ethical Responsibility) shows AI control (option generation) requiring human command (ethical evaluation). Pattern 3 (Adaptive Command) establishes human command (objective-setting) leveraging AI control (environmental sensing). Together, these patterns suggest PME institutions should organise AI integration efforts around the command-control distinction, ensuring future leaders understand which competencies remain essentially human regardless of technological advancement.

## Complexity Theory Analysis – Why This Approach Worked

The February 2025 workshop's success emerged from methodological alignment with complex domain characteristics, though we only recognised this alignment retrospectively through the Cynefin framework lens.

Question-storming proved effective as a probing technique. Traditional methodologies begin with problem definition followed by solution generation, appropriate for complicated problems where expert analysis yields optimal answers (Snowden and Boone, 2007). Complex challenges require different approaches. During Session One, participants generated over forty questions about AI integration before proposing solutions, revealing tensions between innovation and institutional conservatism, ethical evaluation capacity gaps, and trust calibration challenges. Recent military applications validate this questioning approach: NATO's Sentinel Vanguard 2044 wargame and UK Ministry of Defence exercises deliberately suspended traditional assessment frameworks to enable exploratory questioning without constraining outcomes (NATO ACT, 2024; UK MOD, 2023). The patterns documented in the findings section emerged from safe-to-fail exploration rather than prescribed frameworks.

Safe-to-fail experimentation characterises effective complex domain navigation (Snowden and Rancati, 2021). The workshop created conditions enabling participants to explore challenging questions without career risk. When a participant articulated that 'command must remain human, but control can be AI-enabled', this insight emerged from safe exploration of authority concerns, not from doctrinal analysis. Enabling constraints allowed patterns to emerge without governing constraints predetermining outcomes (Kurtz and Snowden, 2003).

Traditional analytical approaches fail in complex domains because they assume expertise determines optimal solutions through pre-implementation analysis. AI integration demonstrates this assumption's invalidity: technology evolves rapidly, operational requirements remain contested, ethical frameworks continue developing, and institutional implementation varies across contexts. No single expert possesses complete understanding, yet institutional pressures demand curriculum guidance. Complex challenges require acknowledging comprehensive understanding emerges through action rather than preceding it (Snowden and Boone, 2007).

Diverse institutional perspectives proved essential for pattern recognition. The workshop assembled participants from thirteen organisations spanning PME institutions, ministries of defence, and NATO headquarters. This approach aligns with recent PME reforms recognising that complex challenges require cross-institutional dialogue rather than single-institution expertise (McConnell, Kaluzny, and Whitaker, 2024; Toci, 2024). During Session Two, different institutions contributed distinct insights: PME representatives emphasised assessment challenges, ministry participants highlighted policy concerns, NATO personnel raised interoperability requirements, operational commanders questioned trust calibration. These diverse perspectives enabled recognising patterns single-institution analysis would miss.

Iterative dialogue-built understanding progressively. Session One revealed unanticipated challenges: AI advancement speed outpacing institutional adaptation, data quality undermining reliability, bureaucratic processes constraining experimentation. Session Two explored how AI might support rather than replace human judgment. Session Three synthesised insights into actionable PME frameworks. This progression demonstrates complex domain navigation requires building understanding through successive approximations (Kurtz and Snowden, 2003).

Retrospective coherence explains why findings possess validity despite emerging without predetermined framework. The three collaboration patterns exhibit internal consistency and align with operational experience from Ukraine. The command-control meta-framework demonstrates similar coherence: NATO doctrinal definitions distinguish command functions requiring human authority from control functions amenable to technological enhancement (Van Rijn et al., 2025), operational examples confirm utility across contexts, and educational implications follow logically. This indicates successful navigation of patterns unpredictable in advance but robust when tested against broader evidence (Snowden and Boone, 2007).

*Transferability: Conditions Enabling Methodology Replication*

The workshop methodology transfers to other complex challenges where best practices remain emergent. Three conditions enable replication: genuine complexity requiring diverse perspectives, institutional commitment to safe-to-fail exploration, and systematic facilitation maintaining probe-sense-respond discipline.

First, challenges must inhabit complex rather than complicated domains. Complicated challenges yield to expert analysis and benefit from traditional planning (Snowden and Boone, 2007). Complex challenges require different methodology. AI integration qualifies as genuinely complex: technology capabilities, operational requirements, ethical frameworks, and institutional contexts evolve simultaneously, precluding comprehensive expert analysis. Other complex military challenges amenable to this approach include cyber defence strategy development, hybrid warfare response frameworks, or coalition interoperability enhancement.

Second, participating institutions must accept uncertainty inherent in safe-to-fail exploration. The workshop succeeded because BALTDEFCOL leadership and participating organisations embraced experimental methodology without demanding predetermined outcomes. Some senior participants initially preferred traditional briefings presenting expert analysis. Facilitation teams maintained discipline, redirecting solution-focused discussions back to expansive questioning during Session One. This persistence proved essential: premature convergence would have prevented pattern emergence.

Third, systematic facilitation must maintain appropriate methodology whilst remaining flexible enough to follow emergent patterns. Our facilitators recognised when Session Two revealed the command-control distinction's significance, allowing extended exploration whilst ensuring planned decision-making analysis continued. This balance characterises effective complex domain facilitation, requiring what collaboration scholars term "dynamic facilitation" that maintains structure while enabling emergence (Kaner et al., 2014; Snowden and Rancati, 2021). The facilitation team navigated this tension by maintaining three-session structure whilst allowing content emergence from participant expertise.

Institutional learning implications extend beyond immediate outcomes. Organisations navigating complex challenges successfully develop capacity for systematic exploration alongside traditional analytical excellence, what scholars term "ambidextrous" organisational capability (Warner and Wäger, 2019). Professional military education institutions operating in VUCA-Plus environments require both: analytical rigour for complicated problems and exploration methodologies for complex challenges where best practices remain emergent. The workshop demonstrated one approach for developing this dual capability, suggesting PME institutions might cultivate complexity navigation competence through iterative experimentation. This represents institutional learning about learning itself, increasingly essential as military organisations confront accelerating technological change where historical precedent provides diminishing guidance.

## Implications and Implementation Realities

The February 2025 workshop generated frameworks that translate directly into operational and educational practice. This section examines how the three collaboration patterns and command-control distinction inform military operations, PME transformation, and institutional change while acknowledging implementation constraints that shape realistic adoption timelines.

*Operational Applications: Command-Control Doctrine in Practice*

The command-control framework emerging from workshop findings requires updating mission command doctrine for AI-enabled environments. Traditional mission command emphasises decentralised execution within commander's intent, human judgment in uncertain situations, and clear accountability structures (NATO, 2022). AI integration preserves these principles while enabling fundamentally different control capabilities.

Pattern 1 (Strategic Sense Making) demonstrates that AI pattern recognition paired with human contextual judgment creates decision advantage without eroding command authority. Estonian Defence Forces' KOLT system illustrates this application: AI processes sensor data identifying activity patterns, but human commanders judge operational significance within broader strategic context (Republic of Estonia Ministry of Defence, 2024). The system detects anomalies; humans determine whether those anomalies constitute threats requiring response. This maintains meaningful human control while leveraging AI's superior data processing capacity.

Pattern 2 (Ethical Responsibility) addresses perhaps the most consequential operational question: who decides when lives are at stake? Workshop participants emphasised that AI can accelerate option generation without assuming ethical evaluation responsibility. Swedish and Norwegian experimentation demonstrate this pattern: AI generates targeting options three times faster than manual planning, but commanders evaluate each option against ethical and strategic criteria before authorisation (Bovet et al., 2025). Military planning traditionally requires hours to develop comprehensive courses of action; AI systems now generate multiple options in minutes, but humans must evaluate alignment with rules of engagement, proportionality principles, and strategic objectives (Cummings, 2017; NATO ACT, 2023). This pattern proves particularly vital in targeting decisions where international humanitarian law requires human judgment regarding military necessity and civilian harm (ICRC, 2024).

Trust calibration emerged as central to Pattern 2 implementation. Recent research demonstrates that military trust in AI exhibits non-linear dynamics: trust builds gradually through consistent performance but collapses rapidly after failures, with early malfunctions having disproportionate negative impact (Poornikoo et al., 2025). Operational implementation therefore requires phased introduction, extensive training with AI tools before high-stakes use, and transparent system limitations. Workshop participants insisted that AI systems, like human teammates, must earn trust through demonstrated reliability rather than assumed competence.

Pattern 3 (Adaptive Command) establishes that humans retain command authority over strategic objectives while AI provides environmental sensing. Norwegian Arctic surveillance operations demonstrate this application: commanders define deterrence posture and domain awareness priorities; AI monitors vast areas for activity anomalies requiring human attention (FFI, 2024). This division preserves human primacy in objectives while exploiting AI's superior continuous monitoring capabilities. The pattern particularly matters in multi-domain operations where information volume exceeds human processing capacity yet strategic decisions require human judgment integrating political, military, and ethical considerations (NATO, 2022).

The operational implications extend beyond tactical application to training requirements. Leaders must develop competencies in trust calibration, understanding AI capabilities and limitations, recognising when to override AI recommendations, and maintaining decision-making skills despite AI assistance (Madison et al., 2025). These competencies do not emerge naturally; they require systematic development through progressive exposure to AI-enabled decision environments.

### *PME Transformation Requirements: Operationalising Seven Focal Points*

Workshop participants identified seven focal points requiring concentrated institutional effort. These focal points are not aspirational; they are requirements derived from operational realities of preparing leaders for AI-enabled warfare.

Future-ready leadership competencies encompass understanding AI capabilities without requiring technical expertise, recognising appropriate human-AI role divisions, and maintaining ethical frameworks under operational pressure. PME institutions must develop these competencies through integration across curriculum rather than isolated AI modules (Miao, Giannini, and Holmes, 2023). Leadership development occurs through repeated exposure to AI-assisted decision-making in progressively complex scenarios, building intuition about when to trust, question, or override AI recommendations.

Understanding AI's role specifically in command and control requires explicit doctrine instruction. The command-control distinction must become foundational to leadership education, clarifying that AI enhances control functions while command authority remains essentially human. This distinction prevents both uncritical over-reliance and excessive scepticism, establishing realistic expectations about AI's contributions and limitations (Scharre, 2018).

Building and validating trust in AI systems emerged as critical competency requiring systematic development. Trust is not binary; it must calibrate to specific contexts, system capabilities, and consequence severity (Lee and See, 2004; Tomsett et al., 2020). PME institutions must create training environments where students experience AI system performance, recognise failure modes, and develop appropriate reliance patterns before operational deployment.

Ethical and legal dimensions require increased emphasis as AI capabilities expand. International humanitarian law principles of distinction, proportionality, and military necessity cannot be algorithmically encoded; they require human judgment applying contextual understanding to specific situations (ICRC, 2024). PME must develop leaders capable of maintaining ethical frameworks when AI acceleration creates pressure for rapid decisions.

Wargaming and synthetic environment integration provides controlled spaces for developing AI-enabled decision-making competencies. Digital exercises enable repeated practice with AI tools, exposure to AI failure modes, and development of override decision-making without operational consequences (Chen, Chen, and Lin, 2020). The Lithuanian Military Academy's AI-enabled wargaming demonstrates how synthetic environments accelerate competency development while maintaining safety.

Multi-domain literacy extending across AI, cyber, and information domains reflects operational reality where adversaries exploit seams between domains. Leaders require strategic understanding of multi-domain effects without technical specialisation (NATO, 2021).

Innovation management and agile project management address institutional adaptation requirements. PME institutions must develop capacity for continuous curriculum evolution, avoiding obsolescence through systematic experimentation (Warner and Wäger, 2019). This requires cultural shift from multi-year development cycles to iterative refinement based on emerging operational requirements.

Faculty development represents perhaps the most critical implementation requirement. Instructors require AI competency development, understanding of human-AI collaboration patterns, and facilitation skills for AI-enabled learning environments (Holmes, Bialik, and Fadel, 2019). This development must occur through experiential learning rather than theoretical instruction, positioning faculty as co-learners exploring AI integration alongside students.

*Implementation Constraints and Mitigation Strategies*

Workshop participants candidly identified eight implementation obstacles clustering into three categories, while simultaneously documenting emerging practices that show promise for mitigation.

Institutional barriers include conservatism spanning from excessive scepticism to uncritical over-trust, bureaucratic rigidity, and the stark reality captured in one participant's observation: 'either you help us win or watch us win'. Regional experience suggests small-scale experimentation and senior leadership advocacy prove essential, though optimal approaches vary by institutional context (Hinings, Gegenhuber, and Greenwood, 2018; Weick and Sutcliffe, 2015).

Technical constraints encompass AI's rapid advancement outpacing curriculum cycles, data quality issues, inconsistent tool availability, and infrastructure limitations. The principle of accepting iterative improvement guides emerging responses, with institutions testing various approaches to rapid adaptation (Vial, 2019; NATO ACT, 2023).

Human factors span student, faculty, and leadership dimensions. Students arrive with varied AI exposure and unrealistic expectations requiring calibrated AI literacy instruction. Faculty face pedagogical adaptation challenges when AI outperforms traditional analytical methods. Leaders must balance innovation encouragement with risk management while navigating institutional identity shifts. These interconnected human elements, from individual skill development to organisational culture, require coordinated approaches acknowledging both practical competency needs and deeper professional transformation (Lepik-Verliin, Hint, and Leijen, 2025; Kaner et al., 2014).

The workshop also identified best and emerging practices across eight implementation categories (Table 2), from trust-building methodologies to resource management, providing practical guidance for institutions to assist their AI integration efforts. The February 2026 workshop will add to these practices as we find solutions to these obstacles in an iterative approach that embodies the complexity methodology necessary when navigating genuine uncertainty. Regional cooperation will lead to the innovation management strategies and organisational change processes essential to sustainable AI integration.

| Category | Key Points |
|---|---|
| Command-Control Education | • Maintain clear distinction between human command functions and AI-supported control functions.<br>• Teach leaders to write commander's intent that both humans and AI can interpret.<br>• Preserve human role in leadership, authority, responsibility, and decision-making.<br>• Treat AI as a control-function enabler rather than command replacement. |
| Trust Building and Validation | • Treat AI systems like new team members who must earn trust.<br>• Build trust through progressive training, exercises, and certification.<br>• Prefer rules-based over black box AI systems for critical functions.<br>• Enable better understanding and validation of AI decisions. |
| Practical Implementation | • Use progressive exposure approach starting with low-risk staff functions.<br>• Integrate AI tools into existing exercises rather than separate activities.<br>• Create synthetic environments for safe experimentation and learning.<br>• Document AI performance and lessons learned.<br>• Build evidence-based trust while contributing to continuous improvement. |
| Educational Approach | • Implement "AI across the curriculum" rather than isolated courses.<br>• Build AI literacy through practical application in multiple domains.<br>• Create learning communities where early adopters guide others.<br>• Balance technical understanding with operational application.<br>• Treat AI literacy as core military competency that must be earned. |
| Continuous Experimentation | • Create structured opportunities to test new AI applications.<br>• Establish clear objectives and evaluation criteria; Implement systematic feedback mechanisms.<br>• Build institutional knowledge while managing risks. |

| | |
|---|---|
| **Guidance Development** | • Develop and regularly update AI employment frameworks.<br>• Align with ethical principles, operational requirements, and educational objectives.<br>• Maintain specific standards while allowing flexibility.<br>• Address both conservatism and over-trust challenges. |
| **Agile Practices** | • Use rapid iteration instead of traditional waterfall approach.<br>• Incorporate lessons learned quickly.<br>• Conduct regular sprint reviews of AI integration efforts.<br>• Prototype new teaching approaches.<br>• Gather frequent student and instructor feedback.<br>• Enable continuous adaptation to new capabilities and challenges. |
| **Resource Management & Sustainability** | • Financial framework development.<br>• IP protection protocols.<br>• Equipment modernisation cycles.<br>• License management.<br>• Digital infrastructure requirements.<br>• Partnership funding models. |

*Table 2: Best and Emerging Practices*

*Future Research Directions: Bridging to Systematic Assessment*

The workshop identified collaboration patterns and established frameworks for PME transformation. Rigorous assessment of implementation outcomes requires longitudinal research spanning multiple years and institutions. Three research directions emerge as priorities.

First, replication studies across diverse PME contexts will test framework transferability. The February 2025 workshop involved Baltic and Nordic institutions; validation requires examining whether patterns hold in different cultural contexts, institutional structures, and security environments. Comparative research identifying which elements prove universal versus context-dependent will refine guidance for adoption.

Second, longitudinal assessment of implementation outcomes must quantify effectiveness claims. Do students trained in AI-enabled environments demonstrate superior decision-making under uncertainty? Does trust calibration training prevent automation bias in operational contexts? Does the command-control framework improve human-AI team performance? Answering these questions requires multi-year studies with operational outcome measures, not just participant satisfaction surveys (Noy and Zhang, 2023).

Third, designing complexity-aware AI systems informed by collaboration patterns represents the natural progression from this research. If Pattern 2 demonstrates that humans must evaluate ethical implications, AI systems should present options highlighting ethical trade-offs rather than recommending single solutions. If Pattern 3 shows humans retain objective authority, AI interfaces should emphasise environmental changes relevant to stated objectives rather than suggesting objective modifications. These implementation insights inform the design requirements for complexity-aware AI systems – the focus of subsequent research exploring how understanding effective collaboration informs AI system design itself.

The February 2026 workshop provides opportunity for initial validation. Participating institutions will report implementation experiences, enabling assessment of which frameworks proved most valuable, what adaptations proved necessary, and what unexpected challenges emerged. This iterative refinement embodies the complexity-aware approach: probe through implementation, sense emerging patterns, respond with framework updates.

Implementation realities do not diminish workshop findings; they position them within institutional contexts where change occurs incrementally through sustained effort rather than revolutionary transformation. The frameworks provide direction; regional cooperation provides mutual support; systematic assessment provides learning. Together, these elements enable military education institutions to navigate AI integration's genuine complexity while maintaining focus on the mission: preparing leaders for warfare where human judgment remains indispensable but increasingly AI-enabled.

## Conclusion

We opened with professional military education's defining challenge: educating tomorrow's leaders to fight with tools we cannot show them, in ways we have not mastered, against threats we do not fully understand. This article documents how practitioners confronted that challenge directly through systematic exploration that revealed transferable patterns of effective human-AI collaboration.

The journey from challenge to framework demonstrates what becomes possible when we accept complexity. Thirteen organisations systematically explored AI integration through structured sessions, recognising patterns that preserve military leadership's essential requirements: human judgment where it matters most. The command-control distinction, confirmed through NATO doctrine and operational experience, provides the organising principle military education needs.

Implementation will prove neither simple nor swift. Institutional conservatism, rapid technological change, resource constraints, and cultural resistance create genuine obstacles that acknowledging honestly serves better than minimising rhetorically. Yet these constraints make collaboration more essential, not less. We cannot wait for perfect conditions before preparing leaders for AI-enabled warfare that adversaries already employ. We must build institutional capacity through systematic experimentation, share lessons learned across the regional PME network, and iterate toward excellence through frameworks that prove implementable rather than merely aspirational.

The path forward requires commitment from across the PME community: developing dual competency curricula that cultivate both AI literacy and human judgment, integrating trust-building exercises that enable appropriate reliance calibration, implementing ethics frameworks compatible with AI-accelerated decision timelines, updating command-control doctrine for AI-enabled operations, and establishing regional cooperation mechanisms that enable continuous learning. These are not optional enhancements to existing approaches; they represent requirements for professional military education that takes seriously its responsibility to prepare leaders for the warfare they will actually conduct.

We are no longer educating tomorrow's leaders about tools we cannot show them. We are developing frameworks that enable leaders to work effectively with AI capabilities they will see in action, in contexts they cannot fully anticipate, guided by patterns emerging from practitioner wisdom and operational experience. Human primacy in command authority remains non-negotiable. What changes is our capacity to execute control functions at speeds and scales previously impossible, enabling human judgment to focus where it proves most essential: defining objectives worth achieving, evaluating options against ethical frameworks, and maintaining responsibility for decisions with operational consequences.

The challenge remains complex. The path forward proves navigable. The mission demands we proceed together.

**AI Statement:** The author details their use of AI in the development of this piece in Appendix A

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## Appendix A: AI-Assisted Research Methodology

*Overview: Demonstrating Human-AI Collaboration Patterns*

This appendix documents how the research process itself embodied the human-AI collaboration patterns identified through workshop exploration. The methodology employed multiple AI platforms as tools while maintaining human authority over all interpretive, strategic, and ethical decisions – demonstrating in practice what the article argues in theory.

*Workshop Facilitation: Human-AI Collaboration in Practice*

The workshop facilitation methodology employed ALEX (Admired Leadership's Claude-based assistant) for preparation, real-time synthesis, and post-workshop analysis. Prior to the workshop, we used ALEX to generate and evaluate workshop structure options. Through iterative refinement, ALEX helped identify the optimal sequence: starting with exploratory questions rather than problem statements, progressing from threat identification through decision-making patterns to requirements, and maintaining question-storming until natural saturation points. This AI-generated structure proved sound: each element reinforced the next, creating conditions for the patterns to emerge.

During workshop sessions, ALEX processed participant contributions, identifying emerging themes across diverse inputs; demonstrating Pattern 1 (Strategic Sense-Making) as AI recognised patterns while we judged their operational significance. The two working groups employed slightly different approaches (one emphasising fluid question-storming until saturation, the other structured frameworks) providing natural triangulation of findings. Facilitators maintained exclusive authority over which themes to pursue, how to frame follow-up questions, and when to transition between divergent and convergent thinking. This demonstrated Pattern 2 (Ethical Responsibility): AI rapidly generated thematic options while we evaluated their relevance to our exploration. The 13 participating organisations observed this collaborative process, experiencing firsthand how AI augments rather than replaces human facilitation judgment.

Following the workshop, ALEX assisted in analysing outputs from both working groups, identifying convergent themes and synthesising findings into the frameworks presented in this article. This post-workshop synthesis directly informed Baltic Defence College's institutional digital transformation roadmap consistent with Pattern 3 (Adaptive Command) and validated the three collaboration patterns.

*Research Architecture: Systematic Exploration*

The article's research phase employed eleven targeted Perplexity Pro deep research queries, each carefully designed to explore specific dimensions of human-AI collaboration. Rather than general searches, I crafted precise prompts such as: 'Analyse open-source documentation of AI-enabled military systems deployed in Ukraine since 2022, focusing on human oversight mechanisms and decision-making protocols documented in peer-reviewed sources or official military publications'.

Perplexity's deep research capability – which conducts multiple search iterations and synthesises findings – served as environmental sensing (Pattern 3) while I maintained primacy over research objectives. I determined which findings warranted inclusion, evaluated source credibility, assessed operational security implications, and identified patterns across queries that the AI system did not recognise as connected. The eleven queries generated over 200 potential sources; I selected 50+ for inclusion based on relevance, credibility, and contribution to argument.

*Writing Process: Command Post Methodology*

For the writing phase I developed a "command post" methodology – a systematic approach to maintaining strategic coherence across multiple AI conversation sessions necessitated by token limitations. This innovation emerged from recognising that complex intellectual work requires both strategic oversight and tactical execution, mirroring military command structures.

I employed Claude Opus 4.1 as a strategic "command post", maintaining manuscript-level coherence, tracking theoretical commitments, and preserving voice consistency across sections. For tactical execution, I initiated separate Sonnet 3.5 conversations for each article section, providing specific parameters while allowing creative exploration within bounds. This demonstrated Pattern 1 (Strategic Sense-Making): AI identified patterns and connections within sections while I provided contextual judgment about their significance to the overall argument.

The editorial process required active curation of AI contributions. I identified and removed stylistic artifacts that revealed AI generation (punctuation choice, generic transitions, overly balanced constructions) while preserving useful structural suggestions. This selective incorporation maintained my authentic voice while benefiting from AI’s capacity for rapid option generation and data analysis.

*Comprehensive Knowledge Development Ecosystem*

The article represents only one output from a broader AI-assisted knowledge development process spanning multiple months and platforms. Following the February workshop, I employed Claude Projects to conduct systematic analysis of workshop findings, generating actionable after-action reports for institutional use. This analysis phase required human-directed exploration, with AI assisting in pattern identification across participant contributions and thematic synthesis of emergent insights.

The workshop findings directly informed Baltic Defence College’s institutional development priorities. I utilised AI assistance to translate workshop patterns into concrete products for our Digital Transformation and AI Working Group, including competency frameworks, implementation guidelines, and assessment criteria. The command-control distinction became central to our institutional AI integration roadmap, providing conceptual clarity for policy development and resource allocation decisions. This institutional application work ensured workshop insights translated into organisational change rather than remaining academic observations.

Parallel to article development, I utilised separate Claude Projects to translate workshop findings into practical educational applications. This included developing curriculum content for student education on human-AI collaboration, creating faculty development products for AI integration in PME, and designing assessment frameworks for measuring educational and management metrics. Each project maintained its own knowledge base while I provided integration across outputs, ensuring consistency of core patterns while adapting presentation for different audiences and implementation contexts.

Preparation for the International Society of Military Sciences (ISMS) 2025 conference required another Claude Project focused on distilling complex findings into accessible presentation format. This work helped identify which aspects resonated most strongly with academic audiences and refined the theoretical framing that ultimately strengthened the article's contribution. Feedback from the ISMS presentation validated the command-control framework's broader applicability and informed final article revisions.

Because of the AI collaboration, I was able to accomplish more over this 10-month period than I could have with traditional methods. However, the primary benefit was not time savings but quality enhancement: AI assistance enabled systematic exploration of multiple output formats simultaneously, revealing connections and applications that linear traditional approaches might have missed. Each project informed the others – curriculum development strengthened theoretical arguments, institutional implementation revealed practical constraints, and presentation feedback sharpened both academic positioning and operational relevance.

This multi-stream approach demonstrates Pattern 3 in practice: I maintained primacy over strategic objectives (research goals, institutional priorities, educational outcomes) while AI provided comprehensive environmental sensing across all work streams, identifying patterns and connections that enhanced each individual output. The workshop's value thus extended far beyond a single article, generating an ecosystem of interconnected knowledge products that advance both scholarship and practice.

*Validation Through Practice*

The methodology validated each collaboration pattern through lived experience:

Pattern 1 (AI Pattern Recognition + Human Contextual Judgment = Strategic Sense-Making): AI systems identified thematic connections across literature and workshop materials. I determined which patterns held operational significance versus statistical correlation.

Pattern 2 (AI Option Generation + Human Ethical Evaluation = Ethical Responsibility): AI generated multiple structural options, phrasal alternatives, and argumentative approaches. I evaluated each against academic standards, operational security requirements, and ethical considerations regarding participant anonymity.

Pattern 3 (Human Primacy in Objectives + AI Environmental Sensing = Adaptive Command): I established research questions, determined article scope, and defined contribution goals. AI provided comprehensive environmental scanning through literature synthesis and pattern identification, alerting me to relevant sources and connections I might have overlooked.

*Methodological Transparency and Ethics*

This transparent documentation serves both scholarly integrity and practical guidance. Ethical considerations included maintaining Chatham House Rule through careful anonymisation, verifying all operational examples existed in open-source literature, and ensuring AI-generated content underwent human evaluation before inclusion. The methodology required constant vigilance against algorithmic hallucination, citation fabrication, false precision, and context rot; risks mitigated through systematic verification and multiple-source triangulation.

*Transferable Insights*

This methodology offers several transferable principles for academic AI integration:

1. Clear role delineation: Explicitly distinguish between human decisions (what to research, which findings matter, how to frame arguments) and AI tasks (information gathering, pattern identification, draft generation).

2. Systematic verification: Every AI-generated claim requires human validation, particularly citations, and factual assertions.

3. Voice preservation: Maintaining authentic scholarly voice requires active curation rather than passive acceptance of AI outputs.

4. Reflexive application: Using AI tools to study AI collaboration provides unique validation opportunities while requiring careful attention to potential bias.

5. Infrastructure requirements: Effective AI-assisted research requires only web-based platform access and prompt engineering skills (informed by task and subject matter expertise), not specialised technical expertise.

The complete methodology demonstrates that human-AI collaboration enhances rather than diminishes scholarly rigor when humans maintain authority over interpretation, evaluation, and strategic direction while leveraging AI's superior information processing capabilities.