Intelligence analysis in multidisciplinary teams - affordances of the collaborative online SWARM platform for public service and education application

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Thesis declaration

This thesis comprises only original work to fulfil full requirements of Master of Philosophy - MDHS (Psychological Sciences) except where indicated. Due acknowledgement has been made in the text to all other material used.

This thesis is fewer than 40 000 words in length, exclusive of tables, reference list and appendices.

Andrew Wright
Digital signature, 14 October 2020

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Glossary of Abbreviations

ACIC	Australian Criminal Intelligence Commission
AFP	Australian Federal Police
AGO	Australian Geospatial-Intelligence Organisation
AIC	Australian Intelligence Community
ASD	Australian Signals Directorate
ASIO	Australian Security Intelligence Organisation
ASIS	Australian Secret Intelligence Service
CA	Contending Analyses
CIA	Central Intelligence Agency
CREATE	Crowdsourcing Evidence, Argumentation, Thinking and Evaluation
DETV	Department of Education and Training Victoria
DIO	Defence Intelligence Organisation
DST	Defence Science and Technology
GEOINT	Geolocation intelligence
HUMINT	Human intelligence
IARPA	Intelligence Advanced Research Projects Activity
IC	Intelligence community
IGIS	Inspector-General of Intelligence and Security
IT	Information Technology
JCTT	Joint Counter Terrorism Team
LAS	Laboratory for Analytic Sciences
MDT	Multidisciplinary teams
MSPS	Melbourne School of Psychological Sciences
NDG	National Disruption Group
NIC	National Intelligence Community
NSSTC	National Security Science and Technology Centre
ODNI	Office of the Director of National Intelligence
ONI	Office of National Intelligence
OSINT	Open source intelligence
PLS	Plain language statement
SAT	Structured analytic techniques
SIGINT	Signals intelligence
SWARM	Smartly-assembled Wiki-style Argument Marshalling

Abstract

Intelligence analysts from Australian Commonwealth, State and Territory Government agencies and departments regularly work in teams with other roles, referred to in this research as multidisciplinary teams (MDTs). MDTs operate within a 'framework', which provides the central mechanism for team coordination and structure. However, there is little available research on intelligence MDT frameworks including challenges.

To address this gap and explore potential MDT frameworks, this thesis examines intelligence MDTs and the Hunt Lab's collaborative software prototype SWARM Platform as a framework to support the functions of intelligence MDTs. The Hunt Lab developed the Platform in 2017 to improve collaboration and quality of reasoning of intelligence analysts. We investigated whether the Platform can move beyond its origins to provide a framework to support the business and training functions of intelligence MDTs, including affordances for managers and educators.

As a first step, we developed a maturity model, informed by the intelligence teamwork literature for the purposes of defining and evaluating the key indicators of intelligence MDTs. We detail the development of our maturity model that contains seven pillars against which MDT performance could be evaluated: Mission, Accountability, Agility, Efficiency, Communication, Collaboration and Output. This maturity model formed the central coding mechanism for this research to evaluate MDT performance.

We conducted three studies to address our research questions focusing on current MDT workplace application and whether the Platform supports business and training MDT framework functions. Study 1 applied the maturity model to a case study of intelligence MDT performance in the Australian Government, where we identified Mission and Collaboration as a strength but Efficiency as a weakness of their MDT framework.

In Studies 2 and 3, we evaluated the Platform as a potential framework to support the business and training functions of intelligence MDTs, first in a small-scale pilot within an Australian Government workplace and then on a larger scale in an analytical competition involving public and intelligence organisation teams. In these two studies, we found the Platform mostly supported key MDT pillars but also identified varying weaknesses across pillars of Accountability, Efficiency and Communication.

Despite the Platform's broad support for the MDT maturity pillars, this research identified technical and cultural issues that prevent adoption of the Platform as a business framework without further prioritised research. Instead, our research indicates the Platform has more immediate benefits in supporting training functions as a computer-supported collaborative learning (CSCL) tool, where research participants reported both cognitive and social learning outcomes in the same studies.

This research developed insights relevant to MDT frameworks more broadly including scaffolding strategies to improve multiple maturity model pillars. These strategies include teamwork schema development; launch meetings; accountability practices; and data management. We also developed insights into engaging and researching government with intelligence functions that are an emergent but not unforeseen result from this research. These findings have implications for future collaboration between the tertiary research sector and government with intelligence functions.

Preface

This research reflects a collaboration between the Melbourne School of Psychological Sciences' (MSPS) research into computer-supported collaborative learning (CSCL), the Hunt Laboratory for Intelligence Research's SWARM project (hereafter the Hunt Lab), and the research requirements of Australian Government stakeholders into multidisciplinary teamwork, reflecting shared goals for improving analytic rigour and possible applications of cloud-based collaborative software in workplace and education settings.

We[1] have structured this research to reflect the shared goals of collaboration, where Chapters 1 through 5 provide the research foundations that inform the three studies of data collection reported over Chapters 6 to 8. These Chapters provide the evidence required to systematically address our research questions in Chapter 9, discuss emergent findings in Chapter 10 and explore future research considerations in Chapter 11.

The central focus of this study is the performance of multidisciplinary teams within organisations with an intelligence function. Within the intelligence context, multidisciplinary teams (hereafter MDTs), are defined as teams that feature employees conducting different roles alongside a central analytical function in a structured manner. While structured, team membership is fluid to allow for different roles to join on an as needs basis.

A MDT may be permanent or established for a defined period to resolve a specific issue. As explored in Chapter 1, there may be a variety of reasons intelligence MDT managers decide to structure a team around a central analytical function. Devanny et al. (2018) highlight the concern of the disconnect between collection functions and their analytical counterparts, particularly with regard to prioritisation and resources (Devanny et al., 2018). In some cases, the formation of a MDT may have more to do with unity against a large-scale threat, where an issue is beyond the scope of an individual or single job family (Fleisher & Hursky, 2016).

Whilst MDTs are increasingly deployed in intelligence work, our Australian Government research stakeholder requirements and the gap in the academic literature highlight the need to understand what high-functioning MDTs look like. Thus, our first step was to develop a maturity model to describe the key process pillars that support high functioning MDTs at increasing levels of maturity, which would then enable the evaluation of MDT performance. Maturity models offer a simple but effective method to measure processes; they contain descriptive statements that articulate different levels of maturity on key performance indicators that allow an observer to evaluate processes and then plan what actions are required to reach a more mature state. The resulting maturity model is a significant contribution of the thesis, providing the basis for evaluation of the current studies and a tool that Australian Government research stakeholders can use to identify strengths and challenges within MDTs. Chapter 2 outlines the theoretical and empirical basis for the maturity model. Given the limited basis for such a model in the existing intelligence teamwork literature, the development of the model required analysing and synthesising literature from other contexts, including healthcare, and adapting it for the intelligence context.

[1] The use of the term 'We' refers to the research candidate, chosen as most appropriate terminology to reflect the joint goals of the collaboration and maintain an active voice for this research thesis. The candidate led over two thirds of the data collection and independently developed the literature review, conducted data analysis and developed conclusions and recommendations. Where research involved other parties, such as the Hunt Laboratory or other stakeholders, this is noted.

The framework used to support a MDT is a crucial consideration for team performance outcomes, as it is the framework that provides the central coordination and structure for the team's operations. Examples of frameworks include guiding templates, scheduled meetings, or other collaboration coordination structures such as workflow organisers and collaboration software. In Chapter 3, we explore the Hunt Lab's SWARM Platform, a cloud-based collaborative software prototype designed to support intelligence analyst collaboration and improve quality of reasoning (Hunt Lab, 2019; SWARM Project, 2019) as a potential framework to support MDT functions. The origins of the Platform stem from 2017 when the United States' Intelligence Advanced Research Projects Activity (IARPA) launched the Crowdsourcing Evidence, Argumentation, Thinking and Evaluation (CREATE) program. This program aimed to achieve fundamental advances in human reasoning, utilising the fields of crowdsourcing and structured analytical techniques. IARPA selected the Hunt Lab and funded the research used to develop the Platform.

Currently, there is a lack of research to inform managers and trainers of the critical components of the 'framework' within which MDTs can perform optimally. In response, the current research sought to map the affordances of the SWARM Platform as a framework for MDTs to the maturity model to identify what support it provides to high-performance teamwork. It is important to note the Platform design is analysis-focused to improve collaboration and quality of reasoning amongst analyst teams, meaning some of the affordances of the Platform are weighted to leveraging team diversity to improve the quality of reasoning for analysts. These affordances not only provide support for the business functions of analysts working in intelligence MDTs but the analysis-centric design means the Platform may provide support for the training functions of teaching analysts and their teammates the skills to operate effectively in intelligence MDTs.

In recognising the Platform's potential to support the training functions of intelligence MDTs, in Chapter 4 we explore the literature of teaching intelligence analysis tradecraft and frame the Platform as a potential computer supported collaborative learning tool (CSCL). In this Chapter, we discuss the complexities of the analyst role and the challenges of recruiting a capable workforce who have the necessary skills. Reflecting on these challenges, we address the CSCL domain to consider how it may be applied to teach the cognitive and social skills required to address the needs of the intelligence sector (Hackman & Connor, 2004) in both the workplace and traditional learning environments such as universities.

While originally designed as an analyst-centric tool, the SWARM Platform affords MDT managers and educators functionality to improve performance. Chapter 5 explores the literature around improving performance and providing scaffolding in both a business and training context. This literature explores what scaffolding strategies are available for managers or trainers to try and increase maturity if applied to MDT maturity model pillars.

Key Research Questions

To address the gaps in literature and the research priorities of our Australian Government research stakeholders, the MSPS and the Hunt Lab, the current research explored three central research questions.

Research Question 1: What are the strengths and weaknesses of how MDTs are utilised in Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions?

Research Question 2: Can the SWARM Platform move beyond its origins as an analysis-focused tool to provide a framework for intelligence MDTs as a business and training tool?

Research Question 3: What does the SWARM Platform afford managers and educators to improve MDT performance?

To address *Research Question 1*, in Chapter 6 we explored a case study of MDT use in the Australian Government intelligence workplace to identify the current strengths and challenges of MDT performance. Through the application of the maturity model, we identified Mission and Collaboration as strengths but Efficiency as a weakness of their current MDT framework. As an emergent result, we identified a bias in Australian Government research stakeholder data collection and an opportunity for increased collaboration between academia and industry to better understand MDT performance.

To address *Research Questions 2 and 3*, we evaluated the SWARM Platform as a potential framework to support MDT workplace application and training, first in a small-scale pilot within an intelligence organisation in Chapter 7, and then on a larger scale in an analytical competition involving public and intelligence organisation teams in Chapter 8. We viewed the inclusion of public teams as important to help identify the Platform's suitability as a tertiary education training tool and how it supported MDT participants from outside the intelligence sector. In these studies, we found the Platform mostly supported key MDT pillars for both public and organisation participants, though additional scaffolding is required to reach high performance across pillars of Accountability, Efficiency and Communication. From a training perspective, participants reported cognitive, affective and social learning outcomes in Platform-based studies.

In Chapter 9, we systematically address our research questions. In this Chapter, we identify Efficiency as a limitation of the case study MDT framework and discuss the Platform's support for high-performance MDTs, including the need for additional support to improve maturity in pillars of Accountability, Efficiency and Communication. We develop insights to improve MDT maturity on the SWARM Platform that are relevant to collaborative MDT frameworks more broadly. In the same Chapter, we discuss the practical limitations of using the Platform in the intelligence community, including some of the technical and cultural issues that prevent adoption of the Platform as a business framework without further research and development.

Recognising these issues that currently prevent Platform adoption in the intelligence community, this research suggests there are more immediate benefits of Platform adoption in the training and education context as a computer-supported collaborative learning (CSCL) tool, where research participants reported learning outcomes in the same Platform-based studies. We have explored some of the practical implications of using the Platform as an education tool and highlighted considerations for educators.

In Chapter 9 we also address some of the study limitations including how COVID-19[2] interrupted elements of data collection. While unfortunate for this research, the pandemic highlighted the need to have suitable cloud-based platforms to support a dispersed online workforce and to facilitate remote learning.

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[2] A pneumonia of unknown cause detected in Wuhan, China was first reported to the World Health Organisation (WHO) Country Office in China on 31 December 2019. The WHO declared a Public Health Emergency of International Concern on 30 January 2020. On 11 February 2020, WHO announced a name for the new coronavirus disease: COVID-19 (World Health Organisation, 2020).

As an emergent but not unforeseen result from this research, in Chapter 10 we discuss the insights learned from conducting research within the intelligence community and the broader implications for future collaboration between the tertiary research sector and government with intelligence functions.

Further research is proposed in Chapter 11 to outline what remains to be explored from this research. We propose further engagement with Australian Government research stakeholders and prioritised application of the MDT maturity model. We also encourage further research to improve how intelligence-related scenarios are utilised on the SWARM Platform. The Chapter concludes that further research is needed to explore how the SWARM Platform may be applied to the training context including in opportunities for greater academic and industry collaboration, such as the fields of recruitment.

Chapter 1: Multidisciplinary Teams in intelligence

In this Chapter, we introduce the central focus of this study, intelligence multidisciplinary teams (MDTs), explore existing teamwork practices within the Australian intelligence context, discuss some of the challenges of these teamwork practices including implementing a MDT framework, and reflect on the importance of leveraging diversity to solve complex problems.

Multidisciplinary teams

Academia and industry have described formalised team collaboration under various common workplace names and descriptors including multidisciplinary teams (MDT), task forces, X-Teams (Ancona et al., 2002) project-management teams, communities of interest, fusion cells and sand dune teams (Ahles & Bosworth, 2004; Hackman, 2011; Mcintyre et al., 2009; Walsh & Miller, 2016).

Hackman (2011) describes sand dune teams as an unbounded work team with dynamic social systems that have fluid rather than fixed composition and boundaries. This is in contrast to co-acting groups which are employees that operate in parallel but do not have collective accountability for a work product (Hackman, 2011). Developing from Hackman's (2011) explanation of sand dune teams, our definition of MDTs explicitly incorporates the different roles that have collective accountability for work outcomes. This definition is drawn from intelligence industry engagement and academic literature from the fields of intelligence (Jameson et al., 2020), health care, education, organisational psychology and design-teams (Beers et al., 2006; Paletz & Schunn, 2010; Saghir et al., 2014; Van Der Vegt & Bunderson, 2005).

What is an intelligence multidisciplinary team (MDT)?

Intelligence MDTs are defined as teams that feature employees conducting different roles alongside a central analytical function in a structured manner. While structured, team membership is fluid to allow for different roles to join on an as needs basis. A MDT may be permanent or set up for a defined period to resolve a specific issue.

Further to our Australian Government research stakeholder interest in the issue, MDTs are the focus of this research due to the inherent complexities for analysts working alongside other roles, and in some circumstances, other agencies, and the gap in literature addressing intelligence MDTs in the Australian context.

Intelligence teamwork in the Australian, State and Territory Government context

In the Australian, State and Territory Government context, there are over 38 agencies, departments and organisations with intelligence functions. Those listed in Appendix A are primarily focused on national security, military, defence, policing and corrections; however, the scope of intelligence analysis is much broader than this. As Marrin (2012) notes, intelligence analysts work in various other domains including public service departments with environmental and emergency management portfolios as well as corporate business (Marrin, 2012). In their research, Corkill and Davies (2013) identified 75 discrete intelligence capabilities across Australian Government agencies and departments at the local, state and federal level (Corkill & Davies, 2013). This considered, the literature this thesis draws upon is primarily focussed on the complexities of the Australian Intelligence Community (AIC), National Intelligence Community (NIC), international intelligence, law enforcement, anti-corruption, corrections, military and corrections functions within the public service.

The complex need for inter-office and inter-agency collaboration amongst analysts and their collection counterparts, technical teams and stakeholders is compounded with the increasingly technology-enabled and transnational nature of many threats (Harrison et al., 2018). Contrary to some claims which suggests police and intelligence agencies rarely work together in Australia (Esparza & Bruneau, 2019), the Joint Counter Terrorism Teams (JCTT) are a partnership between members from the Australian Federal Police (AFP), state and territory police and the Australian Security Intelligence Organisation (ASIO). In addition to the Joint Counter Terrorism Teams, the AFP also plays a role in National Disruption Group (NDG), which features various agencies and departments[3].

Intra-agency and intra-department intelligence teams vary in size and objectives. For example, both sworn and unsworn law enforcement intelligence analysts will work with investigators, informant handlers and dependent on the subject matter, technician divisions (Atkinson, 2019). However, this example may better represent informal collaboration than a unified central team. Formalised intelligence team structures in law enforcement tend to focus around groups (e.g., organised crime) or specific crime problems (e.g., drugs) (Burcher & Whelan, 2019). Straus, Parker and Bruce (2011) suggest from their research that teams within the intelligence community range between three and 18 members, often with an average of 10 members (Straus et al., 2011).

Teams featuring an analytical capability play an integral part in the success of the intelligence team's function. Disregarding information silos and access restrictions, no individual in a team will have all the information. Instead, formal and informal networks must be created to ensure all shared and unshared information is made available to the team. If team members make themselves available, both as a collaborator and a resource, the analyst has the best chance to effectively pool information and inform decision making (Sohrab et al., 2015).

Hackman (2011) notes that not every intelligence problem requires a structured new team and that managers must think critically about when or if a discrete team is required (Hackman, 2011). Sierhuis et al. (2003) describe the process of team generation into five general phases including: 1) recognition of the need for internal and external help; 2) team formation; 3) ongoing coordination, team maintenance and task execution; 4) recognition of resolution or difficulties and, 5) team disbanding (Sierhuis et al., 2003). It is idealistic to assume that all intelligence analysis focussed teams could be set up, actioned and disbanded with such ease as the intelligence analysis profession carries with it inherent issues. One key issue being some intelligence problems may not be so easily resolved completely.

Adding complexity to intelligence MDTs is that the team members are increasingly dispersed across offices, states and even time zones. This is not to say MDTs are necessarily geographically dispersed, rather the framework that coordinates a MDT will need to account for team members not to be permanently collocated. This means teams are increasingly required to depend on electronic communication in place of face-to-face dialogue (Hackman, 2011). Further, dependent on the agency or department, cultural issues may plague an

[3] NDG agencies and departments include the Attorney-General's Department, the Australian Crime Intelligence Commission, Department of Home Affairs, Australian Intelligence Agencies, Australian Taxation Office, Australian Transaction Reports and Analysis Centre, Department of Defence, Department of Foreign Affairs, Department of Human Services, Department of Social Services and State and Territory police (Australian Federal Police, 2019).

intelligence team such as hierarchy, the impact of previous intelligence assessments, norms and time pressures (Vandepeer, 2018).

MDT frameworks

Considering the above cultural issues, whether small or large teams are formed, collaboration does not occur without orchestrating an environment supportive of goal uniformity, information sharing and decision making (Pennington, 2008). Therefore, managers are required to consider what framework they implement for their MDT. The framework of a MDT provides the central coordination and structure for teamwork. Examples of frameworks include guiding templates, scheduled meetings, or other collaboration coordination structures such as collaboration software. We note there is limited research to date on the strengths and limitations of intelligence MDT frameworks. Hackman (2011) suggests there is no 'best' way to structure or manage intelligence work but there is an argument to be made for ensuring all stakeholders or subgroups of a given issue be included in a structured manner when a problem is sufficiently complex or 'wicked', which requires multi-stakeholder and multi-disciplinary decision making (Hackman, 2011; Kirschner & Van Bruggen, 2004).

Leveraging diversity through MDTs

The arguments for leveraging greater diversity to solve complex problems are broad but largely consistent. Callum (2001) claims greater diversity will lead to improvements in analysis (Callum, 2001); Beers et al. (2006) asserts multiple perspectives properly coordinated can tackle a much larger problem than each can on an individual basis but also notes that in doing so, there is no guarantee of success (Beers et al., 2006). In a study designed to explore the interrelationship between team diversity and task complexity in terms of its impact on performance, Higgs, Plewnia and Ploch (2005) suggest team diversity contributed positively to performance on complex tasks and negatively on straightforward tasks (Higgs et al., 2005). This finding supports Hackman's (2011) assertion that the formulation of complex teams (in this instance MDTs) is not required for all tasks (Hackman, 2011).

As Beers et al. (2006) notes, MDTs are often used to resolve issues where team members have different perspectives or roles to play within a problem, where their different knowledge and skills are required to 'solve' a problem through sharing information, decision making and the construction of 'new' collective knowledge (Beers et al., 2006). When members join a MDT, they represent themselves as well as their respective role, skills, knowledge, values and at times management chain (Conklin, 2006). The creation of a new MDT requires team members to acknowledge their prior experience and adopt the new shared team responsibility, where the MDT must work as a cohesive unit to achieve their goals. Teams who adhere to this shared responsibility have been found to contribute positively toward team performance outcomes (Doorewaard et al., 2002).

Johnston (2005) argues that multidisciplinary teams working on repetitive and process driven tasks, such as an air and tank crew, can develop a shared mental model more quickly than teams that deal with wicked or complex problems (Johnston, 2005) such as health professionals or intelligence teams. In a separate but heavily teamwork-oriented industry, Lawn et al. (2013) noted some of the challenges facing the healthcare profession include fragmented communication, overlapping care plans and uncertainty around client and interagency responsibility. The research notes that, for the MDTs to be most effective, communication needed to be open, two-way and inclusive of all members of the healthcare team (Lawn et al., 2013).

Cross, Parise and Weiss (2007) identified team dynamics were limited due to the geographic distances between central and regional offices of a business. The research identified strong collaboration within regions but weak across them, recommending the promotion of central key interlocutors in each of the regions to promote and facilitate communication amongst the regions (Cross et al., 2007). Such collaboration encouraged staff to utilise all the resources available to them as well as ensure the team is composed of those who have a stake in its outcome. Daniel and Davis (2009) note a high-performance team will utilise the unique knowledge that each staff member brings. This relationship between knowledge sharing and high-performance is not necessarily causal and that there are many other factors to consider when it comes to MDT performance.

In this Chapter we have identified that MDTs are utilised across a variety of industries, including intelligence and that harnessing the capabilities of a diverse team is beneficial but also challenging. With so much potential to be gained and a lot at risk in the field of intelligence, harnessing MDT potential is difficult without a clear and easy to apply mechanism to evaluate performance. To identify the qualities of a high-performing MDT, in Chapter 2 we have developed a maturity model to fill this void.

Chapter 2: Multidisciplinary Team Maturity Model

In Chapter 1, we covered MDT practices in the Australian intelligence context, why MDTs are used in the intelligence community and reviewed some of their complexities. In this Chapter, we address the issue of understanding the qualities of what a high-functioning MDT is capable of. As the management of MDTs carries with it natural variation of methodological approaches and culture norms (Typhina & Wilson, 2019), line managers and trainers need to understand the qualities of a high-functioning intelligence MDT. Given the absence of literature to adequately capture the qualities of an intelligence MDT, we have developed a maturity model from academic literature to delineate the indicators of low and high performance intelligence teamwork in a MDT.

Maturity model

Maturity models offer a simple but effective method to evaluate processes, in this case team performance. This method of evaluation originally emerged out of software engineering but has broadened to other fields including project management, healthcare and workplace collaboration (Wendler, 2012). Maturity models are descriptive statements divided into levels of maturity to allow a manager, educator or organisation to evaluate processes then plan what actions are required to reach a more mature state (Magdaleno et al., 2009). Maturity models are not intended to provide rigorous metrics, instead they are designed to help identify potential issues and provide a guide of high-functioning indicators (Boughzala & De Vreede, 2012).

Considering the application of MDTs in either real-world or training contexts, we have developed a maturity model, which draws on academic intelligence and teamwork literatures to synthesise the indicators and requirements for high-performance intelligence MDTs. The maturity model affords managers and educators the ability to review the model and prioritise elements that best meet the requirements of their team. Each element of the maturity model is accompanied with ‘key terms’. These key terms are to help managers and trainers identify thematically where strengths or limitations may exist in their team.

An investigation of all the characteristics and features of a high-performing MDT is not possible in this research. For example, this maturity model does not account for how a manager or educator leads a team. Instead, this maturity model is to be used to better inform managers and educators of their own team’s performance and to inform their actions. As Hackman (2011) notes, the leader’s role is to enable the conditions for a team to perform. The proposed model is intended to help guide decision making to identify if intervention or scaffolding is required. Hackman outlines the following conditions for enabling a high-functioning team which include specifying a clear purpose of the team; putting the right number of people in the team; specifying clear norms of behaviour; providing a supportive organisational context; and, making team-focused coaching available to the team (Hackman, 2011).

Our maturity model distils the literature into seven core pillars: Mission, Accountability, Agility, Efficiency, Communication, Collaboration, and Output. We have outlined these findings into paragraphs below and summarised them into a maturity model table (Table 1 refers).

Mission

For the purposes of a MDT, a clear mission is vital both from an ideological sense, in other words a value proposition, but also in an outcome-oriented sense. This is to say, to have a clearly articulated mission of the teams purpose, which serves as a shared reference point for different roles, allocation of resources and security environment changes (Daniel & Davis, 2009). Following the 11 September 2001 terrorist attacks, the then Director of the Central Intelligence Agency (CIA) George Tenet informed his managers, and therefore their teams, that each person must assume an unprecedented degree of personal responsibility for what happened and what they need to do going forward (Central Intelligence Agency, 2010). This is further mirrored in the comments about patriotism in their mission, "After a long shift at work, many officers would leave late in the evening or early in the morning. They would drive under overpasses with American flags waving gently in the breeze—reminders of what their long work days were all about" (Central Intelligence Agency, 2010, p. 11).

The mission's methodology will change depending on whether it is a temporary or permanent team, but consider how a mission statement such as 'disrupt this terrorist cell' or 'seize this drug shipment', aligns the team members' skills and helps them understand one another's perspectives. Teams struggle to actualise without a shared vision (Pennington, 2008). This shared mission encourages members to care about the work and the outcomes produced. This motivation plays a key role in team members' effort to promote cooperation and to encourage active participation (Peters & Manz, 2007).

A shared mission increases team members' sense of responsibility for the project outcomes (Hackman, 2011). The mission statement clearly articulates the goal of the team without dictating how it will be achieved. This allows for the disparate roles within the MDT to feel supported in moving towards the team's mission while simultaneously pursuing objectives of their given role. As Conklin (2006) suggests, each disparate role or organisation involved in a MDT will have its own values, goals and desires (Conklin, 2006). However, even though team members may have different role-oriented goals, this does not necessarily mean these will interfere with the shared team goals (Sierhuis et al., 2003). Aligning disparate roles under a central mission narrative, a joint mental model or a superordinate goal, provides managers or educators the opportunity to set other joint conditions such as norms and values of the team (Hackman & Woolley, 2008; Hung, 2013; Keyton & Beck, 2008; Pennington, 2008).

Accountability

Whilst state and territory agencies and departments have their own oversight functionality, the Inspector-General of Intelligence and Security (IGIS) oversees the members of the Australian Intelligence Community (AIC) including the Office of National Intelligence (ONI), ASIO, the Australian Secret Intelligence Service (ASIS), the Australian Signals Directorate (ASD), the Defence Intelligence Organisation (DIO) and the Australian Geospatial-Intelligence Organisation (AGO) (Inspector-General of Intelligence and Security, 2019). The IGIS carries out regular inspections of the intelligence community that are designed to identify issues of concern, including in the agencies' governance and control frameworks. Early identification of such issues may avert the need for major remedial action (Inspector-General of Intelligence and Security, 2020).

Considering the IGIS' functionality and purpose, it is vital therefore that all MDTs remain accountable to themselves and their respective organisations, whether AIC members or not. Contrary to some claims who suggest elements of lawlessness in the AIC (McCulloch & Tham, 2005), the inbuilt and external accountability measures build trust externally but also internally within the teams themselves. As Marrin (2007) notes, given the cost of failure and likely high level of scrutiny possible, transparency of decision making is essential (Marrin, 2007). This accountability also solidifies the balance of intelligence collection powers and democratic freedoms (Graaff, 2018; Matei & Halladay, 2019).

Moving beyond remaining accountable to the Commonwealth, State or Territory agencies and departments audit functions, Morse et al., (2007) argues internal team accountability towards each other, including timelines, requirements and responsibilities is essential (Morse et al., 2007). MDT members can demonstrate accountability through the appropriate use of information including storing evidence and intelligence appropriately for use at a later date if a decision or assessment is questioned (Chin et al., 2009). To support this, a non-intelligence-focussed study evaluating virtual design teams suggests high-performing teams effectively managed knowledge and administrative tasks (Ocker & Fjermestad, 2008). We view this adherence to knowledge storing and internal team responsibilities as important to building accountability within a team and to aid external review mechanisms.

Agility

Flexible deadlines allow team members to pace themselves and coordinate with others (Ancona et al., 2002); however, a high-performing intelligence analysis MDT must have the agility to change pace at short notice. The variety of threats facing intelligence analysts are broad with a range of scales and pace; for example, the lead time before actualised threats can be slim, noting that Anders Breivik reportedly distributed his manifesto 90 minutes before commencing his attacks (Antonius & Rich, 2013). The reality of the majority of intelligence-related work is that for the MDT, and specifically the analysts within the team, their literal and proverbial inboxes are never empty (Brown, 2018). But within this onslaught of information, raw or analysed information may trigger new insights such as a formerly trustworthy information source found to be unreliable, and thus require a different course of action (Graaff, 2018; Irwin & Mandel, 2019).

Further, as adversaries continue to employ new methodology to counter law enforcement and intelligence-led approaches, MDTs must be prepared to adapt their approach and innovate (Pfeifer, 2012). A high-functioning agile team prioritises efforts around their core mission and does not get stuck in an 'it's always been done this way' mindset. Noting in the MDT's mission, intelligence analysis may not have the dominant role but should feel empowered to use their craft to promote agility within the team toward achieving the shared mission.

Agile teams not only are structured or framed in such a way that allows them flexibility with shifting priorities but agility also suggests anticipation. A high-performing MDT will seek to anticipate a client or stakeholder's needs as the security environment changes (Brown, 2018). A team's agility, or ability to adapt, may be largely dependent on the framework and structure of a MDT. However, managers and educators should consider their staff and team's readiness (and ability) to change if circumstances dictate it. These changes are not only mission or goal-related but refer to changes in staffing (team membership and leadership), resources (financial or capabilities) and world events (political changes).

Efficiency

Resources need to be used effectively and in some cases, the formation of a MDT is not appropriate. For complex or wicked problems that require multiple roles and disciplines, the establishment of an intelligence MDT is likely justified. However, due to the time and resources required to initiate and maintain a team, managers must consider whether a MDT is appropriate for the given task or problem (Hackman, 2011; Hung, 2013). Unfortunately, due to changes in the security environment, it is a difficult and distinct challenge to appropriately assess a threat to determine if a MDT is required.

Intelligence MDTs, whether focused on tactical, investigative or strategic goals, will each have pressing deadlines and in the case of the public service, a budget (Graaff, 2018). There are rarely enough resources to support every goal of a MDT. Furthermore, it is possible, if not likely, that team members may be members of multiple MDTs, which may conflict with performance (Urban et al., 1995). Therefore MDT implementation, frameworks and management should attempt to minimise the resource impost on both participating staff and the broader participating organisations (Ratcliffe, 2010).

Intelligence analysis is only as useful as its currency, meaning the analyst will never know everything and must assess the information available at that point in time (Chin et al., 2009). MDT participants therefore must be mindful and alert to timeliness of processes, ensuring social team processes such as line management feedback do not prevent pertinent analysis dissemination (Winter & Jackson, 2016). Equally so however, analysts should not be forced to abandon rigorous analytical processes for the sake of self-imposed timelines (Chin et al., 2009).

Conklin (2006) speaks to the issue of misunderstanding of key terms and concepts. Particularly, in a MDT where divergent roles are brought together, misunderstanding of terms and responsibilities can add inefficiencies (Conklin, 2006). A high-performing team should have a clear understanding of the roles of participating members and managers should clearly articulate preferred terms and their meanings. For example, an analyst from one area of an organisation may interpret *PRIORITY* to mean due tomorrow, whereas another could interpret it to mean it is due by the end of the week. As agility is closely linked to efficiency, so is efficiency to communication.

Communication

Communication within a team can take many forms including face-to-face and technology-enabled methods creating distributed communication networks (Champion, 2012). In the intelligence domain, this distributed network further complicates existing 'need-to-know' principles and differences in access depending on classifications and home agency networks (Hackman, 2011). In the qualitative research of Burcher and Whelan (2019), they report interviewees experiences of frustration with both the information technology systems used to manage data as well as the restrictions on how information and intelligence can be shared (Burcher & Whelan, 2019). Despite these communication challenges, MDTs must communicate effectively to achieve their desired outcomes.

Managers and team members alike must combat these challenges and ensure communication is accessible and context appropriate. In the field of intelligence MDTs, accessibility refers to both communication format and content. Due to the diversity of members in a MDT, communication needs to be made available to all team members. For example, if a face-to-face meeting occurs, the outcomes should be transcribed for MDT members not in attendance. This is particularly important as per Hackman's (2011) discussion of 'sand-dune' teams. As team members join and leave, it is important that these staff members can access a MDT's history of communication. Further in regards to the diversity of roles, communication should be accessible in regards to terminology. As noted above in *Efficiency*, MDTs should agree on a common language and when misunderstandings occur, clarify early.

With regards to context appropriateness, there is an outstanding question around the requirement for face-to-face meetings and how efficient communication needs to be with large and diverse teams. Hackman and Woolley (2008) argue their research shows that for dispersed teams there is a notable communication benefit of initialising the team with a face-to-face meeting. They add, ideally the MDT would also utilise further face-to-face meetings to punctuate critical decisions or transition points (Hackman & Woolley, 2008).

In high-pressure and high-threat MDTs, a manager calling a group face-to-face team meeting for a non-priority message may interrupt workflow and reduce the impact of future communication. All MDT members need to consider the method of their communication and whether it is appropriate for the context, for example sending a text-based message which can be read at a later time may be more suitable in the above example (Champion, 2012).

Certain studies have found group performance increases when team members are afforded time apart with periods of separation (Bernstein et al., 2018). However, earlier team studies suggest from a student perspective at least, that high levels of trust were maintained in teams that engaged in continuous and frequent interaction, which led to more productive engagement and focus on completing the team's goals (Iaocono & Weisband, 1997). There is a concern that a large volume of communication can result in an overload for MDT members. Therefore to counter potential asynchronous communication, high-performing teams should semi-regularly review knowledge repositories resulting from electronic communication and summarise key content for other members (Ocker & Fjermestad, 2008).

Perhaps this combination of research suggests high-performing teams need to have the option (whether it be with the aid of communication tools or otherwise) to engage in regular dialogue with their team; however, team members should be supported to disengage where required to focus on tasks with an increased cognitive load. This requires a communication strategy that encourages team members out of the loop to re-engage with communication streams efficiently through inter-team collaboration. A high-performing MDT will emphasise that effective communication leads to better teamwork, where both information providers and recipients are equally responsible for communication efficacy (Moss et al., 2013).

Collaboration

Effective collaboration is a key cornerstone of a high-functioning MDT. Indeed, it is often the desire for increased and formalised collaboration that motivates the formation of a MDT in the first instance. Active participation and information sharing brought about via high-level communication ensures team members have the best opportunity to collaborate and develop shared mental models with regards to tasks, roles and processes (Paletz & Schunn, 2010).

Boughzala and De Vreede (2012) define collaboration maturity as a team's maximum capability to collaborate, where members communicate effectively, share understanding and adjust their behaviours and tasks in accordance with one another to produce high-quality outcomes (Boughzala & De Vreede, 2012). Boughzala and De Vreede also developed their own maturity model solely dedicated to collaboration in teams. Their research focused on attributes including collaboration management; collaboration process (how team members collaborate and the technology they utilise); and, collaboration knowledge integration, which includes how team members manage information.

An important component of collaboration is the learning and development element. Both Monks (2008) and Nolan (2018) describe the experiences of analysts being left by themselves to 'figure it out'; 'it' being their role, where they sit in the organisation and what roles others perform (Monks, 2008; Nolan, 2018). Naturally, bringing diverse groups of staff together into a MDT will afford the opportunity for collaboration as well as vicarious and constructed learning. Considering the training and learning development opportunities of intelligence analysts, Burcher and Whelan (2019) note most analysts undertake initial training when they first join an agency or organisation but their study found limited opportunities for ongoing training (Burcher & Whelan, 2019). Harrison et al's (2018) comments support this, suggesting public service agencies utilise a 70/20/10% learning model for staff where 70% is work-place learning, 20% coaching/mentoring and 10% formal education/training. This approach focuses on 'on the job' learning (Harrison et al., 2018).

In the context of MDTs, this 'on the job' learning presents an opportunity for members to learn from one another, senior or junior, about roles, experiences and methodologies. Effective teams operate in ways that build shared skills, collective commitment and contextually appropriate task strategies, as opposed to antagonistic and divisive behaviour from which little is learned (Hackman, 2011). Hackman (2011) adds these team processes can enhance collective effort and actively develop members' knowledge and skills, which in turns creates new team capabilities from which the organisation and job families can draw from for the current or future teams - a process he describes as 'cross-training' (Hackman, 2011). As Bruce and George (2015) note, agencies require staff to have the capacity to further their expertise and drive their own learning (Bruce & George, 2015) and teamwork experience can aid in this process.

Ancona, Bresman and Kaeufer's (2002) research suggest high-functioning teams emphasise collaboration both within and outside team members' organisation (Ancona et al., 2002). This affords team members the opportunity to leverage outside expertise, to have support, to alert external members to developing issues, and if deemed necessary, invite external staff to become part of the MDT. Cooperation and open engagement is recognised as vital to achieving congruent goals (Daniel & Davis, 2009). Engaging with external collaboration ensures team members view themselves as part of a broader system (Castka et al., 2001). This highlights an element of the collaboration process; firstly, to identify when expertise is required, and secondly, to collaborate in such a way that is meaningful and is best for the end goal (Mayo & Woolley, 2016).

For teams to solve complex problems, they need access to as much relevant information as possible, which is itself a precondition for collaboration to occur (Mcintyre et al., 2009). Teams face changing situations where the relative importance of sets of information may change. In these circumstances, information previously considered irrelevant can take on new importance to the team (Randall et al., 2011). This cites the importance of ongoing collaboration due to the tangible impact it can have on a MDTs output.

Output

Agencies and departments with intelligence analysis functions place considerable value both on producing tangible output as well as client engagement and satisfaction (Dhami & Careless, 2019). Hackman (2011) notes most intelligence teams often have a mission with a specific objective. This objective could be the production of an analytical report; reaching a decision and providing advice; resolving an investigation through disruption; or the successful completion of an operational outcome. If the objective is achieved, members should report outcomes as a form of output. If concrete objectives or identifiable output such as these are not accomplished, it is reasonable to assume it is a signal of poor team performance (Hackman, 2011).

In MDTs featuring intelligence analysts from different agencies, there may be assumptions that the analysts each would use analytical methods (and potentially software) from their own domain to 'solve' the intelligence problem. There is an underlying assumption that these analysts will come to an agreement and apply the 'best fit' of their processes (Johnston, 2005). It is important to note that analytical assessments can inform both internal and external collectors and partners so 'best fit' and subsequent output will also depend on stakeholders and clients (Symon & Tarapore, 2015).

Fox (2013) adds that in some cases increased information sharing within and outside a MDT is itself an output that affords agencies and departments the best opportunity to fulfil their missions, both divergent and overlapping (Fox, 2013). An added complexity is if multiple team members are contributors to a single analytical product or output, where analysts may be incentivised to produce more reports or require recognition for the work they contribute to (van Gelder & de Rozario, 2018).

Intelligence MDT output is difficult to assess standalone, in particular analytic products, due to differences in audience, time constraints and quality of available information (Dorn, 2019). One method of reviewing intelligence analytical product is the Office of the Director of National Intelligence (ODNI) 'IC Rating Scale'[4]. The IC Rating Scale provides a criteria to review written output such as considering alternative and contradictory information; using all information sources as a basis for assessments; and, expressing uncertainties and confidence in judgments (Straus et al., 2011). As van Gelder (2019) notes, the IC Rating Scale is considered the most authoritative guidance for the evaluation of analytic output in the United States intelligence community but carries with it multiple issues. These limitations include reliability, methodological validity, efficiency and standardisation (van Gelder, 2019). Despite these issues, the IC Rating Scale remains the most authoritative standard of evaluating intelligence output and therefore will form the central coding mechanism for evaluating Output quality in this thesis.

Dependent on the type of intelligence MDT and the role of its intelligence analysis function, the managers of the team must acknowledge the type of output their team wants to produce, what they can produce and if there is unlikely to be a tangible output, how this result will be communicated with senior management and other internal and external stakeholders. Further, when considering how the MDT's output will be reviewed, managers should agree with their team that a method of evaluation will be used consistently across the roles and departments involved in the team. A team's awareness, or at least agreement, on how their output will be reviewed provides consistency and transparency of the standards that they will be kept to.

MDT Maturity Model formation

Our proposed maturity model focuses on the pillars of Mission, Accountability, Agility, Efficiency, Communication, Collaboration, and Output explored above. The maturity model provides a summary of indicators of low and high-performing teams against the respective pillars. Key terms are provided to aid managers and trainers recognise indicators of performance in their teams (Table 1 refers). These terms also contributed to the development of the MDT Research Coding Schema (Appendix C refers).

[4] Refer to Appendix B for UNCLASSIFIED summary.

Table 1: Multidisciplinary team maturity model

MDT Pillar	Low-performing	High-performing	Key terms (indicative)
Mission	The MDT does not have a shared mission. If the team has a superordinate goal, members do not understand or adhere to the mission.	MDT members understand and adhere to the team's shared mission.	Superordinate goal, belief and purpose, responsibility, ownership, joint mental model
Accountability	The MDT is not accountable and does not maintain records of information or decision making. The MDT is not transparent and is difficult to maintain oversight of/audit.	The MDT is accountable for their actions. Information, data and records (including decision making) are stored and accessible for later use.	Data management, record keeping, oversight, audit, transparency and recording of decision making
Agility	The MDT is unable to change. This includes items such as mission, methodology or resource availability.	The MDT is agile. The team can adapt to a new mission or task, changes to methodology or resources and is in a state prepared to adapt.	Flexible, adaptable, anticipatory
Efficiency	The MDT does not utilise resources (time, finances, staff) efficiently.	The MDT and its framework support efficient resource use.	Resource allocation (time, finances, staff), deadlines, prioritisation
Communication	MDT does not engage in accessible communication practices. Level of MDT communication is low or non-existent.	MDT engages in regular and accessible communication using consistent language. MDT members can engage / disengage and maintain visibility of communication.	Accessible (current and historical), consistent terminology, context appropriate, engagement / disengagement opportunity
Collaboration	MDT does not share knowledge or information	MDT members collaborate through	Cooperation, engagement, information and

	internally or externally. MDT does not utilise available software or tools to maximise collaboration.	information and knowledge sharing internally and externally. MDT members cross-train one another and utilise available software to maximise collaboration.	knowledge sharing, utilise available software, cross-training, internal and external engagement
Output	MDT does not produce or make records of outcomes or output. MDT does not have an agreed method of evaluating work. MDT does not meet stakeholder or client needs.	MDT produces output or outcomes that meet stakeholder requirements. MDT has an agreed method of evaluating their output.	Meets objectives, meets stakeholder or client needs, record outcomes, agreed evaluation method

Organisations must consider what information and data they have on team performance to evaluate a team's maturity and performance and whether their current MDT framework is sufficient. Managers may wish to employ additional data collection mechanisms such as surveys to evaluate team performance as traditional team frameworks of meetings, email and Microsoft Office products only affords certain visibility for managers.

In this Chapter, we have documented the capabilities and traits of high and low performance in the MDT maturity model. This MDT maturity model is a tangible contribution to this and future research including studies of MDTs and MDT frameworks. This model will guide our evaluation of the SWARM Platform, a possible MDT framework, to explore how it supports users, managers and trainers, to achieve high-performing MDT maturity.

Chapter 3: SWARM Platform as a MDT framework

After developing a maturity model to evaluate MDT performance, in this Chapter we turn our attention to whether applying a particular framework, in this case the SWARM Platform, may provide the required support to achieve high-performance across the MDT maturity pillars. We will first examine the history and theoretical underpinnings of the SWARM Platform design, explore the affordances and explicitly map them in accordance with the MDT maturity model. This mapping to the MDT maturity model will take the form of a table, to highlight each design component and how it supports MDT maturity.

History of the SWARM Platform

Originally titled the Smartly-assembled Wiki-style Argument Marshalling (SWARM) project, the Hunt Lab developed the SWARM Platform as the Hunt Lab's primary research and development activity (Hunt Lab, 2019; Sinnott et al., 2019).

The origins of the Platform stem from 2017 when the United States' Intelligence Advanced Research Projects Activity (IARPA) launched the Crowdsourcing Evidence, Argumentation, Thinking and Evaluation (CREATE) program. This program aimed to achieve fundamental advances in human reasoning, utilising the fields of crowdsourcing and structured analytical techniques (Sinnott et al., 2019).

IARPA intended the CREATE program to be in three-phases with a four-and-a-half-year schedule. The CREATE program initially funded four separate system-design projects targeted at supporting improvements in evidence-based reasoning. CREATE required the developed systems meet certain specifications. These included that systems needed to produce 'products' to be evaluated for quality; the systems needed to apply one or more structured analytical technique (SAT); and finally, the system needed to incorporate some form of crowdsourcing (optional for Phase One) (van Gelder et al., 2018).

During Phase One, the four project teams focused on the development of the core systems and their evaluation. The project team's systems needed to clearly demonstrate they offered significant improvements over other collaborative approaches such as Google Docs (Sinnott et al., 2019). Out of the four projects, IARPA selected the Hunt Lab to continue into Phase Two and funded the research used to develop the SWARM Platform (SWARM Project, 2019). The program did not continue into Phase Three (Intelligence Advanced Research Projects Activity (IARPA), 2020).

Platform design

The SWARM Platform is built up of multiple micro-elements as opposed to a single application. This supports the Cloud infrastructure and scalability to larger numbers of users. While the technical specifications are not the focus of this study, Sinnott et al., (2019) provide a high-level overview of the system design as at 2019 in Figure 1, which documents some of the interlinking elements of the SWARM Platform functionality that include messaging systems, security and mobile phone compatibility (Sinnott et al., 2019).

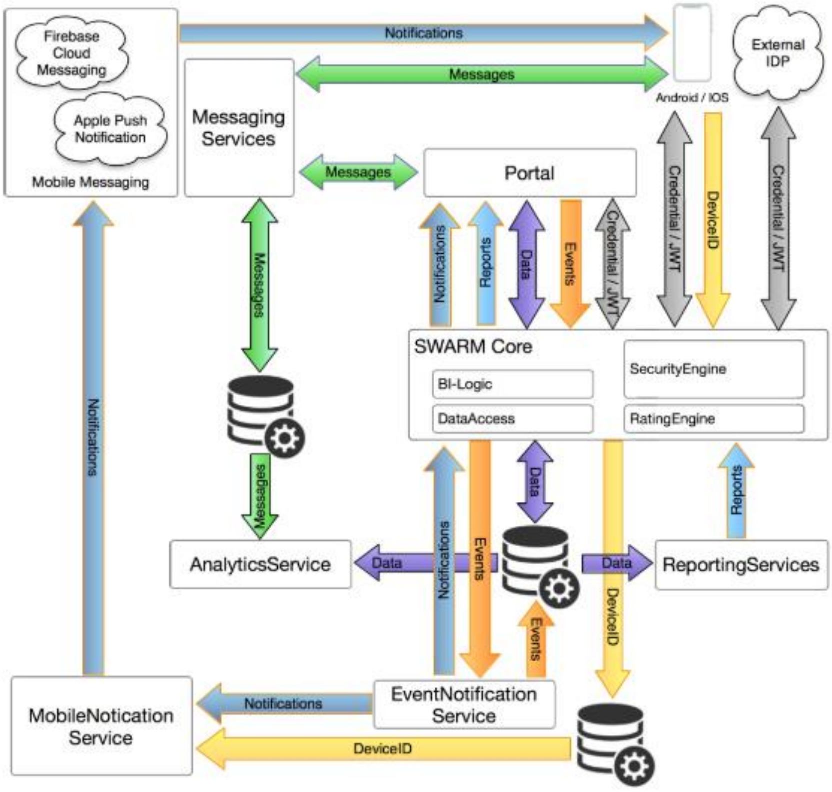

Figure 1: Overall SWARM System Architecture (Sinnott et al. 2019).

Using the SWARM Platform

To sign into the Platform, administrators provide users with an anonymous animal-based username, for example quokka46. After signing in, users see a landing page with the available problems. On the landing page (Figure 2), there are open and closed problems. After accessing an intelligence problem from the landing page, users will then see the main interface (Figure 3). This contains a section for the intelligence problem posed to the team (left); a collaborative space to share resources and co-draft reports (middle); and, a chat functionality for the team to communicate with (right). On the top of the right hand-side, all users who are active and 'online' are listed, so teams can identify who is available to collaborate.

Figure 2: SWARM Platform problem interface landing page

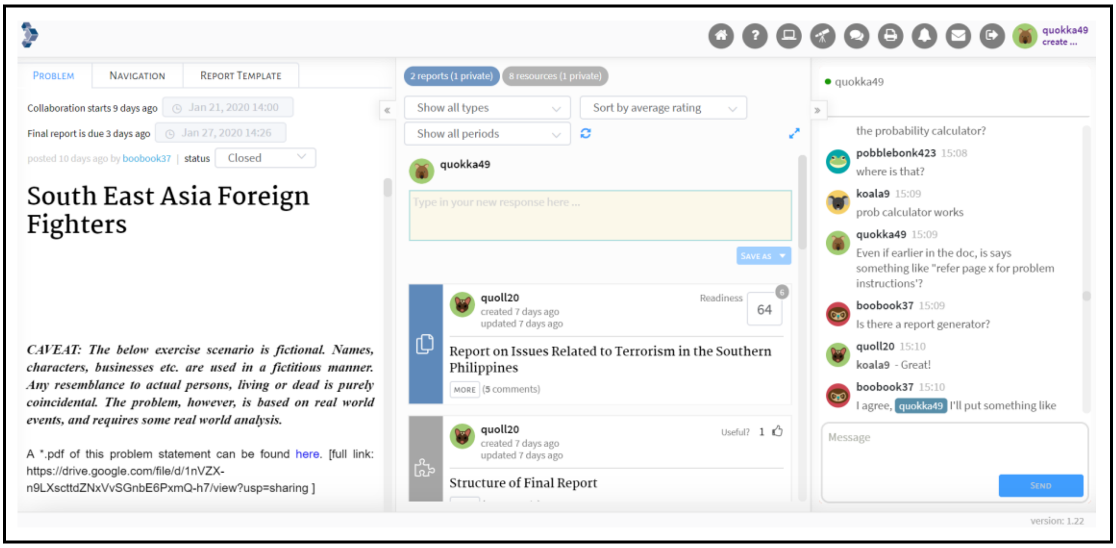

Figure 3: Screenshot of SWARM Platform.

Theoretical underpinnings of the Platform

The specific intricacies of the Platform design are multifaceted and designed to work towards this goal of improving analytical reasoning in high-performance teams. To achieve this, academic expertise, domain scientists and experimental teams designed the system to cultivate engagement, natural expertise, and collaboration (Sinnott et al., 2019; van Gelder et al., 2018).

Sinnott et al., (2019) detail the specific design-focused criteria that set the foundations of the Platform to support teamwork and minimise the technological demands of adopting new technology. These criteria are as follows. *Collaborative report creation:* this is what underpins the Platform design. The design encouraged users to leverage all the team's work including large or small contributions. *Feedback and review*: the design encourages participants to provide feedback both formally through a rating system (discussed below) and informally. *Engagement*: the design aims to make Platform experience smooth and intuitive, always encouraging engagement. *Social warmth*: the design is focused around promoting social interaction through multiple vectors of engagement. *Few constraints on users*: the Platform is not designed to replace or automate human reasoning. *Access to support for structured analytic techniques and other problem solving tools*: the Platform should not constrain users to a particular analytical technique or methodology. *Anonymity*: the Platform design supports anonymity, so users can express opinions more freely and rate others work without fear of reprisal. *Support multiple large team sizes* : team size and scale should not negatively impact Platform performance (Sinnott et al., 2019).

Affordances of the SWARM Platform

Moving forward from the theoretical and technical base of the SWARM Platform, this research explores the application of the Platform prototype in terms of what it affords users practically. When considering applying a software or system tool, the notion of affordance is often applied to low-level features of the interface. For instance, a button in the SWARM Platform affords clicking (van Gelder et al., 2018).

Intelligence teams use a wide range of computer software in their work ranging in sophistication and complexity, each designed for a different purpose (Hackman, 2011). Recognising the theoretical and technical design of the Platform, van Gelder, de Rozario and Sinnott (2018) argue that a tool can also afford higher-level actions to promote behaviours or provide opportunities dependent on the user. Here we are focusing on the high-level affordances of how these factors can be directly linked to achieving high-performance across the pillars of MDT maturity. To do this, we must first explore the theory behind affordances as a concept.

Gibson (1986) suggests affordance is derived from the concepts of invitation and demand but with a crucial difference. Affordance of something (in this case a software tool) does not change as the needs of the observer changes (Gibson, 1986). He adds that the observer instead may or may not attend to the affordance according to their needs but the affordance remains constant (Gibson, 1986). Withagen, de Poel, Araujo and Pepping (2012) suggests Gibson conceives affordance as action possibilities.

Rebuffing Gibson's theory around the needs of the observer and drawing on Donald Norman's looser definition of affordance, they seek to move beyond this and assert that the vast majority of affordances do not invite certain activity but are dependent on the users behaviour (Withagen et al., 2012). This reimagining asserts users are far more active in their environment; however, in the realm of the software design, McGrenere and Ho (2000) incorporate Norman's definition and suggest that usable system designs should have indicators specifying affordances that account for the various requirements of the end-user, including cultural conventions (McGrenere & Ho, 2000). The research behind the SWARM Platform supports this mindset suggesting that the software should support a user's activities and minimise the technological demands that prevent adoption of new technologies (Sinnott et al., 2019).

Given the extensive affordances of the SWARM Platform prototype, we are progressing the existing research into the Platform to articulate the affordances of the Platform and how specifically they contribute to achieving high-performance across the MDT maturity model pillars. We note in evaluating the Platform we may also identify strategies to improve performance on Platform through enhancing existing affordances that are relevant to other MDT frameworks.

We have mapped the SWARM Platform's design features and highlighted how they support each element of the MDT maturity model. We have also summarised this mapping process into an easy to digest table (Table 2 refers).

Platform affordances: Mission
As illustrated on the left-hand side of Figure 3, the Problem Statement is available and accessible to all team members. Given intelligence problems are often complex and wicked, the Platform encourages managers (or task setters) to be explicit in their directions to the MDT. Managers can update this Problem Statement pane at any time, to reflect the changing dynamics of the security environment. This sets the overall Mission for team members in a clear and transparent way.

Due to the complexity of intelligence problems, intelligence teams may find it more difficult to develop a shared mental model or in other words, a team schema (Johnston, 2005). The team schema encapsulates how the team digest information and sets guidance or expectations on how to interact and complete the goal (Champion, 2012; McNeese, 1998).

The Hunt Lab have developed a 'How to' guide for conducting analysis on the Platform to help teams develop their teamwork schema (Figure 4 refers). These guides include advice and instructions on 'Responding to the Problem', 'Rating responses', 'Report writing' and 'Collaborating on SWARM'. As Hackman (2011) notes, stable teams have a more integrative shared mental model developed with time and experience; this considered, the guides cannot replace time spent together rather they provide a base from which new teams can develop a new schema or experienced teams can integrate the Platform's functionality into an existing schema.

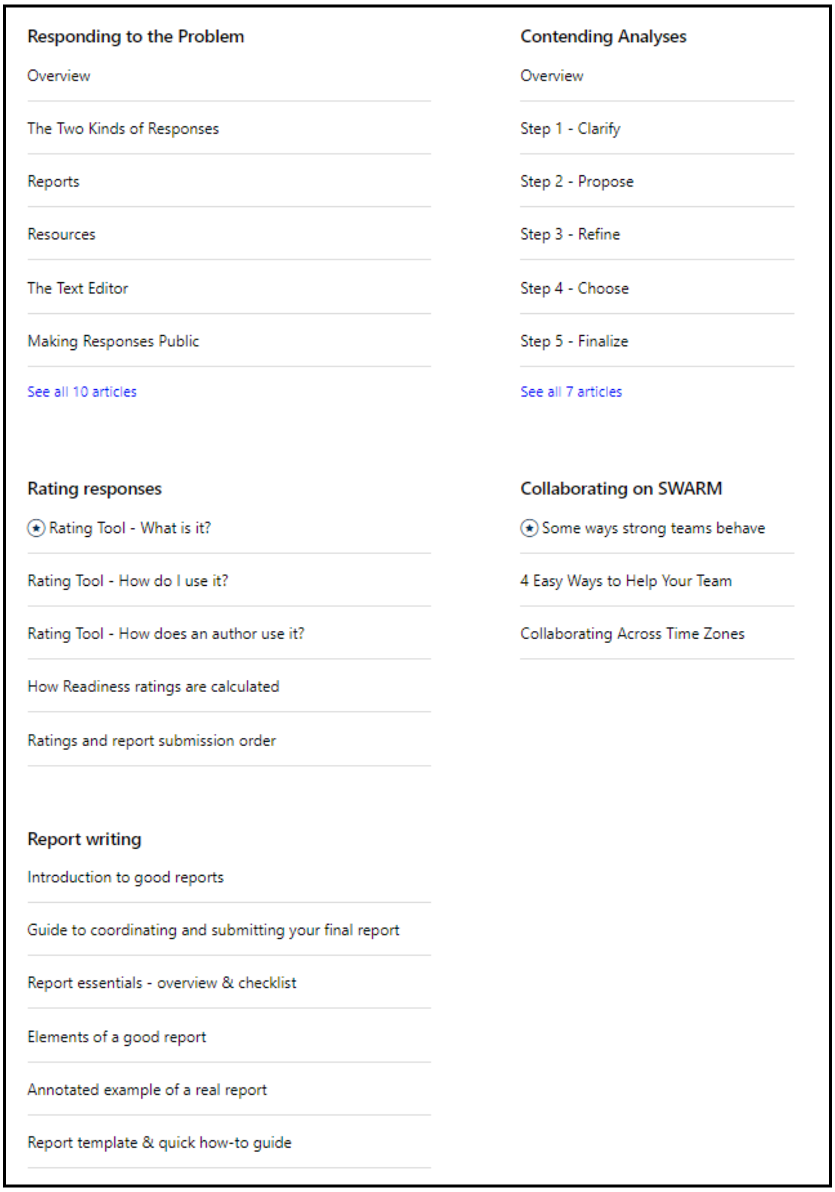

Figure 4: SWARM Platform 'How to SWARM' manuals.

Platform affordances: Accountability

A prime affordance of the SWARM Platform rests in its transparency and information capture functionality. The Platform offers managers and team leaders data analytical insights into how their team is operating. This Platform captures data indicating the level of engagement of team members in the chat function, their resource contributions and report drafting involvement. As nearly all activity on Platform is available to the team (except private or deleted resources/reports), managers and team members can also view their team work in real time, or go through the historical chat and work done to date (Sinnott et al., 2019).

Platform affordances: Agility
As noted above, managers can change the Mission statement at any time. This is an important feature to support an agile team in a fluctuating security environment. Managers can use this function to realign team priorities alongside these changes in the security environment.

The Platform also supports teams to tackle one or more problems. Platform testing to date has also given teams considerable freedom to self-organise to solve the problems and focus their efforts where they can have the most impact. As teams utilise the Platform to produce a single written report in each problem scenario, and present their conclusions and supporting reasoning (van Gelder et al., 2018), a manager can prioritise their teams efforts within these one or more of these problem scenarios.

Platform affordances: Efficiency
Given the Agility affordances of the Platform to realign priorities, the Platform also affords visibility to users of these shifts. All deadlines are set and visible on the Platform, this transparency of expectations means teams can reallocate resources to meet these priorities. As team composition is not fixed, managers can also add or remove team members to meet resourcing requirements.

Platform affordances: Communication
The Platform provides a centralised communication tool in the Chat functionality, which is open to all users to access current and historical communications. Users can 'tag' one another in the Chat to highlight issues within the team. The text-based chat is searchable and transparent. In the design of the Platform prototype, the Hunt Lab did not envision this Chat functionality to be the only communication tool available to users if an organisation used the Platform in a workplace setting. However, to effectively evaluate and test the Platform as an analytical tool and observe analytical reasoning, the Hunt Lab have not incorporated private chat functionality and in research exercises, requested participants limit their use of non-Platform communication tools.

Platform affordances: Collaboration
The Hunt Lab designed the Platform to cultivate engagement and collaboration meaning it has considerable Collaboration affordances. Firstly, the Platform provides teams with avenues to share resources and perhaps more importantly, a tool with which to co-edit reports. All resources uploaded to the Platform are available to the whole team (unless originating user elects to keep it private). Users can invite one another to coedit a report with one or more team members. Users can also provide comments to resources and reports as well as 'like' or 'upvote' comments and resources, to indicate resource or comment usefulness. Platform users are also provided anonymous usernames to encourage a freedom of collaboration, where they can collaborate free of prejudice or fears of repercussions.

The Platform also provides supporting materials in a tool linked to help inform a team's analysis and collaboration. Support materials include the 'Lens Kit', a searchable archive of analytical lenses from which team members can draw upon (Sinnott et al., 2019; van Gelder et al., 2018). The Platform encourages users to explore the tools available and provides a compendium of resources ranging from basic analytic training to more complex analytical methodologies (Sinnott et al., 2019). One such resource that is central to the Platform's design with respect to improving quality of reasoning and collaboration is the structured analytical technique (SAT) 'Contending analyses'.

Contending analyses
The Platform design encourages users to engage in a structured analytical technique (SAT) entitled 'contending analyses'. Contending analyses involves members of an analyst group drafting and improving multiple different analyses methodologies and output of an intelligence problem. The focus of contending analyses is for the team members to approach a problem in different ways analytically, as opposed to a SAT like Analysis of Competing Hypothesis (ACH) which is an analytical approach that could be used in applying contending analyses as an alternate analytical methodology to other SATs. Team members can leverage the full breadth of analytical methodologies and analysis (including diagrams and visualisation aids) to produce a report. Team members utilise the 'rating system' (refer Figure 5 below) to select which reports and methodologies are 'best' to respond to the problem scenario and develop into a collective report (Sinnott et al., 2019; van Gelder et al., 2018).

Platform affordances: Output
The Platform provides users with a centralised reporting system, where 'Output' is recorded. As highlighted above, this output takes the form of a 'report' where teams collaborate to produce the 'highest rated' product. The Platform affords users an inbuilt rating system and encourages them to evaluate written products on Completeness, Correctness, Logic, Evidence, Alternatives, Clarity and Format (van Gelder et al., 2018). As illustrated in Figure 5, there have been four ratings (top right hand corner) with an overall middle rating of 56 (out of 100); observers can also identify where there may be weaknesses/strengths in each report, in this example the report may need to consider addressing a lack of alternative hypothesis. Through using a standardised rating system, users (and co-editors) can get an objective sense from their team of the report's quality. The Platform does not allow users (or co-editors) to rate their own reports (Sinnott et al., 2019).

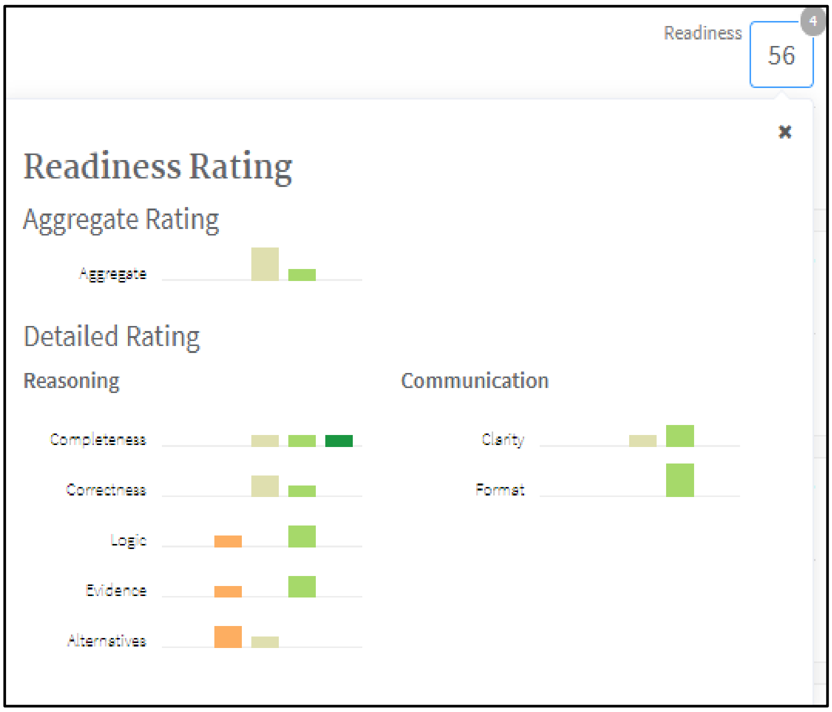

Figure 5: SWARM Platform imbedded report rating framework.

SWARM Platform affordances mapped to MDT Maturity Model
For a summary of the explored Platform's features and affordances with regards to the MDT Maturity Model refer Table 2 below.

Table 2: SWARM Platform affordances.

	Platform feature	Likely affordance
Mission	Problem statement accessible to all user	All team members can access and view the problem statement.
	'How to SWARM' guide	Guide provides users with a reference of how to approach organising and problem solving on the Platform in a structured manner.
Accountability	All activity (except private resources / reports) is visible to all users and observers	Line managers, educators or auditors (depending on role) can view analysis real-time or post-event.
	Platform records all chat, comments, resources, reports (unless deleted by user)	Same individuals above can retrospectively review analysis conducted on the Platform.
Agility	Problem statement can be changed at any stage	The world security environment rarely remains stagnant. The ability to change problem tasks allows for these fluctuations in priorities.
	Users can work on multiple problems at the same time and self-organise how to solve problems	Platform affords users to self-organise around problems they feel they can contribute most positively.
Efficiency	Deadlines set and visible on Platform	Admins/supervisors can set report deadlines affording users transparency of expectations.
	Change team-size depending on scale of threat	Admins can add/remove users depending on requirements.
Communication	Chat function (ongoing and accessible) User tagging	Users have an immediate and transparent method of communication with team members, affording communication access current

	function	and historical. Users can also ‘tag’ one another, affording the ability to highlight issues to relevant team members.
Collaboration	Co-editable reports Shared resources	Users can collaboratively edit the same report, if invited to do so. All users share resources when posted to the Platform (unless originating user elects to keep it private). This affords increased collaboration of sharing of resources and opportunities to collaboratively edit reports.
	Anonymity	Users are provided anonymous usernames to encourage collaboration.
	The Lens Kit	The SWARM Platform contains a link to the Hunt Lab created ‘Lens Kit’. This is a repository of various SATs and analytical strategies for teams to draw on.
	‘Contending analyses’	Contending analyses is a collaborative-based structured analytic technique designed to improve quality of reasoning if implemented correctly. It is closely linked with Output due to its purpose to increase quality of reasoning in output.
Output	Report function	Platform provides the format in which reports should be produced.
	Report readiness rating system	The report readiness rating system is closely linked with collaboration, as it encourages a team to rate one another’s reports. We have included it as an Output affordance as it provides users with a standardised methodology with which to review and evaluate the quality of the developed report.

The Platform has undergone extensive development based on theoretical and practical research to support teamwork and collaboration. In this Chapter we have mapped the affordances of the Platform design to the MDT maturity model, providing insight how it supports performance across the MDT maturity pillars. As an analyst-centric tool designed to improve quality of reasoning and team collaboration, in the next Chapter we will divert our attention to how the analyst-centric affordances of the Platform may predispose the Platform to increased support for the training functions of intelligence MDTs. To appropriately consider and evaluate the Platform as a training tool, we first need to explore the requirements of industry both in terms of analytic capability and recruitment standards; training avenues; and, computer-supported collaborative learning research and identify where the SWARM Platform fits in this literature.

Chapter 4: SWARM Platform as a training tool – requirements of industry

As explored in Chapter 3, we have mapped the affordances of the Platform to the MDT maturity model, which demonstrates the areas of support it provides to users and teams to reach higher levels of MDT maturity. Recognising these affordances, we turn our attention to some of the practical considerations of applying the Platform to industry including training intelligence analysts with the skills to operate in a MDT. Our Australian Government research stakeholders have set a deliverable to explore how the Platform may be used as a training tool to improve the skills of intelligence analysts, so in this Chapter we focus on the complexities of the intelligence analyst role, the challenges of recruiting a capable workforce and review the literature of computer-supported collaborative learning (CSCL) to inform how the SWARM Platform could facilitate the upskilling of the current analytical cohort as well as train future generations of analysts operating in MDTs.

The intelligence analyst role

Intelligence analysis is recognised as a critical function that supports decision-making in multiple areas of government (Corkill & Davies, 2013). Depending on the type of agency or department an intelligence analyst works for, they may specialise in analysing a type of intelligence. For example, HUMINT (human intelligence), SIGINT (signals intelligence), GEOINT (geolocation intelligence) and OSINT (open source intelligence). They often work in secure spaces with restrictions on information sharing (Coulthart, 2019). Further, an analyst may have a different analytical focus, for example they could have a tactical/operational, investigative or strategic mandate (Weston et al., 2019). As Bruce and George (2015) suggest, there are varying complexities to the different roles, each of which may require different skills and approaches (Bruce & George, 2015).

While Vandepeer (2018) warns against generalising too broadly when evaluating the complexities and objectives of each intelligence analysis role (Vandepeer, 2018), there are certain commonalities that are observed across the intelligence analyst cohort. The core responsibilities of an intelligence analyst can be boiled down to identifying issues, sense-making (Gartin, 2001), evaluating intelligence, generating hypotheses, recognising patterns or outliers and providing considered advice in the form of judgements, recommendations or assessments to stakeholders (Straus et al., 2011). It is important to note stakeholders in this context vary, some intelligence analysis stakeholders include information collectors, managers, senior government and both external public and corporate agencies. This ongoing process of information collection, analysis and advice, is often referred to as the intelligence cycle.

Intelligence analysts are active in their world. They are not sitting back passively letting information wash over them. An analyst will set intelligence collection priorities, collate existing and new intelligence, evaluate and assess the intelligence, provide assessment or advice to stakeholders, then provide feedback to collection agencies on the relative usefulness of the intelligence collected (Brown, 2014; Bruce & George, 2015). As Burcher and Whelan (2019) put it plainly, to plan, collect, evaluate, analyse, disseminate and provide feedback (Burcher & Whelan, 2019). Analysts battle preconceptions and bias, both of the information they consume and of the teams they interact and share intelligence and assessments with (Gajic et al., 2017; Wastell, 2010). This process is ongoing and will only cease when the intelligence analyst has no more information requirements, at which point, they will move onto the next issue.

Therefore, considering the above intelligence cycle, a key responsibility of analysts is evaluating the intelligence they receive, to determine its validity and credibility before considering to include it as part of their broader analytical processes and assessment (Irwin & Mandel, 2019; Symon & Tarapore, 2015). As Matei and Halladay (2019) note, the analyst transforms the raw data into a timely, tailored, digestible and useful product for stakeholders (Matei & Halladay, 2019). Raw and untested intelligence can be unnecessarily persuasive without first determining its credibility and analysis applied. This is not to say that there isn't a time and a place for raw unassessed intelligence but that its passage should be carried with a warning (Mclennan, 1995).

Intelligence analysts also draw on 'intuition' in order to effectively analyse information (Behm, 2007; Marrin, 2007). Marrin (2007) describes intuition as an analytical process but also as a skill that is developed with experience. The outcomes of this 'skill' are valued but difficult to communicate and therefore other more concrete evidence-based arguments are required to substantiate this type of analytical decision-making.

Now that we have explored the complexities of the analytical role, we focus on how analysts are recruited and consider how training forms a crucial component to the success of an analyst's membership of MDTs. If new recruits who join agencies and departments with intelligence functions do not have the analytical or teamwork skills required, it places an increased burden on internal training departments and senior staff (Breckenridge, 2010).

Recruiting the right people, with the right skills

A key goal of agencies and departments with intelligence functions is to recruit capable employees who have both analytical and social skills (Hackman, 2011). Depending on the analytical role or agency/department, the process of recruitment can involve up to weeks or months of standardised testing, interviews, group exercises and scenario-based aptitude testing (Harrison et al., 2018). Once recruited, another pivotal step is to train and develop the required skills to operate effectively within the agency or department. This process is both time and financially costly.

Agencies and departments with intelligence functions have long had high standards set for the calibre of individuals they hire. Consider the steps the CIA took in the mid-20th century to ensure they met these goals. The then CIA considered it a necessary step to eliminate personnel who "can never achieve a sufficiently high degree of competence to meet the CIA standard...There is no place in the CIA for mediocrity" (Central Intelligence Agency, 1954, p. 20).

Corkill and Deering (2017) identified 56 specific criteria agencies and departments with intelligence functions look for in their analysts through researching and evaluating job advertisements. Summarising their findings, they identified three dominant criteria. Firstly, communication: criteria related to relationship development, interpersonal skills, negotiation and liaison. Secondly, analysis: criteria related to research, problem solving, computer aptitude and processing (including data analytics). Finally, experience: criteria related to thematic knowledge, prior 'relevant' experiences (Corkill & Deering, 2017). Put simply, recruiters need to balance hiring those with the strongest interpersonal skills over applicants who have better analytical skills. There is perhaps a misplaced assumption that organisations will favour a team composed of the strongest analysts over those who have the communication and collaboration to form a strong team (Krause et al., 2011).

With an increase in intelligence-related employment opportunities, there is an increasing demand for programs that tackle issues of policing, counter-terrorism, security studies and more (Corkill & Davies, 2013). The breadth of intelligence-focused courses, ranging from certificates, undergraduate and graduate degrees, suggests there is no uniformity to what is available in Australia[5] (Gearon, 2019). Historically, intelligence-fields have favoured studies in history, international studies, national security, political science and law (Gearon, 2019). While recruitment differs between agencies and departments, there is some consensus that intelligence analysts require at least an undergraduate degree (Corkill & Deering, 2017). It is also expected that intelligence analysts will likely sit amongst other analysts with a variety of tertiary experience and backgrounds (Dorn, 2019).

An in-depth analysis of each of the available intelligence analysis-focused courses is not possible in the context of this research; however, Walsh's (2017) interrogation of courses available in intelligence analytical training and education focus on several core competencies. These include development of critical thinking skills; communication skills; structured analytical techniques; application of collection methodologies; counterintelligence; security legislation; and the application of analytical software (Walsh, 2017). Others suggest that intelligence-focused training is the theoretical space that places intelligence skills into perspective within the larger domestic, national and international security framework (Gearon, 2019). Noting that in both these studies, the research did not identify developing team-work skills as a key pillar.

Weston, Benett-Moses and Sanders (2019) investigated how interpersonal skills are essential for analysts and analyst managers to succeed effectively in their respective roles (Weston et al., 2019). Bar-Joseph and McDermott (2008) suggest intelligence agencies in particular recruit analysts with good communication and time management skills as well as an ability to work under pressure (Bar-Joseph & McDermott, 2008). Moss, Corkill and Gringart (2013) support these findings suggesting employers highly valued recruit's understanding of communication styles and appreciation of individual differences in the workplace (Moss et al., 2013). Finally, Behm (2007) argues that students seeking to enter the intelligence domain are not taught the fundamentals of teamwork or the core capacities of the intelligence business and recommends further investment in developing these skills at universities (Behm, 2007).

Reflecting on the above literature, we have identified analysts require both analytical (cognitive) as well as communication and teamwork (social) skills to be successful in the workplace but that teamwork training is limited in targeted tertiary intelligence-related training. Therefore, to better understand how the Platform may be used as a training tool, we will address some of the successes in teaching multidisciplinary teamwork from other domains.

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[5] Some courses include Intelligence and Security degree (Australian National University); Intelligence and Counter Intelligence degree (Open Universities Australia); Master of Intelligence (Open Universities Australia) Bachelor of Counter Terrorism Security and Intelligence (Edith Cowan University); Graduate Certificate in Intelligence Analysis (Charles Sturt University); Master of Intelligence Analysis (Charles Sturt University); Graduate Certificate in Intelligence (Macquarie University); Graduate Certificate in Cyber-Security, Policing, Intelligence and Counter Terrorism (Macquarie University); Master of Security and Defence Management (University of New South Wales, UNSW); Master of Strategy and Security (UNSW); Master of War Studies (UNSW); Master of Decision Analytics (UNSW); Master of Data Science (University of South Australia) (The Good Universities Guide, 2020).

Teaching teamwork, lessons from other domains

We have explored how teamwork skills are required in intelligence analyst roles but need to consider how universities address these skill requirements more broadly. Riebe, Girardi and Whitsed (2016) suggest there has been considerable attention paid to teaching teamwork in tertiary education and research therein. However, they propose employers continue to claim tertiary education institutions do not do enough to prepare graduates to work in team-based environments. In their review of the literature, they found no consistent strategy to teach teamwork skills across the tertiary education sector. They raise the multitude of factors including educator, student, and institutional factors that contribute to the challenges of implementing teamwork pedagogy. Not conclusive in their findings, they report further research is needed to explore this challenging subject (Riebe et al., 2016).

One sector that has incorporated teamwork training is in healthcare. Multidisciplinary health care teams with members from multiple professions regularly work together towards a central coordinated goal, a patient's health. Hall and Weaver (2001) note that the skill of working together seamlessly and understanding one another's perspectives do not come automatically and requires training (Hall & Weaver, 2001). Nancarrow et al. (2013) note in their research of 253 staff from 11 health care teams that training and development as well as respecting and understanding others roles were key characteristics underpinning effective interdisciplinary team work (Nancarrow et al., 2013). Frame et al. (2015) noted in their study of team-based learning for pharmacy students, they reported students valued team-based learning activities early in a curriculum which affords students the time to build on their teamwork-related skills (Frame et al., 2015).

Research and training of healthcare professionals has also included cross-disciplinary programs to instil foundational level knowledge of the different roles and develop effective teamwork skills. Anderson et al. (2019) evaluated the training of 345 students from five disciplines through survey data and found students were able to identify the benefits (and the challenges) of working in a multidisciplinary team in a healthcare environment (Anderson et al., 2019). This research used an asynchronous, flexible approach, providing teams with various resources including a learning management system accessible to all students and staff. Professional education in healthcare is therefore used to foster collaborative practice with the goal of improving patient care (Vereen et al., 2018). Like intelligence analyst teams, the stakes for healthcare professional teams are high and require all staff members to be empowered to voice their concerns and engage proactively with another (Mayo & Woolley, 2016).

Clark, McKague, Ramsden and McKay (2015) discuss 'service-learning', meaning a type of experiential learning where students learn through helping others in the health-care sector. This type of learning places a clear goal towards a team's actions and seeks to mirror education with professional experiences (Vereen et al., 2018). Though noting the resource intensiveness to operate this type of learning into the curriculum, Clark et al., noted key outcomes including improvements in professional and teamwork skills as well as relationship development and communication skills (Clark et al., 2015).

When looking at younger students, The Department of Education and Training Victoria (DETV) recommends collaborative learning as one of ten high-impact teaching strategies, developed from research on effective teaching strategies (Department of Education and Training Victoria, 2019). There are various collaborative learning approaches; however, the DETV suggests collaborative learning involves small group collaboration and meaningful tasks where students are actively participating in negotiating roles, responsibilities and outcomes (Department of Education and Training Victoria, 2019).

Due to personal cognitive or learning styles, students respond differently to alternative teaching methods (Breckenridge, 2010). Challenges to training students in collaborative practices also include a lack of interdisciplinary education and a gap in educators' willingness to incorporate teamwork skill learning outcomes into curriculum. Educators cite a lack of space within the curriculum to facilitate the development and implementation of meaningful practices (Vereen et al., 2018).

Adopting the lessons learnt from the above literature, any attempt to teach both the cognitive and social skills required to undertake the analyst role and perform in MDTs, needs to mirror professional experiences and have a clear goal and purpose. In the context of this research where we are framing the Platform as a potential computer-supported collaborative (CSCL) tool, we need to consider the strengths and limitations of implementing this type of training mechanism to facilitate learning outcomes.

Computer-supported collaborative learning

CSCL covers a wide range of technology-enabled learning tools including communication platforms, collaborative software, dialogue mapping, wiki-style editing platforms and in some cases computer games (Conklin, 2006; Gilbert et al., 2018; Rowe et al., 2011). In this context, the focus is on the SWARM Platform, as a technology-enabled platform that could support and train social interactions, analytic techniques, teamwork and group cognition as well as empower educators.

High-functioning CSCL tools need to empower students to prioritise their learning. As Kirschner and Van Bruggen (2004) note, learners tend to concentrate on the task at hand and neglect learning outcomes. For example, neglect documenting or recognising what they have learned, feedback received and reflecting on personal or collective growth (Kirschner & Van Bruggen, 2004). CSCL tools also need to provide a set of objectives and rules that guides users towards producing a tangible outwards facing product or outcome (Beers et al., 2006). Gilbert et al. (2018) discuss the concept of an 'intelligence team tutoring system' (ITTS) that affords educators a monitoring capability to identify how learners find common ground, traverse the problem task and develop teamwork skills. They highlight that monitoring important factors in collaborative learning such as motivation, accountability and engagement have previously been difficult to track but use of a CSCL tool that affords visibility of team collaboration eases these difficulties (Gilbert et al., 2018).

One of the challenges of CSCL is the introduction of computer-enabled communication at the expense of all other forms of collaboration. As research suggests, without any face-to-face interaction, facial expressions and body language are lost between team members, which can lead to misunderstandings, especially when teams are composed of cultural and linguistically diverse members (Peters & Manz, 2007; Popov et al., 2013). A key development in collaboration software is enabling users to communicate on an ongoing basis regardless of their geographic location (Fleisher & Hursky, 2016). While the development of confrontation and robust discussion skills are fundamental to a team member's collaboration ability (Railean, 2012), the CSCL program or tool should support the development of these skills and not introduce conflict unnecessarily or without purpose.

When used effectively, CSCL platforms can support problem-based and project-based learning (Papanikolaou & Boubouka, 2010) where analysts negotiate meaning to 'solve' an intelligence problem (Nussbaum et al., 2009) and upskill while engaging in meaningful activities. For collaborative problem-solving scenarios, the CSCL can drive valuable teamwork and communication learning outcomes (Gilbert et al., 2018). However, education institutions and organisations need to adapt and change any implemented CSCL program to prevent it becoming obsolete as the world changes around it (Geitz et al., 2005).

CSCL may also be applied to simulation-based training, which research has identified as relatively cost-effective and more beneficial compared to traditional classroom education (Vogel-Walcutt et al., 2011), with more of the public service steadily adopting virtual learning training programs (Criado et al., 2019). A key learning outcome of simulation training is providing staff exposure to scenarios in a controlled environment. As Hutchins (1995) indicates, there is an inevitability of error in systems that rely on on-the-job learning, for where there is the need for learning, there is room for error (Hutchins, 1995). The key purpose of a workplace simulation exercise using a CSCL tool is for members to adopt their roles as they would in the workplace and to make the course content as relevant to their work to maximise engagement (Becker et al., 2015).

Working closely with other roles within a MDT provides staff an opportunity to increase self-awareness of where a staff member sits in the intelligence community (Heuer, 1999) as well as learn and adopt cross-discipline terminology and workplace relevant intelligence jargon (Morse et al., 2007). Educators can 'pause' the a simulation-based training exercise at any stage and utilise guided reflection to get participants to articulate acquired knowledge or in the face of conflict or issues, how they propose to problem solve as a team (Jimenez & Pantoja, 2008).

Recognising the different types of teamwork development that trainers can provide including using CSCL, the current research positions the SWARM Platform as a potential CSCL tool, bringing together diverse participants to conduct problem-based learning. Leveraging the above literature, for the SWARM Platform to effectively teach new recruits or existing intelligence staff, it will need to provide structure to teaching cognitive skills; teamwork and collaboration learning outcomes; encourage learners to recognise their learning processes including positive and constructive feedback; and, afford educators visibility of group interaction and ability to provide both real-time and post-event feedback and scaffolding.

In this Chapter, we have explored the complexities and requirements of the analyst role, the recruitment requirements of industry, the successes and challenges of teaching teamwork in tertiary education and explored CSCL including what it offers in the training and education field, to teach the cognitive and social skills required to be an intelligence analyst operating in a MDT. As this research frames the Platform as a potential business and CSCL tool for application, we will next consider how the Platform supports managers and trainers to improve MDT maturity and to do this, we need to explore scaffolding approaches and their application.

Chapter 5: Scaffolding as a tool to improve MDT maturity

In Chapter 4, we discussed the scope and skills required to undertake the intelligence analysis role, available training for future analysts in tertiary institutions, how teaching teamwork may successfully be applied and what role CSCL could have in this process, including framing the SWARM Platform as both a potential business tool to facilitate MDTs and as a framework for education. This Chapter will explore the role of managers and educators and explore the scaffolding strategies they may use to improve performance after assessing their team's maturity using the MDT maturity model.

Scaffolding

Managers and educators need to both evaluate their team and identify if scaffolding is required to achieve a given task or learning outcomes. The added complexity for managers and educators is to consider what scaffolding is required and when to deliver it. A framework or CSCL platform may afford managers and educators an ability to both evaluate their team through performance metrics (such as a maturity model) and provide a vector to facilitate management direction.

Scaffolding comes in various forms including tools, question prompts, guidance and resources (An, 2010). Educators, managers, peers and computer programs provide these scaffolds to help their staff or students complete a task they would not successfully complete independently (An & Cao, 2014).

Types of scaffolding

Scaffolding is often classified into subtypes, hard and soft scaffolding. Hard scaffolding refers to planned or constant support made available prior to, or during a task. Conversely, soft scaffolding refers to the dynamic and spontaneous support provided to problem-solvers (An & Cao, 2014).

Looking deeper, Hannafin et al. (2001) identified four types of scaffolding, which include conceptual, metacognitive, procedural, and strategic scaffolds. Conceptual scaffolding refers to well defined task information and guides users what to consider to complete a task such as identifying key conceptual knowledge, particularly for reasoning of complex problems (Hannafin et al., 2001). Metacognitive scaffolding supports the underlying self-management processes associated with performance. Metacognitive scaffolding also may remind users to reflect on the task objectives or prompt them to leverage and apply a resource or tool to complete the task (Hannafin et al., 2001). Procedural scaffolding provides guidance on how to use the available tools. It can orient the features of a system while users are undertaking a task. Procedural scaffolding may not be required until the user has the need to utilise the tool or resource. Finally, Strategic scaffolding provides alternative approaches to aid users. These approaches may support analysis, planning, strategy, and tactical decisions. This type of scaffolding focuses on evaluating resources, identifying required information and how to collect and collate this information with existing knowledge. Users often leverage strategic scaffolding at points of change or decision making (Hannafin et al., 2001).

Scaffolding application

Scaffolding research to date has identified various issues relevant to this research. An's (2010) study exploring the effectiveness of scaffolds and the use of multi-editor documents in ill-structured problem solving process suggests soft scaffolding is necessary, especially for conceptual guidance, to support students' problem solving (An, 2010). An (2010) found different groups require different support across other problem-solving areas such as research and information collation. This considered, students responded well to a clearly defined problem to support those who did not have experience responding to complex or ambiguous issues. Structured scaffolding in this case is used to wean students off traditional teacher-centred problem methodology (An, 2010). Problem-solving focused learning and sufficient scaffolding affords educators a mechanism through which they can transition from a central knowledge repository to a facilitator of collaborative learning (Hmelo-Silver, 2004).

Problem solving-focussed environments support the removal of the leadership figure to increase collaboration and co-learning. Doorewaard et al. (2002) suggest that teams with a shared responsibility contribute more substantiality to team performance outcomes over traditional hierarchical teams (Doorewaard et al., 2002). Considering team structure in education settings, Keyton and Beck (2008) advocate that membership of teams should seldom be left to students to determine and hard scaffolding should be utilised in team formation. Student selected teams, they suggest, will have limitations on their diversity and not challenge the development of new personal relationships in a collaborative environment (Keyton & Beck, 2008). Diverse groups may need to form a cohesive identity to process information, inform decision making and resolve conflict (Janssens & Brett, 2006). Popov et al. (2013) suggest their use of scaffolding in the form of a collaboration script for diverse groups effectively fostered increased questioning, feedback provision and check-ins that increased congruent strategic planning and thinking (Popov et al., 2013).

A challenge for educators, and line managers for that matter, is identifying if or when this scaffolding, feedback or direction is given and how it is delivered and to whom. In the case of this research, scaffolding may be required to improve MDT maturity in one or more pillars. Gilbert et al. (2018) note feedback or scaffolding may be required for an individual or for the broader team and that an effective CSCL platform should support real-time feedback without negatively impacting team performance (Gilbert et al., 2018). Hackman (2011) notes that process-based interventions may introduce complexities, which do not mitigate pre-existing underperformance (Hackman, 2011).

From its design, the SWARM Platform affords leaders the means to structure team work patterns (Johnston, 2005) and to collect 'business intelligence' data to improve future practices. In Abhari, Davidson and Vomero's (2020) exploration of 'business intelligence' tools, they define them as tools that help an organisation capture the data required to reason, innovate, increase abstract thinking and solve problems (Abhari et al., 2020). They suggest there is merit for future research in this domain to explore tools that could empower organisations and employees to meet performance goals (through data-driven decision making). The use of the tool then affords organisations and teaching staff an opportunity to support daily activities, collect data, enhance decision-making processes and provide structure to processes (Abhari et al., 2020). In considering the opportunities to use business tools to both structure and improve teamwork as well as collect data, we will need to consider and explore what affordances the SWARM Platform provides managers and educators in this space.

In this Chapter, we have considered the type and range of scaffolding managers and trainers may implement to improve performance and MDT maturity and noted a research requirement to explore what affordances the Platform provides managers and trainers. In understanding the literature on scaffolding and identifying the affordances for leaders, we are best placed to address how scaffolding may be used to improve MDT maturity on Platform either from a manager or trainer perspective.

Research Questions

In this research literature review, we have identified that MDTs are used in Australian agencies and departments with intelligence functions and we have developed a maturity model to evaluate MDT performance across seven core pillars. We have identified a need for frameworks to support higher levels of MDT maturity and discussed the SWARM Platform and how it may progress beyond its roots as an analyst-centric tool and develop into a MDT framework. To demonstrate this, we have mapped the affordances of the Platform to the maturity model and demonstrated how it supports the seven pillars. We have reflected on the requirements of the intelligence sector to recruit and develop intelligence analysts cognitive and social skills, including teamwork skills which we identified are not taught with any consistency across intelligence-focused courses. Here we frame the Platform as both a business framework to support MDTs as well as a CSCL tool. In this framing, the use of the Platform may provide managers and educators with previously unexplored affordances to manage their team and improve performance.

The research questions of *'Intelligence analysis in multidisciplinary teams - affordances of the collaborative online SWARM platform for public service and education application'* reflect the unique collaboration between the MSPS, the Hunt Lab, and our Australian Government research stakeholders. The SWARM Platform presents exciting potential for use as a MDT framework, the benefits and challenges of which have not yet been fully explored. This research will utilise the developed MDT maturity model and explore the strengths and weaknesses of how MDTs are currently used in the workplace. Understanding these current MDT challenges will inform the subsequent evaluation of the SWARM Platform as a MDT business and education framework and will aid the investigation of its affordances for managers and educators.

Research Question 1: What are the strengths and weaknesses of how MDTs are utilised in Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions?

Research Question 2: Can the SWARM Platform move beyond its origins as an analysis-focused tool to provide a framework for intelligence MDTs as a business and training tool?

Research Question 3: What does the SWARM Platform afford managers and educators to improve MDT performance?

Chapter 6: Study 1 - Australian Government research stakeholder MDT experience

Aim

The aim of this study (Study 1) is to inform *Research Question 1: 'What are the strengths and weaknesses of how MDTs are utilised in Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions?*'. This study aimed to collect information to improve our understanding about how MDTs are utilised in the Australian Government intelligence context including views on the strengths and weaknesses of current MDT frameworks. In particular, this study aimed to evaluate our Australian Government research stakeholder's MDT experience.

Method

Data collection

We engaged our Australian Government research stakeholders who indicated they were conducting an internally-run survey to evaluate their MDT performance and staff experience to date. This survey included three open questions and 27 closed Likert scale questions. The open questions asked about staff's positive and negative experiences with MDTs ('What I liked about MDT concept', 'What I disliked' and 'Other Comments') and the closed questions asked staff to rate statements about MDT experience from Strongly Disagree to Strongly Agree (Appendix D refers).

The Australian Government research stakeholders provided us with a copy of the results of this internally run survey. The stakeholders provided their consent for the survey and results to be used for research purposes. This consent included stipulations that the stakeholders review the research thesis prior to publication.

We adapted this survey to invite other members of the intelligence community to participate in this research and strengthen our understanding of MDT use. We adapted the internally-run survey and utilised Qualtrix to ask six open and 26 closed Likert scale questions (Appendix D refers). As in the original survey, we asked participants about their MDT experiences. We utilised this methodology to remain as consistent as possible across the data sets.

Based on previous research methods of the Hunt Lab to protect participant identities, we communicated to invited participants that all data from the survey would be collated under Commonwealth, State and Territory Government agencies with intelligence functions. Appendix A details the types of agencies invited to participate in the research; however, participating agencies are not identified in this research to further protect the security of these agencies and departments. This research had ethics approval and invited participants were provided with a Cover Letter detailing the research, a Plain Language Statement (PLS) and asked to sign an Informed Consent form.

We utilised publicly available email addresses to contact the agencies and departments and invite them to participate in the research. However, despite these efforts we received no further survey responses.

Analysis

We received survey contributions from only one Australian Government research stakeholder, which included survey responses from sixty staff members (N = 60) (Table 3 refers). To collate and analyse the participant responses, we adopted the coding methodology of previous SWARM Platform research (Saletta et al., 2020). Saletta et al. (2020) used qualitative, thematic analysis of their data, drawing on exploratory sense making and thematic coding (Braun & Clarke, 2006, 2019; Gibbs, 2007). We drew upon and adopted the same processes of coding the results for this and other studies in this thesis research. We developed a coding schema from the MDT Maturity Model outlined in Chapter 2, which is detailed in Appendix C.

Table 3: Study 1 - Number of participating agencies/departments.

Number of participating agencies/departments	1
Number of survey responses	60

We conducted qualitative, thematic analysis and applied the coding schema both to open and closed questions. For open questions, we utilised NVivo12 software to conduct initial thematic coding of the responses in accordance with the MDT Maturity Model coding schema. The initial exploration of the results identified the coding themes were too narrow to cover the breadth of positive and negative MDT experiences of staff in the workplace. Accordingly, we updated the coding schema used to analyse the results, primarily through expanding the criteria to cover related terms. Of note, we did not incorporate themes of leadership into the new coding model as this research is not evaluating leadership styles, rather observing MDT benefits and limitations, and the affordances of collaborative software. We utilised the NVivo12 software again to conduct the final thematic coding of the open questions, where we filtered the open questions regarding their positive or negative sentiment. The results of which have been tabulated to identify the amount of responses, which fit within the MDT Maturity Model (Table 4) as well as an exploration of the core sub-themes in responses for discussion (Table 5).

For closed questions, after collating results, we grouped questions quantitatively per the framework themes of the coding schema (Mission, Accountability, Agility, Efficiency, Communication, Collaboration, Output) (Table 6 refers).

Results

We collated and analysed the data for this case study of MDT maturity in the Australian Government intelligence sector. We will first address the open questions, then the closed Likert scale questions.

Case study of MDT maturity: Open questions

Our investigation of the case study open questions drew out staff member MDT experiences to identify the strengths and weaknesses of their current framework in accordance with the MDT maturity model. Of the total number of survey responses (N = 60), we identified 39 responses to the open question 'What I liked about MDT concept', 33 responses to 'What I disliked' and 15 to 'Other Comments'. We coded these responses in terms of their sentiment (positive or negative) about their MDT experiences and used the above qualitative coding schema to identify which pillar their comments aligned with.

The results below in Table 4 suggest participants held positive views about their MDT maturity regarding pillars of Mission and Collaboration; however, overall we identified much more negative responses toward Efficiency maturity.

Table 4: Study 1 - Coded open survey questions (Quantity).

	Positive comments about MDT experience	Negative comments about MDT experience
Mission	14	5
Accountability	6	1
Agility	4	1
Efficiency	4	23
Communication	7	4
Collaboration	14	8
Output	1	2

Here through the application of the MDT maturity coding schema, common themes are drawn out from the participant's responses (quotes of participant responses to these open questions are elaborated further in Table 5). Participants wrote positively about their MDT experience as it set a "strategic goal" (Mission), helped "record decisions" (Accountability), assisted "creative problem solving" (Agility), "increased and improved communication" (Communication); enabled "greater collaboration" (Collaboration) and helped "deliver mission outcomes" (Output). However, we also identified a common theme of the negative time and resource impost (Efficiency).

In addition to the above, survey respondents wrote that their MDTs were primarily structured using centralised Microsoft Word Documents and structured meetings (unclear if face-to-face or utilising digital technology such as video-teleconference facilities). We have included this result to note as a comparison to the affordances of other collaborative frameworks such as the SWARM Platform.

Table 5: Study 1 - Coded open survey questions (sub-themes).

	Positive comments about MDT experience	Negative comments about MDT experience
Mission	"framework around decision making" "agreed action items" "action plan and strategic goal" "clear direction" "common goal" "goal setting"	cultural resistance, "getting buy-in has been a struggle" ill-defined problem/purpose
Accountability	"record decisions" "record decision making" "excellent review and progress tracking tool"	requires more accountability (no further information provided)
Agility	"innovative ideas", "creative problem solving"	"administrative burden" which delays response to "emerging leads"
Efficiency	"Well-suited for non-routine problems" "resolved duplication"	Inconsistent use for routine and non-routine tasks time/resource impost: "waste of time", "drain on resources", "too large". "one step forward and two back while everyone absent gets up to speed"
Communication	improves visibility / communication, "increased and improved communication", "better communication" "reduce miscommunication"	"communicating to a large MDT is difficult and hard to track tasks" "communications from stakeholders were still lacking" Lack of, or inaccessible, clear communication to MDT
Collaboration	"structure for cooperation" "sharing knowledge" "collaboration discussions", "greater collaboration", "everyone is on the	"limited MDT training", "lack of training", "negligible training" "reduced personable communication and relationships" that existed previously use of MDT to "exert control" over others

	same page”	Requires integration with other corporate systems
Output	“recognises differing requirements” to “deliver mission outcomes”	The MDT is a “template for what we already did” “not focused on actionable outcomes”

Case study of MDT maturity: Closed questions (Likert scale)
We coded the closed Likert scale survey responses, which each participant had responded to (N = 60). These results provided further indications towards the strengths and weaknesses of the case study MDT framework. Investigation of these Likert scale questions also demonstrated the priorities of the data collection.

As noted below in Table 6, the internally-focussed survey focused on collaboration-themed questions (37% of questions), an apparent priority for the stakeholder. However, with the application of the MDT Maturity Model coding schema, we note the survey originators may not have collected sufficient data to identify if their MDTs are high-performing due to the bias towards collaboration-related questions.

Table 6: Study 1 - Coded Closed Questions.

Coded Closed Questions	**Amount**
Mission-themed questions	2
Accountability-themed questions	1
Agility-themed questions	4
Efficiency-themed questions	5
Communication-themed questions	2
Collaboration-themed questions	10
Output-themed questions	3

In Figure 6, we collated participant responses to the Likert scale questions and graphed them in a stacked bar chart with neutrals split, ranked from least to most amount of ‘Disagree’ and ‘Strongly Disagree’ responses. In this Figure, we have also identified which questions correspond to each of the MDT maturity model pillars, identified in brackets.

The most positive responses received were to the following questions: “MDTs are a useful tool to encourage collaboration in an agency/department” (Collaboration); “The output is of a higher value using a MDT than working in isolation” (Output); “MDTs encourage better planning” (Efficiency); and, “Within a MDT, I have a better understanding of what others are currently doing” (Collaboration); “Within a MDT, I have a better understanding of what others are capable of doing” (Collaboration). In contrast, just under half of all participants responded negatively to “The MDT framework saves me time” (Efficiency) and “The MDT framework saves me effort” (Efficiency). Also of note, a third of participants responded negatively to “I feel my agency/department has sufficient communication and collaboration tools to support MDTs” (Collaboration).

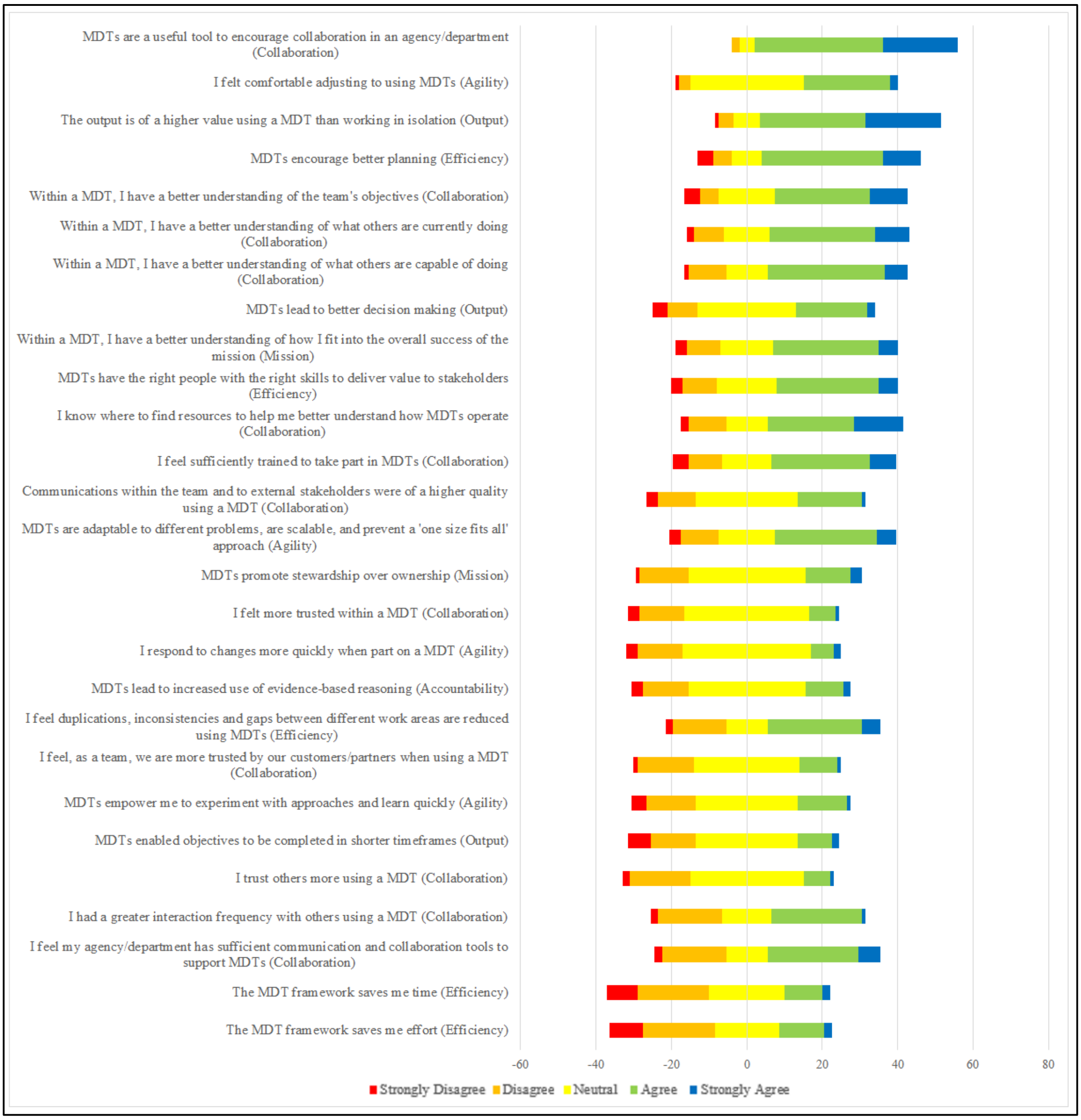

Figure 6: Study 1 – Participant views on MDT experience.

Key findings
Investigating this case study of Australian Government research stakeholder MDT use, we identified that staff reported higher-levels of maturity in Mission and Collaboration pillars. Of interest to the Collaboration pillar, a third of participants reported that they do not have sufficient communication and collaboration tools to support MDTs. This latter finding is particularly relevant to this research as we investigate the SWARM Platform as a potential framework to support MDTs. A small number of participants also reported their need for more or improved training in response to open questions.

While most participants reported that MDT participation encouraged better planning, we identified staff reporting lower levels of maturity with respect to Efficiency. We identified signs of low maturity in Efficiency in both responses to open and closed questions, particularly as it related to time and resource impost. Another finding from this case study is the survey design methodology, as we identified bias towards Collaboration-focussed questions.

From the findings of this study, we have confirmed the need to explore MDT tools for business and training use and we will further discuss issues of Efficiency as it relates to MDT maturity in Chapter 9 and opportunities to improve survey design through increased industry and academic collaboration in Chapter 10.

Chapter 7: Study 2 - Practical application of the SWARM Platform as a business tool for intelligence MDTs

Aim

Study 2 aimed to explore the practical application of SWARM Platform within the Australian Government intelligence context and work environment. This study occurred early in the research process, prior to the development of the MDT maturity model. The study took the form of a pilot aimed to investigate human factors elements of the research such as how intelligence professionals used the Platform within a secure environment as well as investigate the Platform's suitability as a business and training tool to support MDTs. As Study 2 presented a unique opportunity, elements of other research were incorporated into the study, including investigations into analytical processes and challenges as well as research into the impact of the structured analytic technique 'contending analyses'.

Method

In Study 2, we organised a pilot trial of the SWARM Platform within a public service setting in a secure environment with the assistance of our Australian Government research stakeholders.

Participants

We did not select the participants for Study 2; however, representatives from our Australian Government research stakeholders identified and recruited research participants (N = 14) from three Australian Commonwealth agencies and departments with intelligence functions and divided them into two teams of seven. These representatives also divided the participants equally along gender, approximate age, role, department and level of experience.

Table 7: Study 2 - Number of participating agencies/departments.

Number of participating agencies/departments	3
Number of participants	14

Representatives informed us that each participant had some level of analytical training; however, the participant's analytical roles varied. Due to security constraints, we were not provided with participants' exact roles. The Australian Government representatives informed us they had divided the groups to form equally represented MDTs of differing roles and experiences.

Study 2 had ethics approval and all participants were provided with a Plain Language Statement (PLS) and signed an Informed Consent form. We reminded participants that as they were participating in the research as part of their employment that they could withdraw from the research at any stage with no explanation required or repercussions.

Study 2 design

Study 2 required participants to complete reports for two intelligence-type problems. Firstly, the participants worked collaboratively as teams to produce a 'report' for their fictional line-manager using normal methods. Normal methods in this context meant the team used collaboration tools such as Email, verbal interactions and the word processing tool Microsoft Word. We note the phrase 'normal methods' is required for research purposes and is not entirely reflective of standard business practices, which we were not able to observe due to security requirements.

We provided participants with training on how to use the IC Rating Scale as introduced in Chapter 3; how to apply Contending Analyses (CA) and how to use the Platform. We only provided training on how to use the SWARM Platform and apply CA after participants had completed their first scenario report in normal methods (Table 8 refers).

Table 8: Study 2 - Schedule.

Stage	**Method**	**Team A**	**Team B**
Stage 1	Normal Methods	Scenario 1	Scenario 2
Stage 2	Contending Analyses and SWARM Platform training		
Stage 3	SWARM Platform	Scenario 2	Scenario 1

Following the completion of the 'normal methods' report, teams swapped problem scenarios and completed the reports for their line manager using the SWARM Platform and leveraged its inbuilt word processing and chat functionality to complete the task. We requested participants limit their communication and workings entirely to the SWARM Platform. These conditions were required to properly evaluate the differences between the two research exercise stages. We provided each participant with a unique anonymous username on the Platform, which meant participants were initially anonymous unless they chose to declare their identity to their team.

The two scenarios were fictional 'real world' intelligence-type problems. A summary of the two scenario problems can be found in Table 9.

Table 9: Study 2 - Research Scenario Problems.

Scenario 1	**Scenario 2**
Scenario 1 focused on the terrorist threat emanating from South-East Asia. Participants were required to evaluate evidence provided as well as solve geo-location problems. Participants then provided an assessment of the available information to a fictional line manager.	Scenario 2 focused on the extreme right-wing terrorist threat. Participants were required to evaluate a range of evidence designed to challenge their assumptions. Participants then provided an assessment of the available information to a fictional line manager.

Data collection

We collected the analytical reports produced in both Scenarios and a peer-evaluation of the reports based on the IC Rating Scale. Further, we also requested participants complete three surveys throughout Study 2. Participants completed the first survey at the beginning of the research exercise; the second after completing the 'normal methods' report; and the third, after completing a report on the SWARM Platform. The Entry Survey aimed to achieve a baseline understanding of the participants' analytical capabilities and training as well as the analytical and collaborative challenges they face. The second survey asked how the analysts and teams approached the 'normal methods' report including strengths and challenges experienced. The third survey also asked how analysts approached the report as well as how the SWARM Platform enabled or impeded their analysis and teamwork.

Participants were invited to provide responses to five SWARM Platform-specific open questions, which included 'What was the primary challenge of conducting analysis (on the SWARM Platform)?'; 'To what extent did the SWARM process improve your reasoning?'; 'To what extent did the SWARM platform enable members of your multi-disciplinary team to leverage and share their expertise?; 'How could the SWARM platform be used more effectively to support a multi-disciplinary team?'; and, 'Additional comments?'. These questions provided the central mechanism to collect participant experience on Platform and its support for MDT maturity. For a full list of survey questions refer to Appendix F.

To gain additional insight into participant's behaviour and to contextualise the research, we conducted active participant observation throughout the course of both 'normal methods' and on-Platform problem solving. Participant observation in this context refers to the collection of data through social observations and interactions between the participants and ourselves, where these findings are recorded for evaluation (Taylor & Bogdan, 1984). Due to the interactive nature of this research exercise, we took the form of research instruments, whereby we focused on participants' experience either perceived by researchers or as described by the participants (Creswell, 1998). We took unstructured notes of observations and interactions, including when participants described their experiences as well as participants' behaviour conducting analysis on and off Platform.

In addition to manually collected data, the Platform inherently captured chat logs and user activity metadata.

Clearance requirements
Australian Government research stakeholders advised that the 'normal methods' used in this study were as close to 'real world' conditions given the research requirements to provide training and observe the participants at the same time. Representatives from the Australian Government research stakeholders requested all survey data be cleared through their internal review process prior to passage. Once cleared, representatives provided us with copies of the survey data, observation data and written analytical reports. We were not advised what, if any results, were redacted from the data.

Data analysis
As per the methods outlined in Chapter 6, we conducted exploratory qualitative, thematic analysis and applied the coding schema to open survey questions using NVivo12. We found the coding schema adequately captured the themes and no further updates were required for final thematic analysis.

We summarised the participant responses to open questions into the themes of the MDT maturity coding schema (Mission, Accountability, Agility, Efficiency, Communication, Collaboration, Output) in accordance with Platform experience, with attention paid to affordances. We noted where participant's responses indicated the Platform provided affordances and where it limited performance. We identified the differences and delineated coded results between current Platform capabilities and desired future capabilities (in accordance with the model). This is an important delineation as the Platform is a prototype and remains in research and development.

For our observation notes, we analysed these findings through the lens of the coding schema, and extracted recurring themes and results relevant to inform this research and future studies. For closed survey questions, we calculated the participants' responses quantitatively.

We had planned to apply the same coding schema in an exploratory sense to the captured Platform chat log data to identify participant's Platform experiences, which supported or rejected the survey findings. However, due to data storage issues that operate behind the Platform, we were unable to access this data.

These data storage issues also impacted our ability to conduct in-depth analysis of participant engagement data. However, we drew out a base analysis of team engagement as an indicator of Platform engagement record keeping, to inform line manager and trainer affordances.

Noting the Output portion of the MDT Maturity Model, we compared the team's report quality. We collected one report each from the groups for 'normal methods' and then collected the highest rated report for each group on Platform. Two experienced assessors associated with the Hunt Lab applied the IC Rating Scale and provided a rating of the output quality. Assessors applied this to both participants 'normal methods' and SWARM Platform reports. We investigated the ratings of on and off-Platform quality and the participant's peer-evaluation.

Results

Intelligence analyst collaboration - current practices

We utilised Study 2 as an opportunity to improve our understanding of collaboration practices of analysts. Participant survey responses indicated most analysts collaborate with others during their working week, for some this collaboration occurs daily (57%). While participants reported email as the primary method of collaboration (50%), over half of participants responded that they collaborate with others face-to-face daily.

Platform support for MDT maturity

We applied the MDT maturity model coding schema to identify to what extent the SWARM Platform supported MDT maturity. We have summarised the coding of responses to the five open questions outlined above in *'Data Collection'* about participant's experience on Platform per the pillars of the MDT maturity model. We have highlighted where our observations supported or contradicted the survey responses. We have addressed the expert assessor's ratings of the teams' Output per the IC Rating Scale, as this presents a crucial element of the MDT maturity model.

Mission

A participant reported the Platform helped provide direction and rallied team members on the 'same page'. Participants clarified with us in both scenarios who the recipient of their report was for, to tailor their analysis. We did not observe any other behaviour during Study 2 that reflected the Platform's impact on Mission.

Accountability

A participant reported the Platform acted as a storage tool and another participant reported the Platform provided a record of communication. We observed participants speak fondly of the record-keeping element of the Platform during the study.

Participants highlighted potential Accountability-related changes to the Platform including an intelligence and evidence tracker and integrated report referencing. They also noted that anonymity would need to be removed from Platform for business use due to its impact on transparency.

We asked participants to record their work administratively similarly as they would in their normal work. We observed participants creating folders to store on their desktop to record important documents or decisions in ‘normal methods’ and fewer on Platform.

Agility
A participant reported the Platform supported flexibility for team members to adopt different roles in producing an analytical report. Other participants reported that the Platform did not suit fast-paced analysis and another participant reported that experienced members left lower-skilled team members behind.

We did not observe any behaviour during Study 2 that reflected the Platform’s impact on Agility.

Efficiency
A participant reported the benefits of the deadline visualisation function of the Platform. Multiple participants reported various efficiency issues including: claims that too many participants were allocated to the problem type; issues with resource allocation and participants taking responsibility for too much or too little; and, others reported feeling the contending analyses approach was a duplication of effort. A participant noted the Platform did not support efficiency any more than ‘normal methods’.

A participant highlighted potential Efficiency-related changes to the Platform including the inclusion of ‘sub-folders’ to sort current and archive old and redundant information.

During the exercise, multiple participants said they would never dedicate the number of analysts (seven) to the type of problem scenario used in the study. A small number of participants described the use of contending analyses as an inefficient use of resources. We are unsighted if these participants are the same who reported the same in the survey.

We asked participants to calculate their percentage contributions to each of their team’s reports. As reported in Table 10, both teams reported higher contributions overall in ‘normal methods’ than on Platform.

Table 10: Study 2 - Self-reported percentage contribution.

	Team A	**Team B**
Percentage contributions ('Normal Methods')	155% (average 22% per participant)	190% (average 27% per participant)
Percentage contributions (SWARM Platform)	129% (average 18.4% per participant)	145% (average 24% per participant)

Communication

Multiple participants reported support for the Platform's chat function, which they found beneficial to facilitate communication, discussion and information sharing. Participants also reported the chat function would support communication across locations and is transparent so team had visibility of team activity.

In contrast, participants also reported that the chat function did not provide the same experience as face-to-face communication. Participants reported the group chat quickly became overwhelming, that it was difficult to organise diverse opinions through the chat and difficult to find consensus. A participant reported that anonymity prevented open communication and was not suitable for the workplace.

Multiple participants highlighted potential Communication-related changes to the Platform including inclusion of a private chat function, an 'attention all' function, and a sub-group private chat.

Within minutes of beginning the SWARM Platform exercise, two participants requested that we provide them new usernames as their previous identities had been compromised. We observed a small group of participants using the co-editing function of the report format to engage in semi-private chat instead of using the chat function to communicate. We also observed a team become frustrated with on-Platform only communication and break away mid-way through the on-Platform scenario to organise a group face-to-face meeting. We observed the other team follow this lead and organise a face-to-face meeting.

Collaboration

A participant reported support for the Platform's co-editing functions, another suggested the Platform helped less experienced team members contribute to the written product output; and another participant suggested contending analyses helped them identify and apply structured analytic techniques to their analysis. In contract, another participant suggested they received insufficient training to properly apply contending analyses.

A participant reported they felt some team members were hesitant to have their work critically examined by others on Platform (ratings / comments). Another participant reported they found it difficult to integrate feedback on Platform. Other participants reported frustrations that anonymity inhibited their team's previous collaboration and interpersonal relationships.

Multiple participants called for Collaboration-related improvements to the Platform, these improvements largely centred around the co-editing functions of the Platform. Some reported issues with losing work to co-editing not saving and others requested Microsoft Word-like ‘track changes’ functionality. A participant highlighted a desire to have an additional document type, separate from the resource or report document, to be purely for analysis.

After the on-Platform element of the study, we observed positive indications of the learning and development elements of on Platform activity, though it was caveated with prior experience in ‘normal methods’. Self-reported junior analysts told us they benefited from listening and working with other more experienced participants. These analysts said the interpersonal ‘normal methods’ scenario helped contribute to their on-Platform analysis. The same junior participants told us they saw value in the Platform as a training and development tool.

Participants explained to us they were limited in what they could contribute on Platform from their own experiences. Participants noted there were sensitivities to their knowledge, which hampered their ability to collaborate and contribute fully to the unclassified scenarios.

Output

We did not identify any open question responses that addressed the Output element of the coding schema. That said, we collected other data sets to inform Output maturity including observation data, closed survey questions, expert rating of reports using the IC Rating Scale and peer-evaluations of output quality.

The central finding of our observations focused on what participants told us about their ‘standard’ output. Participants told us that they were from different analytical work areas and the type of analytical report we asked them to produce differed from their normal work ‘output’.

Looking at the closed survey responses, a small number of participants indicated they believed their report would have been a higher quality without their team members. This is reflected both in ‘normal methods’ (four participants) and analysis on-Platform (four participants). Of the four responses in both scenarios, only two participants indicated their work output would have been improved if working alone both in ‘normal methods’ and on Platform. Of the 11 participants that responded to the question ‘To what extent did the SWARM process improve your reasoning’, three participants indicated it hindered performance with the remainder indicating there was no change or it improved performance.

As reflected in Table 11, when investigating the assessors’ evaluation of Output quality using the IC Rating Scale, we did not observe a substantial improvement in performance when using the Platform in comparison to ‘normal methods’.

In our comparison of assessor and peer evaluation of Output quality per the IC Rating Scale, we identified individual peer evaluations on average rated the ‘on Platform’ reports as of a lower quality. However, there is little consistency with peer rating between reports developed in ‘normal methods’ or on Platform and are not aligned with the expert evaluations.

Table 11: Study 2 - Expert IC Rating scale rating of Output.

<u>Expert rating</u> using IC Rating Scale	**Scenario 1**		**Scenario 2**	
Criterion	**Team A (Normal Methods)**	**Team B (SWARM Platform)**	**Team A (SWARM Platform)**	**Team B (Normal Methods)**
Criterion 1 – Properly describes quality and credibility of underlying sources, data and methodologies.	Fair	Poor	Good	Fair
Criterion 2 - Properly expresses and explains uncertainties associated with major analytic judgments.	Fair	Poor	Fair	Fair
Criterion 3 - Properly distinguishes between underlying intelligence information and authors' assumptions and judgments.	Fair	Poor	Good	Fair
Criterion 4 – Incorporates analysis of alternatives.	Fair	Good	Good	Fair
Criterion 5 – Demonstrates relevance and addresses implications.	Good	Good	Fair	Good
Criterion 6 – Uses clear and logical argumentation.	Fair	Fair	Fair	Fair
Criterion 7 – Makes accurate judgements and assessments.	Good	Good	Good	Good
Criterion 8 – incorporates effective visual information where appropriate.	Good	Poor	Fair	Good
Overall Score / 24	**11**	**7**	**12**	**11**

Table 12: Study 2 - Individual peer-evaluation.

Individual peer-rating (Overall Score / 24) using IC Rating Scale					
Team B rating of Team A reports			Team A rating of Team B reports		
	Scenario 1 Expert rating: 11/24	Scenario 2 Expert rating: 12/24		Scenario 1 Expert rating: 7/24	Scenario 2 Expert rating: 11/24
Participant 3	16	8	Participant 1	DID NOT COMPLETE	
Participant 4	18	13	Participant 2	13	13
Participant 6	18	20	Participant 5	12	14
Participant 7	10	18	Participant 8	13	16
Participant 9	12	20	Participant 10	13	20
Participant 11	19	14	Participant 13	11	17
Participant 12	15	6	Participant 14	12	16
Average	15.4	14.1 (on Platform)	Average	12.3 (on Platform)	16

Manager and trainer affordances

During Study 2, we collected data to inform our understanding of the Platform's affordances for managers and trainers. A key component of these affordance is the collection of user activity metadata and engagement metrics, which the Platform records. This metadata supports the inherent visibility a manager has of on-Platform activity in real time or in post-event review.

We have displayed some of the collected metadata in Table 13. In this data, we can see that Team A produced more reports (which follows our training to use Contending Analyses) but were less active across other areas such as the chat function and comments. Whereas Team B were much more active in the chat and with the provision of comments.

Table 13: Study 2 - Key engagement Platform metrics.

Key engagement metrics on Platform		
	Team A	**Team B**
Reports	11	7
Resources	9	13
Comments (on resources / reports)	9	31
Chat messages	566	869
Active users	7	7
Top report readiness rating (out of 100)	85.33	90.97
Number of report ratings	4	5

As Table 13 shows, teams provided ratings for their reports using the Platform's inbuilt readiness rating; Team A rated theirs at 85.33/100 and Team B at 90.97/100. Each report only has four or five ratings as the Platform prevents report contributors from rating their own reports. This high self-rating compared to the low Expert Rating above is noteworthy as we observed participants manipulating this review system by focusing on making their report the ‘highest rated’ for submission late in the report drafting process, rather than applying the ratings with rigour throughout the development of a report as intended.

Interrogating the user engagement data further, the Platform identified which users were most engaged in Study 2, including who they tagged in the chats, the reports/resources they commented on and who they co-edited reports with. As demonstrated in Figure 7, circles and squares represent team members, with the square representing the lead author of the final report. The thickness of lines between these square and circle nodes calculates the strength of the engagement with others on Platform. The metrics of this network graph are not analysed in depth here as the focus is to demonstrate the types of insights the Platform provides to managers and educators, which will be further explored in future studies.

We note the Platform would normally capture all the chat data on the Platform, which provides managers and trainers additional oversight and post-exercise audit functionality. Unfortunately, in this instance, due to data storage issues we were unable to access the chat log data.

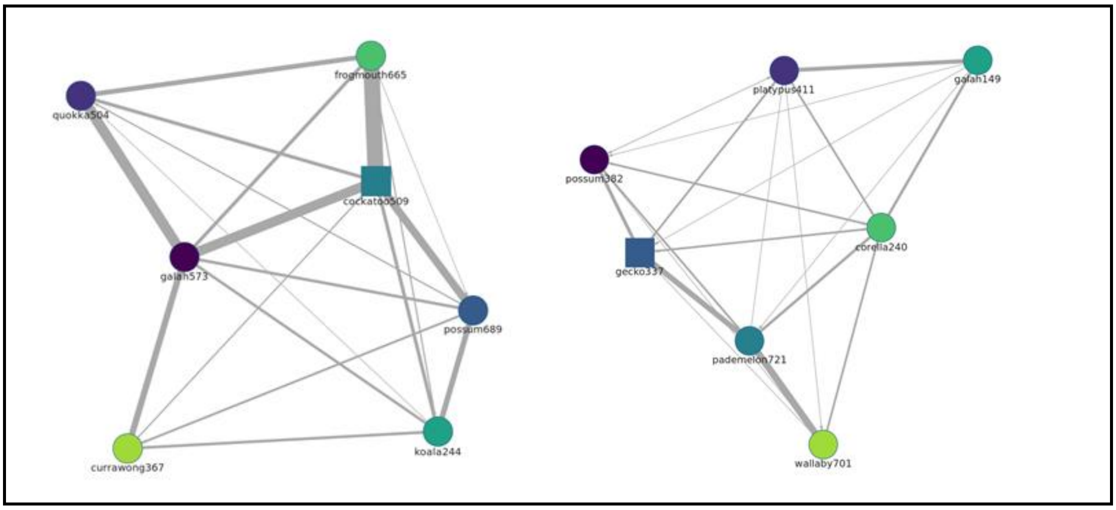

Figure 7: Study 2 - Platform user engagement analytics for Team A (left) and Team B (right) (Credit: Dr. Ariel Kruger, the Hunt Lab).

Key findings

Investigation of the results from Study 2 revealed multiple key findings. Firstly, in evaluating the Platform’s suitability as a business tool to support MDTs, we found reports of resource overallocation and duplication of effort (*Efficiency*) and issues with anonymity (*Accountability*/*Collaboration*) and restrictions on communication (*Communication*). The core Efficiency and Communication issues inform our understanding of the Platform’s support for MDT maturity and business application considerations, which will be addressed in Chapter 9.

We identified that the Platform collected insightful team engagement metrics, including information that could be presented in diagram format. These metrics provide a unique perspective for managers of MDTs. We also identified analysts regularly collaborate with others, with most participants reporting regular face-to-face interactions. This supports the research identified in our literature review, which explored the increasing collaborative role of analysts and the requirements to facilitate some form of face-to-face engagement with other MDT participants.

As an emergent result, we increased our understanding of some of the benefits and challenges of engaging and researching government with intelligence functions. We identified areas for further collaboration including technical improvements that could be made to the Platform and additional training opportunities. These training opportunities could address the inconsistencies we observed in how participants evaluated their report quality (Output). We will elaborate on the emergent findings of this research including the benefits and challenges of engaging and researching government with intelligence functions in Chapters 10.

Chapter 8: Study 3 - Business and training application of the SWARM Platform in public and organisation MDTs

Aim

Study 3 aimed to progress this research into MDTs through the inclusion of both public and organisation participants, to further investigate the support the Platform provides intelligence MDTs as a business and training tool. We aimed to identify any differences in perceived support of the Platform between public and organisation users. We aimed to identify how the Platform supported high-functioning MDTs and explore the learning outcomes of exercises held on the Platform. These aims aligned with the guidance of our Australian Government research stakeholders, who expressed an interest in the wider benefits of exposing members of the public to intelligence-type scenarios to identify outreach opportunities.

Method

Background

The Hunt Lab held a research exercise titled the 2020 Hunt Challenge and we led the human factors element of this exercise for the purposes of this research. This exercise invited teams from government including our Australian Government research stakeholders, corporations and members of the public to compete in an intelligence analysis tournament.

Participants

The Hunt Lab recruited participants from the public primarily through social media and online tools, and recruited organisation teams through proactive outreach and engagement. We were not involved in the selection of private teams as government and corporate teams selected and submitted their own participants. These teams are hereafter broadly referred to as organisation teams. For the public teams, we randomly allocated members of the public to multidisciplinary teams, each with varying levels of expertise, skills and education levels. A total of 415 participants took part in Study 3, made up of seven organisation teams (N = 100) and 13 public teams (N = 315).

Study design

The teams operated asynchronously and anonymously over two weeks, solving a different hypothetical intelligence problem each week on the Platform. Hunt Lab advertised that participants were expected to dedicate between five and ten hours per week to the research exercise.

Prior to their participation in Study 3, participants were provided a slide-deck of instructions, including information about how to use the Platform, conduct ‘Contending Analyses’ and how to apply rating methodology including the IC Rating Scale. As part of the participant onboarding process, participants were also required to read a PLS and provide Informed Consent. After completing this onboarding process, the participants then completed two weeks of scenario-based problem solving in teams.

After the second week of scenarios, the Hunt Lab utilised the user activity metadata of the public teams to form ‘super-teams’. These teams were formed from public users (N = 97), who the Hunt Lab identified as having the most engagement and positive contributions to their teams through Platform engagement metadata. The organisational teams remained as they were with no changes to participant level (N = 100).

The super-teams and the organisations then completed a further two scenarios on the Platform. A summary of the four scenario problems can be found in Table 14. Due to COVID-19, which escalated as a pandemic during Study 3, two organisational teams withdrew from Scenario 4.

Table 14: Study 3 - Hunt Challenge Scenario Problems.

Scenario 1	**Scenario 2**
Scenario 1 focused on the terrorist threat emanating from South-East Asia. Participants were required to evaluate evidence provided as well as solve multiple geo-location problems and one translation problem.	Scenario 2 focused on international piracy. Participants were required to forecast the likely number of piracy incidents in a set period and consider all the various factors which could impact this number.
Scenario 3	**Scenario 4**
Scenario 3 focused on corporate espionage in a technology company. Participants were required to consider the indicators of espionage and evaluate competing hypotheses based on uncorroborated intelligence. This scenario also tested participants' ability to learn and apply a different type of analytical reasoning - probability analysis.	Scenario 4 focused on a kidnap/murder mystery set in Melbourne. Participants were required to evaluate the available information, which included various reasoning challenges including flaws, and provide an assessment of the most likely course of events and likely perpetrator.

Data collection

We collected multiple data sets to inform our research questions, including survey data, assessor report evaluations and Platform engagement data.

Our initial data collection took the form of an Entry Survey (Appendix G refers), which participants were invited to complete prior to conducting any analysis on the Platform. In this survey, we asked questions related to core Hunt Lab research, including acquiring demographic data. We also asked participants to provide details of their MDT experience, to better understand how and where MDTs are used across intelligence and non-intelligence sectors.

Our second survey data collection took place after the conclusion of all four scenarios. We invited all participants (N = 415) to complete an Exit Survey (Appendix H refers). This survey covered several themes including Platform support, usability and experience; teamwork and collaboration; and, learning and professional development.

To evaluate participants' experience on the Platform and its support for high-functioning MDTs in the Exit Survey, we asked targeted quantitative Likert scale questions. These questions aimed to test (through self-evaluation) the support of the Platform in accordance with the MDT Maturity Model. We designed these questions with the guidance of Nemeth's (2004) human-factors research methods, where the survey questions were drafted, re-drafted and tested both with research colleagues and potential industry participants. Following feedback, we redrafted the questions for inclusion (Nemeth, 2004).

We prioritised the Likert scale questions as most indicative of the Platform's support for MDT maturity. We weighted the questions equally across the MDT pillars to best reflect strengths and weaknesses of the Platform experience. We balanced the number of questions between reflecting the intricacies of the MDT pillars and an overly lengthy survey subsection, which could potentially harm participant engagement. We did not include the MDT pillar themes in italics in survey.

Do you think the Platform supported you in the following areas? (Yes / No / Not Sure)

1. Developing a shared mission amongst team members (*Mission*)
2. Working towards a unified goal (*Mission*)
3. Managing contributions (*Accountability*)
4. Keeping track of team decisions (*Accountability*)
5. Working in flexible and agile way as analysis progressed (*Agility*)
6. Innovative problem solving (*Agility*)
7. Enabling an efficient workflow (*Efficiency*)
8. Meeting deadlines (*Efficiency*)
9. Clear communication amongst team members (*Communication*)
10. Ability to move easily between engaging with others, or disengaging for independent work (*Communication*)
11. Information sharing amongst team members (*Collaboration*)
12. Worked together positively (*Collaboration*)
13. Making decisions (*Output*)
14. Production of useful output (*Output*)

The scoring metric of these questions drew on the learnings of Hernandez, Espejo and Gonzalez-Roma (2006) and Gonzalez-Roma and Espejo (2003) who researched the appropriateness of middle responses such as 'Not Sure'. While their earlier work suggests a preference for using 'In between' instead of 'Not sure' (Gonzalez-Roma & Espejo, 2003), they later address the issues of possible misinterpretation of the middle label by participants. They note the position of the middle option here may instead express doubt or indecision or even ambivalence (Hernandez et al., 2006).

For the purposes of investigating affordances and Platform support, the 'Not Sure' middle option is preferred. It is intentionally weighted to capture this feeling of doubt, as we wanted to identify in what areas participants felt the Platform supported them (i.e. Yes), where they did not feel supported (i.e. No) and where the Platform may afford support but the user does not identify or recognise it (i.e. Not sure). Considering the various theoretical discussions around affordances (Gibson, 1986; McGrenere & Ho, 2000; Withagen et al., 2012), we focused on how the user interprets support, whether it exists or not. This scoring helps guide what scaffolding is required to facilitate support to the user in each MDT performance area. In addition to Likert scale questions, participants were also invited to provide responses to an open question, asking for their comments about how the Platform affected their teamwork to draw out context to their closed question responses.

In this Exit Survey, we also targeted questions to identify responses relevant to the education element of this research focus. We targeted questions about participants' learning experience on Platform, including questions specifically seeking to get participants to articulate what they learnt during the research exercise – an important element of the learning process. We targeted these questions at the end of the research study to not negatively impact team performance. We drew on the lessons and research of Billman et al., who when attempting to evaluate an intelligence analysis collaborative platform in a tertiary education setting, found that repeated measurements of participant's activities disrupted their work on the task (Billman et al., 2006).

A final element of data collection included the data the Platform captured. This included the completed analytical reports of each team and the user engagement data. We note that we did not review the captured Platform chat data due to the scale of information and direct relevance to our research questions, though we recognise the potential of the chat data for future studies and insights into collaborative teamwork and reasoning.

Coding and analysis

We collated Entry and Exit Survey questions quantitatively where possible. For open question responses in the Entry Survey detailing their MDT experiences, we coded responses using the list and type of intelligence agencies and departments outlined in Appendix A as a guide of what constitutes an intelligence role. For open question responses in the Exit Survey, we coded responses relevant to the Platform's impact on teamwork according to the MDT maturity coding schema.

Noting the Output portion of the MDT Maturity Model, we compared the teams' report quality. Hunt Lab trained assessors applied the IC Rating Scale to each report of each team for the four weeks. Three assessors reviewed each report, where substantial conflict or disagreement existed between the three assessors, a fourth assessor rated the report. We used these ratings to produce a leader board, both for the first fortnight and the super-team rounds. These ratings were an essential element to evaluate whether on Platform analysis could develop high-quality output.

Progressing from MDT maturity, this research exercise also included an open question specific to learning outcomes in the form of 'What was the one most valuable thing you learned?'. To code responses to this open question, we leveraged the research of Kraiger, Ford and Salas (1993) and their classification scheme of learning outcomes. They categorised learning into the categories of cognitive outcomes (verbal knowledge, knowledge organisation and cognitive strategies); skill-based outcomes; and, affective outcomes (attitudinal and motivational) (Kraiger et al., 1993). This research also drew on Green (2011) to include the modern take and inclusion of information technology under both a generic skill-based outcome as well as a cognitive skill, where the skill utilised is not procedural and drives greater critical thinking or problem solving (Green, 2011). This is an important distinction when determining learning outcomes from a CSCL platform such as the SWARM Platform.

We note the above studies of Kraiger, Ford and Salas (1993) and Green (2011) do not sufficiently cover the requirements of this research in its entirety with respect to the social and teamwork skills required for intelligence analysis and Platform considerations. As discussed in Chapter 4, social and teamwork skills are viewed as a requirement for intelligence professionals joining the workforce and hence these skills are important to evaluate from a learning and development perspective. Therefore, we also drew on other studies who report social and teamwork skills as important learning outcomes. Strom and Strom (2011) discuss the importance of tracking teamwork either through peer or self-assessment. They investigated skills such as attending to teamwork, seeking and sharing information, communication skills and behaving amicably with others (Strom & Strom, 2011). Further, in Ellis et al.'s (2005) study, results from 65 teams revealed that teamwork skills training had a significant positive impact on both cognitive and skill-based outcomes. Key proficiencies demonstrated in this research included collaborative problem solving and task coordination (Ellis et al., 2005).

In considering the above, we adapted the learning outcome coding schema from Kraiger, Ford and Salas (1993) to include social learning. This coding schema (Table 15 refers) breaks down the learning outcome themes (cognitive, skill-based, affective and social) and their constructs and focus. However, unlike the Kraiger, et al. model which discusses potential evaluation methods for each learning outcome, Study 3 relies solely on self-evaluation.

Table 15: Learning outcome coding schema, adapted from Kraiger, Ford and Salas (1993) to include social learning (Ellis et al, 2005; Strom & Strom, 2011).

	Category	**Learning constructs**	**Focus of measurement**	**Evaluation methods**
Cognitive	Verbal knowledge Knowledge organisation Cognitive strategies	Declarative knowledge Mental models Self-insight Meta-cognitive	Amount of knowledge: accuracy, recall, speed, accessibility Self-awareness / regulation	Recognition and recall tests Structured assessment Self-report
Skill-based	Compilation Automaticity	Composition Proceduralisation Automatic processing	Skill-based outcomes Speed, errors, fluidity Available cognitive resources	Observations Hands-on testing Interviews Embedded measurement
Affective	Attitudinal Motivational	Targeted objective / attitude strength Self-efficacy / Goal setting	Attitude direction / strength Performance orientation / Goal structures and commitment	Self-report
Social	Teamwork experience	Collaborative problem solving techniques Communication strategies	Teamwork prioritisation Seeking and sharing information Positive social behaviour	Peer and self-report

To collate and draw insights from the large amount of participant engagement metric data from Study 3, we sought the assistance from the Hunt Lab's resident data scientist Luke Thorburn, who assisted with the graphing of engagement data to demonstrate the Platform's affordances for managers and educators.

Results

Demographics and MDT experience: Entry Survey

Before turning our attention to the results most relevant to our research questions, we will first address the demographics of the participants of Study 3. We have categorised the demographic results according to public or organisation participants in Table 16. Of note, not all participants completed each element of the surveys so we have articulated this number at the top of each table section.

In our categorisation of the participant demographics, we identified that the organisational teams were proportionally younger, mostly in full-time employment and more experienced in analysing complex data; whereas education levels are consistent in proportionality to the public teams. Nearly half (45.45%) of organisation participants had experience analysing complex problems or data in an intelligence or related field compared to only 9.35% of public participants.

Table 16: Study 3 - Participant demographic data.

Demographic	Public	Organisations
Age	N = 304 18-25: 3.62% 26-35: 25.00% 36-45 21.71% 46-55 25.66% 56-65 17.43% Over 65: 6.25% Prefer not to say 0.33%	N = 97 18-25: 12.37% 26-35: 38.14% 36-45: 29.90% 46-55: 16.49% 56-65: 1.03% over 65: 1.03% Prefer not to say 1.03%
Gender	N = 302 Male: 52.32% Female: 44.70% Other: 1.99% Prefer not to say 0.99%	N = 97 Male: 49.48% Female: 48.45% Other: 0.00% Prefer not to say: 2.06
Current Occupation	N = 305 Full Time: 49.51% Part time: 11.80% Retired: 5.57% Not working right now: 8.52% Other/Prefer not to say: 3.28% Self-employed: 13.44% Full Time Student: 6.23% Part Time Student: 1.64%	N = 97 Full Time Employment: 92.78% Part time Employment: 5.15% Other/Prefer not to say: 2.06%
Highest level of education	N = 305 High School: 6.56% Trade or Technical Qualification: 8.52% Bachelors: 25.25% Masters: 29.18% PhD: 7.54% Prefer not to say: 4.26% Graduate Certificate, Diploma or equivalent: 18.69%	N = 97 High School 5.15% Trade or Technical Qualification 2.06% Bachelors 31.96% Masters 29.90% PhD 10.31% Prefer not to say 2.06% Graduate Certificate, Diploma or equivalent 18.56%
Experience analysing complex problems or data	N = 353 Yes, in an intelligence or related field: 9.35% Yes, in another field, e.g. business strategy, risk analysis, etc.: 38.53% Yes, in a scientific field: 23.80% No direct experience: 25.50% Prefer not to say: 2.83%	N = 97 Yes, in an intelligence or related field: 45.45% Yes, in another field, e.g. business strategy, risk analysis, etc.: 16.36% Yes, in a scientific field: 20.91% No direct experience: 11.82% Prefer not to say: 5.45%

In Chapter 1, we explored why MDTs are a priority research area and the focus of Research Question 1. In Study 3, we collected data on participants' experience working in MDTs and details of this experience within and outside intelligence roles (Table 17 and 18 refers). This data reflected the breadth of MDT experience across all participants. Roughly 70% of both the public and organisational teams had experience working in MDTs. As noted below in Table 18, participants' descriptions of their MDT experiences indicate MDTs are utilised across the intelligence sector. Our results indicate a breadth of MDT experience in the public teams outside intelligence as well, with science, technology, engineering, and mathematics (STEM), Health and IT fields well-represented.

Of note, a small percentage referred to their participation in SWARM / IARPA exercises as their noteworthy MDT experience. Noting this small percentage who raised their previous SWARM Platform MDT experience, 63% (N = 198) of public participants in this study had used the Platform before, including some who had participated in the 2018 SWARM Challenge (a similar exercise to this research study). It is unknown if any organisation participants had used the Platform previously.

Table 17: Study 3 - Hunt Challenge participant MDT Experience (amount).

MDT experience	**Public**	**Organisations**
Have you had experience working in a multidisciplinary team[6]?	N = 291 Yes: 70.10% No: 29.90%	N = 96 Yes: 69.79% No: 30.21%

Table 18: Study 3 – Hunt Challenge participant MDT Experience (thematic area).

Detail MDT experience	**Public**	**Organisations**
Total number of responses	N = 181	N = 46
Number that specify intelligence MDTs	18 (9.9%)	16 (34%)
Brief descriptions of intelligence MDT experiences	Police, military/defence, intelligence, finance crime, incident and emergency management, corrections, security, emergency services	Investigative and strategic analysis, military/defence, finance crime, cyber security
Health	17	0
IT	21	0
Education	11	0
STEM	31	2
Finance	4	1
Previous SWARM / IARPA exercises	6 (3.3%)	0
Other / non-descript	73	27

[6] MDT is defined as a team composed of members with varied but complementary experience, qualifications, and skills that contribute to the achievement of a specific objective.

Exit Survey

The escalation of the COVID-19 pandemic during the latter stages of Study 3, resulted in withdrawal of two organisation teams and impacted survey data collection. We note of the 415 original participants in Study 3, 88 public participants and 18 organisation participants completed the Exit Survey by the set due date (N = 106). We will further address the impact of COVID-19 and other study limitations in Chapter 9.

We collected and analysed the Exit Survey findings under the following themes. Firstly, Platform support for MDT maturity; Platform impact on teamwork and collaboration; and, Output - Report quality. These themes address how the Platform can move beyond being an analyst-centric tool to a business framework that supports high-performing MDTs. Next, we address learning and development, to explore the Platform's benefits and limitations as a training tool, including its benefits to recruitment efforts. These two thematic groupings address Research Question 2.

We then focus on manager and trainer affordances (Research Question 3), in which we explore the Platform engagement metric data captured during Study 3. Finally, we review participants' experience on Platform including where they identified improvements to the system design, which informs future Platform-related research.

Platform support for MDT maturity

We investigated how the Platform supported users, from both public and organisations, across the MDT maturity pillars: Mission, Accountability, Agility, Efficiency, Communication, Collaboration and Output. We split public and organisation responses to differentiate the level of Platform support across the pillars. We graphed both public and organisation responses to the Likert scale questions as a stacked bar chart with neutrals split, ranked from most to least amount of 'Disagree' and 'Strongly Disagree' responses. Through identifying where there is a perceived lack of support, it will help guide our discussion in Chapter 9 about what scaffolding may be required to improve performance in these areas.

Due to inconsistency in sample sizes, we utilised the statistical analysis program R to determine 95% confidence intervals (R Companion, 2020). These intervals are marked on the below tables to indicate proportions (in percentages) of responses and the low and high confidence intervals (in square brackets).

Public

Analysing the results across all public responses to MDT maturity targeted Likert scale questions (N = 88), the majority of participants reported that the Platform supported them across MDT pillars of Mission, Agility, Collaboration and Output. However, as reflected in Figure 8, participants provided mixed responses with respect to 'Clear Communication amongst team members' (Communication) and 'Managing contributions' (Accountability). The majority of participants also identified that they did not feel the Platform supported them with 'Keeping track of team decisions' (Accountability); and, 'Enabling an efficient workflow' (Efficiency).

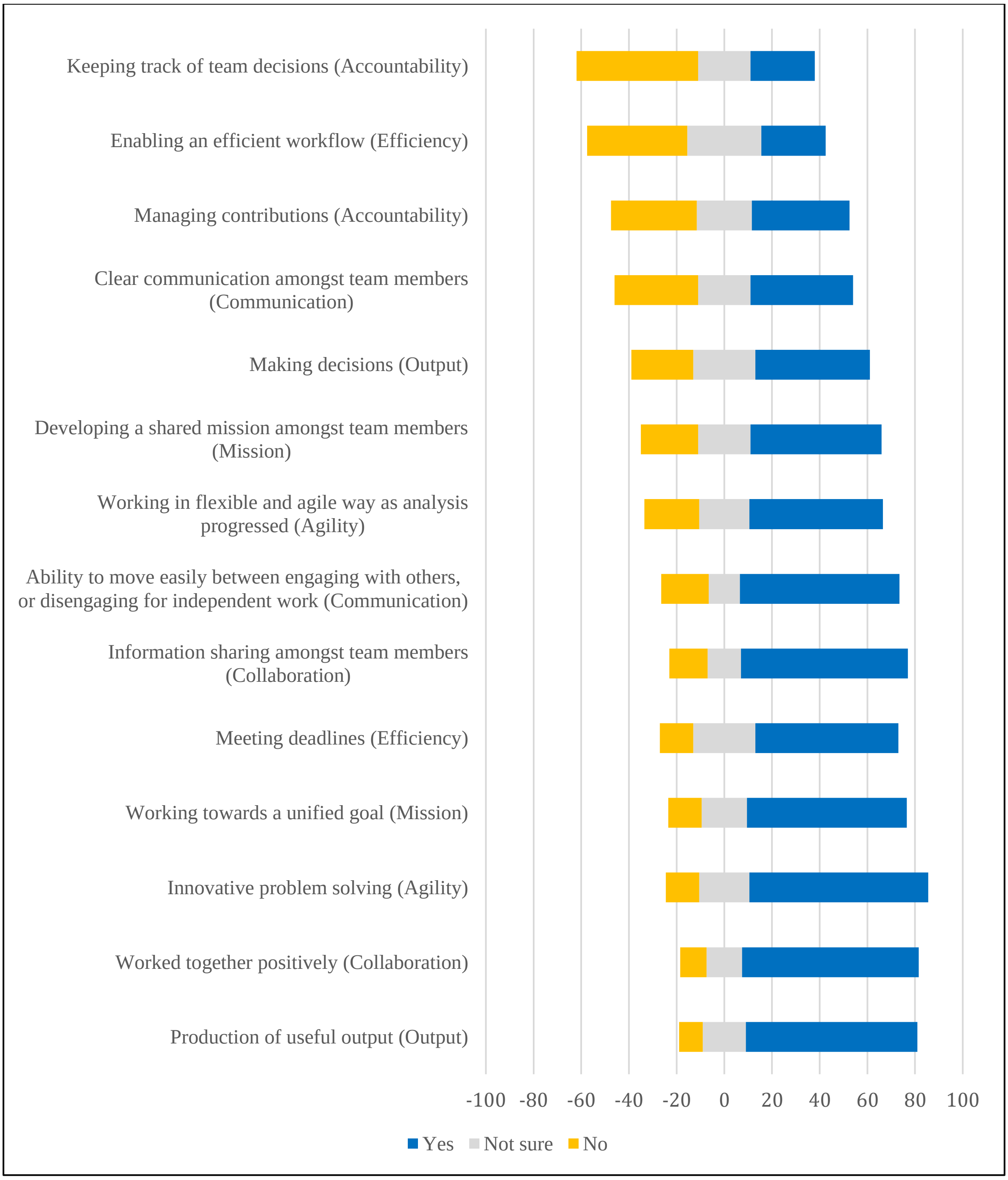

Figure 8: Study 3 - Platform support for MDT maturity (Public response proportions, ranked least to most support).

Table 19: Study 3 - Platform support for MDT maturity (proportion of public responses and 95% confidence intervals in square brackets – low/high).

	Yes	Not Sure	No
Developing a shared mission amongst team members	55% [44, 65]	22% [11, 32]	23% [12, 33]
Working towards a unified goal	67% [58, 77]	19% [10, 29]	14% [5, 24]
Managing contributions	41% [31, 53]	23% [13, 35]	36% [26, 38]
Keeping track of team decisions	27% [17, 39]	22% [11, 33]	51% [41, 62]
Working in flexible and agile way as analysis progressed	56% [45, 66]	21% [10, 31]	23% [22, 33]
Innovative problem solving	75% [67, 84]	11% [3, 20]	14% [6, 23]
Enabling an efficient workflow	27% [17, 39]	31% [21, 43]	42% [32, 54]
Meeting deadlines	60% [51, 71]	26% [17, 37]	14% [5, 25]
Clear communication amongst team members	43% [33, 55]	22% [11, 33]	35% [25, 47]
Ability to move easily between engaging with others, or disengaging for independent work	67% [57, 77]	13% [3, 23]	20 [10, 30]
Information sharing amongst team members	70% [62, 80]	14% [6, 24]	16% [8, 26]
Worked together positively	74% [66, 83]	15% [7, 24]	11% [3, 21]
Making decisions	48% [38, 59]	26% [16, 38]	26% [16, 38]
Production of useful output	72% [64, 82]	18% [10, 28]	10 [2, 20]

<u>Organisations</u>

When we analyse the organisation team responses and take into account the smaller sample size (N = 18), the majority of organisation participants reported that the Platform supported them across MDT pillars of Mission, Accountability, Agility, Collaboration and Output. Replicating some of the findings of the public responses in Figure 9, the majority of organisation participants identified that the Platform did not support 'Enabling an efficient workflow' (Efficiency). While almost half of organisation responses reported that the Platform did not support 'Clear communication amongst team members' (Communication), confidence intervals indicate the results are not necessarily representative of the broader population and are more reflective of a mixed response as observed in public responses (Table 20 refers).

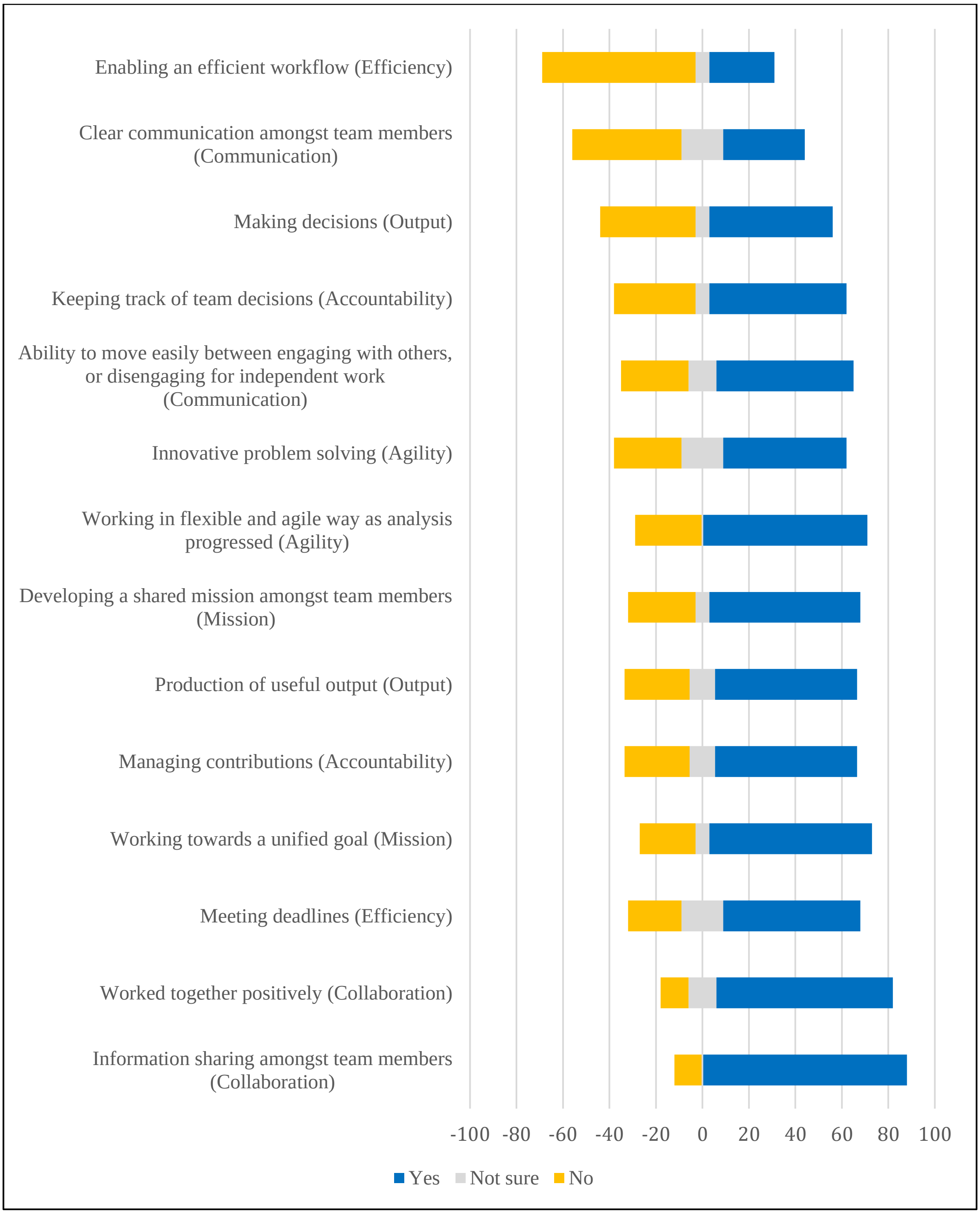

Figure 9: Study 3 - Platform support for MDT maturity (Organisation response proportions, ranked least to most support)

Table 20: Study 3 - Platform support for MDT maturity (proportion of organisation responses and 95% confidence intervals in square brackets – low/high).

	Yes	Not Sure	No
Developing a shared mission amongst team members	65% [47, 89]	6% [0, 30]	29% [12, 54]
Working towards a unified goal	70% [52, 91]	6% [0, 27]	24% [6, 44]
Managing contributions	61% [44, 86]	11% [0, 36]	28% [12, 53]
Keeping track of team decisions	59% [41, 85]	6% [0, 32]	35% [18, 61]
Working in flexible and agile way as analysis progressed	71% [54, 92]	0 [0, 21]	29% [12, 50]
Innovative problem solving	53% [35, 80]	18% [0, 45]	29% [11, 56]
Enabling an efficient workflow	28% [11, 54]	6% [0, 29]	66% [49, 89]
Meeting deadlines	59% [41, 85]	18% [0, 44]	23% [5, 49]
Clear communication amongst team members	35% [18, 63]	18% [0, 46]	47% [29, 75]
Ability to move easily between engaging with others, or disengaging for independent work	59% [41, 85]	12% [0, 38]	29% [12, 56]
Information sharing amongst team members	88% [82, 100]	0% [0, 17]	12% [6, 39]
Worked together positively	76% [65, 99]	12% [0, 34]	12% [0, 34]
Making decisions	53% [35, 80]	6% [0, 33]	41% [24, 68]
Production of useful output	61% [44, 86]	11% [0, 35]	28% [11, 53]

Platform impact on teamwork and collaboration

All participants were invited to provide responses to an open question about how the Platform affected teamwork and collaboration. As per the coding process outlined in previous Chapters, we coded public (N = 63) and organisation (N = 16) responses whether they contributed positively or negatively to the MDT pillars. We have marked organisation responses with an 'O'.

As illustrated in Table 21, we identified that most responses reflected that the Platform negatively affected teamwork and collaboration. This is a surprise given the mostly positive reflection in the Likert scale. Reflecting on this conflict, we contend participants may have seen the open question as an opportunity to provide constructive feedback to help develop the Platform and improve future exercises.

Both public and organisation participants provided responses that the Platform negatively affected teamwork, particularly impacting MDT pillars of Communication and Collaboration. The core components of these responses related to the chat functionality becoming overwhelming impacting Efficiency; and, issues with the co-editing function of the Platform, which impacted Collaboration. This open question also identified organisation-specific limitations, including that in some cases organisation management restricted how participants could access the Platform as well as restricted participation in Study 3 to set hours. These issues relate more to exercise design than Platform support but are worth acknowledging for further discussion to inform future research

Table 21: Platform impact on teamwork and collaboration (Organisation responses marked with 'O').

	Positive comments	**Negative comments**
Mission		
Accountability	The platform absolutely helped to keep track of what was going on and to allow contributions.	No clarity of team-size or membership. (O)
Agility	Easy to use Platform was well-suited to simple short problems.	Platform was less suited to larger, complex problems
Efficiency	Better results when resources coordinated on Platform at same time	Editing issues led to inefficiencies. Due date on Platform was to a specific time zone, misleading for some participants. Two participants felt monitoring the team's chat, resources and reports was time consuming. Three participants reported the group size too large - highlighted requirement for 'breakout' rooms (refer below). Large divide between productive team members (35 hours per week) compared to less productive (less than 10 hours per week)

		Restricted access to Platform only while at work (O)
Communication	Comment and chat capability were useful tools. (O)	Six participants wrote that the chat function was overwhelming. One of these said they used WhatsApp video conferencing to collaborate with others. Chat function is “a nightmare” Four participants described the difficulty of trying to ‘catch-up’ if away for a day Regimented control over corporate equipment to access chat (O) Team used internal communications (off Platform) to organise and coordinate (O) Chat function fills up quickly and can become challenging, then the participant felt they missed communication. (O)
Collaboration	Excellent for collaboration A participant wrote that the Platform supported collaboration but their team misunderstood how to use it. (O)	Difficult to contribute if outside the dominant sub team. Five participants reported issues with co-editing and saving documents on Platform Two participants wrote the Platform did not support collaboration Contributions were lost in collaboration process Multiple participants reported wanting to ‘group’ resources and reports Misunderstanding of ‘contending analyses’ (O) Eight participants reported issues with editing and saving

		documents on Platform, resulting in using other tools to share/edit documents (incl. 'O')
Output	Platform produced a better output than if completed independently. (O)	Old ratings prevented 'best' report being selected

Output - Report quality

Three trained assessors graded every team's reports per the IC Rating Scale, in only one case did we require a fourth assessor to rate a single report from one team. The scores we have collated are an average across the assessors and we have differentiated between organisation teams and public teams (first two weeks); and, organisation teams and super teams (final two weeks).

As illustrated in Figure 10 and Figure 11 below, on average the 13 Public teams (19.05) outperformed the seven Organisation teams (17.45) in Scenarios 1 and 2, though noting there is disparity of 10 points between the highest and lowest performing public teams so we did not observe all teams produce consistently high-quality Output (in accordance with the IC Rating Scale). On average, the five Public Super-teams (21.8) outperformed the five[7] Organisation teams (18.63). As reflected in Figure 12 and 13, four out of five Public super teams produced higher quality Output than Organisation teams.

Through using the IC Rating Scale as a standard of evaluating analytic product, we identified the Platform supports the creation of high-quality analytical output. There are numerous factors that contribute to why there is disparity between high and low rated Output performances such as team cohesiveness and time spent on Platform. We will further address these issues in Chapter 9, including specifically highlighting Study 3 limitations.

[7] Two Organisation teams did not complete Scenario 3 and/or 4 (Figure 12 and 13 refers).

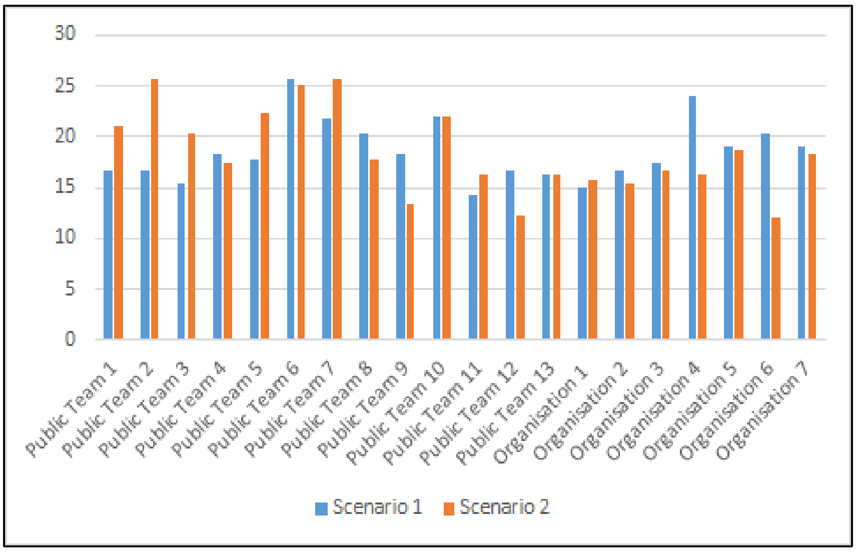

Figure 10: Study 3 - Public and organisation team Hunt Challenge performance - Scenario 1 and 2.

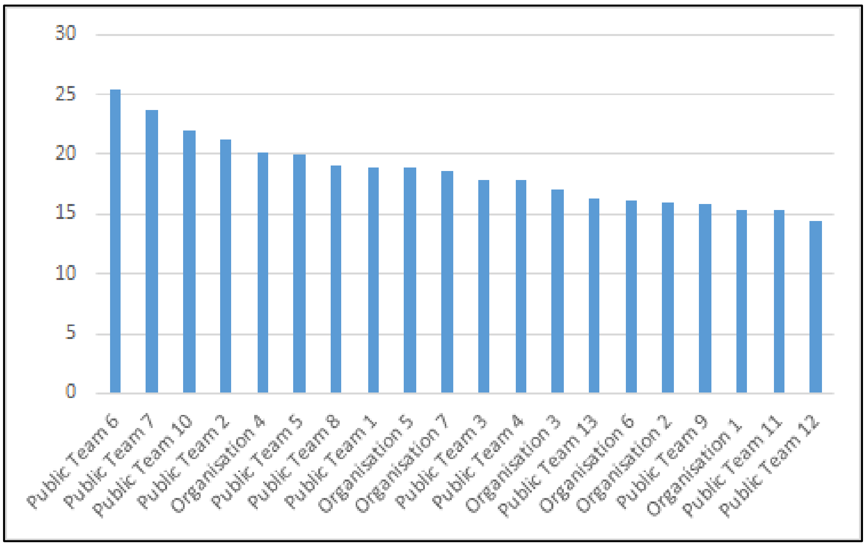

Figure 11: Study 3 - Ranked average of Hunt Challenge performance in Scenario 1 and 2.

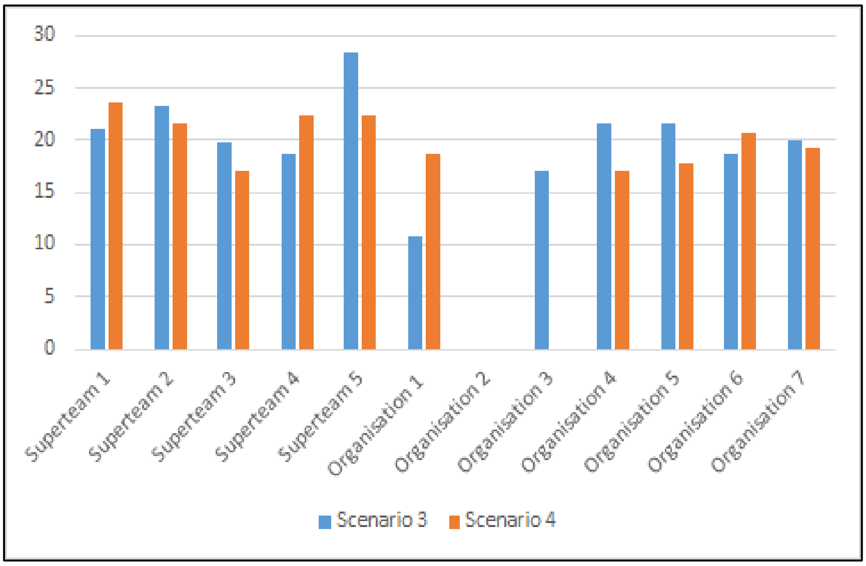

Figure 12: Study 3 - Superteam and organisation team Hunt Challenge performance - Scenario 3 and 4.

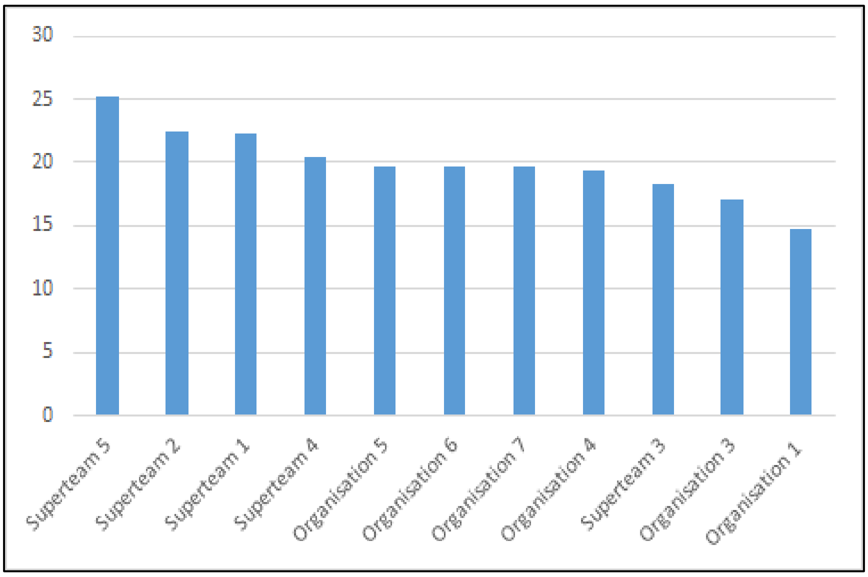

Figure 13: Study 3 - Ranked average of Hunt Challenge performance in Scenario 3 and 4.

Learning and development

In this Study, we aimed to address Research Question 2 to evaluate the Platform's support for training functions, including exploring learning and development outcomes from on-Platform exercises.

As illustrated in Figure 14 and 15, we asked participants to consider the following question "After participating in the Challenge, do you think your capability has improved in the following areas?" and provide Likert scale responses to seven categories. Results indicate at least 87% of public participants responded that their capability improved across four of the categories including 'Using structured analytic techniques'; 'Using OSINT tools and resources'; 'Identifying and analysing assumptions'; and, 'Evaluating quality of analytic reasoning'.

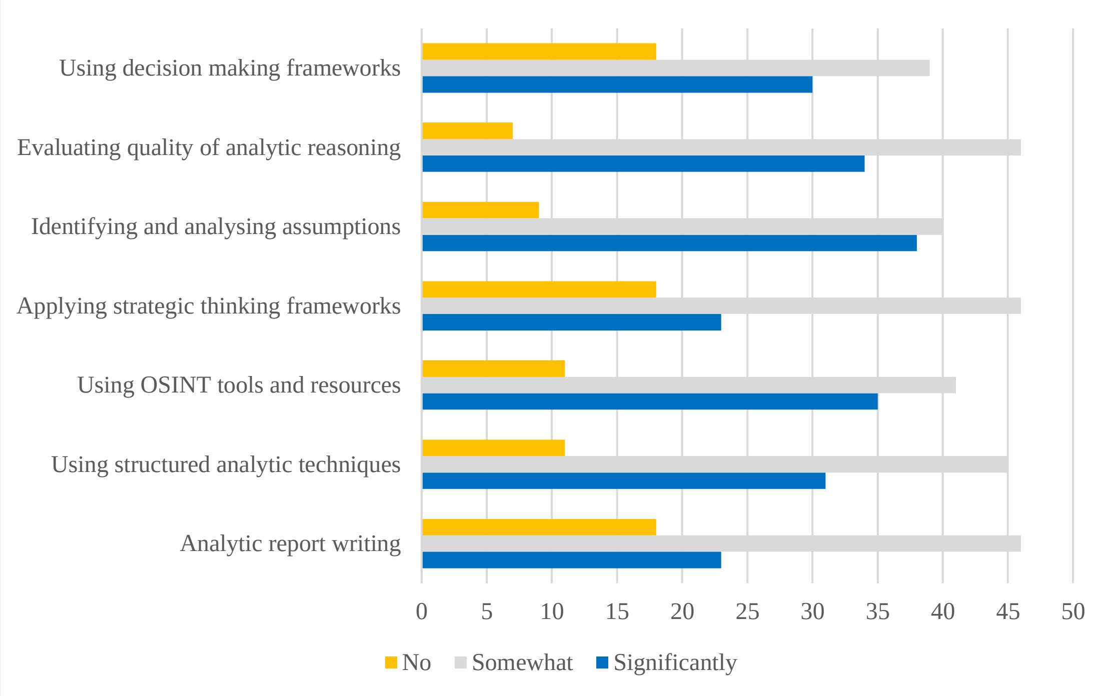

Figure 14: Study 3 - Analytical capability development (public).

At least 82% of participants from Organisations indicated their capability improved across 'Using structured analytic techniques'; 'Identifying and analysing assumptions'; and, 'Evaluating quality of analytic reasoning'. In comparison to public teams, 30% of Organisation participants indicated they did not improve their capability with respect to 'Using OSINT tools and resources', though unsurprising, the small sample size makes this result less meaningful.

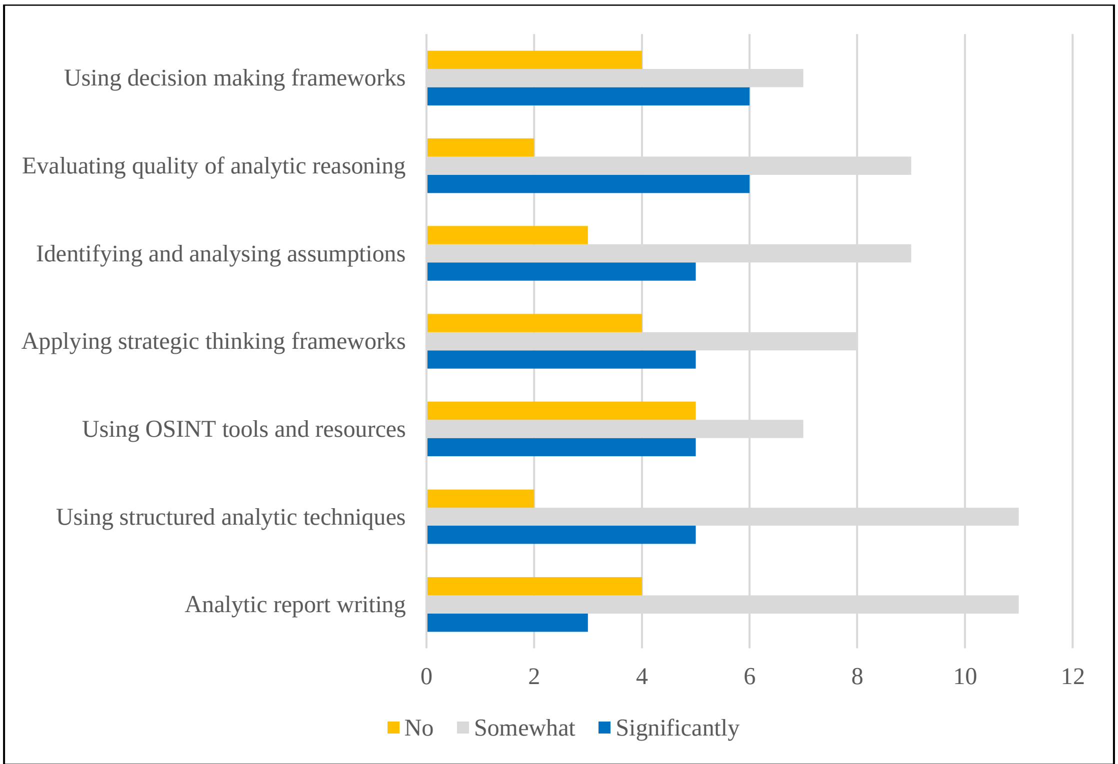

Figure 15: Study 3 - Analytical capability development (organisations).

Understanding that Study 3 participants may have learning outcomes outside the above, we asked the open question ‘What was the one most valuable thing you learned in the Challenge?’. We applied the learning outcomes coding schema to these responses. We grouped the coded public (N = 60) and organisation (N = 14) results in Table 22, delineating Organisation responses with ‘(O)’.

Proportionally, the most ‘valuable’ learning outcomes identified for participants were Cognitive, including strategies to approach a problem, improve analysis and to develop and rate the quality of reports. These participants reported learning (or improving) how to implement SATs, including analysing their assumptions. Both public and organisation participants reported Social learning outcomes, including benefits of teamwork experience and working in diverse teams. Only public participants reported Skill-based learning outcomes, which either focused on using OSINT tools or using the SWARM Platform. We also identified a proportion of public participants report Affective learning outcomes, revolving around attitudinal or motivation developments. These respondents reported an increased level of confidence in their abilities to conduct analysis and to collaborate in a team; others reported discovering an interest in an intelligence analysis career as their most valuable learning outcome.

Table 22: Study 3 - Hunt Challenge learning outcomes.

Cognitive	Affective
To approach problems in a logical manner but be open to change. Strategies to overcome stagnated workflow (not reaching conclusions). Strategies to manage pace of thought processes. Value of approaching problems in a structured manner (O) Strategies to develop concise and resource efficient output. Participants reported development /improvement of cognitive strategies including analysing assumptions (four participants), statistical analysis (two participants), implementing SATs (nine participants) Flaw detection methodology (O) Leveraging the Lens Kit (O) Contending analyses (O) Developing nuanced conclusions. Developing persuasive reasoning Three participants reported learning how reports can be rated / evaluated. Strategy to present evidence in report format (O)	Five participants reported a newly discovered interest in intelligence analysis career Desire to learn more and practice. Importance of commitment to the project. Not all problems stem from technical issues (O) Two participants reported appreciation for time management. Experience preparing mentally (getting into mindset) to work with others. Three participants reported building confidence to collaborate and trust judgement. Two participants reported learning to value all contributions. Level of detail required for high-level reports (O)
Skill-based	**Social**
Nine participants reported Open Source Intelligence tools, particularly related to imagery analysis Two participants reported how to use SWARM Platform	Ten participants reported developing teamwork skills. Three organisation participants reported developing teamwork skills (one in diverse teams) (O) Value of brainstorming amongst team (O)

Training delivery

We asked participants to consider how Study 3 in the form of the Hunt Challenge compared to typical training methods. Both public and organisation participants indicated a Hunt Challenge-like exercise is both more effective and engaging than traditional training methods (Figures 16 and 17 refers).

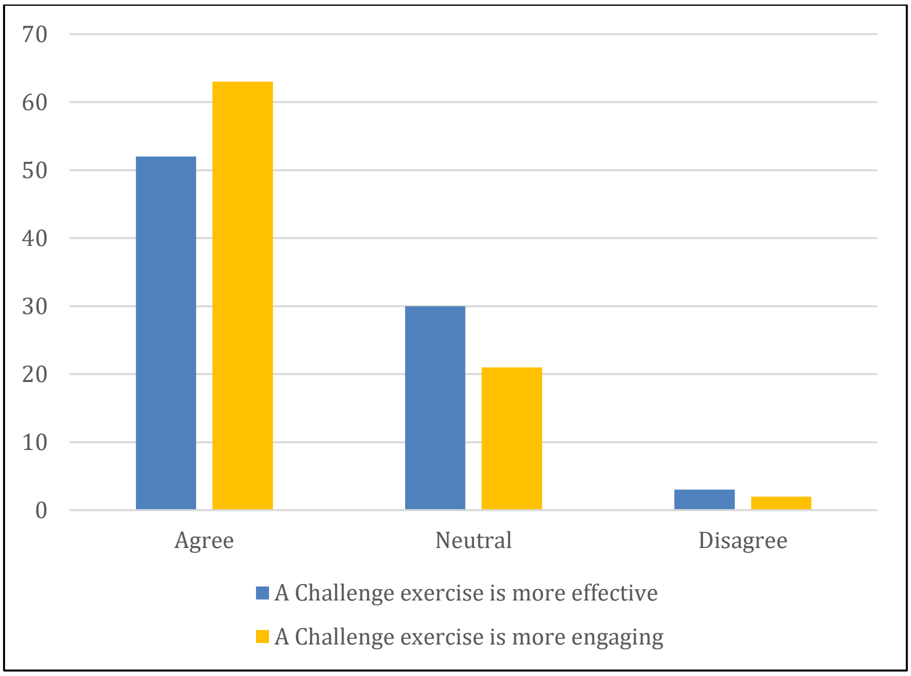

Figure 16: Study 3 - Experience as a training exercise (public).

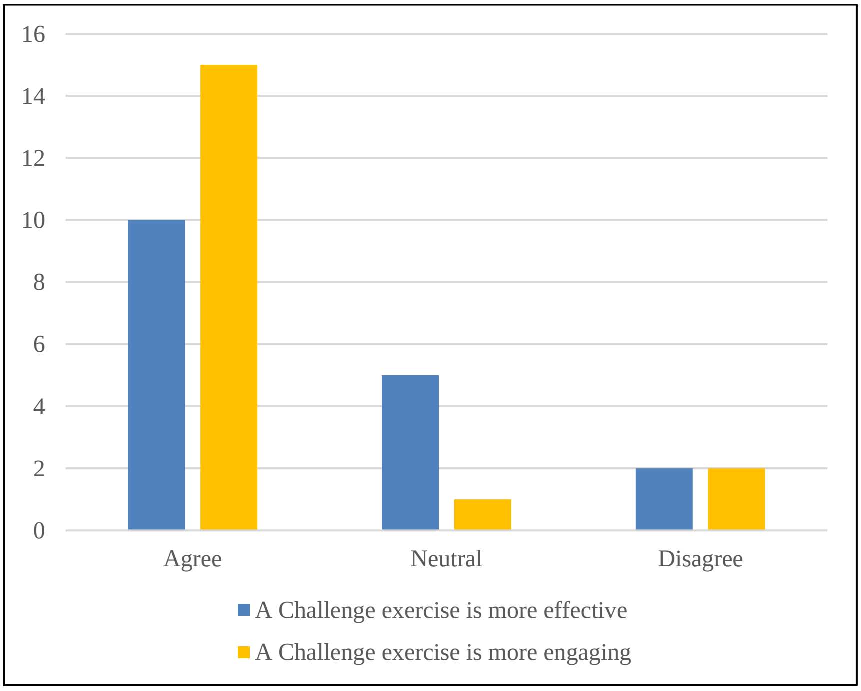

Figure 17: Study 3 - Experience as a training exercise (organisations).

Recruitment

As noted above in *Learning and development*, five participants indicated their most valuable learning outcome related to discovering an interest in an intelligence analysis career. Further to this, to investigate areas for future industry and academia collaboration, we targeted a specific question to investigate the impact of Study 3 participation on a change in interest in an intelligence analysis career. As reflected in Figure 18, of the public respondents (N = 87), 71 (81.6%) participants indicated their interest in an intelligence analyst career increased following participation in the exercise. Zero participants indicated that their interest decreased.

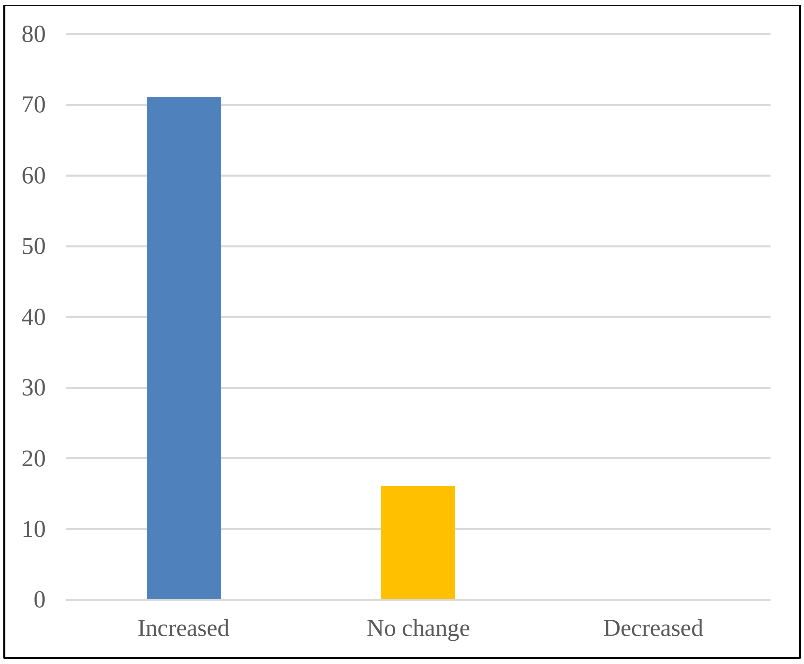

Figure 18: Study 3 - Change in interest in an intelligence analyst career following Hunt Challenge (public).

Manager and trainer affordances

In this research, we investigated what the Platform affords managers and trainers (Research Question 3). A major component of these affordances is the user engagement data that the Platform captured in each scenario. The captured user data included the amount of reports and resources created; comments and chat quantity; upvoting of resources and comments; and, simple, partial and complete ratings of reports.

For the purposes of this research to demonstrate what the Platform affords managers and educators we have included a comparison of engagement metrics of two users from the same team when completing Scenario 3 in Table 23. This metric allows managers and trainers to compare team member contributions and performance.

Table 23: Study 3 - Engagement metrics of high and low-level contributors in Hunt Challenge Scenario 3.

	High-level contributor	Low-level contributor
Reports created	2	0
Resources created	14	4
Comments	21	2
Chat contributions	858	22
Votes on comments	2	1
Votes on resources	7	1
Simple rating	0	0
Partial rating	1	0
Complete rating	3	0

The Hunt Lab have devised a coding mechanism to create ‘engagement scores’ from this data. This coding mechanism assigns an amount of ‘points’ for each of the respective actions, valued for their assigned ‘value-add’. The ‘engagement score’ includes seven points for a draft report, four for a resource, three for a complete rating, two for a comment and one for a chat message, simple or partial rating or a resource or comment vote. However, depending on the priorities of a manager or trainer, the values of each action could be weighted differently to suit the business or training needs.

Schwarz et al. (2020) explored the roles users adopt on Platform and how these roles are reflected in available Platform data. They summarised the roles into eight different categories and their behaviour traits (Table 24 refers).

Table 24: User Roles and Group Dynamics in Online Collaborative Problem-Solving (adapted from Schwarz et al. 2020).

Description	Characteristics
All Rounders	High contribution on all levels usually including writing a report
Quick-Rating Multi Talents	Good contribution on all levels with multiple quick ratings
Resourceful Multi Talents	Good contribution on all levels, tending to one complete rating
Slow-Rating Multi Talents	Good contribution on various levels, mostly multiple complete ratings
Report Gurus	Medium contribution mostly by writing a report
Quick Raters	Little contribution beyond 1-2 quick ratings
Slow Raters	Little contribution beyond 1-2 complete ratings
Drop Ins	Little contribution beyond some chat, maybe a resource or comment

Developing insights from Schwarz et al.’s research, the Hunt Lab’s lead data scientist Luke Thorburn has demonstrated how the data captured can be reflected in visualisation. In Thorburn’s graph titled ‘Characterisation of User Role Clusters’ (Figure 19 refers), he has identified participants who displayed patterns of activity on the Platform, including nominal roles such as ‘Report Guru’ who were heavily involved in report production and ‘Resource Guru’ who contributed a larger number of resources.

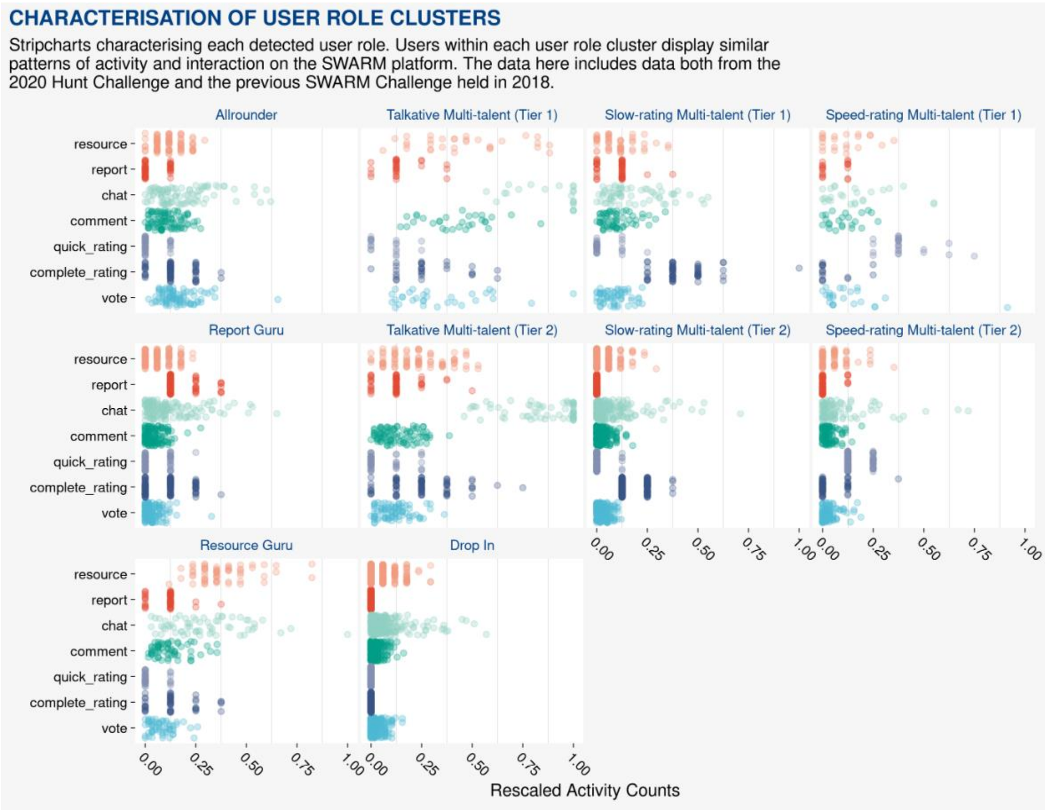

Figure 19: Study 3 - Characterisation of user role clusters (Credit: Luke Thorburn, the Hunt Lab).

In addition to managers and educators observing the roles of their team, the Platform collection of meta data also allows visibility of how the team is engaging and interacting with one another. As Luke Thorburn demonstrates again with his data analysis, we can observe network engagement comparisons between a highly connected high-performing team and a low-performing team (Figure 20 refers).

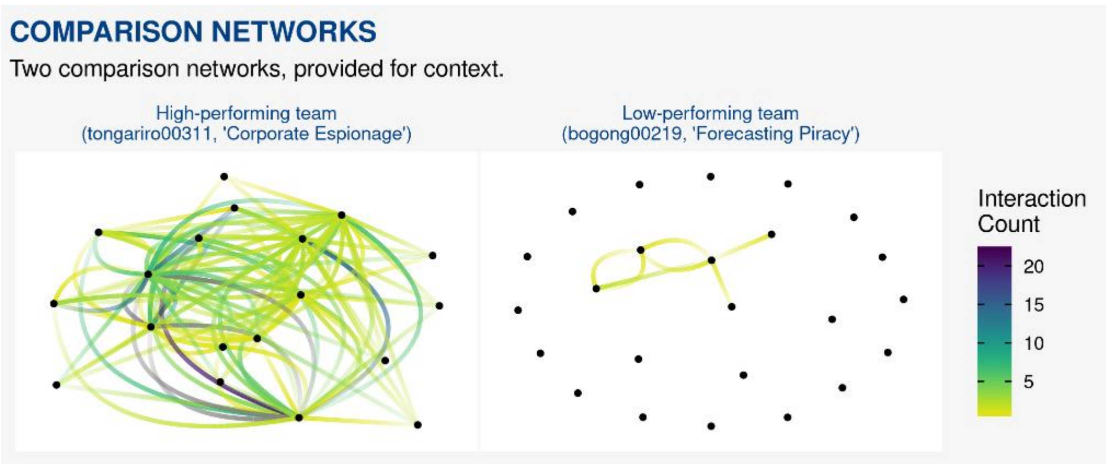

Figure 20: Study 3 - Comparison Networks (Credit: Luke Thorburn, the Hunt Lab).

The Platform also captures chat data for each of the teams. We did not analyse this data due to the scale, though we acknowledge it presents a useful resource for managers and trainers to observe team performance or review the chat collaboration at a later date.

These insights into individual and team performance are highlighted here as a reflection of the manager and trainer affordances of the Platform. They are noteworthy as they are not available in some other MDT frameworks such as email and Microsoft Word products.

Hunt Challenge experience

As noted in the Method section above, we set estimated expected time commitments (per week) for participants in Study 3. While public participants had to balance their own personal commitments, this differed from organisation participants who were participating as part of their employment. Despite the small sample size, a third of organisation participants who responded to the Exit survey suggested their organisation did not allow enough time off from ‘regular duties’ to participate fully in the exercise. If this is representative of the larger cohort, it suggests a decent proportion of organisation participants did not participate fully in Study 3, limiting their exposure to the Platform and associated experiences.

We also collected information on what other tools participants utilised during the Study 3, noting the affordances of these tools could impact overall experience. 70% of public respondents (N = 84) and 60% of organisation respondents (N = 18) indicated they used tools not included on the Platform. In an open question, participants were invited to provide details of what tools they used. We collated these responses and summarised them into themes or brands where appropriate (Table 25 and 26 refers). Outside Google Maps (which was required for the completion of Scenario 1), text-editor and data analysis tools were most common for public participants. While organisation participants also listed text-editor and data tools, they also listed collaboration tools such as email and ‘face-to-face’ meetings. We are cognisant that this is not a comprehensive list of tools used; for example, in unrelated open questions a public participant reported using WhatsApp to contact their teammates.

Table 25: Study 3 - Other tools used during Hunt Challenge (public).

Tool type / name	Number of participants who used tool
Excel (or Google Sheets)	34
Text editor (Microsoft Word)	18
Google Maps	12
Collaborative text editor (Google Docs)	9
Graphing tool (Miro)	7
PowerPoint	3
Statistics analysis / modelling (R)	2
Latex	1
Email (to distribute Microsoft Word documents)	1
Google Translate	1
Skype	1
Photoshop	1
Dropbox	1
Compendium	1

Table 26: Study 3 - Other tools used during Hunt Challenge (organisations).

Tool type / name	Number of participants who used tool
Excel	4
Skype	4
Email/chat (within organisation)	3
Microsoft Word	3
PowerPoint	2
Face-to-face	2
Telephone conferencing (within organisation)	1
Statistics analysis / modelling (R)	1

Future SWARM Platform development

As the SWARM Platform remains in research and development, and considering the above that participants continue to leverage other tools, we asked participants to consider future improvements to the Platform. Participant responses were coded against MDT pillars to identify in which pillar public and organisational teams saw opportunities for affordances to be improved.

As tabulated in Table 27, the concentration of desired Platform improvements largely centre on Communication and Collaboration. Communication improvements focused on expanding the mechanisms of communication and changes to how users are notified of communications. For Collaboration, multiple participants requested improvements to the text editor including implementing ‘track changes’ functions.

Table 27: Study 3 - Desired future Platform affordances (tools and features).

	Public	Organisations
Mission	Complete redesign	
Accountability	Report version control (two participants)	Report version control Greater clarity on who can see information uploaded to Platform
Agility		
Efficiency	Improved search tool (two participants) Integration of other tools (Word/Excel) to ease import/export (four participants) 'Bookmark' in chat	Make Platform more 'user friendly' Make it easier to upload contributions
Communication	Threads/likes/comments in Chat function (three participants) Block comments from users Private chat function Chat channels (for themes) Improved notification system Voice chat and Video conferencing Face-to-face communication (including video record for away members)	Improved notification tools (changes/tagging/new reports) (two participants) Private chat function
Collaboration	Tracked changes (four participants) Improved text editor (five participants)	Tracked changes (three participants) More collaboration options, including voice and video Rating sections of reports.

	Improved collaboration / mind map tools (two participants) Task checklist list for team members All team members as report contributors (as a default) Third post option (general information or thoughts) (two participants) Implement mitigations to prevent report rating 'gaming'	Task checklist list for team members Sort resources / reports by theme
Output	Improved report creation tool Report templates Spelling/Grammar check	

Key findings

Despite the negative impact of COVID-19 on the latter half of data collection of Study 3, we identified key findings relevant to our research questions. Firstly, we identified roughly 70% of public and organisation participants had MDT experience in various fields, including intelligence. These findings support our literature review and hypothesis that MDTs are used across the intelligence sector. This supports our research agenda that frameworks to support MDTs are required and that training of the skills to operate effectively in MDTs are relevant to the intelligence domain and others.

With respect to the Platform's support for MDT maturity as a business tool, we identified that for both public and organisation participants, they felt the Platform did not support them with 'Enabling an efficient workflow' (Efficiency). Further, we identified mixed responses from both public and organisation participants with respect to 'Clear Communication amongst team members' (Communication). For public participants, they indicated the Platform did not support them with 'Keeping track of team decisions' (Accountability) and mixed responses to 'Managing contributions' (Accountability).

We will further explore the reported lack of, or deficiencies in, support for MDT maturity across the pillars of Accountability, Communication and Efficiency in Chapter 9. Given these limitations, we will also address how scaffolding may be applied to increases Platform support for these pillars.

With respect to the Platform's potential application as a training tool, Study 3 identified that participating in this type of research exercise is a more engaging and beneficial learning experience than other traditional training methods. We identified the most 'valuable' learning outcomes for public participants were Cognitive, including strategies to approach a problem, improve analysis and to develop and rate the quality of reports. Both public and organisation participants reported Social and Affective learning outcomes, including recognising the benefits of teamwork and experience working in diverse teams. Given the Platform's support for Cognitive and Social learning outcomes, we will discuss the practical implications of Platform application as a training tool, including considerations for professional and tertiary education implementation.

Another key finding of this research confirmed our understanding of the Platform's manager and educator affordances. We identified that the data the Platform naturally captures can provide a unique insight into individual and team engagement that 'traditional' MDT frameworks do not provide. We will reflect on how this affordance may be used by managers as a business tool and how educators may leverage this affordance in the education context.

This study identified the reliance of participants to use tools outside the Platform. We will consolidate the areas for Platform development we identified in this research such as chat format changes and to collaboration system issues that could help increase the Platform's support for MDT maturity and minimise the need to utilise other software or tools.

As a tangential result, we identified public participants report an increase in interest in pursuing an intelligence analysis career following participation in Study 3. We recognise this as an opportunity for further collaboration with our Australian Government research stakeholders and an item for future research.

Chapter 9: General Discussion

Reflecting on the key findings of the three studies in this research, this Chapter will systematically discuss how we have addressed each of the research questions. We will first discuss the Efficiency immaturity identified in the case study of MDT use in the Australian Government intelligence context. We will then discuss the support the SWARM Platform provides for MDTs as a framework, including the theoretical implications of affordances. We will focus on the practical implications of using the Platform as a business tool in the Australian Government intelligence context, highlighting the barriers that would prevent full adoption. Considering these barriers, we will then address the second element of our research questions, to explore the Platform's suitability as a learning and development tool. To address our final research question, we will articulate what the Platform offers managers and trainers, including prioritised scaffolding strategies to improve MDT maturity that are relevant to MDT frameworks including but not limited to the Platform.

After addressing the central research questions, we will consider the technical developments to the SWARM Platform that are of most priority to support MDTs. We will then address the limitations of the three studies in this research and discuss the next steps for this research including emergent findings.

Research Question 1: What are the strengths and weaknesses of how MDTs are utilised in Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions?

This research explored the strengths and weaknesses of how MDTs are utilised in Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions. While not a representative sample across the Australian intelligence sector, the data collected represents a case study to examine our Australian Government research stakeholder's MDT framework experience.

Analysing the benefits and limitations of MDT use in this case study within the lens of the maturity model, we identified signs of low maturity in the Efficiency pillar, views that reflected their MDT framework did not save time or effort. Further, we identified themes related to issues of time and resource inefficiency. Another indicator of low Efficiency maturity we identified is their reported inconsistent use of MDTs for tasks. There is a recurring theme from respondents that the establishment of a MDT is required for non-routine tasks rather than 'normal business'. This supports Hackman's (2011) research who argues that not every intelligence problem requires a structured new team and that managers must think critically about when or if a discrete team is required.

While respondents had issues with resource impost, we also identified positive Efficiency themes including that their MDT framework "encouraged better planning", had the right people involved and reduced "duplications, inconsistencies and gaps". So, despite the perceived resource consuming nature of the MDT framework, there were notable benefits. This is important to recognise as decision making may take place over the course of days, weeks or months (Sohrab et al. 2015), which suggest MDT participants may need patience and that better planning may assist overall efficiency processes.

Turning our attention to the other pillars of the MDT maturity model, we identified indicators of high-performance in Mission, Collaboration and to a degree Accountability and Agility.

Participants were not unanimous in their support for Mission; however, the negative responses focused on elements of cultural resistance to adopt the framework. From their in-depth case study of a high-performance research and development team, Daniel and Davis (2009) identified the importance of establishing, communicating and understanding a team's mission and shared agenda (Daniel and Davis 2009). The negative views that reflect a hesitance to adopt a framework are not necessarily a low-performance indicator, rather a wider institutional and cultural reticence to change.

Through applying the MDT maturity model to the collected survey data in Study 1, we identified the likely prioritisation and intention of the stakeholder-run survey, this being a notable focus on Collaboration. Leaders play an important role in breaking down organisation and cultural barriers suggests Brown (2014), so this survey may have been intended to focus on identifying if a collaboration-focussed transition had occurred (Brown 2014). This would explain our finding of the bias towards Collaboration-related Likert scale questions and the focus of respondents on Collaboration to open questions.

Acknowledging this focus, participants rated their current MDT framework positively with regards to Collaboration. Our findings suggest the participants in our case study felt there had been a lack of improvement on existing processes from implementing their MDT framework than actual failings or flaws with the framework. Most participants agreed their MDT framework, in this case structured team meetings and planning Word documents, were a useful tool to encourage collaboration, with many respondents adding statements such as “sharing knowledge” and “greater collaboration”. Unsurprisingly, information sharing and collaboration are consistent themes of high-performance teams across similar research and literature reviews (Brown 2018; Chong 2007).

Where respondents were most split with regards to Collaboration is with the tools they have at their disposal. While almost half of the participants in Study 1 responded that they felt their “agency/department has sufficient communication and collaboration tools to support MDTs”, around a third disagreed with this statement. This suggests a decent portion of the MDT members are unsatisfied with their collaboration tools. Due to the method of how we collected this data, it is impossible to differentiate between responses and roles, therefore we do not know if these respondents were analysts or from other job families. Regardless, it suggests a portion of staff members have a need for improved collaboration tools. Also of interest, some participants also highlighted the need for improved training to participate in MDTs.

From our application of the maturity model to this case study, we contend our stakeholder's current MDT framework is not supportive of high-functioning MDTs at this stage. While meeting most requirements across the pillars, issues of resource efficiency and practical application of MDT teams require additional management.

The findings of the current processes of this case study also illustrate the shortcomings of current MDT frameworks. Despite the push in the 21st century to use increasingly technological tools to enable regular collaboration (Bernstein et al. 2018; Boughzala and De Vreede 2012), the MDT framework of the case study appears inefficient. Remaining cognisant of the inherent prioritisation of the case study survey design, it is important to consider the limitations of current frameworks, in this case efficiency, and how future frameworks (such as the SWARM Platform) may provide more affordance to users and managers to achieve higher levels of maturity.

We reflect on the importance of developing appropriate frameworks as this is a wider issue that is not limited to our Australian Government research stakeholders. Demographic data collected in Study 3 supports our contention that MDTs are used across the intelligence sector, as both public and organisation participants reported MDT experience in the fields of investigative and strategic intelligence analysis, law enforcement, military and defence, incident and emergency management, finance crime, cyber security and corrections. These findings support our research agenda that frameworks to support MDTs are required and that training of the skills to operate effectively in MDTs are relevant to the intelligence domain and others.

Research Question 2: Can the SWARM Platform move beyond its origins as an analysis-focused tool to provide a framework for intelligence MDTs as a business and training tool?

This research explored whether the SWARM Platform could support intelligence MDTs through testing the software in a small-scale pilot within an intelligence organisation and on a larger scale in an analytical competition involving public and intelligence organisation teams. We tested the Platform's support for MDT maturity to evaluate the Platform's suitability as a framework for business and training application. We have also addressed the practical application of the Platform as a professional business tool and as a training tool.

MDT maturity

In our evaluation of the Platform against the MDT maturity pillars, we identified the Platform provides affordances as 'action possibilities' (Gibson, 1986) across pillars of Mission, Agility, Collaboration and Output to support high-performance. Meaning, results from this study indicate that the Platform appears to support high-levels of maturity across these pillars without outside actor stimulus. While our findings suggest some users may require scaffolding or management for these pillars when using the Platform, they are not the highest priority. Rather, our findings indicate the Platform did not provide sufficient support to reach a higher level of MDT maturity across the pillars of Accountability, Efficiency and Communication. The affordances for these pillars may be viewed instead as action possibilities that are dependent on how they are conveyed or presented to the user, which is more in line with McGrenere and Ho's interpretation and incorporation of Norman's definition of affordance (McGrenere & Ho, 2000). We will discuss the reported lack of support for each of these pillars in turn, then address how these issues impact the practical implications of using the Platform as a business and training framework.

Accountability

As explored in Chapter 3, the Platform provides unique Accountability-relevant affordances relevant to providing visibility to team members and automated Platform data record keeping. Surprisingly, our findings indicate public participants in Study 3 did not feel the Platform supported them for this pillar. We found participants indicated that the Platform did not support them with 'Keeping track of team decisions' and provided mixed responses to 'Managing contributions'. In contrast, we found organisation participants in our studies did not identify the same Accountability issues, noting our small sample sizes prevent inferences to the wider intelligence community.

There may be a reason for this difference between public and organisations as intelligence organisations need to keep accountable documentation of records and decisions as part of their normal processes and may have applied these skills to their on-Platform activities. As Conklin

(2006) notes, wicked problems, like those intelligence organisations face, have a no stopping rule, meaning at some point the people, places or issues addressed may arise again (Conklin, 2006). It is then essential that intelligence MDTs have a record of what has previously occurred as future intelligence MDTs may rely on it at a future date to inform critical decision making and protect the public (Pfeifer, 2012; Ratcliffe, 2010).

Efficiency

The results from the case study of our stakeholder's MDT experience and the findings of our SWARM Platform framework research support our contention that multidisciplinary teamwork is inherently time and resource consuming. Our research findings support the efficiency challenges explored in the teamwork literature in Chapter 2 and wider efforts to improve teamwork and collaboration. As noted at the heart of the CREATE program, it is a challenge to effectively and efficiently coordinate a large team and pull together diverse contributions into a single outcome (van Gelder et al., 2018). Therefore, it is unsurprising users from both the public and organisations felt the Platform did not enable an efficient workflow and that our MDT case study participants also identified efficiency issues. Being mindful of these existing challenges, we reflect on the importance of prioritising the development of a MDT framework that supports Efficiency maturity.

As observed in both Studies 2 and 3, some participants reported feeling their team size exceeded the requirements for the problem at hand. This suggests there remains an imbalance between problem scenario complexity and the theoretical intentions of Contending Analyses to support sub-teams to form from the larger team size. Some participants in Study 2 described Contending Analyses as a duplication of effort, despite research suggesting properly using it leads to improved quality of analysis (van Gelder & de Rozario, 2018). This latter issue of inefficiency may rest more in Study design than Platform support, with misunderstanding of concepts a factor. We also note that some of the efficiency challenges with the Platform are likely conflated with other issues, most notably technical issues with editing functions and most relevant to Communication, the reported time-consuming nature of the chat function, which will be addressed in *Communication*.

Communication

Communication is a central mechanism to a MDT and issues with it impact other MDT pillars including efficiency, as referenced above. Our research findings identified conflicting views on the level of support the Platform provides the Communication pillar of the MDT maturity model. These conflicts centred around how clear communication is on Platform and the method of communication chosen.

Our research identified that public and organisation participants in Study 3 did not provide a consensus view as to whether the Platform provided support for 'Clear Communication amongst team members'. An issue we identified relevant to this finding in both Studies 2 and 3 revolved around participants feeling overwhelmed by the chat functionality. In Study 2, we observed participants demonstrate some ingenuity to avoid the chat function where they leveraged the co-editing function of the report format to have a semi-private chat. In addition to the participants concerns around the size and speed of chat data, we also identified a compounding issue of participants' desire to use communication methods outside the Platform.

In Study 2, most of the organisation participants reported they undertake daily face-to-face collaboration and half of the participants indicated their primary methods of collaboration were verbal. Considering this baseline of 'normal communication' methods, we identified in both

Studies 2 and 3 participants needing to utilise communication mechanisms outside the Platform. In Study 3, public and organisation participants used communication tools including Skype, voice-chat and collaborative email. In Study 2, both of our participant groups became frustrated with Platform-only communication and organised face-to-face group meetings. Various research supports this finding, indicating face-to-face and vocal-based communications were preferred and led to higher levels of user satisfaction (Champion, 2012; Warkentin et al., 1997; Woods & Ebersole, 2003). Gibson and Cohen (2003) also support these findings and this need for off-Platform communication as they suggest periodic face-to-face meetings between team members help build networks, strengthen shared understanding including divergent perspectives and develop mutual accountability (Gibson & Cohen, 2003).

We have identified how the Platform supports, or does not support, MDT maturity – including the areas of Accountability, Efficiency and Communication that managers and trainers need to address to improve MDT maturity on Platform. Before we address the potential scaffolds for improving maturity in these pillars, we first need to consider the practical issues of implementing the Platform as a business tool in intelligence teams and as a training tool.

Platform application as a professional business tool

Despite the broadly positive support for MDT maturity, this research revealed cultural and technical issues that may prevent adoption of the Platform as a business tool without prioritised research and development. We recognise the analyst-centric origins of the Platform, which the Hunt Lab developed to fulfil the requirements of the CREATE program. This program aimed to achieve fundamental advances in human reasoning, utilising the fields of crowdsourcing and structured analytical techniques and did not prioritise workplace application. Therefore, in this research we explore workplace application implementation issues. These issues centre around some of the core Platform design features such as Contending Analyses and anonymity as well as more organisation-specific challenges such as system integration between the Platform and other tools.

Contending Analyses

We first raised some of the issues of Contending Analyses with respect to Efficiency as organisation participants in Study 2 reported they would not dedicate the number of analysts to the type of problem scenario used in the study and described the process of Contending Analyses as an inefficient use of resources. We note there is no requirement to utilise Contending Analyses when applying the Platform as a MDT framework and that some participants reported they did not fully understand the concept to apply it properly. However, if we view Contending Analyses as an essential component of the Platform's design and that it demonstrably improves quality of analysis despite the perceived resource impost, then implementation will likely be met by the same cultural resistance to adoption as a framework, if not more, than what we observed in MDT framework implementation in our case study of Study 1.

Anonymity

The next cultural issue we identified in this research that may impede professional adoption of the Platform in intelligence MDTs focuses on anonymity. Despite being designed as an affordance to improve collaboration, anonymity remained a sticking point for some participants in Study 2 who indicated it would not be sustainable and participants in both Studies 2 and 3 lamented anonymity's impact on collaboration. For example, in Study 2, participants indicated that using anonymous usernames undercut the positive relationship building they had conducted in the off-Platform exercise immediately prior.

Anonymity may also impact the principles of transparency in intelligence analysis. The intelligence community is subject to substantial scrutiny (McCulloch & Tham, 2005) and it must maintain the principles of remaining accountable to the community and government (Monks, 2008). In using the Platform, managers would have access to users' pseudonyms to maintain a level of oversight. However, for users, not knowing their team members and team size may reduce the motivation to keep oneself and others accountable, particularly in an asynchronous work environment. For example, almost half of an organisation team remained inactive for the duration of Study 3, even though participating as part of their employment. Further investigation is required to determine if anonymity reduces MDT participants' shared accountability for the collective goal and what impact it has on record keeping culture.

Further to the cultural issues that anonymity poses, it also creates considerable administrative hurdles. In all SWARM Platform exercises, including Studies 2 and 3, we assigned anonymous animal-based usernames to participants. Within minutes of beginning the SWARM Platform phase of Study 2, multiple participants had revealed their identities. In Study 3, members of one organisation team revealed their identities promptly at the beginning of the exercise. The potential here is staff members either require new logins on a semi-regular basis, disregarding anonymity entirely (and the research principles behind the Platform), or a resource intensive and administratively burdening requirement to maintain and log each username, who it belongs to, and in what context the staff member used the username. An Information Technology (IT) support area would likely be responsible for assigning and managing anonymous usernames, as without their involvement and active ownership would lead to negative outcomes as demonstrated in other studies (Olesen & Myers, 1999). Considering these cultural and administrative barriers, future Hunt Lab system design need to consider the capability to switch anonymity off-and-on and what impact it has on the Platform's other affordances.

System integration

Following on the issue of administrative barriers, our final research finding that may impede Platform implementation is integration with other systems. At no stage has the Hunt Lab research team claimed the Platform will replace all existing analysis and communication tools and it is expected to integrate with other in-house systems, if used. However, in Study 3 we observed participants using an array of different analysis and collaboration tools, which we cannot account for their impact on MDT maturity. One participant in Study 2 supported this, suggesting system integration is essential to the success of a MDT framework. If the Platform is still reliant on other base-level collaboration tools and is not tested as part of existing workflows, it will become part of 'another system to check' for MDT staff, which could limit the explored benefits and potentially exacerbate existing issues.

Considering these cultural and technical issues that may prevent adoption of the Platform as a MDT framework without further research and development, we propose that the Platform may have more immediate benefit to support training functions.

SWARM Platform application as a training tool

While the Platform supports some elements of high-functioning MDTs as a business framework, it is unlikely to do so in its current form in the workplace without prioritised research and development to consider technological improvements and cultural change. Therefore, the Platform appears to have more immediate application in the training environment. From our research, we have developed various insights and have outlined educator considerations relevant to structuring high-impact teaching strategies on Platform.

We will discuss these in order of learning outcomes; measuring performance; scaling research results; and accessibility considerations.

Learning outcomes
In Study 3, key learning outcomes from participation centred around the development of cognitive strategies, affective attitudinal changes and improved social collaboration skills. Cognitive strategies largely related to how to approach a problem; strategies to improve analysis; and, to develop and rate report quality. Participants also reported learning (or improving) how to implement SATs, including analysing their assumptions. In the fields of health and nursing, research supports findings that team-based learning can assist self-regulated learning and improve critical thinking and problem-solving (Frame et al., 2015; Whittaker, 2015).

Regarding development of social collaboration skills, both public and organisation participants reported learning from their teamwork experience, with some highlighting the benefits of working in diverse teams. These findings mirrored those of junior participants who participated in Study 2, though they noted they attained additional benefit from having worked previously in the off-Platform part of the study. Other research supports these findings, also across the disciplines of nursing and healthcare, suggesting diverse team-based learning improved training experience, gave insight into team members perspectives and subsequently improved patient outcomes (Bujac et al., 2009; Ishii et al., 2009; Saghir et al., 2014).

Of interest, after the completion of Study 3, only public participants reported developing Skill-based learning outcomes, including using open source intelligence tools. Educators may consider creating a scenario, like the South-East Asia Foreign Fighter scenario used in Studies 2 and 3 as an example, which encourages using open source intelligence tools in new ways. Another example is engaging students with tools relevant to higher education such as Google Scholar. Plos and Kjellgren (2008) note the benefits of a well-developed and stimulating education plan that helps introduce secondary school students to higher education (or tertiary students to workplace scenarios), so educators should not be hesitant to challenge students and include tools relevant to the next stages of learning (Plos & Kjellgren, 2008).

Ahles and Bosworth (2004) suggest that even at the end of teamwork exercises, students do not automatically process what characteristics are necessary for good teamwork (Ahles & Bosworth, 2004) and that educators can help students solidify learning outcomes through implementing reflective practices (Walsh, 2017). Reflecting on how we collected data on learning outcomes, we propose that this encouragement of self-reflection after Study 3 assisted participants solidify and acknowledge the learning outcomes. According to Aleksander at al. (2005) team members' declarative knowledge regarding teamwork competencies positively affected planning and task coordination, collaborative problem solving, and communication skills (Aleksander et al., 2005). In future studies, this declarative knowledge does not necessarily have to be provided to an educator and can also be provided to peers. Research from Ge and Land (2004) supports this, suggesting the process of providing and receiving feedback from peers can help students engage in deeper cognitive processing and develop new understanding (Ge & Land, 2004).

The learning outcomes demonstrated in the findings of this research are particularly relevant to the training of current and future intelligence analysts. As Corkill and Deering (2017) note in their review of the required skills for intelligence analyst roles, three dominant forms of criteria emerged: interpersonal and communication skills; analytical ability; and, thematic knowledge (Corkill & Deering, 2017), which the on-Platform scenarios provided experience in.

Measuring performance

If the SWARM Platform is to be utilised in the education field, trainers will need to consider how they measure performance and provide grading. Students reportedly need to receive specific and personal feedback on activities in order for learning to be effective (Glasgow & Hicks, 2009). The Platform supports multiple opportunities for independent and collective feedback. Firstly, educators may choose to get their students to create an independent report on the Platform then also contribute to a collective report with team members, which would provide two opportunities for report grading. Educators may also use Platform metrics to identify level of participation as a grading scale. As noted in the example of the high and low-contributing users in Study 3, educators can set a 'pass/fail' requirement for a certain metric level of engagement. This means that even if students are not lead contributors of the final report, they can achieve a metric 'pass' mark by commenting, rating and other supporting activities. If educators do use a metric evaluation of engagement, Snow (2018) argues educators should be transparent what rubrics are used to evaluate competencies, suggesting this creates better learning outcomes for students (Snow, 2018).

Scaling research results

One limitation of using the Platform in an education setting is the time and financial cost of coordinating large-scale collaborative teamwork on the Platform. Study 3 required substantial academic and technical support given the 20 teams participating. Research experience in implementing team-based learning strategies in the health context also found it required significant faculty time, drive and commitment (Whittaker, 2015). While Study 3 was a large-scale research exercise, the learning outcomes are demonstratively scalable and not necessarily reliant on groups more than 20. This is feasible if we assume Australian universities tutor group sizes average between 10 and 30 pupils and the average Victorian secondary class size is 21 (Department of Education and Training Victoria, 2020). For single classes, this affords a minimum of two teams to encourage the 'challenge' or 'competitive' element of the studies in this research. One element that is potentially not scalable is that most participants in Study 3 reported that the exercise design (which took the form of 'the Hunt Challenge') is more engaging and effective than traditional training measures. As coordinating large scale exercises are time consuming and expensive, it is unclear if using the Platform as an education framework would remain as engaging without the 'competitive' element of a large-scale exercise.

Accessibility considerations

To appropriately implement high-impact teaching strategies, educators must also consider the accessibility of their learning environments (Milhouse, 1995). In the context of this research, all scenarios tested on Platform, including instructions and training, were provided in English with no alternate languages available. In addition to language, cultural background may also impact how the Platform is used. Problem scenario design for on-Platform analysis should aim to be country agnostic and remain as inclusive to multinational student groups. Inclusion of multilingual and multicultural elements in teaching can have a powerful identify-affirming impact for participating students (Cummins, 2015; Plos & Kjellgren, 2008). Whitford and Prunckun (2017) note in their experience of needing to alter their language and jargon-use when communicating to an audience where English was not the student group's first language (Whitford & Prunckun, 2017). In the Australian context, Harrison (2011) suggests educators need to empower inquiry-based learning for Aboriginal and Torres Strait Islander students who may require additional scaffolding to learn effectively. He notes in his experience Aboriginal and Torres Strait Islander students rarely work at the expense of others so may benefit from teamwork oriented problem solving such as the scenarios tested on the Platform (Harrison, 2011).

When considering implementing technology-enabled collaborative learning programs, educators need to consider potential inequality where many students lack the resources at home such as access to computers or Internet access (Glasgow & Hicks, 2009), which are required to access the Platform. Also, when considering accessibility of the Platform, colours such as the green and orange of the in-Platform rating scale, may be difficult for users with deuteranomaly to distinguish (Colour Blind Awareness, 2020). For the purposes of this research, we did not provide additional scaffolding or direction to improve accessibility for culturally or linguistically diverse groups or for those with other accessibility requirements. Additional consideration should be given for accessibility to the Platform if utilised in education settings, and how these factors may impact participation.

Research Question 3: What does the SWARM Platform afford managers and educators to improve MDT performance?

Our final research question for this thesis concerns what the Platform affords managers and educators. We note this research has identified the Platform presents more immediate benefits as a training tool as opposed to a business tool due to cultural and technical barriers; however, we will address this research question fully to demonstrate the capabilities of the Platform and what it affords both business managers and educators. To address this research question we will explore the unique affordances of the Platform compared to traditional MDT framework including how we utilised the data in this research; and, how managers and trainers could implement scaffolding strategies to overcome the maturity support issues identified earlier in this chapter.

The most pressing benefit of the Platform is the visibility and metrics it provides managers. Where previous research has suggested virtual managers have difficulty monitoring individual and team performance (Lepsinger & DeRosa, 2015), this research has demonstrated with leveraging self-reporting surveys, managers can evaluate MDT performance on an individual and group basis. The added affordance of the Platform is in the individual and team user engagement metrics it collects. We showed in both Studies 2 and 3 how this data can be visualised at an individual and team level. If data retention strategies are used in each use case of the Platform, it also provides professional organisations and education institutions with data to conduct longitudinal studies, potentially testing hypotheses that have not been envisioned at the time of collection (Agarwal & Dhar, 2014).

The Platform also affords leaders with a breadth of support to hold their team accountable including visibility of all public activity on Platform. However, as reflected in the findings of Study 3, and to a degree Study 2, teams continue to leverage tools including communication mechanisms outside the Platform, where managers do not have visibility. Therefore, it is imperative that appropriate scaffolding is implemented to maximise Platform affordances, both for team members and leaders.

The practice of evaluating a team’s work is important and the Platform offers various tools for managers and trainers to review their team’s progress. They can view users' in-Platform ratings of their reports and identify if there is a disparity between their views and the team in real time as the report output is developed. Given rating scales change and vary between organisations and education standards, it will be important that the Platform integrates measures that contain universally ‘important’ metrics (Moore & Hoffman, 2019) and that report grading can be tailored to the requirements of the manager and educator. With ongoing use of the Platform, it may provide managers and trainers with a repetitive and quantifiable output to measure how successful their teams are in rating their own output. An issue with this in terms of professional application is that team members join and leave, so longer-cycle reviews may not be possible (Sundstrom et al., 1990).

As demonstrated in this research, on Platform scenarios can create substantial data for managers and educators to digest. For example, metadata, chat logs, resources, reports, comments and off-Platform data collection (including observation and survey data). This research elected not to review all chat data from teams due to the scale of data available, it is conceivable managers and educators may equally not prioritise this data due to timeliness considerations. A second consideration regarding data availability is technological aptitude and data literacy. Given secondary and tertiary schools are already implementing online collaborative tools such as Google Classrooms (Railean, 2012), the digital literacy required to operate the SWARM Platform should not exceed those already acquired. Further as Mills, Wakefield and Knezek (2015) highlight, educators should not use tools that rely entirely on the teacher being the technological expert who needs to direct all student activity (Mills et al., 2015). As the Platform contains advice on how to use the system, the Platform design encourages self-directed student learning.

The affordances of the Platform for managers and trainers to gain insights into individual and team performance remotely is notably important as the technological environment continues to move towards a dispersed and asynchronous workforce, particularly in light of COVID-19 but also because employees are more insistent on not relocating for work and prioritising family stability (Fisher & Fisher, 2011) and an increasing availability of online training courses.

Considering the demonstrated affordances of the Platform for managers and trainers, if it used to support business or training functions, they will need to consider the MDT maturity support issues identified in this research. To overcome these issues without immediate technical solutions requires the creation of a well-defined strategy (Lee-Kelley & Sankey, 2008) and in this case, well-designed scaffolding strategies.

Scaffolding strategies to improve MDT performance

In this research, we identified users of the Platform did not feel entirely supported across MDT maturity pillars of Accountability, Efficiency and Communication. We have developed scaffolding strategies to address the latter half of our final research question, to identify how managers and trainers can use the affordances of the Platform to improve MDT maturity. The proposed management and scaffolding strategies are prioritised to improve MDT maturity across more than one of the pillars in need of additional support. These scaffolding strategies cover creating a teamwork schema (hard conceptual); launch meeting and set times for planned activity (hard and soft procedural); enhancing communication through high-level accountability practices (hard procedural / soft metacognitive); and, reducing cognitive load through data management (soft strategic). While referencing the SWARM Platform, the proposed scaffolding strategies are intended to provide the principles to improve MDT maturity across MDT frameworks more broadly, not limited to the SWARM Platform.

Creating a teamwork schema: hard conceptual

The first proposed scaffolding measure for leaders to implement is the development of a teamwork schema. With respect to the Platform, the design already encourages teams to begin this process through engaging with the 'How to SWARM' guides. As a hard conceptual scaffolding tool that helps guides users to complete the task (including tips and considerations), the 'How to SWARM' guides help address issues of how a team can use the Platform and incorporate considerations such as how MDTs store information (Accountability), what issues may impede workflow (Efficiency) and what tools outside the Platform may be used (Communication). Rather than what we observed during Study 2, where participants individually would read (or ignore) the training material and delve into the problem, this proposed scaffolding requires all MDT members to engage with the material and then come together to discuss the guides, including how they will engage with the Platform, prior to problem solving - thereby creating a teamwork schema.

Developing a teamwork schema helps guide a team's assumptions, expectations and behaviour to work together (McNeese, 1998; Van Der Vegt & Bunderson, 2005). This collaborative development of a schema informed by the 'How to SWARM' guides is an important distinction from a dictatorial templated or scripted set of rules for a team to follow. Imposing strict non-consultative controls on a team can hinder satisfaction (Piccoli et al., 2004) and blind members from external realities but that without boundaries, chaos can ensue (Hackman, 2011). For MDT frameworks that do not afford such guides, managers should consider the creation of materials to help their team develop a teamwork schema.

This scaffold is not about providing teams with a template but is a key step which informs other scaffolding activities. As Hutchins (1995) suggests, solution procedures help guide how a task should be completed; however, if too sequential and relied on too heavily, a student or staff member who learns to 'fill in the blanks' of this solution procedure may not have any conceptual idea of what they have done and may be unable to perform the task in the absence of the solution procedure (Hutchins, 1995). As van Gelder, de Rozario and Sinnott (2018) attest, the Platform is designed to provide latitude and not impose a strict step-by-step process (van Gelder et al., 2018). This considered, if leaders do not promote the adoption of this hard conceptual scaffolding, teams may not effectively develop a teamwork schema, or if using the Platform as a MDT framework, they may not leverage the affordances of the Platform.

Launch meeting and set times for planned activity: hard and soft procedural

Building on the above, we observed some participants during Study 3 struggle with not knowing their team members or team size and a lack of an agreed schedule to collaborate at the same time. Most staff and students would be familiar with the "quick introductions around the room" technique, whereby team members are encouraged to quickly introduce themselves in new teams. Leaders are faced with a difficult balance decision between improving interpersonal relationships with efficiency and deadlines as this can be a laborious process (Daniel & Davis, 2009) but as observed in Study 3, some participants struggled not knowing their team size or the expertise within it.

Two intertwined pieces of hard and soft procedural scaffolding are proposed, which guide teams on how to orient themselves when undertaking a task and using a particular tool or system (Hannafin et al., 2001), to improve accountability to one another, open communication and reduce inefficiencies of anonymity and asynchronous communication. Procedural scaffolding is proposed in the assumption that circumstances dictate the Platform or similar framework is used as the central coordination structure and if in some cases, there is a requirement of anonymity.

Teams benefit from having a mutual understanding of the skills and attributes of a diverse MDT. When a team knows where expertise resides, it is much more efficient in accessing that expertise (Gibson & Cohen, 2003). Therefore, it is proposed that leaders schedule a 'start' or 'kick off' meeting where all MDT participants are required to attend in person or virtually (on Platform). To minimise the efficiency losses of introductions (for larger MDTs), leaders should collate expertise summaries to be aligned with the anonymous Platform pseudonyms (if using), which would be available as a resource on the Platform. This hard procedural scaffold would ensure teams have a structured procedure of how to commence a project and that all team members are then aware of one another should they need to leverage expertise. This scaffolding strategy also allows for clarity of team size and responsibilities in the event of team member absences.

Recognising that team membership can change and mission objectives shift, it is likely this collation of expertise summaries will need to be updated and follow up 'all hands' meetings organised to realign priorities or mark important events (Hackman, 2011). While managers may not need to take an active voice in these meetings, the opportunity for team members to meet semi-regularly is important to gauge progress, adjust priorities, welcome new team members, consult on ideas that require all team members present and update on strategic planning issues such as staff absences and planned leave (Gibson & Cohen, 2003). The frequency of these intermittent semi-regular all team meetings, will depend on the priority and pace of the mission at hand. This considered, periods of distance from 'all hands' meetings are important to facilitate team collaboration while maintaining individual productivity and a high level of independent exploration (Bernstein et al., 2018). Utilising the Platform as a framework, managers (and team members) can monitor who from the MDT is 'online' at a given time, to ensure the team maintains accountability to attending these meetings.

Enhancing communication through high-level accountability practices: hard procedural / soft metacognitive

Considering the above scaffolding strategies, which incorporate the Platform focus of anonymity and on-Platform coordination, the below hard procedural scaffolding strategy is designed to facilitate off-Platform communication though high-level accountability practices and encourage soft metacognitive scaffolding. Metacognitive scaffolding supports the underlying self-management processes associated with performance (Hannafin et al., 2001). This scaffolding strategy is applicable for all MDT frameworks that utilise diverse communication methods.

This research discovered two key issues impacting multiple MDT pillars, which were users declaring that the Platform did not support recording decision making and the prevalence of users in both Studies 2 and 3 needing to use diverse communication methods including those off-Platform. We propose leaders leverage a hard procedural scaffolding requirement for users to record all activity on Platform or central MDT framework. This procedure incorporates two elements; firstly, all MDT communication that occurs off-Platform need to be summarised and uploaded onto the Platform as a resource and when posted, the uploading must indicate in the chat they have posted the resource (including who it was with and core themes). Secondly, at a set time (end of each day/week/project cycle) a MDT member or members need to summarise the key decisions and outcomes of that period and post a resource on Platform for manager review. Hard procedural scaffolding 'requirements' should be kept in a shared file for all team members to access and leaders should update as required and communicate any changes to the team (Lepsinger & DeRosa, 2015).

The frustration of participants wanting to use other forms of communication outside the Platform's chat function is not entirely surprising. As noted above, in-person and phone communication can have a multitude of benefits including interpersonal social advantages (Griffiths, 2007; Pinjani & Palvia, 2013). Further, the Hunt Lab did not design the Platform to be the 'one-stop-shop' for all communication, rather testing has focused on on-Platform communication to evaluate its impact on improvements in reasoning.

From an education perspective, students have reported that attending in-person classes creates a stronger sense of community, increases retention rate and learning experience satisfaction (Woods & Ebersole, 2003); however, later research suggests learning outcomes are improved when utilising blended learning (combining both online and face-to-face communications) (Means et al., 2009). While some research indicates that face-to-face groups exhibit same or worse bias than individual decision making (Billman et al., 2006), through implementing a strong procedure of record keeping, Platform users would be able to adopt non-Platform communication methods and leverage their aforementioned benefits while maintaining the affordances of the Platform.

Recording decision making is an essential piece of scaffolding for users who found the Platform chat function overwhelming or too hard to track. While implemented under the guise of keeping line managers up to date on current assessments and decisions made, the process of developing the daily/weekly summary will help clarify team issues, assist an asynchronous workforce and implement team accountability. Communication management strategies can reduce feelings of stress and overload (Dabbish & Kraut, 2006), build accountability, promote group motivation, metacognition and increased willingness to leverage peer resources (Whittaker, 2015). In addition to being accountable to their team, intelligence MDTs must remain accountable to line management as well as audit functions such as the IGIS, therefore these records are not only helpful teamwork scaffolds but also administratively important to core business (Roach, 2010). This hard procedural scaffolding helps inform and improve MDT member metacognitive scaffolding regardless of MDT framework, providing users with a process to self-manage and have awareness of accountability and information sharing.

Reducing cognitive load through data management: soft strategic

As opposed to the clear directive above, we also propose the implementation of soft strategic scaffolding to help users increase general Efficiency. This is relevant both to on Platform activity and to other MDT frameworks such as the case study in this research. Strategic scaffolding provides alternative approaches to aid users. This type of scaffolding focuses on evaluating resources, identifying required information and how to collect and collate this information with existing knowledge (Hannafin et al., 2001). The proposed scaffolding centres around information and data management. As observed in numerous teams across Studies 2 and 3, the middle resource/report pane of the Platform would become busy and cluttered with contributions. This flow of information can increase the cognitive load on users and impact how they can effectively contribute to the team. As Hackman (2011) notes, even smart teams do poorly when they are not tasked to develop strategies for coordinating team members' contributions (Hackman, 2011).

In the education context, question prompts such as "What can you do to consolidate your work to date?", will encourage students to reflect on their practices (Ge & Land, 2004). Depending on the scenario or level of students, an educator may wish to provide more procedural-based scaffolding to instruct students what to do. However, these scaffolds should be balanced against the possible increase to cognitive processes. For example, a proposed instruction may increase cognitive loads if overly complicated (Kalyuga, 2007).

Outside the training environment, encouraging staff to effectively coordinate as a team and consolidate resources is not a simple task. Hannafin and Hannafin (2010) argue that familiarity and experience with the relevant tool will help the user implement such strategies (Hannafin & Hannafin, 2010). Managers should leverage MDT experience and draw out lessons learnt to help all team members determine which resources need to be prioritised and conversely, which are no longer as relevant and should be consolidated.

Further research is required to implement and test all (or a combination of) the proposed scaffolding strategies to evaluate their effectiveness in improving MDT maturity across the Accountability, Efficiency and Communication pillars when applied to a MDT framework such as the Platform.

Technical developments

The Platform remains in research and development and therefore there is scope to improve some of the technical components. Users in both Studies 2 and 3 proposed a range of different requirements for Platform development; however, the most requested or most impactful to improve MDT maturity are summarised and included below.

Improved text editor including tracked changes and version control: participants attribute some of the Efficiency-related issues raised in this research to negative experiences with the Platform's text editor. Multiple participants reported losing work on the Platform mid-draft. Other participants reported collaboration constraints without tracked changes and version control capabilities.

Private chat function: Proposed communication strategies are designed to overcome current Communication-related issues. This considered, using multiple systems to conduct analysis and collaborate reduces efficiencies. Consideration should be given to the benefits and costs of private or semi-private chat functionality with the same scaffolding practices implemented above.

Sub-folders to sort resources/reports: Multiple participants reported a desire for sub-folders to partition resources and reports. This reflects the data management scaffolding practices proposed above. Such a technical development would provide managers and educators with additional resources to propose and implement tailored data management practices.

Study limitations

Reflecting on the findings of Studies 1, 2 and 3, each had limitations that impacted the data collection that informed this research. We will address these limitations in turn, noting the more strategic findings as they pertain to engaging and researching government with intelligence functions are addressed in Chapter 10 as an emergent finding of this research.

Study 1

Study 1 and the collected data presents a very good example of a developing collaboration between our research efforts and our Australian Government research stakeholders. However, this collaboration needs to develop further to remove bias from survey design and implement deeper collection. The bias of the survey design led to a limitation of the study, as the Likert scale questions were not weighted equally across the pillars of our developed MDT maturity model. This limitation could be overcome with greater collaboration with the survey originators to evenly weight survey questions and pursue other data collection mechanisms such as semi-structured interviews.

An additional limitation of this research is how representative the case study is of the broader community of intelligence MDTs, noting we collected data to form one case study. We cannot suggest these findings are representative of other agencies and departments, noting they each will have their own frameworks and priorities. As Atkison (2019) notes, intelligence departments including police forces have different legislative, organisational and cultural underpinnings which means the 'normal methods' of an organisation will be inherently different (Atkinson, 2019). However, the sentiments and concerns raised in our case study are reflective of broader workplace teamwork issues observed in the literature.

Study 2

In Study 2, due to stakeholder implemented security requirements, we were unable to collect any meaningful demographic data to identify the roles that our participants had in the three agencies and departments with intelligence functions. Further, the study took place in a very artificial setting. Participants visibly tried to avoid cross-contamination between their scenarios. However, participants were in the same room for the duration of the exercise and regularly had visibility of one another's screens. Another element of artifice included the comparison of 'normal methods' to on-Platform activities, a requirement to evaluate impact of Contending Analyses, a core Hunt Lab research question. Limitations such as restricting participants to only on-Platform communications meant the study did not reflect how the Platform could be incorporated into existing business practices. This considered, this restriction did reveal insights into current practices that will inform future engagement with Australian Government research stakeholders.

A minor limitation of Study 2 involved unintentional prioritisation of Accountability. At the beginning of the week-long study, we encouraged participants to consider how they would record their decision making and important documents under research conditions. This led to multiple participants creating separate storage folders under 'normal conditions' to meet this requirement. It is unclear how this minor instructive scaffolding impacted participants' perspective of the prioritisation of Accountability. However, it demonstrates that even a minor prioritisation, with additional scaffolding, could improve existing cultural practices (Simons and Klein 2007). As Beers et al. (2006) suggests, scripted instructions in online platforms can help participants adhere to prioritised pillars and improve their practices (Beers et al. 2006).

Study 3

Study 3 was a complex and resource intensive research exercise, with an added complexity of operating within a pandemic. We reflect on the COVID-19 impact on participation in Study 3, with organisation teams identifiably impacted, including some withdrawing from the study completely. We also note the impact COVID-19 had on competing Hunt Lab research priorities[8]. Following this reprioritisation, we sent the Exit survey to participants a fortnight

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[8] The Group of Eight (Go8) universities convened a group of over 100 of leading academic experts including epidemiologists, infectious disease consultants, public health specialists and healthcare professionals amongst others to develop a 'Roadmap to Recovery' in response to the COVID-19 pandemic. The core collaboration of

after the conclusion of the final scenario. This meant for participants who did not participate in the 'Super-team' rounds there was a delay of one month between Platform experience and opportunity to complete the Exit survey. While not an overly lengthy delay, we are mindful of the currency of participant's responses and what, if any, impact this delay had on the quality of responses.

Focusing on some of the methodological limitations of Study 3, team size and time spent on Platform appeared the most impactful limitation of this study. Platform metadata suggests public teams were larger and spent more time on Platform. Previous SWARM Platform research suggests larger teams, from which smaller core teams develop, perform better (Output). The public team size of 20 fits with this previous research (Schwarz et al., 2020). While time spent on Platform is no guarantee of success, Exit Survey results suggest organisational teams were unable to spend as much time participating in Study 3 due to existing work obligations or time restrictions set by their organisation. It is unclear how this impacted the perceived support and affordances of the Platform, though it is hypothesised reduced familiarity with the Platform would lead to a reduction in feeling of MDT pillar support.

Due to the smaller sample size of Exit Survey responses from organisation participants, we can make inferences from these findings but they cannot be considered conclusive or representative of the wider intelligence community. From a public participant perspective, 63% of public participants in Study 3 were previous Platform users, meaning they had participated in Platform-based activity before. It is unclear exactly to what degree this experience impacted participant's feeling of Platform support for high-performance and education benefits. It is reasonable to expect that additional experience with the Platform would increase familiarity with the tool and improve performance. Even more so, experienced team members can advance analysis more quickly than new users, spending less time on 'how it works' (functionality) and are faster to leverage the tools and collaboration affordances of the Platform. As Chikersal et al. (2017) suggests, prior adoption of technology allows users and teams to harness existing knowledge and reach higher collective performance (Chikersal et al., 2017). For future studies, consideration should be given to differentiating between experienced and inexperienced users, to effectively delineate user experience and impact of Platform familiarity on quality of output.

Next steps and considerations

In this Chapter we have explored MDT use in a case study within the Australian Government intelligence context and identified a requirement for improved MDT collaboration tools, and a priority to improve the Efficiency pillar of the MDT maturity model. We also observed and investigated the positive indications that the Platform could support intelligence MDTs as a business framework with appropriate scaffolding but highlighted the cultural and technical hurdles that prevent immediate uptake of the Platform in its current form. Despite identifying the Platform requires additional scaffolding to support MDT maturity across pillars the Accountability, Efficiency and Communication, this research has identified the Platform presents more immediate benefits in support of training functions as an education and assessment tool, one which could be used to facilitate high-impact teaching strategies.

Recognising these findings, the next chapter of this research explores the emergent findings of this research and discusses the lessons learnt from engaging and researching government with

this project occurred on the SWARM Platform with the assistance of Hunt Lab researchers and staff (Group of Eight, 2020).

intelligence functions. This chapter will inform our final chapter, where we address Future Research.

Chapter 10: Engaging and researching government with intelligence functions

As an emergent but not surprising result, this research obtained a clearer understanding of the benefits and challenges of engaging with Australian Government research stakeholders with intelligence functions to inform future testing of the SWARM Platform; application of the MDT maturity model in experimental settings; and, other academic research involving the intelligence community. This Chapter explores the unique insight of researching the intelligence community but also the limitations of information sharing, participant restrictions and procedural burdens. These limitations considered, this research also identified where there are advantages to mitigating or accepting these limitations to improve the relationship between academia and the intelligence community to pursue mutually beneficial outcomes.

A unique insight

Intelligence and policing agencies in particular have traditionally put up barriers against prying outsiders (Atkinson, 2019; Punch, 1979), which means research of this type provides a unique insight into a secluded industry. It is not often academics will have the opportunity to collect three distinct data sets, which provide insight into teamwork and the actualised challenges of the intelligence profession. As Marrin (2012) notes, there is a history of intelligence analysts' dismissive attitude towards academia and research (Marrin, 2012), so for the agencies, departments and organisations to take part in this research is unique and heartening. It is also encouraging that the public service senior management supported employee participation in this research. Considering the above, this research thesis and the data collected is unique and should be recognised as such.

Participant restrictions

While the scenarios used in this research were unclassified and open source, we are mindful of the restrictions placed on participants with security clearances on their ability to communicate and collaborate freely to their full potential in unsecure and unclassified research exercises. The anecdotal findings from Study 2 suggests maintaining security in these exercises occupied a degree of the participants' capacity and cognitive load. Open source information holds significant value (Antonius & Rich, 2013) but participants indicated they were hampered as they could not utilise or share their complete classified knowledge. For research that examines teamwork (where factors such as collaboration are important), it is difficult to ascertain exactly how this restriction of information sharing impacted participants' ability to utilise the Platform. This mirrors findings of others (Chin et al., 2009) who discussed the limitations of working in the classified space. Others add that understanding the limitations of information sharing is important so academics do not compromise or negatively impact security requirements (Geitz et al., 2005).

Procedural burdens

Due to the time restrictions placed on this research, the limited amount of responses we received in Study 1 is not necessarily surprising. When we first contacted organisations and departments and invited them to participate in the research, we received mixed responses. While one invited organisation indicated they had no interest in the research topic, others provided comprehensive procedures outlining the steps for the research proposal to be considered by the organisation's senior management and whether they would allow their staff to participate. These procedures varied from organisation to organisation, with most procedures exceeding the time available to complete this research project. While unfortunate for this research, it serves as a reminder for future intelligence-related research projects to factor in the procedural approval processes, some of which exceeded six to eight months before research could begin.

An additional procedural requirement, which has an unknowable impact on research, is the Australian Government research stakeholder vetting of data and results. For results from Studies 1, 2 and 3, Australian Government research stakeholders reviewed the data and removed any information they deemed sensitive before passing on the results. Further, Australian Government research stakeholders have reviewed and vetted this research thesis in its entirety. As Coulthart (2019) notes, this control of information flow out of the secure organisations restricts the dissemination of information to academic institutions. While other industries have sensitivities to their proprietary information, the intelligence arena has a different layer of restrictions (Coulthart, 2019). Information (including when obtained through research) is classified when the organisation deems that the information disclosure would damage national security (Nolan, 2018). We are therefore unsighted as to what data the Australian Government research stakeholders redacted and whether it would have had a meaningful impact on the findings.

Mutually beneficial relationship

Despite some of the inherent restrictions and limitations of conducting research within the intelligence realm, this research has identified where greater collaboration is required to achieve a mutually beneficial relationship. The concept of intelligence agencies and departments partnering with expert consultants is not new. As CIA reports from 1954 suggest "we have also had the benefit of advice from certain civilian consultants who are working on such special projects. We are impressed by what has been done, but feel that there is an immense potential yet to be explored" (Central Intelligence Agency, 1954, p. 8).

The first look at a partnership between academia and the intelligence sector should consider management. In Study 1, we collected an internally-run survey from our Australian Government research stakeholders. With the application of the MDT maturity model, we identified a clear bias in the survey on collaboration. The focus on collaboration in this survey is unsurprising; however, academic insight and context could provide guidance to clarify what exactly the stakeholders hoped to test. This follows therefore also to the type of questions being asked and how they are asked.

As Jozsa and Morgan (2017) note, there is debate as to the most effective survey methodology, particularly with regard to Likert scale question design - noting they suggest the removal of reversed items (Jozsa & Morgan, 2017). However, if a relationship exists, academics can provide guidance and ensure internally run surveys meet organisational requirements. Further, reflective of the mutually beneficial relationship, through academics providing advice they will then be afforded an opportunity to gain a unique insight into industry and further their research aims. Coulthart (2019) suggests academics' focus has traditionally been misaligned from the 'real-world' problem solving of practitioners, and these aforementioned partnerships bring the two worlds together (Coulthart, 2019). The use of semi-structured interviews with practitioners will help inform the academic community of practical implications of real-world decision making and impact of issues such as internal team dynamics and processes (Greenberg et al., 2007).

Another area for greater collaboration is in the rating of report quality. As identified in Studies 2 and 3, research participants used an unfamiliar mechanism for evaluating their reports, the IC Rating Scale. In Study 2, we observed an inconsistency between expert assessors and team member ratings as is indicative of a participant misunderstanding of quality of work and a lack of experience with the rating tool. However, as relationships between academia and the intelligence community solidifies, evaluation measures should be agreed upon, or as Breckenridge (2010) suggests, fully integrated both within organisations and the academic curriculum (Breckenridge, 2010). This unfamiliarity with the IC Rating Scale speaks to the requirement of training. Agencies and departments with intelligence functions are often reliant on the base level skills of graduates, rarely who will have intelligence-specific skills unless fortunate to have exposure in other roles or tailored courses. There is scope for industry to engage academic institutions to create coherent and structured courses, as opposed to ad-hoc and disaggregated training packages (Brown, 2018).

Various consultants and governmental reports have advocated for a closer partnership between the intelligence community and academia including the Jeremiah Report (Devanny et al., 2018), the Thodey Review and most recently from the Academy of Social Sciences in Australia. In 1998, Admiral Jeremiah provided a review of the United States of America's Intelligence Community's performance in India, with a focus on their nuclear program. While partially classified, the then Director of the CIA publicly accepted all recommendations, including that experts be brought in from the 'outside' in a systematic fashion, leveraging analytic thinkers and substantive specialists to act as 'Red Teams' on complex analytical challenges (Central Intelligence Agency, 1998; Federation of American Scientists, 1998). Separately in the Australian context, in 2017 the then Director General of ASIO commissioned Mr David Thodey AO to conduct a review of ASIO's approach to technology and its relationships with people, culture and collaboration. One recommendation of this review included establishing strategic partnerships with academia (Australian Security Intelligence Organisation, 2018). In 2019, the Academy of the Social Sciences in Australia recommended that the NIC establish a dedicated academic outreach branch to coordinate and oversee interactions with the social science research community (Academy of the Social Sciences in Australia, 2019). Recognising the broad support for greater engagement, both academics and government should capitalise on these examples and the increased potential openness to non-governmental expertise, where universities and government could work together in pursuit of joint research objectives (Ertas et al., 2015).

Consider the Defence Science and Technology's (DST) coordination of the National Security Science and Technology Centre (NSSTC). One of the central aims of this Centre is to coordinate a whole of government national security science and technology research strategy. Through this, the NSSTC aims to foster academic and industry partnerships to build capability and deliver outcomes to Australian national security agencies and departments (Defence Science and Technology, 2020). The NSSTC also seeks to create a "National Security Science and Technology Research Forum" to facilitate academic engagement with the national security innovation community (Defence Science and Technology, 2020).

As identified throughout this research, there is scope for academia and the intelligence community to work more closely together. Programs like the NSSTC are a positive step. However, this collaboration needs to align with the priorities of the agencies and departments with intelligence functions and focussed on outcomes. As Vogel and Tyler (2019) discuss, they view collaboration and partnerships to represent any joint efforts whether they be short or long-lived. They note strategic relationships are long-term, which need to exist for three to five years (Vogel & Tyler, 2019). They speak to the National Security Agency's (NSA) ambitious Laboratory for Analytic Sciences (LAS) established in 2013 as an example of such a strategic partnership. The LAS focused on conducting classified and unclassified research on innovative technologies and tradecraft to help intelligence analysts solve intelligence problems in the future (Vogel & Tyler, 2019). The LAS brings together intelligence analysts with practical understanding, academic experts from diverse disciplines and industry professionals with technology know-how. This grouping of roles and capabilities creates an environment what they title as immersive collaboration. The LAS presents as not just innovative collaborative undertaking but as a reflection of how intelligence analysis and collaborative research can be done (Jameson et al., 2020).

The above international example considered, The University of Melbourne's Hunt Lab provides an Australia-based research arm to agencies and departments with intelligence functions to progress research in analytic reasoning; evaluation methods; cloud platforms; methodology (Structured Analytic Techniques); high performance teams; and, crowdsourcing intelligence (Hunt Lab, 2020). As this research thesis suggests, through this and similar research the Hunt Lab continues to improve their understanding of the requirements and limitations of intelligence-focussed research, with scope to both broaden and refine the findings of intelligence-sector research going forward.

In this chapter, we have reflected on the broader strategic lessons learnt from engaging and researching government with intelligence functions. These lessons will inform future research and encourage greater collaboration between academia and industry. Reflecting on the space for greater collaboration, we turn our attention to the future and what elements of this research need to be further investigated.

Chapter 11: Future research

This Chapter reflects on the findings of this research and proposes further research opportunities in four domains: improving MDT efficiency; shifts to Hunt Lab's intelligence research scenarios; SWARM Platform application as an education tool; and, recruitment.

This research has identified Efficiency as a weakness of a case study MDT framework with respect to MDT maturity and identified similar immaturity in trialling the SWARM Platform as a MDT framework, which indicates further research is needed to explore how to improve Efficiency in MDT frameworks, potentially through prioritisation of the MDT maturity model and exploration of other frameworks as they are developed.

This research has also identified the cultural and technological restrictions that limit adoption of the Platform as a business tool to support MDTs and that the Platform has more immediate application as an education training tool. In recognising these findings, we propose shifts in methodology for future SWARM Platform research, pivoting how the Hunt Lab structures future research exercises on Platform to better reflect 'real world' intelligence scenarios.

We propose further research that examines the SWARM Platform as an education tool to progress the findings of this research. Finally, on this note we propose further research is undertaken to explore the potential recruitment benefits of this education research and other intelligence-focused research involving the SWARM Platform.

MDT framework research: prioritising Efficiency maturity

Managers and educators may choose to prioritise one element of the maturity model over the others when using the Platform and implement scaffolding to improve MDT Maturity. For example, an educator may prioritise collaboration high-performance over efficiency to meet learning outcomes; whereas a manager may prioritise efficiency when understaffed. This is supported in Hackman and Connor's (2004) research into evaluating team effectiveness, who suggest managers need to weight criteria across circumstances and teams (Hackman and Connor 2004).

From our research and the apparent Efficiency immaturity of tested MDT frameworks, further research is needed to identify frameworks that support all pillars of the MDT maturity model, including Efficiency. Future research into MDT frameworks should identify what data that framework provides managers to inform MDT maturity evaluation. This research should also prioritise identifying frameworks more supportive of the Efficiency pillar. The challenge for leaders will be to identify as Gilbert et al (2018) suggest, what data analysis lens is required, meaning what can be measured, and how (Gilbert et al. 2018). This will force leaders to consider other intersecting elements such as group size, structure and ultimately as this research has discussed, what scaffolding is implemented (Keyton and Beck 2008).

Realistic MDTs and intelligence flow

The Platform affords a range of opportunities to provide scaffolding to improve team performance. However to date, no SWARM Platform research has tested the Platform's performance to include a manager providing leadership. To appropriately test 'real-world' application, further research is required to identify impact of leadership and the benefits of implementing all (or a combination) of the scaffolding proposed.

Further, the six scenarios (hypothetical problems) tested in this research were stagnant problems, meaning we provided all the information available to participants in one batch or teams collected information from open sources. Intelligence analysts typically are challenged with complex problems featuring incomplete and contradictory information (Straus et al., 2011). Further, analysts typically receive information in increments over time, where the analysts build on their knowledge and update their assessment (Heuer, 1999). This is a key challenge of good intelligence analysis, particularly in fast-paced and high-pressure cases where analysts must triage and prioritise their information sources, while conducting rigorous analytical tradecraft (Cruickshank, 2019). Future Platform research should consider providing participants with information piecemeal, where analysts are not able to view everything at the same time as this will provide further information as to the suitability of the Platform for public service use.

Teaching intelligence analysis tradecraft

As identified in the learning outcomes of Study 3 in this research, participating in exercises on the Platform carries with it unstructured learning outcomes. The Platform provide affordances to educators who could leverage it to develop computer-supported collaborative problem-based learning lesson plans. From a tertiary education perspective, there is substantial scope to evaluate the effectiveness of the Platform as a tool to introduce students to intelligence analysis tradecraft. This includes exposure to terminology, departmental roles, functions and culture (Breckenridge, 2010) but also to deep-dive into subject matter and exposure learners to nuances theoretical and methodological processes (Devanny et al., 2018). This should be a collaborative engagement opportunity between industry and education institutions to ensure the promotion of practice-based competencies that are aligned with student learning outcomes and teaching strategies.

The skills required to be a high-performing intelligence analyst are applicable to various professions; therefore, the provision of problem-based learning through the Platform should be investigated to identify if it is an effective tool in teaching the skills students need to perform effectively as an intelligence analyst in the workplace. This future research of the education benefits of the Platform in the tertiary sector will inform potential application of it as an education tool in the public service. As Walsh (2017) notes, there is an ongoing challenge of creating and continuing professional development pathways for intelligence analysts already in the sector (Walsh, 2017) so with proper research and development, the Platform could play a role in this professional development.

Recruitment

Despite the clandestine nature of many intelligence analysis roles (Matei & Halladay, 2019), it is necessary for these agencies, departments and organisations with intelligence functions to recruit capable and high-performing staff. As explored in this research, there is substantial scope to apply the Platform as an education tool, to further learning outcomes directed at improving intelligence analysis and teamwork. Education courses that focus on improving analysis, judgement, innovation, collaboration and problem solving are inherently beneficial for aspiring analysts (Breckenridge, 2010). However, the present research also identified that participating in Study 3 increased public participants' interest in an intelligence analysis career.

Considering this result, the Platform may have application beyond purely educational benefits and may stem into encouraging public interest more generally in the profession as a possible career. Certain intelligence professions require particular analytical characteristics or traits (Gajic et al., 2017). For example, the exploitation of imagery is key to working as an Australian

Geospatial-Intelligence Organisation (AGO) analyst (Australian Geospatial-Intelligence Organisation (AGO), 2020). Tertiary academic programs could run tailored ‘challenges’ to promote the work of a particular organisation and encourage interest from applicants.

Organisations spend large amounts of money ensuring they recruit the correct staff. In particular, organisations with intelligence functions deem writing and communication skills as essential skills for intelligence analysts (Dorn, 2019). Therefore, noting the affordances of the Platform, for example the high-level visibility of activities and affordances for managers and educators, Australian Government research stakeholders should consider exploring the Platform’s use as a ‘assessment centre’ tool, which could also inform ‘vetting’ procedures on how staff handle sensitive material. Assessment centres are used widely across the Australian Government public service, particularly for graduate intakes to mass test and evaluate employee candidates (Keele et al., 2010). Security vetting has the primary goal of ensuring that only trustworthy personnel have access to classified or sensitive information (Brooks et al., 2010).

It is a challenge to test applicant’s aptitude to applying training to workplace practice, meaning organisations may spend further money, after an applicant is recruited, training them only to find out they are unable to apply themselves to the role (Harrison et al., 2018). However, organisations should leverage the tools available to test applicant’s capabilities, which the Platform affords over a range of issues including analytical reasoning, collaboration and communication, producing written product and teamwork skills.

As discussed throughout this research, we believe it essential that future research efforts continue to be a collaborative process between academia and industry. This collaborative process is exemplified in this research thesis as it involved and supported the interests of The University of Melbourne School of Psychological Sciences (MSPS), the Hunt Laboratory for Intelligence Research and our Australian Government research stakeholders.

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Appendix A: List of Australian Commonwealth, State and Territory Government agencies and departments with intelligence functions

Australian and National Intelligence Community (AIC) and (NIC) agencies, departments and coordinators:

- Office of National Intelligence (ONI)
- Australian Border Force (ABF)
- Australian Crime Intelligence Commission (ACIC)
- Australian Cyber Security Centre (ACSC)
- Australian Federal Police (AFP)
- Australian Geospatial-Intelligence Organisation (AGO)
- Australian Signals Directorate (ASD)
- Australian Security Intelligence Organisation (ASIO)
- Australian Secret Intelligence Service (ASIS)
- Australian Transaction Reports and Analysis Centre (AUSTRAC)
- Defence Intelligence Organisation (DIO)
- Department of Home Affairs
- Inspector-General of Intelligence and Security
- Australian Commission for Law Enforcement Integrity
- Australian Defence Force (Army, Navy and Airforce)

State and Territory agencies and departments with intelligence functions:
Australian Capital Territory

- ACT Corrective Services
- ACT Integrity Commission (begin hearing complaints 1 December 2019)

New South Wales

- Independent Commission Against Corruption
- NSW Police
- NSW Government Corrective Services

Northern Territory

- Office of the Independent Commissioner Against Corruption
- Northern Territory Police
- Department of Attorney-General and Justice - Correctional Services

Queensland

- Queensland Corrective Services
- Queensland Police Service
- Crime and Corruption Commission

South Australia

- Department of Correctional Services (SA)
- South Australia Police
- Independent Commissioner Against Corruption (Office for Public Integrity)

Tasmania

- Tasmania Police

- Department of Justice - Corrective Services
- Integrity Commission Tasmania

Western Australia
- Corruption and Crime Commission (WA)
- Western Australia Police Force
- Department of Justice - Corrective Services (WA)

Victoria
- Victoria Police
- Independent Broad-based anti-corruption Commission
- Corrections Victoria

Appendix B: IC Rating Scale

Assessment	Poor	Fair	Good	Excellent
Numeric Value	0	1	2	3

Criterion
Criterion 1 – Properly describes quality and credibility of underlying sources, data and methodologies.
Criterion 2 - Properly expresses and explains uncertainties associated with major analytic judgments.
Criterion 3 - Properly distinguishes between underlying intelligence information and authors' assumptions and judgments.
Criterion 4 – Incorporates analysis of alternatives.
Criterion 5 – Demonstrates relevance and addresses implications.
Criterion 6 – Uses clear and logical argumentation.
Criterion 7 – Makes accurate judgements and assessments.
Criterion 8 – incorporates effective visual information where appropriate.

Appendix C: Multidisciplinary team maturity Coding Schema

MDT Pillar	Key terms	Thematic Coding terms
Mission	Superordinate goal, belief and purpose, responsibility, ownership, joint mental model	goal, mission, purpose, belief, responsibility, direction
Accountability	Data management, record keeping, oversight, audit, transparency and recording of decision making	accountable, accountability, storage, data, oversight, audit, transparency, records
Agility	Flexible, adaptable, anticipatory, innovative	agile, agility, flexible, adaptable, anticipatory, accommodating, versatile
Efficiency	Resource allocation (time, finances, staff), deadlines, prioritisation,	efficient, structure, applicable, appropriate, time, resources, staff, money, budget, deadline, prioritise
Communication	Accessible (current and historical), consistent terminology, context appropriate, engagement / disengagement opportunity	communication, message, email, phone, mobile, meeting,
Collaboration	Cooperation, information and knowledge sharing, utilise available software, cross-training, internal and external engagement	collaboration, discuss, understand, cooperation, sharing, software, tools, cross-training, training, liaison
Output	Meets objectives, meets stakeholder or client needs, record outcomes, agreed evaluation method	output, product, completed, evaluate, requirements, actionable, outcome

Appendix D: Study 1 - Multidisciplinary team stakeholder-run survey

Open Questions

- What do you like about MDTs?
- What do you dislike about MDTs?
- Other comments.

Closed Likert scale questions (Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree)

- I felt comfortable adjusting to using MDTs
- I respond to changes more quickly when part on a MDT
- I feel duplications, inconsistencies and gaps between different work areas are reduced using MDTs
- I feel, as a team, we are more trusted by our customers/partners when using a MDT
- I trust others more using a MDT
- I felt more trusted within a MDT
- Communications within the team and to external stakeholders were of a higher quality using a MDT
- I had a greater interaction frequency with others using a MDT
- The output is of a higher value using a MDT than working in isolation
- MDTs empower me to experiment with approaches and learn quickly
- MDTs enabled objectives to be completed in shorter timeframes
- MDTs lead to better decision making
- MDTs lead to increased use of evidence-based reasoning
- MDTs encourage better planning
- The MDT framework saves me effort
- The MDT framework saves me time
- Within a MDT, I have a better understanding of how I fit into the overall success of the mission
- Within a MDT, I have a better understanding of what others are capable of doing
- Within a MDT, I have a better understanding of what others are currently doing
- Within a MDT, I have a better understanding of the team's objectives
- I feel my agency/department has sufficient communication and collaboration tools to support MDTs
- I know where to find resources to help me better understand how MDTs operate
- I feel sufficiently trained to take part in MDTs
- MDTs have the right people with the right skills to deliver value to stakeholders
- MDTs promote stewardship over ownership
- MDTs are adaptable to different problems, are scalable, and prevent a 'one size fits all' approach
- MDTs are a useful tool to encourage collaboration in an agency/department

Appendix E: Study 1 - Multidisciplinary team survey (adapted)

Open Questions

- Does your agency/department utilise multi-disciplinary teams (MDTs) to support intelligence analysis functions?
- Describe how your MDTs operate
- Describe the structure/framework used to support your MDTs
- Describe your role in a MDT
- What do you like about using / being a part of MDTs?
- What do you dislike about using / being a part of MDTs?

Closed Likert scale questions (Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree)

- I felt comfortable adjusting to using MDTs
- I respond to changes more quickly when part on a MDT
- I feel duplications, inconsistencies and gaps between different work areas are reduced using MDTs
- I feel, as a team, we are more trusted by our customers/partners when using a MDT
- I trust others more using a MDT
- Communications within the team and to external stakeholders were of a higher quality using a MDT
- I had a greater interaction frequency with others using a MDT
- The output is of a higher value using a MDT than working in isolation
- MDTs empower me to experiment with approaches
- MDTs empower me to learn quickly
- MDTs enabled objectives to be completed in shorter timeframes
- MDTs lead to better decision making
- MDTs lead to increased use of evidence-based reasoning
- MDTs encourage better planning
- The MDT framework saves me effort
- The MDT framework saves me time
- Within a MDT, I have a better understanding of what others are capable of doing
- Within a MDT, I have a better understanding of what others are currently doing
- Within a MDT, I have a better understanding of the team's objectives
- I feel my agency/department has sufficient communication and collaboration tools to support MDTs
- I know where to find resources to help me better understand how MDTs operate
- I feel sufficiently trained to take part in MDTs
- MDTs have the right people with the right skills to deliver value to stakeholders
- MDTs promote stewardship over ownership
- MDTs are adaptable to different problems, are scalable, and prevent a 'one size fits all' approach
- MDTs are a useful tool to encourage collaboration in an agency/department

Appendix F: Study 2 - Survey Questions

First Survey: Entry Survey

Question	*Set Answers*
Do you conduct analyses in your current role?	Yes / No
How often do you produce written analytical reports/product (of any length) in your current role?	Daily / Weekly / Fortnightly / Monthly / Never
Have you conducted analysis in previous roles?	Yes / No
What is the primary challenge of conducting analysis?	Communication / Accuracy / Application of SATs / Timeliness / Other
What is your primary method of collaboration with others?	Email / Phone / Do not collaborate / Other
Have you received structured analytical technique (SAT) training?	Yes / No
How regularly do you apply structured analytical techniques (SATs) to your analysis?	Always / When I am asked to / If I remember / Never
Additional comments:	

Second Survey: Post ‘normal methods’

Question	*Set Answers*
Rate the quality of your report (out of 10)	1-10
What did your team do well in producing the report?	Communication / Accuracy / Application of SATs / Timeliness / Other
What percentage of the final report did you contribute?	0-100
What other techniques have you applied in the current analysis?	
How do the techniques used in your current analysis compare to methods that you would typically use?	
If your team assigned roles to complete your report, what role(s) did you perform?	
How often do you collaborate with others in conducting analysis?	Daily / Weekly / Fortnightly / Monthly / Never
When collaborating with others, how often does this occur face to face?	Daily / Weekly / Fortnightly / Monthly / Never
When collaborating with others, how often do you seek informal feedback (e.g. casual conversation)?	Daily / Weekly / Fortnightly / Monthly / Never
When collaborating with others on analysis, do you collaborate on a shared	

document of some form? If so, is this document on a shared platform, or is the document emailed from collaborator to collaborator?	
Would your report have been of higher quality if you were the only analyst working on the problem?	Yes / No
Additional comments:	

Third Survey: Post 'SWARM Platform methods'

Question	*Set Answers*
Rate the quality of your report (out of 10)	1-10
Please briefly justify your rating, stating the criteria you used to rate the quality of the report	
What did your team do well in producing the report?	Communication / Accuracy / Application of SATs / Timeliness / Other
What was the primary challenge of conducting analysis?	Communication / Accuracy / Application of SATs / Timeliness / Other
What percentage of the final report did you contribute?	0-100
Please list the structured analytical technique(s) you used to develop the report?	
If your team assigned roles to complete your report, what role(s) did you perform?	
To what extent did the SWARM process improve your reasoning?	It improved performance / It hindered performance / There was no change
To what extent did the SWARM platform enable members of your multidisciplinary team to leverage and share their expertise?	
How could the SWARM platform be used more effectively to support a multi-disciplinary team?	
Would your report have been of higher quality if you were the only analyst working on the problem?	Yes / No
Additional comments:	

Appendix G: Study 3 - 'Hunt Challenge' Entry Survey

Question	*Set answer(s)*
Thinking about the Hunt Challenge, what are you most interested in? Please choose all that apply.	What the problems will be like The tools in the Lens Kit Platform functionality The Contending Analyses methodology How reports are created The structured training available Whether the public do as well as the professionals The evaluation methods How my team performs Team collaboration experience Other
What are your expectations for your Challenge experience? Interesting problems Reasonable time commitment Difficult problems I will learn new skills and tools Problems are achievable, for a team The Platform will be a productive work space Training in analytical techniques Positive team working experience An effective collaboration, compared to my normal methods What I learn from the Challenge can be applied in my workplace	I don't expect this / Neutral / I do expect this
How important to you are the following reasons for taking part in the Challenge? Seeing how my team performs against the others Testing my own skills and abilities I think it will be fun Developing my overall analytic skills Learning how the SWARM Platform works Learning about Contending Analyses Trying a new style of team collaboration Contributing to research in intelligence analysis Getting selected for a Super Team Exploring the Lens Kit Participating in crowd sourced intelligence analysis	Not important / Neutral / Important

Other	
Allowing oneself to be convinced by an opposing argument is a sign of good character. People should take into consideration evidence that goes against their beliefs. People should revise their beliefs in light of new information or evidence. Changing your mind is a sign of weakness. Intuition is the best guide in making decisions. It is important to persevere in your beliefs even when evidence is brought to bear against them. One should disregard evidence that conflicts with one's established beliefs. People should search actively for reasons why their beliefs might be wrong. When we are faced with a new question, the first answer that occurs to us is usually best. When faced with a new question, we should consider more than one possible answer before reaching a conclusion. When faced with a new question, we should look for reasons why our first answer might be wrong, before deciding on an answer.	Strongly Disagree / Disagree / Somewhat disagree / Neither agree nor disagree / Somewhat agree / Agree / Strongly agree
Age	18-25 26-35 36-45 46-55 56-65 over 65 prefer not to say
Are you?	Male Female Other

	Prefer not to say
Current occupation?	Full Time Employment Part time Employment Self employed Full Time Student Part Time Student Retired Not working right now Other/Prefer not to say
What's the highest level of education you have completed?	High School Trade or Technical Qualification Bachelors Graduate Certificate, Diploma or equivalent Masters PhD prefer not to say
If you have completed university studies, in which area/s have you studied?	Law Mathematics Engineering Social Science(s) Business/Commerce Politics Arts/Humanities Economics Other (please describe)
How many years work experience do you have?	
Do you have experience analysing complex problems or data?	Please select all applicable. Yes, in an intelligence or related field Yes, in a scientific field Yes, in another field, e.g. business strategy, risk analysis, etc. No direct experience Prefer not to say
Do you have experience analysing complex problems or data? How many years of experience do you have analysing complex problems or data?	
How would you assess your current capability in the following areas? This may be from your job, from studies, or from other activities. Analytic report writing Using structured analytic techniques Using OSINT tools and resources Applying strategic thinking frameworks	None / Low / Moderate / High

Identifying and analysing assumptions Evaluating quality of analytic reasoning Using decision making frameworks	
Have you had experience working in a multidisciplinary team? (i.e. composed of members with varied but complementary experience, qualifications, and skills that contribute to the achievement of a specific objective)	Yes / No
Please describe your experience working in a multidisciplinary team:	

Appendix H: Study 3 - 'Hunt Challenge' Exit Survey

Question	Set answer(s)
Please rate your overall Challenge experience out of 5 stars:	
Did you feel that your participation was time well spent?	Yes / No / Unsure
What was the one BEST thing about your Challenge experience?	
What was the one WORST thing about your Challenge experience?	
How do you rate these aspects of the Challenge? The onboarding process Our communication with you The training The feedback The Help Centre	Good / Average / Poor
Given your expectations prior to the Challenge, how did we do? Interesting problems Reasonable time commitment Difficult problems Learning new skills and tools Problems are achievable, for a team The Platform will be a productive work space Good training in using OSINT tools Positive team working experience An effective collaboration, compared to my normal methods What I learnt from the Challenge can be applied in my workplace	Exceeded / Met / Below / I had no expectations
Thinking about the teamwork aspect of the Challenge, do you agree or disagree with the following statements? I enjoyed the team social experience I enjoyed the team collaboration experience I could positively contribute to my team My efforts were recognized by other team members I found it easy to keep track of my team's contributions I felt that some team members were too dominant	Agree / Neutral / Disagree

I felt that I had to lead to get the job done	
Do you think the Platform supported you in the following areas? Developing a shared mission amongst team members Working towards a unified goal Managing contributions Keeping track of team decisions Working in flexible and agile way as analysis progressed Innovative problem solving Enabling an efficient workflow Meeting deadlines Clear communication amongst team members Ability to move easily between engaging with others, or disengaging for independent work Information sharing amongst team members Worked together positively Making decisions Production of useful output	Yes / No / Not sure
Any additional comments about how the Platform affected teamwork and collaboration?	
Thinking about the feedback you received on your team's submitted reports, do you agree or disagree with the following statements The feedback accurately reflected the quality of our reports. The feedback helped me understand the strengths and weaknesses of our reports The feedback helped me build expertise in analytic reasoning. My team used the feedback to improve their submitted reports.	Agree / Neutral / Disagree
After participating in the Challenge, do you think your capability has improved in the following areas? Analytic report writing Using structured analytic techniques Using OSINT tools and resources Applying strategic thinking frameworks Identifying and analysing assumptions	Significantly / Somewhat / No

Evaluating quality of analytic reasoning Using decision making frameworks	
What was the one most valuable thing you learned in the HC2020?	
If you consider participating in an exercise like the HC2020 as analytical skills training, how does it compare with more typical training methods? A Challenge exercise is more effective A Challenge exercise is more engaging A Challenge exercise works better for some people, but not as well for others	Agree / Neutral / Disagree
How has participating in the Challenge changed your interest in an intelligence analysis career? My interest has:	Increased / Not Changed / Decreased
Thinking about Contending Analyses, do you agree or disagree with the following statements? I understood what Contending Analyses is My team used Contending Analyses Using Contending Analyses helped improve the quality of reasoning in reports I intend to apply Contending Analyses in my work	Yes / Not Sure / No
Thinking about the Platform, do you agree or disagree with the following statements? Working on the Platform produced better reasoned reports than my normal methods My team's reports were better than I could have produced on my own. Using a Platform like this would improve intelligence analysis in my organisation. If my organisation introduced a Platform like this, I would want to use it.	Strongly agree / Agree / Neutral / Disagree / Strongly disagree
Thinking about the Lens Kit, do you agree or disagree with the following statements? It was easy to find the relevant tools The tools were well explained Overall, the Lens Kit was very helpful I preferred the tools already known to	Agree / Neutral / Disagree

me The Lens Kit was difficult to navigate I personally used it often	
Do you have any suggestions to improve the Lens Kit?	
Thinking about creating responses (both Resources and Reports) on the platform, Please select all that apply:	My team created a lot of resources, but not many were useful It was easy to keep track of all the resources posted on the Platform It was too time consuming to read through everyone's resources. The resources were an important contribution to problem solving
Did you use the Report rating tool to rate the Reports your team created? If you tended not to rate Reports, can you say why?	Yes / No
When you used the Report rating tool, which of the following was your primary purpose? You can select more than one.	I used rating to push my preferred report to the top I used rating to give guidance to the author I used rating to fairly indicate the readiness or quality of a report
What additional features or tools would you like to see implemented on the Platform?	
Did you use any tools to support your work on the Challenge problems that were not included on the Platform? (e.g. other software such as Excel, Google Docs, Mapping tools, Chat, Conferencing, etc...)	Yes / No
Please briefly describe these tools and your main reason for using them.	
What's the best question that wasn't asked on this survey?	
Anything else that you would like to say?	