Royal Commission
into Defence and Veteran Suicide

MACHINE LEARNING ANALYSIS OF RISK FACTORS FOR PROGRESSION FROM SUICIDE IDEATION TO SUICIDE-RELATED BEHAVIOURS IN CONTEMPORARY AUSTRALIAN DEFENCE FORCE MEMBERS

Research Paper

May 2023

The Royal Commission into Defence and Veteran Suicide was established by Letters Patent on 8 July 2021. An amendment to the Letters Patent was subsequently issued on 10 April 2022.

Mr Nick Kaldas APM, the Hon James Douglas QC and Dr Peggy Brown AO have been appointed as Royal Commissioners. They are required to provide an interim report by 11 August 2022, and a final report by 17 June 2024.

The Royal Commission intends to release consultation, research and background papers. This research paper has been prepared by Phoenix Australia (Centre for Posttraumatic Mental Health) for the information of Commissioners and the public. The views expressed in this paper are not necessarily the views of the Commissioners.

Content Warning

Please be aware that this research paper contains material dealing with suicide and suicidality that could be distressing for some people.

If this research paper raises any questions or issues for you, please contact the Royal Commission.

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Machine learning analysis of risk factors for progression from suicide ideation to suicide-related behaviours in contemporary Australian Defence Force members

Report for Royal Commission into Defence and Veteran Suicide – April 2023

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Executive Summary

Background

The risk of suicide is a significant concern across many military and veteran populations (Sareen et al., 2016; Hom et al., 2017), including in Australia (Sadler et al., 2021). Ex-serving Australian Defence Force (ADF) members as a population group are at increased risk of suicide, with male veterans 27% more likely to die by suicide than Australian males, and female veterans 107% more likely to die by suicide than Australian females (Australian Institute of Health and Welfare; AIHW, 2022). Suicidality (i.e., suicidal ideation, plans and attempts) in current serving ADF members is also higher than in the general community and increases following transition out of full-time military service (Sadler et al., 2021; Van Hooff et al., 2018).

There are complex and interconnected factors associated with suicide risk in serving and ex-serving military members. However, just as in the broader community, the causes of suicidal thoughts and behaviours are still not fully understood. It remains unclear which factors lead to the progression from suicide ideation to plans and attempts, noting that although ideation is an important precursor to attempts, most suicide ideators never attempt suicide (O'Connor & Nock, 2014). There is also recognition of a continuum of ideation, with active suicidal ideation (e.g., specific thoughts of killing yourself) representing a more severe form of ideation than passive suicidal ideation (e.g., wishing to be dead) (Posner et al., 2011). Further, current suicide risk identification methods, such as assessments scales used in clinical settings, are only marginally better than random chance at correctly predicting increased risk of suicide (Franklin et al., 2017).

Consequently, there is considerable motivation to utilise techniques that may improve the identification of those at increased risk of suicide, including through machine learning (ML) techniques. Machine Learning, a type of artificial intelligence, creates systems and algorithms that can learn from and make predictions or decisions based on the available data, and the techniques are particularly useful in analysing large, unprocessed datasets. More traditional classification methods, such as logistical regression, require data analysis to be guided by the researcher through the application of a hypothesis. The application of ML to suicide research has been viewed as an opportunity to discover new areas for future suicide research by identifying predictors and their combinations from large, multi-domain datasets. The analysis is driven by the data, rather than a particular theory or hypothesis.

This exploratory study builds upon analysis undertaken on ADF serving and transitioned (those no longer serving full-time) members as part of the 2010 ADF Mental Health Prevalence and Wellbeing Study (McFarlane et al., 2011) and the 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018). These programs provide large cross-sectional, self-report demographic, occupational, mental and physical health, trauma history and psychosocial and suicidality databases. Core-validated measures of mental and physical health were included in both the 2010 and 2015 surveys. Further, a substantial group completed surveys in both 2010 and 2015 and consented to their data being linked to create a longitudinal dataset, enabling additional investigation of how suicidality changes over time for this population.

Longitudinal predictive modelling has an important role in early intervention and prevention, as it facilitates the identification of risk factors and patterns of development that may contribute to the onset of a particular condition or disease.

The primary aim of this exploratory study was to use ML techniques to identify which variables (survey items) best distinguished those who reported suicidal ideation only versus those who reported action (planning and or attempts), with or without ideation at a given point in time (i.e., estimated independently for the 2010 and the 2015 datasets) (Analysis 1 – cross-sectional data) and across time (Analysis 2 - longitudinal data). Predictive modelling ML techniques were then applied to assess which of the identified variables were most important in accurately predicting cases (those at risk of progressing from ideation to suicide behaviours) in previously unseen components of the dataset (to establish validation accuracy) using both the cross-sectional data (Analysis 1) and the longitudinal data (Analysis 2).

A secondary aim of the study was to assess how well the ML techniques performed in building predictive models from the available data, compared to more traditional statistical methods, such as logistic regressions. Unlike ML which learns from the available data, logistic regression is a statistical technique which requires testing of a hypothesis in relation to which variables will predict the outcomes. While there has been a proliferation of ML approaches in suicide-related research, the reported outcomes from these studies have been mixed. Some have criticized prediction models created by ML as being too complex to interpret, with the findings difficult to apply beyond a research setting (Cox et al., 2020). Therefore, in this study step-wise logistical regressions are also applied to the cross-sectional analysis to examine how well more traditional statistical methods were able to accurately predict cases from the dataset (Analysis 3). This provided a point of comparison to the findings derived from the ML approaches, allowing assessment of the utility of ML approaches when answering these types of research questions.

Methods

The analysis included survey data of all participants who endorsed at least one suicidality item in 2010 (n=1684), in 2015 (n=2245), and the longitudinal dataset (n=8498; which included n=701 who had endorsed at least one suicidality item in 2010). The primary outcome in this study was suicidality which was measured in 2010 and 2015 with the same four self-report items assessing: passive suicide ideation (have you ever felt that your life was not worth living?); active suicide ideation (have you ever felt so low that you thought about committing suicide?); suicide plans (have you made a suicide plan?); and suicide attempts (have you attempted suicide?) in the past 12-month period. All items had a dichotomous (yes/no) response. A large number of variables were used from the 2010 and 2015 self-report surveys as predictors, including sociodemographic information and measures of mental, physical, and social health.

In Analysis 1, ML techniques (feature selection) were used to identify the top 20 variables (individual survey items) to differentiate those who reported ideation (either passive or active suicidal ideation) only versus those reporting action (with or without ideation) at each time point (2010 and 2015). Predictive modelling (Random Forests) was then undertaken to examine the power of the top 20 selected features to accurately

predict from those who reported ideation, those who would also report suicide planning and/or suicide attempt. As the 2015 dataset included those still serving and those who had transitioned out of full-time ADF service in 2015, additional analysis was undertaken separating the current serving and transitioned populations to identify any differences.

In Analysis 2, the longitudinal dataset was firstly analysed using a Sankey diagram (a visual representation of the flow of information between stages) to examine how self-reported suicidality changes across time in this population. Then ML approaches (Feature Selection and Random Forest) were used to identify which variables from 2010 provided important information on those who had reported ideation (either passive or active suicidal ideation) only in 2010 and had progressed to reporting action (with or without ideation) in 2015 (n=66).

In Analysis 3, step-wise logistical regressions were undertaken on the cross-sectional data as a point of comparison to the ML analysis findings.

Results

Analysis 1

The key themes of interest from the feature analysis on the cross-sectional data in both 2010 and 2015 in identifying those reporting ideations only from those reporting action (plans and / or attempts) included active and passive suicidal ideation, lowered mood and reporting impacts on general functioning. Amongst the additional measures included in the 2015 Transition and Wellbeing Research Programme, key themes emerged regarding the perceived negative impact of the individuals' ADF service on their mental health and disruptions to functioning, including ability to work and sleep disturbances. The ML predictive modelling revealed the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts. In 2010, the strongest differentiators were reporting active suicide ideation, and to a lesser degree, passive suicide ideation, symptoms negatively impacting current ability to work, and lowered mood. In 2015, the strongest differentiators were active suicide ideation, and to a lesser extent passive suicide ideation, restlessness, sleep problems impacting quality of life, reporting that symptoms were negatively impacting current ability to work/meet responsibilities/sleep, and reporting that ADF service had negatively impacted their mental health.

Different but generally complementary themes were found in those still serving and those who had transitioned out of the full-time ADF in 2015. In the transitioned cohort, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and to a lesser extent passive suicide ideation, that symptoms were negatively impacting ability to function (work, meet responsibilities, sleep), a belief that ADF service had negatively impacted their mental health, and feelings of worthlessness. In those still serving in 2015, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and to a lesser extent passive suicide ideation, feeling restless and depressed, and that symptoms were negatively impacting ability to function (work, meet responsibilities).

Analysis 2

The longitudinal analysis highlighted the diverse trajectories across time in self-reported suicidality, including shifts into no longer reporting any suicidality, as well as progression from reporting ideation only into reporting suicide-related behaviours. This reinforces the importance of ongoing monitoring for changes in suicidality across time, including following transition out of full-time service. In the sub-group of particular interest in this study (those who progressed from reporting ideation only in 2010 to reporting suicide-related behaviours in 2015), endorsement of having experienced a lifetime trauma 'worst event' was most strongly associated with progression from ideation only to suicide-related behaviours over time. The variables of sleep behaviour and how well one felt supported or recognised/rewarded in the workplace also contributed to progression from ideation only to suicide-related behaviours, which are complementary with the themes identified in the ML analysis on the cross-sectional data. As the size of this group was small and a predictive model could not be generated using ML approaches from the identified features, the findings on the longitudinal data should be interpreted with caution. There are various reasons which may have contributed to the inability to generate a predictive model, including the small sample size, however the identified factors are still considered to be meaningful, and should be investigated further.

Analysis 3

A secondary aim of the study was to assess how well the ML techniques performed in building predictive models from the available data, compared to more traditional statistical methods. The themes of interest which emerged from the logistical regressions – active suicidal ideation, avoidance of reminders of a past stressful experience, and impact on sleep – were largely complementary with the themes identified from the ML analysis. This provides general confidence that both statistical approaches provide valuable information in addressing the research questions. However, overall, based on the ability of the respective models to accurately predict those who would progress from suicide ideation only to suicide-related behaviours, the ML techniques performed better than the logistical regression results (noting the potential impact of the different sample sizes). The ML models were able to perform at least as well in accurately predicting cases in the 2010 dataset and more strongly in the 2015 dataset than the logistical regressions. This demonstrates the potential value of incorporating ML approaches into studies examining these types of research questions, particularly as it enables atheoretical approaches to discovering potential themes of interest in large, multi-domain datasets.

Implications of findings

Suicide risk is dynamic and multifactorial, making it difficult to predict who will or will not attempt suicide. As identification and appropriate intervention remain important goals for clinicians and organisations such as the military, the identification of any themes or factors which may guide assessment and decision-making is of interest and value.

To our knowledge, this study is the first to apply ML techniques to examine predictors of the progression from suicidal ideation to action in a contemporary Australian military cohort. It demonstrates the potential

value of ML in developing predictive, data-driven models to identify those at increased suicide risk within this population, particularly in large multi-domain datasets. Although the findings are exploratory, there are consistencies with other research findings and theories relating to those at increased risk of progressing from ideation to action in military and veteran populations, indicating potential opportunities to supplement clinical decision making and to enhance current programs and services for serving and ex-serving ADF members, as well as opportunities for further research. Themes of particular interest are active suicide ideation, mental health symptoms (particularly lowered mood), trauma exposure, beliefs about the negative impact of ADF service on mental health, and disturbances in functioning.

While it could be argued that no new or unexpected factors were derived from the ML analysis, the findings highlight themes or areas for examination that may not be routinely considered or included in assessments for escalating suicide risk but appear to be relevant for this population. The datasets analysed contained information across a range of domains (psychological and social, symptoms of mental and physical disorders, as well as phenomenological - how the individual perceives and interacts with the world around them). As ML takes an atheoretical approach to data analysis, it independently weighs each piece of information on its ability to answer the research question. The results demonstrate that important information regarding escalating suicide risks is derived across these categories, and that identification of people with increased risk requires consideration of multiple factors, for example through the conduct of a thorough clinical assessment. These assessments may be conducted by a range of health and allied health service providers, both within and external to the military. The results also indicate other areas that could be targeted in services and supports for serving and transitioned ADF members, including by those in military leadership, administrative or judiciary roles or by providers of services to ex-serving members.

Key Implications for Screening and Service Delivery

- Reporting active suicide ideation (i.e., thoughts of killing self) should be considered an indication of a higher level of risk of the individual progressing to suicide-related behaviours, even if they are not currently reporting suicide-related plans or attempts.
- Consideration should be given to routinely including items assessing not only suicide ideation, but both passive and active suicide ideation in screening for military populations, including for those who have transitioned out of full-time service.
- Suicidality trajectories are diverse, and individuals should be monitored for changes over time in suicide risk.
- Co-morbid mental health conditions, particularly depressive and trauma-related disorders, are important risk factors to consider in the progression from ideation only to suicide-related behaviours in this population (serving and ex-serving).
    - Suicide risk screening should be undertaken with those reporting or exhibiting mental health symptoms.
    - As those with psychiatric disorders are at higher risk of suicide, and those reporting suicidality are at higher risk of developing disorder over time, accurate diagnosis and the provision of

effective treatment (for disorders and sub-syndromal symptoms) are critical components of suicide prevention.

- Clinical assessments should consider not only current suicidal ideation and mental health status, but also the perceived role of ADF service in negatively impacting their mental health and ability to function and meet responsibilities. These themes are relevant for serving and ex-serving ADF members.
- Alongside the delivery of evidence-based treatments for any mental health conditions, additional areas clinicians could consider targeting include:
    - therapeutic interventions to address the impact of negative beliefs surrounding military service on mental health and wellbeing
    - development of safety plans for those who are reporting active suicide ideation
    - ensuring the impact of significant lifetime traumas are explored, and as required, evidence-based treatments are provided.
- Other items which may be useful for inclusion in ADF and veteran screening protocols are indicators of sleep disturbances, as well as other disturbances to ability to function adequately in work, social and / or personal domains. These additional questions or themes could supplement current screening and provide additional information to clinicians on who may benefit from additional risk assessment, even though they may not be actively disclosing suicidality. A proportion of those who die by suicide deny having suicidal ideation, and therefore, alternative approaches or screening questions for identifying those at risk is also of great interest.
- Suicide risk assessments should not focus purely on direct suicidality questions – this is particularly relevant for current serving members, who may be concerned about the potential implications for their career if they disclose suicidal thoughts or behaviours.
- It is possible that having negative perceptions about the impact of their military service on their mental health and functioning may also influence help seeking behaviours either within military health services or with services designed for ex-serving ADF members. This is an area that should be investigated further.
- There is a small but significant group of people at risk of suicide who do not interact with the medical system. Others, including military leaders and those in administrative and judiciary roles, should be trained and supported to be able to assist in identifying those at increased risk of suicide, and how to be an effective pathway to care.
- Higher levels of feeling well supported, appropriately recognised, and connected within the military unit may reflect a protective factor against the mental health impacts of service-related and other psychosocial stressors. This may represent a factor amenable to intervention which may be targeted by programs aiming to increase team cohesion amongst current-serving members, or by increasing efforts to facilitate connection and community amongst ex-serving members.

Introduction

The risk of suicide is a significant concern across many military and veteran populations (Sareen et al., 2016; Hom et al., 2017), including in Australia (Sadler et al., 2021). Ex-serving Australian Defence Force (ADF) members as a population group are at increased risk of suicide, with male veterans 27% more likely to die by suicide than Australian males, and female veterans 107% more likely to die by suicide than Australian females (Australian Institute of Health and Welfare; AIHW, 2022). Suicidality (i.e., suicidal ideation, plans and attempts) in current serving ADF members is also higher than in the general community and increases following transition out of full-time service (AIHW, 2021; Sadler et al., 2021). Significant research has been undertaken into suicides within serving and ex-serving military populations, including attempts to understand the specific risk factors for, and characteristics of, suicidal behaviour (e.g., AIHW, 2021; AIHW 2022). As research supports a continuum of suicidal expression whereby suicidality predominantly precedes future completed suicides (O'Connor & Nock, 2014; De Leo et al., 2005; Joiner, 2002), investigation of suicidality offers the opportunity to potentially identify factors associated with prevention and early intervention. Research on contemporary ADF serving and ex-serving members has identified multiple factors related to suicidality. While many are linked to mental health, there are also other demographic, sub-clinical and psychosocial factors, and there is evidence of a small, but significant group of serving and ex-serving ADF members who report suicidality without a probable mental disorder (Sadler et al., 2021; Bryant et al., 2019). The first few years following transition out of full-time military service has also been identified as a high-risk period for deteriorating physical and mental health and general wellbeing (Shields et al., 2016; Wang et al., 2020), including increases in suicidality (e.g., Van Hooff et al., 2018; Bryant et al., 2019).

While suicide is generally regarded as resulting from a complex interaction of factors with a diversity of pathways, it remains unclear which factors may lead to the progression from suicide ideation to a suicide attempt, noting that most individuals who report suicide ideation never attempt suicide (O'Connor & Nock, 2014). There is also recognition of a continuum of ideation, with active suicidal ideation (e.g., specific thoughts of killing yourself) representing a more severe form of ideation than passive suicidal ideation (e.g., wishing to be dead) (Posner et al., 2011). Over recent years, researchers have focused on more nuanced examination of risk factors whereby the development of suicidal ideation, and the progression from ideation to action (suicide attempt) are regarded as distinct phenomena with different explanations and risk and protective factors. This distinction has important implications for identification and clinical decision-making and has been reflected in the development of several 'ideation to action' theories of suicide, such as Joiner's interpersonal-psychological theory of suicide (Joiner et al., 2005), Rudd's (2006) Fluid vulnerability theory, O'Connor's (2011) integrated motivational-volitional model, and Klonsky and May's three-step theory of suicide (2015). Nonetheless, the ability to accurately predict who will suicide remains poor across all population groups (Franklin et al., 2017; Carter et al., 2017; Sall et al., 2019). Clinical assessments to identify those at risk perform only marginally better than random chance (Franklin et al., 2017; Steeg et al., 2018;

Nock et al., 2016), and suicide risk assessment scales remain unable to determine suicide risk with acceptable levels of accuracy or reliability (Franklin et al., 2017; Steeg et al., 2018).

Consequently, there is considerable motivation to utilise techniques that may improve the identification of those at increased risk of suicide, including through machine learning (ML) techniques. Application of ML to suicide research has been viewed as an opportunity to discover novel areas for future suicide research by identifying predictors and their combinations, and potentially to improve the precision of diagnosis and treatment, including through the integration of information from different modalities and across large non-standardized datasets (Rozek et al., 2020). Machine Learning approaches create systems and algorithms that can learn from and make predictions or decisions based on the available data, and the techniques are particularly useful in analysing large, unprocessed datasets. More traditional classification methods, such as logistic regression, require data analysis to be guided by the researcher through the application of hypothesis. This means that potentially meaningful trends in the data may not be detected, as analysis is being driven by the knowledge of the researcher in relation to existing theories of prediction. The ML algorithms assist in identifying which independent variables (features) to include in the prediction model based on the data alone, as well as their relative importance in maximising prediction. These methods can accommodate multiple and complex interactions among independent variables and the outcome, and algorithms can be cross validated (using either a different 'training' dataset or component of a dataset) to increase generalizability and reduce overfitting (when the model becomes overly complex and fits the training data too closely, rather than learning general patterns it can apply to new data) (Littlefield et al., 2021). A proposed strength of this atheoretical, data-driven approach is the generation of prediction models through identifying relationships between variables that may not have been anticipated by theory, clinical observation, or experiments (Riberio et al., 2016).

Over recent years ML techniques have been increasingly applied to identify suicide-related risk factors and pathways within military and veteran populations (e.g., Nock et al., 2018; Rozek et al., 2020; Littlefield et al., 2021; Ursano et al., 2018). Improving the identification of military members and veterans at elevated risk of suicide may inform investment into intensive, targeted interventions, or the allotment of existing resources. Relevant applications of ML have included detecting patterns predictive of self-harm and suicidal ideation in large datasets from self-report surveys administered to Canadian military and police veterans (Colic et al., 2022); examining predictors of suicidal behaviours in treatment seeking US soldiers (Rozek et al., 2020); identifying US soldiers at high suicide attempt risk prior to transition (Stanley et al., 2022); and identifying risk factors for transition from suicide ideation to suicide attempts from the Army Study to Assess Risk and Resilience in Servicemembers (Army STARRS) datasets (Nock et al., 2018).

To our knowledge, this type of ML analysis has not been undertaken on the large datasets available on contemporary ADF serving and ex-serving members. Conducting ADF-specific research on suicidality in serving and ex-serving personnel is valuable as the findings from research conducted on one military or veteran population are not necessarily generalisable to the military or veteran population of another country. This is due to differences in a range of factors including demographic composition (e.g., cultural diversity),

recruitment criteria and training protocols, and the level of health care provided (Sareen et al., 2016). There are also differences observed between serving and ex-serving populations (Van Hooff et al., 2018), highlighting the need to examine these groups separately where possible. Further, as current suicide identification and prediction methods remain sub-optimal, and identification and appropriate intervention remain important goals for clinicians as well as the Australian military, government and broader community, seeking new approaches to identify any population-specific themes or factors which may guide improvements in assessment and decision-making arguably has value (Kirtley et al., 2022). In particular, being able to identify factors that distinguish between those who think about suicide (ideators) versus those who progress to suicide-related behaviours, including plans and attempts, may provide important information to more effectively target interventions, with implications for policy development and service delivery.

This research project builds upon analysis undertaken on contemporary ADF serving and transitioned (those no longer serving full-time) members as part of the 2010 ADF Mental Health and Wellbeing Prevalence Study (McFarlane et al., 2011) and the 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018). These programs provide large cross-sectional, self-report datasets capturing demographic, occupational, mental and physical health, trauma history and psychosocial information, including four suicidality items in ADF serving members in 2010 and in serving and transitioned ADF members in 2015. Further, a substantial group completed surveys in both 2010 and 2015 and consented to their data being linked to create a longitudinal dataset. The reliance on cross-sectional data has been a common limitation in research related to suicide (Franklin et al., 2017), and the establishment of this longitudinal cohort enables additional investigation of how suicidality changes over time for this population. Longitudinal predictive modelling has an important role in early intervention and prevention, as it facilitates the identification of risk factors and patterns of development that may contribute to the onset of a particular condition or disease. Previous research has demonstrated the long-term course of suicidal ideation is diverse, and it may remain stable, intensify, remit over time, or fluctuate as stressors change (Baca-Garcia et al., 2011).

The primary aim of this exploratory study was to use ML techniques to identify which variables (survey items) best distinguished those who reported suicidal ideation (either active or passive ideation) only versus those who reported action (planning and or attempts), with or without ideation at a given point in time (i.e., estimated independently for the 2010 and the 2015 datasets) (Analysis 1 – cross-sectional data) and across time (Analysis 2 - longitudinal data). The ML techniques were used to identify new factors that may be of interest derived from all the available data on this population, rather than simply factors related to a particular hypothesis driven by theory or other research findings. Predictive modelling ML techniques were then applied to assess which of the identified variables were most important in accurately predicting cases (those at risk of progressing from ideation to suicide behaviours) in previously unseen components of the dataset (to establish validation accuracy) using both the cross-sectional data (Analysis 1) and the longitudinal data (Analysis 2).

A secondary aim of the study was to assess how well the ML techniques performed in building predictive models from the available data, compared to more traditional statistical methods, such as logistic

regressions. It is acknowledged that alongside the proliferation of ML approaches in suicide-related research, the reported outcomes from these studies have been mixed. While some researchers report that ML approaches are better able to identify suicide ideators from those who also report suicide-related behaviours than logistic regressions (e.g., Huang et al., 2020), others report similar results produced by ML approaches and more traditional statistical methods (Littlefield et al., 2021; Zuromski et al., 2019; Salganik et al., 2020). Further, some have criticized prediction models created by ML as being too complex to interpret, with the findings difficult to apply beyond a research setting (Cox et al., 2020). Therefore, in this study step-wise logistical regressions were also included in the cross-sectional analysis to examine how well more traditional statistical methods were able to accurately predict cases from the dataset (Analysis 3). Unlike ML which learns from the available data, logistic regression is a statistical technique which tests a hypothesis in relation to which variables will predict the outcomes. This provided a point of comparison to the findings derived from the ML approaches, allowing assessment of the utility of ML approaches when answering these types of research questions.

Methods

Participants

Data on the prevalence of suicidal thoughts, plans and attempts (suicidality) in ADF serving and ex-serving personnel was extracted from two studies: the 2010 ADF Mental Health and Wellbeing Prevalence Study (McFarlane et al., 2011) and the 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018). The 2010 ADF Mental Health and Wellbeing Prevalence Study consisted of Regular ADF personnel serving in 2010 (n=50,049) who were invited to complete a self-report survey, and it was completed by n=24, 481. The 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018) investigated the impact of contemporary military service on the mental, physical, and social health of serving (Regular ADF) and Transitioned (no longer serving full-time) ADF personnel. Of those invited, 18% (n = 4326) of the Transitioned ADF population and 42.3% (n = 8480) of the 2015 Regular ADF population completed a self-report survey (n=12,806). A longitudinal dataset was created from those ADF members who completed the surveys in 2010 and in 2015 and consented to their data being linked. This comprised 40.6% (n=8,497) of those invited who had completed the 2010 survey (n= 2,334 Transitioned ADF and n = 6,163 Regular ADF). The methodologies of these research programs are described in detail elsewhere (Van Hooff, M., et al, 2014; Van Hooff, M., et al., 2018).

Measures

The primary outcome in this study was suicidality as measured by questions adapted from the 2017 Australian National Survey of Mental Health and Wellbeing (Australian Bureau of Statistics, 2008). This consisted of four self-report items assessing passive suicide ideation, active suicide ideation, suicide plans, and suicide attempts in the past 12-month period. All items had a dichotomous (yes/no) response. Item 1

was developed by the investigators. The items were ‘in the last 12 months, have you ever felt that your life was not worth living?’ (passive ideation: suicide_1); ‘in the last 12 months, have you ever felt so low that you thought about committing suicide?’ (active ideation: suicide_2); ‘in the last 12 months, have you made a suicide plan?’ (planning: suicide_3); ‘in the last 12 months, have you attempted suicide?’ (attempt: suicide_4). These questions were asked at Time 1 (T1-2010) and at Time 2 (T2-2015).

A large number of variables were used from the T1-2010 and T2-2015 self-report surveys as predictor variables in this study. Annex A provides a summary of the demographic and background information collected, including gender, age, education, information on military service, relationship status and employment status. Annex B provides a summary of the constructs and measures used to assess mental, physical, and social health across the studies (including citations). Items were largely replicated from the T1-2010 self-report survey (McFarlane et al., 2011) in the T2-2015 self-report survey (Van Hooff et al., 2018). In 2015 participants received different questionnaires relevant to their current ADF status (Regular ADF or Transitioned) relating to demographics, military service and deployment history; however, the core-validated measures of psychological and physical health remained the same.

Analysis 1 - Cross-sectional data

Procedure

Two cross-sectional datasets were created for analysis. The first dataset (Dataset T1-2010) consisted of the 2010 survey data of all participants who endorsed at least one suicidality item (n=1684). The second dataset (Dataset T2-2015) consisted of the 2015 survey data of all participants who had endorsed at least one suicidality item (n=2245). In both datasets, anyone who did not endorse any suicidality item was removed. Conducting the same analysis on the 2010 and the 2015 datasets enabled the analysis to be independently verified, noting there are some different survey items between Dataset T1-2010 and Dataset T2-2015. Of particular interest was identifying any consistent variables across both time points to distinguish between those that report ideations only and those who report action (with or without ideation).

To answer the research question “which variables at a given point in time best distinguished between those who reported ideation only and those who reported action (with or without ideation)” each cross-sectional dataset was analysed separately (Dataset T1-2010 and Dataset T2-2015).

Sample composition

Table 1 provides a summary of the basic sociodemographics of the Dataset T1-2010 sample (n=1684). Of those reporting any suicidality in 2010, the majority were male (80.4%) with an average age of 36.6 and in a relationship and living together (55%). About half were Non-Commissioned Officers (rank of Sergeant to Warrant Officer or equivalent) (50.1%) and in the Army (46%) and many had served in the military for considerable periods of time (29.1% over 20 years). Table 2 provides results on the key mental health measures, which revealed that the most highly endorsed suicidality item was passive suicide ideation (93.4%), followed by active suicide (54%), suicide planning (14%) and attempts (5.3%). About one-third reported problem anger (DAR-5: 33.8%), high or very high levels of posttraumatic stress symptoms (PCL-C: 17.1% and 20.6% respectively), moderate, moderately severe or severe depressive symptoms (PHQ-9: 19.7%, 11.5% and 8.5% respectively) and problematic levels of alcohol consumption (AUDIT, Band 2 -31%, Band 3 - 6% and Band 4 - 5.4%). Around a half reported high or very high levels of psychological distress (K-10: 32.3% and 22.1% respectively). Those who endorsed any suicide plans and / attempts also reported higher levels of psychological symptoms across the measures, including problematic anger (41.4%), very high levels of posttraumatic stress symptoms (37.2%), very high psychological distress (36.7%), severe depressive symptoms (21.5%) and alcohol misuse (9% Band 4 on the AUDIT).

Table 1_ Sociodemographic characteristics of current serving ADF members reporting any suicidality in 2010

	Any suicide (n=1684)	Suicidal ideation only (no plans/ attempts) (n=1337)	Any suicide plans or attempts (n=256)
Age (M, SD)	36.6 (9.4)	36.8 (9.5)	35.7 (9.3)
18-27	316 (20.8)	243 (20.2)	55 (23.7)
28-37	495 (32.6)	390 (32.4)	72 (31.0)
38-47	491 (32.3)	386 (32)	81 (34.9)
48-57	205 (13.5)	174 (14.4)	24 (10.3)
58+	12 (0.8)	12 (1.0)	0 (0.0)
Sex			
Male	1354 (80.4)	1066 (79.7)	210 (82.0)
Female	330 (19.6)	271 (20.3)	46 (18.0)
Rank			
Commissioned Officers (CO)	481 (28.6)	398 (29.8)	58 (22.7)
Non-Commissioned Officer (NCO)	844 (50.1)	675 (50.5)	127 (49.6)
Other Ranks	359 (21.3)	264 (19.7)	71 (27.7)
Service within Defence			
Army	774 (46)	607 (45.4)	125 (48.8)
Navy	407 (24.2)	323 (24.2)	60 (23.4)
Air Force	503 (29.9)	407 (30.4)	71 (27.7)
Years served in ADF			
1 month – 3.9 years	218 (13.0)	157 (11.8)	43 (16.8)
4 - 7.9 years	301 (17.9)	245 (18.4)	47 (18.4)

8 - 11.9 years	291 (17.3)	231 (17.4)	45 (17.6)
12 - 15.9 years	221 (13.2)	183 (13.7)	
16 - 19.9 years	158 (9.4)	125 (9.4)	25 (9.8)
20+ years	489 (29.1)	390 (29.3)	69 (27.0)
Relationship status			
Not in a relationship	535 (31.9)	421 (31.6)	89 (34.8)
Relationship/ living together	923 (55.0)	742 (55.7)	126 (49.2)
Relationship/ not living together	221 (13.2)	169 (12.7)	41 (16.0)

Table 2_ Mental health characteristics of current serving ADF members reporting any suicidality in 2010

	Any suicide (n=1684)	Suicidal ideation only (no plans/ attempts) (n=1337)	Any suicide plans or attempts (n=256)
Suicidality (past 12 months)			
Felt life was not worth living	1572 (93.4%)	1337 (100.0%)	235 (91.8%)
Felt so low thought about committing suicide	904 (54.0%)	575 (43.3%)	238 (93.0%)
Made a suicide plan	235 (14.0%)	0 (0.0)	235 (92.2%)
Attempted suicide	88 (5.3%)	0 (0.0)	88 (34.6%)
DAR-5 Anger (M, SD)	10.4 (4.6%)	10.3 (4.4)	11.4 (5.4)
No problem anger	1113 (66.2)	898 (67.3)	150 (58.6)
Problem anger (12+)	569 (33.8)	437 (32.7)	106 (41.4)
PCL-C PTSD (M, SD)	36.9 (15.1)	36.0 (14.3)	42.6 (18.4)
Low (17-29)	620 (38.5)	496 (38.8)	82 (32.8)
Moderate (30-39)	383 (23.8)	332 (26)	33 (13.2)
High (40-49)	276 (17.1)	222 (17.4)	42 (16.8)
Very High (50-85)	332 (20.6)	227 (17.8)	93 (37.2)
K10 Psychological Distress (M, SD)	23.5 (7.9)	23.3 (7.3)	25.5 (10.2)
Low distress (10-15)	270 (16.1)	195 (14.6)	55 (21.5)
Moderate distress (16-21)	496 (29.5)	410 (30.7)	47 (18.4)
High distress (22-29)	544 (32.3)	463 (34.7)	60 (23.4)
Very high distress (30-50)	372 (22.1)	267 (20)	94 (36.7)
PHQ-9 Depression (M, SD)	9.2 (6.3)	8.9 (5.9)	11.5 (8.1)
Minimal (0-4)	413 (24.6)	320 (24.0)	65 (25.4)
Mild (5-9)	600 (35.7)	508 (38.1)	52 (20.3)
Moderate (10-14)	331 (19.7)	278 (20.8)	42 (16.4)
Moderately severe (15-19)	194 (11.5)	142 (10.6)	42 (16.4)
Severe (20-27)	143 (8.5)	86 (6.4)	55 (21.5)
AUDIT Alcohol Use (M, SD)	7.8 (6.2)	7.6 (6.0)	9.0 (7.3)
Band 1 (0-7)	967 (57.6)	787 (59.0)	133 (52.0)
Band 2 (8-15)	521 (31)	405 (30.4)	82 (32.0)
Band 3 (16-19)	101 (6.0)	77 (5.8)	18 (7.0)
Band 4 (20-40)	91 (5.4)	64 (4.8)	23 (9.0)

Table 3 provides a summary of the basic sociodemographics of the Dataset T2-2015 sample (n=2273). This dataset includes both current serving (46%) and transitioned ADF members (54%). Of those reporting any suicidality in 2015, the majority were male (81.4%) with an average age of 41.2 and in a relationship and living together (63.2%). About half were Non-Commissioned Officers (52%) and in the Army (53.9%), and many had served in the military for considerable periods of time (37.1% over 20 years). Their scores on the key mental health measures revealed that the most highly endorsed suicidality item was passive suicide ideation (95.2%), followed by active suicide (64.9%), suicide planning (21.6%) and attempts (5.2%). Around half reported problem anger (DAR-5: 49.6%) and moderate, high or very high levels of posttraumatic stress symptoms (PCL-C: 23.8%, 13.4% and 18% respectively), high or very high levels of psychological distress (K-10: 26% and 35.5% respectively), moderate, moderately severe or severe depressive symptoms (PHQ-9: 20.7%, 18.3% and 21.1% respectively), moderate or severe levels of anxiety (GAD-7: 20.4 and 22.3% respectively) and problematic levels of alcohol consumption (AUDIT, Band 2 – 27.4%, Band 3 – 7.4% and Band 4 – 10.3%). Those who endorsed any suicide plans and / attempts also reported higher levels of psychological symptoms across the measures, including reporting problematic anger (66.1%), very high levels of posttraumatic stress symptoms (30%), very high psychological distress (58.1%), severe depressive symptoms (42.8%), severe anxiety symptoms (39.1%) and alcohol misuse (19.9% Band 4 on the AUDIT).

Table 3_ Sociodemographic characteristics of current serving and transitioned ADF members reporting any suicidality in 2015

	Total population (n=2273)	Suicidal ideation only (no plans/ attempts) (n=1673)	Suicide plans or attempts (n=508)
Age (M, SD)	41.2 (10.3)	41.5 (10.3)	40.3 (10.1)
18-27	229 (10.2)	158 (9.6)	59 (11.7)
28-37	630 (28.2)	455 (27.7)	152 (30.2)
38-47	750 (33.6)	550 (33.5)	170 (33.8)
48-57	490 (21.9)	373 (22.7)	97 (19.3)
58+	136 (6.1)	106 (6.5)	25 (5.0)
Sex			
Male	1849 (81.4)	1359 (81.2)	413 (81.3)
Female	423 (18.6)	314 (18.8)	95 (18.7)
Rank			
Commissioned Officers (CO)	672 (29.6)	512 (30.6)	120 (23.6)
Non-Commissioned Officer (NCO)	1181 (52.0)	871 (52.1)	269 (53.0)
Other Ranks	418 (18.4)	288 (17.2)	119 (23.4)
Service within Defence			
Army	1224 (53.9)	877 (52.4)	298 (58.7)
Navy	488 (21.5)	369 (22.1)	99 (19.5)
Air Force	560 (24.6)	427 (25.5)	111 (21.9)
Years served in ADF			
1 month – 3.9 years	146 (6.5)	100 (6.1)	39 (7.7)
4 - 7.9 years	384 (17.2)	268 (16.3)	106 (21)

8 - 11.9 years	357 (16.0)	256 (15.6)	89 (17.7)
12 - 15.9 years	315 (14.1)	228 (13.9)	76 (15.1)
16 - 19.9 years	205 (9.2)	153 (9.3)	41 (8.1)
20+ years	829 (37.1)	636 (38.8)	153 (30.4)
Transition status			
Transition	1227 (54.0)	848 (50.7)	349 (68.7)
Current	1046 (46.0)	825 (49.3)	159 (31.3)
Relationship status			
Not in a relationship	570 (25.4)	396 (24.0)	153 (30.2)
Relationship/not living together	256 (11.4)	197 (11.9)	47 (9.3)
Relationship/living together	1421 (63.2)	1057 (64.1)	306 (60.5)

Table 4_ Mental health characteristics of current serving and transitioned ADF members reporting any suicidality in 2010

	Total population (n=2273)	Suicidal ideation only (no plans/ attempts) (n=1673)	Suicide plans or attempts (n=508)
Suicidality (past 12 months)			
Felt life was not worth living	2163 (95.2)	1673 (100.0)	490 (96.6)
Felt so low thought about committing suicide	1469 (64.9)	888 (53.4)	489 (96.4)
Made a suicide plan	488 (21.6)	0 (0.0)	488 (96.3)
Attempted suicide	118 (5.2)	0 (0.0)	118 (23.3)
DAR-5 Anger (M, SD)	12.2 (5.2)	11.6 (4.9)	14.4 (5.6)
No problem anger	1144 (50.4)	911 (54.6)	172 (33.9)
Problem anger (12+)	1124 (49.6)	758 (45.4)	335 (66.1)
PCL-C PTSD (M, SD)	35.1 (14.8)	34.3 (14)	41.6 (18.2)
Low (17-29)	449 (44.9)	366 (46.3)	46 (30.7)
Moderate (30-39)	238 (23.8)	187 (23.7)	36 (24.0)
High (40-49)	134 (13.4)	104 (13.2)	23 (15.3)
Very High (50-85)	180 (18.0)	133 (16.8)	45 (30.0)
K10 Psychological Distress (M, SD)	25.8 (9.5)	24.6 (8.7)	31.1 (10.3)
Low distress (10-15)	346 (15.3)	272 (16.3)	40 (7.9)
Moderate distress (16-21)	527 (23.2)	439 (26.3)	67 (13.2)
High distress (22-29)	589 (26)	458 (27.5)	106 (20.9)
Very high distress (30-50)	806 (35.5)	499 (29.9)	295 (58.1)
PHQ-9 Depression (M, SD)	12.7 (7.2)	11.8 (6.7)	16.6 (7.7)
Minimal (0-4)	291 (12.8)	234 (14.0)	33 (6.5)
Mild (5-9)	614 (27)	491 (29.3)	86 (17.0)
Moderate (10-14)	471 (20.7)	374 (22.4)	79 (15.6)
Moderately severe (15-19)	416 (18.3)	313 (18.7)	92 (18.1)
Severe (20-27)	480 (21.1)	261 (15.6)	217 (42.8)
GAD-7 Anxiety (M, SD)	9.2 (5.9)	8.6 (5.6)	12 (6.2)
Minimal (0-4)	556 (24.5)	451 (27.0)	71 (14.0)
Mild (5-9)	745 (32.8)	586 (35.1)	119 (23.5)

Moderate (10-14)	463 (20.4)	332 (19.9)	118 (23.3)
Severe (15-21)	505 (22.3)	302 (18.1)	198 (39.1)
AUDIT Alcohol Use (M, SD)	8.7 (7.5)	8.2 (6.9)	11 (9.1)
Band 1 (0-7)	1182 (54.9)	905 (56.8)	216 (45.7)
Band 2 (8-15)	590 (27.4)	456 (28.6)	113 (23.9)
Band 3 (16-19)	160 (7.4)	105 (6.6)	50 (10.6)
Band 4 (20-40)	222 (10.3)	126 (7.9)	94 (19.9)

Data Analysis

The ML analysis was separated into two distinct stages: Stage 1 - feature selection and Stage 2 - predictive modelling. These two processes are described in detail below.

Feature Selection

Machine learning techniques were used to identify the top 20 variables (individual survey items) to differentiate those who reported ideation only (endorsing the item suicide_1) versus those reporting action (with or without ideation) at each time point (2010 and 2015). Using those who had endorsed suicide_1, regardless of whether they had also endorsed suicide_2, enabled the largest ideation group to be analysed without having to collapse passive and active suicide ideation into one group. However, it is noted that many individuals will have endorsed both passive (suicide_1) and active suicide (suicide_2). Details of data pre-processing is provided in Annex C. ***Feature selection*** was used to calculate the information gain of each survey item (rank ordering items on how much information they contributed to predict the outcome of interest), based on mutual information. This is the quantity that measures a relationship between two variables that are sampled simultaneously (Learned-Miller, E., 2013). During this analysis, all variables were compared one-by-one, and any interactions were not taken into account. The approach was non-theoretical and individual survey items were included in the analysis.

Predictive modelling

To provide additional validation to these exploratory results, ***predictive modelling*** was undertaken to examine the power of the top 20 selected features to accurately predict those who report suicide planning (suicide_3) and/or suicide attempt (suicide_4) compared to those who report ideation only (suicide_1). Due to the relatively small sample sizes, responses to the items relating to suicide planning (suicide_3) and suicide attempt (suicide_4) were collapsed to create the outcome variable. The two ideation items were kept separate in the analysis to examine the impact of reporting more active ideation in the progression to suicide behaviours. The technique used was ***Random Forest*** (a supervised classification algorithm for large datasets with a high number of features) and analysis was undertaken firstly on Dataset T1-2010 and then Dataset T2-2015. This technique constructs decision trees on subsets of the data and takes the average of their predictions for classification. Highly accurate and versatile, this technique is resistant to overfitting and

can handle missing values in the data. It can be used for both regression and classification problems and can identify the relative importance of features (e.g., survey items) in contributing to the classifier.

A ***baseline classification measure*** was also calculated for each model to determine if the model's accuracy in prediction was better than random chance. This process examines how many cases (those who would progress from ideation to action) are correctly identified through a 'random guess' only, and then compares it to the level of predictive accuracy yielded by the predictive model created through ML techniques. The baseline classification is generated through applying a simple rule-based algorithm that makes predictions based on a random prediction, which serves as a benchmark for assessing the performance of more complex models. The difference is reported as the ***reduction in the error of prediction*** generated by the model. As an example, if a random guess correctly identified 85% of the cases (the baseline measure), and there is unexplained variance in the model produced of 10%, and the ML predictive model correctly identified 90% of the cases with unexplained variance of 0.7%, the resulting reduction of error of prediction would be 7% (0.7 divided by 10 x 100 = 7%).

As Dataset T2-2015 includes data from those still serving and those who had transitioned out of full-time ADF service in 2015, additional analysis was undertaken separating the current serving and transitioned populations to identify any differences.

For each analysis undertaken, ***cross validation*** was undertaken. Cross validation evaluates the performance of a predictive model on a previously unseen dataset or unseen component of a dataset to assess its ability to generalise to new data. This is an important part of the ML process. In this study, each dataset was split into two sections: 80% of the dataset to 'train' the model (training set), with the remaining 20% of the dataset (the data unseen by the model) used to 'test' the model (validation set). The ***k-fold cross-validation technique*** was used, with the data randomly divided into five equal-sized folds (the 20%). The model was then 'trained' five times, and on each occasion a different 'fold' of the data was used. This means that the model is internally validated on the entire dataset and the outcome for each individual case (person) is predicted without the model having 'seen' that individual's data before. Therefore the model does not train and test itself on the same data.

The initial feature selection analysis was undertaken using WEKA version 3, and the predictive modelling (Random Forest) was conducted in R.

Results – Analysis 1

Feature Selection

Table 5 lists the top 20 variables which differentiate those who reported ideation only (suicide_1) versus those reporting action (planning and or attempts, with or without ideation) in 2010 and 2015 respectively, as well as the item ranking comparison between the two time points. Of the top 20 variables in 2010, 10 of these variables also appeared in the 2015 top 20 (shaded blue), while eight were survey items only included

in the 2015 survey (shaded green), and two variables were in the 2015 top 20 but outside of the 2010 top 20 variables (shaded orange). The ‘action’ items from the suicide scale (suicide_3, suicide_4) also appeared in the top 20, but as these were used to create the outcome variable, they serve more as a validation of the process. The 10 variables that were consistent across both time points (shaded blue) are key variables to distinguish between those that report ideations only and those who report action (with or without ideation) in a single survey. The other top 20 variables that appeared in either the 2010 or 2015 surveys provide important complementary information. The themes across these variables include active and passive suicide ideation, feeling depressed, hopeless, worthless, and or sad, and reporting impacts on sleep or social functioning and/or their ability to do their job.

Table 5_Comparison of top 20 variables from Feature Selection analysis in T1-2010 and T2-2015 from those who endorsed suicide ideation only (Suicide 1 _ in the past 12months, have you ever felt life was not worth living?)

T1- 2010		Rank T1-2010	T2 - 2015		Rank T2-2015	Item ranking 2010 vs 2015
Suicide_3	In the past 12 months, have you made a suicide plan?	1	Suicide_3	In the past 12 months, have you made a suicide plan?	1	In top 20 in 2010 (1) and 2015 (1)
Suicide_4	In the past 12 months, have you attempted suicide?	2	Suicide_4	In the past 12 months, have you attempted suicide?	2	In top 20 in 2010 (2) and 2015 (2)
Suicide_2	In the past 12 months, have you ever felt so low that you have thought about committing suicide?	3	Suicide_2	In the past 12 months, have you ever felt so low that you have thought about committing suicide?	3	In top 20 in 2010 (3) and 2015 (3)
PHQ_9	(Over the last 2 weeks, how often have you been bothered by) Thoughts that you would be better off dead or hurting self in some way	4	PHQ_9	(Over the last 2 weeks, how often have you been bothered by) Thoughts that you would be better off dead or hurting self in some way	4	In top 20 in 2010 (4) and 2015 (4)
K10_7	In the past 4 weeks, about how often did you feel depressed?	5	K10_7	In the past 4 weeks, about how often did you feel depressed?	5	In top 20 in 2010 (5) and 2015 (5)
K10_10	In the past 4 weeks, about how often did you feel worthless?	6	PHQPlus	If you checked off any of these problems, (in the past 2 weeks) how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?	6	In top 20 in 2010 (7) and 2015 (6)
PHQPlus	If you checked off any of these problems, (in the past 2 weeks) how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?	7	K10_10	In the past 4 weeks, about how often did you feel worthless?	7	In top 20 in 2010 (6) and 2015 (7)
PHQ_2	(Over the last 2 weeks, how often have you been bothered by) Feeling down, depressed or hopeless?	8	Adf_impact_mental	I believe my current mental health has been negatively impacted upon by my ADF career.	8	New variable in 2015
PCL_10	Feeling distant or cut off from other people? (in the past month)	9	K10_9	In the past 4 weeks, about how often did you feel so sad that nothing could cheer you up?	9	In top 20 in 2010 (14) and 2015 (9)
PHQ_6	(Over the last 2 weeks, how often have you been bothered by) Feeling bad about yourself, or that you are a failure, or have let yourself or your family down	10	K10_4	In the past 4 weeks, about how often did you feel hopeless?	10	In top 20 in 2010 (12) and 2015 (10)
Seen_doctor_past4w	In the past 4 weeks, how many times have you seen a doctor or any other health professional about these feelings?	11	Disrupt_work	Thinking about all of the symptoms you have reported in this survey so far, how much have the symptoms disrupted your work	11	New variable in 2015
K10_4	In the past 4 weeks, about how often did you feel hopeless?	12	Adf_prevent_mental	I believe my mental health will prevent me from serving out my full career as an ADF member	12	New variable in 2015
PCL_9	Loss of interest in activities that you used to enjoy? (in the past month)	13	Income_transitioned	What is your main source of income now? (e.g., wage, pension etc.)	13	New variable in 2015
K10_9	In the past 4 weeks, about how often did you feel so sad that nothing could cheer you up?	14	Sleep_index_6	(in the past 2 weeks) How noticeable to others do you think your sleeping problem is in terms of impairing the quality of life?	14	New variable in 2015
PHQ_7	(Over the last 2 weeks, how often have you been bothered by) trouble concentrating of	15	K10_3	In the past four (4) weeks, about how often did you feel so nervous that nothing could calm you down?	15	Outside top 20 in 2010 (38)

	things, such as reading the newspaper or watching TV					
PHQ_8	(Over the last 2 weeks, how often have you been bothered by) Moving or speaking so slowly that other people could have noticed? Or the opposite – being so fidgety or restless that you have been moving around a lot more than usual	16	Main_activities	Which of these best describes your main activities? (work, student, retired)	16	New variable in 2015
Unable_ work_past4 w	In the past four (4) weeks, how many days were you TOTALLY UNABLE to work, study or manage your day to day activities because of these feelings? (items from K-10)	17	Disrupt_social	Thinking about all of the symptoms you have reported in this survey so far, how much have the symptoms disrupted your social life / leisure activities	17	New variable in 2015
PCL_7	Avoiding activities or situations because they reminded you of a stressful experience from the past? (in the past month)	18	Delighted_terribl e	How do you feel about your life as a whole, taking into account what has happened in the last year and what you expect to happen in the future?	18	New variable in 2015
GA_6	Trouble concentrating on things, such as reading a book or watching TV (over the last 2 weeks)	19	K10_6	In the past four (4) weeks, about how often did you feel so restless that you could not sit still?	19	Outside top 20 in 2010 (80)
PD_7	Did you have chest pain or pressure? (think about your last bad anxiety attack)	20	PHQ_2	(Over the last 2 weeks, how often have you been bothered by) Feeling down, depressed or hopeless?	20	In top 20 in 2010 (8) and 2015 (20)

Blue = Variable in top 20 in 2010 and 2015
Green = Variable only included in 2015 survey
Orange = Variable outside of top 20 in 2010

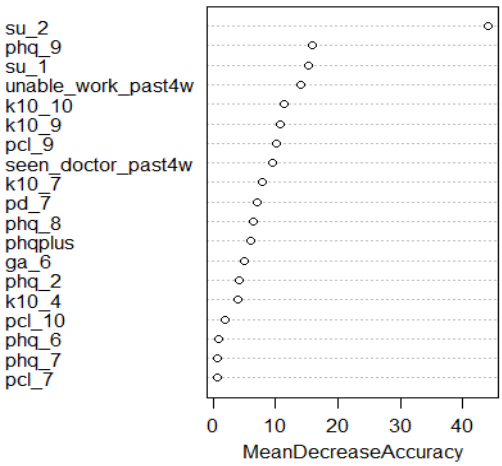
Predictive modelling

Dataset T1-2010

When predictive modelling analysis (Random Forest) was applied to the top variables for Dataset T1-2010 (after collapsing suicide_3 and suicide_4), they provided predictive accuracy of 86.1% (with 0.7% unexplained variance). In contrast the baseline classification measure was 85.4% (with unexplained variance of 13.9%). This indicates that the predictive model created through ML techniques yielded a higher predictive accuracy than a random guess, with a reduction in error of prediction of 5.1% (0.7/13.9)[1] (see Table 6 for a summary of the findings of all the predictive models). Graph 1 illustrates the relative contribution each variable (individual survey item) provides to the predictive model (vertical axis). The horizontal axis provides the ***'mean decrease accuracy***'. This is a measure of variable importance, indicating the decrease in accuracy of the model when a particular variable is removed from the model during training. Therefore variables with a high mean decrease accuracy are more important for the model's performance as they have a greater impact on the accuracy of the predictions – and they sit in rank order with the most important feature in the model at the top of the vertical axis.

In Graph 1 the variables making the highest contribution to the predictive model in the 2010 data (i.e. the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among current serving ADF members in 2010) were related to reporting active suicide ideation (su_2) and to a lesser degree (passive suicide ideation (phq_9 and su_1), symptoms negatively impacting current ability to work (unable_work_past4w). Other variables contributing to the predictive model related to reporting lowered mood (e.g., feeling worthless (k10_10), sad (k10_9), loss of interest in activities they used to enjoy (pcl_9)), as well as reporting recently seeking medical care for their mental health (seen_doctor_past4w).

[1] A random guess correctly identified 85.4% of the cases (the baseline measure) with unexplained variance of 13.9% and the ML predictive model correctly identified 85.4% of the cases with unexplained variance of 0.7%, resulting in a reduction of error of prediction of 5.1% (0.7 divided by 13.9 x 100 = 5.1%).



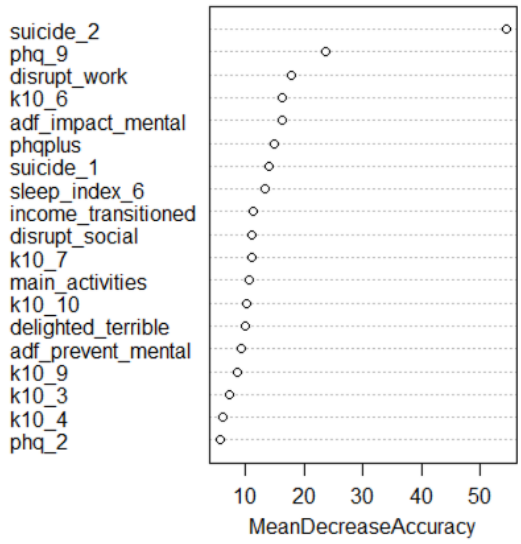
* variables with a higher mean decrease accuracy are more important for the model's performance

Graph 1_Relative contribution each variable provides to ML predictive model in Dataset T1-2010

Dataset T2-2015

The top 19 variables for Dataset T2-2015 provided predictive accuracy of 81.3% (with unexplained variance of 3.3) (see Table 6). As the baseline classification measure was 78% (with unexplained variance of 22), the predictive model created through ML techniques once again yielded a higher predictive accuracy than a random guess, which represents a reduction in error of prediction of 15% (3.3/22).

Graph 2 illustrates the relative contribution each variable provides to the predictive model. The variables making the highest contribution to the predictive model in 2015 (i.e., the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among current serving and transitioned ADF members in 2015) were active suicide ideation (suicide_2), and to a lesser extent passive suicide ideation (phq_9), as well as feeling restless (k10_6), reporting that symptoms were negatively impacting current ability to work (disrupt_work), that their symptoms were negatively impacting their ability to function/meet responsibilities (phqplus), reporting that their ADF service had negatively impacted their mental health (adf_impact_mental), and sleep problems impacting quality of life (sleep_index_6).



* variables with a higher mean decrease accuracy are more important for the model's performance

Graph 2_ Relative contribution each variable provides to ML predictive model in Dataset T2-2015

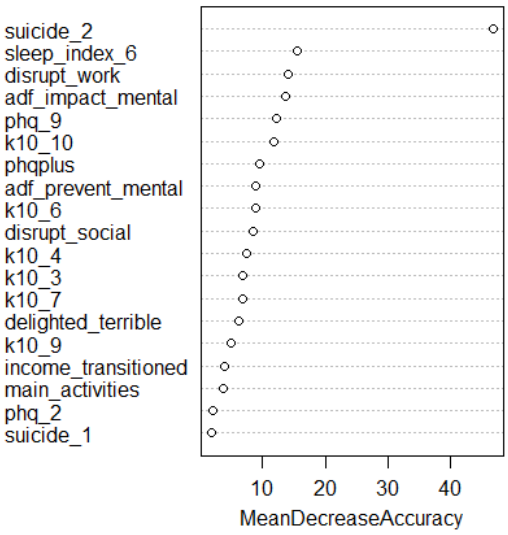
Predictive modelling for serving versus transitioned ADF members in 2015

Additional analysis was undertaken using Dataset T2-2015 to determine if there were a different pattern of predictors of suicidal behaviour (with or without ideation) among those who were still serving in 2015 (current serving) versus those who had transitioned out of full-time service.

The model created for the transitioned ADF from Dataset T2-2015 (n=1227) had a predictive accuracy of 87.8% (unexplained variance of 2.6%) (baseline classification measure of 85.2% with unexplained variance of 14.8%), representing a reduction in error of prediction of 17.5% (2.6/14.8) (see Table 6). As shown in Graph 3 the variable making the largest contribution to the predictive model (i.e. the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among *transitioned* ADF members in 2015) related to active suicide ideation (suicide_2), and to a lesser extent passive suicide ideation (phq_9), as well as sleep problems impacting quality of life (sleep_index_6), reporting that symptoms were negatively impacting current ability to work (disrupt_work), reporting that ADF service had negatively impacted their mental health (adf_impact_mental), that their symptoms were negatively impacting their ability to function/meet responsibilities (phqplus), and feelings of worthlessness (k10-10).

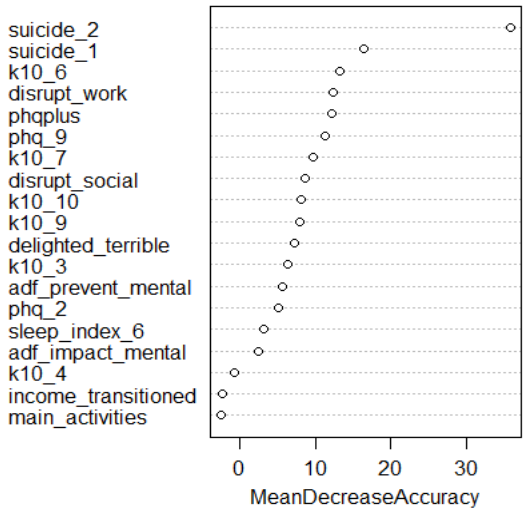
The model created for the current serving ADF personnel from Dataset T2-2015 (n=1046) had a predictive accuracy of 76.8% (unexplained variance of 4.9%) (baseline classification measure of 71.9% with 29.1%), representing a reduction in error of prediction of 16.8% (4.9/29.1) (see Table 6). As shown in Graph 4 the variables making the largest contribution to the predictive model (i.e. the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among *current serving*

ADF members in 2015) were active suicide ideation (suicide_2), and to a lesser extent passive suicide ideation (suicide_1 and phq_9), as well as feeling restless (k10_6), reporting that symptoms were negatively impacting current ability to work (disrupt_work), that their symptoms were negatively impacting their ability to function/meet responsibilities (phqplus), and feelings of depression (k10_7).



* variables with a higher mean decrease accuracy are more important for the model's performance

Graph 3_ Relative contribution each variable provides to ML predictive model in Dataset T2-2015 Transitioned ADF



* variables with a higher mean decrease accuracy are more important for the model's performance

Graph 4_ Relative contribution each variable provides to ML predictive model in Dataset T2-2015 Serving ADF

Table 6_Predictive Modelling (Random Forest) Baseline vs Predictive Accuracy Summary Table

Dataset being Analysed	Accuracy of predictive model		
	Predictive accuracy from ML Predictive model	Predictive accuracy from Baseline classification measure	Reduction in error % (unexplained variance predictive model / unexplained variance in baseline measure x 100)
Dataset T1 – 2010 (n = 1684)	86.1%	85.4%	5.1% (0.7/13.9)
Dataset T2 – 2015 (n = 2273)	81.3%	78.0%	15% (3.3/22)
Dataset T2 – 2015 Transitioned ADF (n = 1227)	87.8%	85.2%	17.5% (2.6/14.8)
Dataset T2 – 2015 Serving ADF (n=1046)	76.8%	71.9%	16.8% (4.9/29.1)

In summary, the themes of interest from the feature analysis on the cross-sectional data in both 2010 and 2015 in identifying those reporting ideations only from those reporting action (plans and / or attempts) included: active and passive suicidal ideation, lowered mood and reporting impacts on general functioning. From the additional measures included in the 2015 Transition and Wellbeing Research Programme sample, key themes emerged regarding the perceived negative impact of the individuals' ADF service on their mental health and disruptions to functioning, including ability to work and sleep disturbances. The ML predictive modelling revealed the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among current serving ADF members in 2010 were related to reporting active suicide ideation, and to a lesser degree, passive suicide ideation, symptoms negatively impacting current ability to work, and lowered mood. In 2015 the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts, related to active suicide ideation, and to a lesser extent passive suicide ideation, restlessness, sleep problems impacting quality of life, reporting that symptoms were negatively impacting current ability to work/meet responsibilities/sleep, and reporting that ADF service had negatively impacted their mental health.

Different but generally complementary themes were found in those still serving and those who had transitioned out of the full-time ADF in 2015. In the transitioned cohort, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and then to a lesser extent passive suicide ideation, that symptoms were negatively impacting ability to function (work, meet responsibilities, sleep), a belief that ADF service had negatively impacted their mental health, and feelings of worthlessness. In those still serving in 2015, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and then to a lesser extent passive suicide ideation, feeling restless and depressed, and that symptoms were negatively impacting ability to function (work, meet responsibilities).

Analysis 2: Longitudinal data

Procedure

Two datasets were used for the longitudinal analysis. The first dataset (Dataset Longitudinal 1) was created from individuals who had completed surveys in both 2010 and 2015 and had consented to their data being linked (n = 8498). This dataset was used to examine how reported suicidality changed in the cohort across the two time points (2010 and 2015). Within this cohort, 701 individuals had endorsed at least one of the suicidality items in 2010.

Results from Longitudinal Dataset 1 were plotted in a ***Sankey diagram*** (a visual representation of the flow of information between stages) to examine how self-reported suicidality changed in this population between 2010 and 2015.

The second dataset (Dataset Longitudinal 2) included all those from Dataset Longitudinal 1 who had scored positively on the passive suicide ideation item (suicide_1) in 2010 (n=625), regardless of whether they had also endorsed suicide_2. This enabled the largest group to be analysed without having to collapse passive and active suicide ideation into one group, but it is noted that some individuals will have endorsed both passive (suicide_1) and active suicide (suicide_2). Those who had not endorsed any suicidality items in 2010, as well as those who had endorsed suicide_3 and/ or suicide_4 (action items) were removed from the dataset. This dataset linked the 2010 survey data of these remaining participants to their responses to the four suicidality items in 2015, which were grouped as ideation only (positive response to suicide_1 or suicide_2) and action (positive response to suicide_3 or suicide_4, regardless of whether they had also endorsed suicide_1 or suicide_2).

The sub-group of interest from this dataset were those who had reported ideation only in 2010 (measured by endorsing suicide_1) and progressed to reporting action (with or without ideation) in 2015 (n=66).

Dataset Longitudinal 2 was analysed to answer the research question “which variables predicted moving from ideation to action across time.”

Sample composition

Table 7 provides a summary of the basic sociodemographics of the participants in the longitudinal cohort who had endorsed any suicidality item in 2021 (n=701). Of those reporting any suicidality (in 2010), the majority were male (82.7%) with an average age of 38.8 and in a relationship and living together (57.1%). They were Non-Commissioned Officers (51.9%), in the Army (45.8%), and many had served in the military for considerable periods of time (37.3% over 20 years). Their scores on the key mental health measures revealed that in 2010 and 2015 respectively the most highly endorsed suicidality item was passive suicide ideation (93%; 53%), followed by active suicide (54.2%; 38.5%), suicide planning (13%; 13.8%) and attempts

(4.4%; 2.5%). The reduction in the overall reported levels of passive and active suicidal ideation between 2010 and 2015 is notable, particularly when considering the rates within the entire 2015 population were 95.2% for passive ideation and 64.9% for active suicide (64.9%) (see Table 2).

Table 8 provides the results for this sample on key mental health measures in 2010 (the only data used in the analysis from 2015 was for the suicidality items). About one-third reported problem anger (DAR-5: 32.5%), high or very high level of posttraumatic stress symptoms (PCL-C: 17.3% and 18.6% respectively), moderate, moderately severe or severe depressive symptoms (PHQ-9: 19.1%, 11.7% and 6.6% respectively), problematic levels of alcohol consumption (AUDIT, Band 2 -30.2%, Band 3 – 5.9% and Band 4 - 4%), and about half reported high or very high levels of psychological distress (K-10: 31.5%; 20.1% respectively). Those who endorsed any suicide plans and / attempts in 2010 also reported higher levels of psychological symptoms across the measures, including problematic anger (40.6%), very high levels of posttraumatic stress symptoms (44.2%), very high psychological distress (38.5%), severe depressive symptoms (20.8%) and alcohol misuse (7.3% Band 4 on the AUDIT).

Table 7_ Sociodemographic characteristics of those from the longitudinal cohort reporting any suicidality

	Any suicide (n=701)	Suicidal ideation only (no plans/ attempts) (n=563)	Any suicide plans or attempts (n=96)
Age (M, SD)	38.8 (9.2)	38.9 (9.3)	38.1 (8.8)
18-27	86 (13.8)	68 (13.4)	12 (14.5)
28-37	191 (30.6)	160 (31.6)	20 (24.1)
38-47	221 (35.4)	167 (33)	38 (45.8)
48-57	123 (19.7)	107 (21.1)	13 (15.7)
58+	4 (0.6)	4 (0.8)	0 (0.0)
Sex			
Male	580 (82.7)	460 (81.7)	83 (86.5)
Female	121 (17.3)	103 (18.3)	13 (13.5)
Rank			
Commissioned Officers (CO)	241 (34.4)	205 (36.4)	24 (25.0)
Non-Commissioned Officer (NCO)	364 (51.9)	284 (50.4)	55 (57.3)
Other Ranks	96 (13.7)	74 (13.1)	17 (17.7)
Service within Defence			
Army	321 (45.8)	253 (44.9)	47 (49.0)
Navy	170 (24.3)	134 (23.8)	24 (25.0)
Air Force	210 (30.0)	176 (31.3)	25 (26.0)
Years served in ADF			
1 month – 3.9 years	56 (8.0)	46 (8.2)	5 (5.2)
4 - 7.9 years	100 (14.3)	82 (14.6)	16 (16.7)
8 - 11.9 years	120 (17.1)	91 (16.2)	22 (22.9)
12 - 15.9 years	94 (13.4)	79 (14.1)	10 (10.4)
16 - 19.9 years	69 (9.9)	60 (10.7)	7 (7.3)
20+ years	261 (37.3)	204 (36.3)	36 (37.5)

Relationship status			
Not in a relationship	202 (28.9)	165 (29.4)	26 (27.1)
Relationship/not living together	98 (14.0)	77 (13.7)	16 (16.7)
Relationship/living together	400 (57.1)	320 (56.9)	54 (56.3)

Table 8_ Mental health characteristics in 2010 of those reporting any suicidality in the longitudinal cohort

	Any suicide (n=701)	Suicidal ideation only (no plans/ attempts) (n=563)	Any suicide plans or attempts (n=96)
2010 Suicidality (past 12 months)			
Felt life was not worth living	652 (93.0)	563 (100.0)	89 (92.7)
Felt so low thought about committing suicide	378 (54.2)	247 (44.1)	89 (92.7)
Made a suicide plan	91 (13.0)	0 (0.0)	91 (94.8)
Attempted suicide	31 (4.4)	0 (0.0)	31 (32.6)
2015 Suicidality (past 12 months)			
Felt life was not worth living	364 (53.0)	290 (52.5)	59 (63.4)
Felt so low thought about committing suicide	265 (38.5)	194 (35.1)	55 (59.1)
Made a suicide plan	95 (13.8)	58 (10.5)	32 (35.2)
Attempted suicide	17 (2.5)	10 (1.8)	6 (6.6)
DAR-5 Anger (M, SD)	10.2 (4.6)	10.1 (4.4)	11.3 (6.0)
No problem anger	472 (67.5)	385 (68.6)	57 (59.4)
Problem anger (12+)	227 (32.5)	176 (31.4)	39 (40.6)
PCL-C PTSD (M, SD)	36.3 (14.8)	35.2 (13.7)	43.9 (19.1)
Low (17-29)	272 (39.9)	222 (40.7)	30 (31.6)
Moderate (30-39)	164 (24.1)	146 (26.8)	9 (9.5)
High (40-49)	118 (17.3)	97 (17.8)	14 (14.7)
Very High (50-85)	127 (18.6)	80 (14.7)	42 (44.2)
K10 Psychological Distress (M, SD)	22.9 (7.5)	22.7 (7.0)	25 (9.7)
Low distress (10-15)	123 (17.5)	91 (16.2)	23 (24.0)
Moderate distress (16-21)	216 (30.8)	186 (33.0)	12 (12.5)
High distress (22-29)	221 (31.5)	187 (33.2)	24 (25.0)
Very high distress (30-50)	141 (20.1)	99 (17.6)	37 (38.5)
PHQ-9 Depression (M, SD)	8.9 (6.0)	8.5 (5.5)	11.5 (8.1)
Minimal (0-4)	180 (25.7)	141 (25.1)	27 (28.1)
Mild (5-9)	258 (36.9)	222 (39.5)	18 (18.8)
Moderate (10-14)	134 (19.1)	120 (21.4)	10 (10.4)
Moderately severe (15-19)	82 (11.7)	53 (9.4)	21 (21.9)
Severe (20-27)	46 (6.6)	26 (4.6)	20 (20.8)
AUDIT Alcohol Use (M, SD)	7.6 (5.8)	7.3 (5.7)	8.5 (6.4)
Band 1 (0-7)	419 (59.9)	351 (62.6)	49 (51.0)
Band 2 (8-15)	211 (30.2)	159 (28.3)	33 (34.4)
Band 3 (16-19)	41 (5.9)	31 (5.5)	7 (7.3)
Band 4 (20-40)	28 (4.0)	20 (3.6)	7 (7.3)

Data Analysis

Results from Longitudinal Dataset 1 were plotted in a Sankey diagram to examine how self-reported suicidality changes across time in this population. Then ML approaches (Feature Selection and Random Forest) were used to identify which variables from 2010 provided important information on those who had reported ideation (either passive or active suicidal ideation) only in 2010 and had progressed to reporting action (with or without ideation) in 2015.

The Sankey diagram was conducted in R.

Feature selection analysis was conducted on Dataset Longitudinal 2 to identify which variables from T1-2010 provided important information in the group who had reported ideations only in 2010 and had progressed to reporting action (with or without ideation) in 2015. The technique utilised was feature selection, based on mutual information and was conducted in WEKA version 3. Consistent with the analysis undertaken on the cross-sectional datasets, feature selection was used to calculate the information gain of each survey item based on mutual information. During this analysis all variables were compared one-by-one, and any interactions were not taken into account. The approach was non-theoretical and individual survey items were included in the analysis.

Machine Learning predictive modelling was then undertaken to examine the power of the key features identified to accurately predict from those who reported ideation (suicide_1), those who would also report suicide planning (suicide_3) and/or suicide attempt (suicide_4) across time. Again, only passive suicide ideation (suicide_1) was used for ideation, and it acknowledged that some of this group will also have endorsed active suicide ideation. The technique used was Random Forest and was conducted in R.

Results – Analysis 2

The Sankey diagram (Figure 1) illustrates the broad movement of individuals from the Longitudinal Dataset 1 (n=8497) between 2010 and 2015. From the three key groupings of ‘no ideation in 2010’ (n=7796), passive suicide ideation in 2010’ (n=605) and ‘action (with or without ideation) in 2010’ (n=96), there were 9 possible trajectories to self-reported suicidality in 2015.

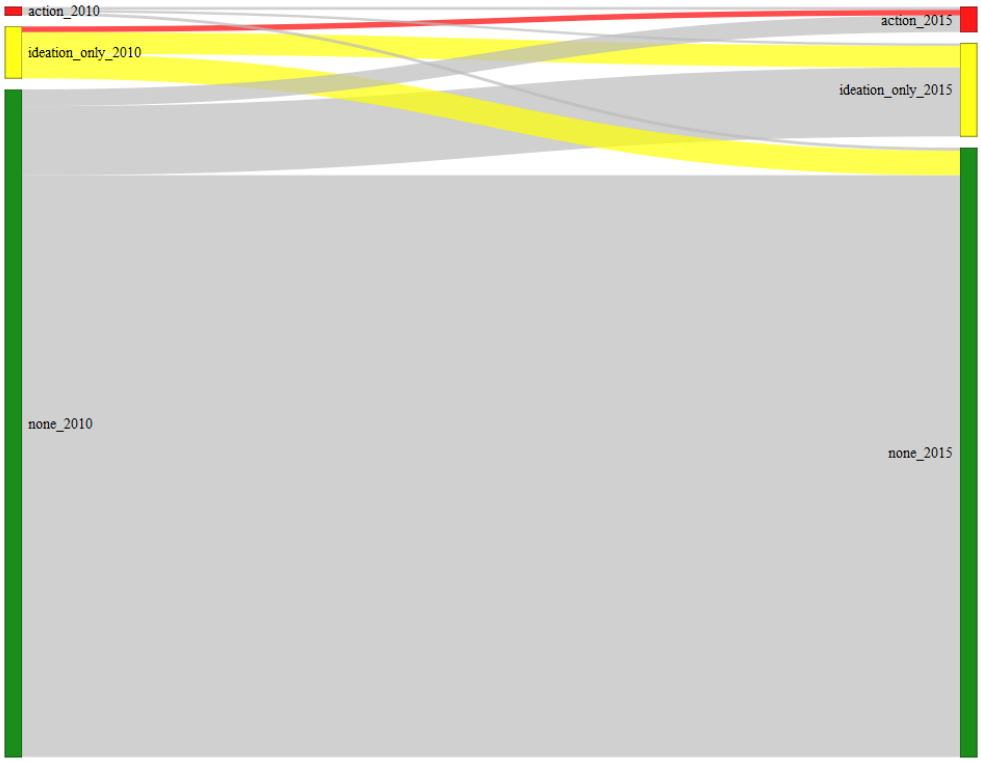


Figure 1_Sankey Diagram of trajectory of suicidality in longitudinal cohort 2010 to 2015

The diagram highlights that while the majority of people who did not report any suicidality in 2010 (n=7796), also did not in 2015 (n=6795), a sub-group would progress to reporting ideation only in 2015 (n=806), and another smaller group would progress to reporting action (with or without ideation) in 2015 (n = 195). Of those who reported ideation only in 2010, the group was relatively evenly split between those who reported no suicidality in 2015 (n=287) and those who again reported ideation in 2015 (n = 252). Sixty-six respondents who had reported ideation only in 2010 reported action (with or without ideation) in 2015.

The small group of individuals who had reported 'action' (with or without ideation) in 2010 (n= 96), moved relatively evenly into reporting no suicidality in 2015 (n=35), ideation only in 2015 (n=29) or continuing to report action in 2015 (with or without ideation) (n=32).

The group of particular interest in this study are those who reported ideation only in 2010 (measured by endorsing suicide_1) and progressed to reporting action (with or without ideation) in 2015 (represented by the red line in Figure 1, n=66).[2] Machine Learning techniques were applied to identify which survey items from T1- 2010 provided important information as to whether those reporting ideations only in 2010 would progress to reporting action (with or without ideation) or not in 2015.

[2] There is no fixed minimum number of samples required for machine learning analysis, however generally at least 50-100 samples per class or category is recommended to train a machine learning model.

Feature selection analysis

Feature selection analysis on Dataset Longitudinal 2 (n = 66) revealed that endorsing the survey item relating to lifetime traumatic exposures and specifically the type of event which was identified as the 'worst event' was the key variable to identify what will happen to the 'ideation only' group between 2010 and 2015. Lifetime exposure to traumatic events was measured in the survey by asking participants to indicate if they had ever in their lifetime experienced a range of traumatic events, including ones that relate to childhood and personal experiences, as well as to military experiences such as combat. The list of potentially traumatic events included in the T1-2010 survey was taken from the posttraumatic module of the CIDI 3.0 (Haro et al., 2006). Participants were then required to indicate which was their 'worst event' (McFarlane & Van Hooff, 2009). The events they could endorse were: Direct combat; Life-threatening accident; Fire, flood, or other natural disaster; Witness someone badly injured or killed; Rape; Sexual molestation; Serious physical attack or assault; Threatened / harassed without weapon; Threatened with weapon / held captive / kidnapped; Tortured or victim of terrorists; Domestic violence; Witness domestic violence; Finding dead body; Witness someone suicide or attempt suicide; Child abuse – physical; Child abuse – emotional; Any other stressful event; Event that happened to someone close to you.

Figure 2 provides a graphical representation of the responses to the 18 possible events the participant could endorse (one bar per item), listed in the same order as the items are listed above. The figure above each bar indicates the number of participants who endorsed this item. The red component of the bar represents the proportion who had also endorsed the suicide 'action' questions, and the blue representing the proportion of those who did not endorse the suicide 'action' questions. The figure illustrates the diversity of trauma experiences endorsed across the options, with the most highly endorsed events overall being 'Any other stressful event' (85), followed by 'Life-threatening accident' (36) and 'Witness someone badly injured or killed' (36).

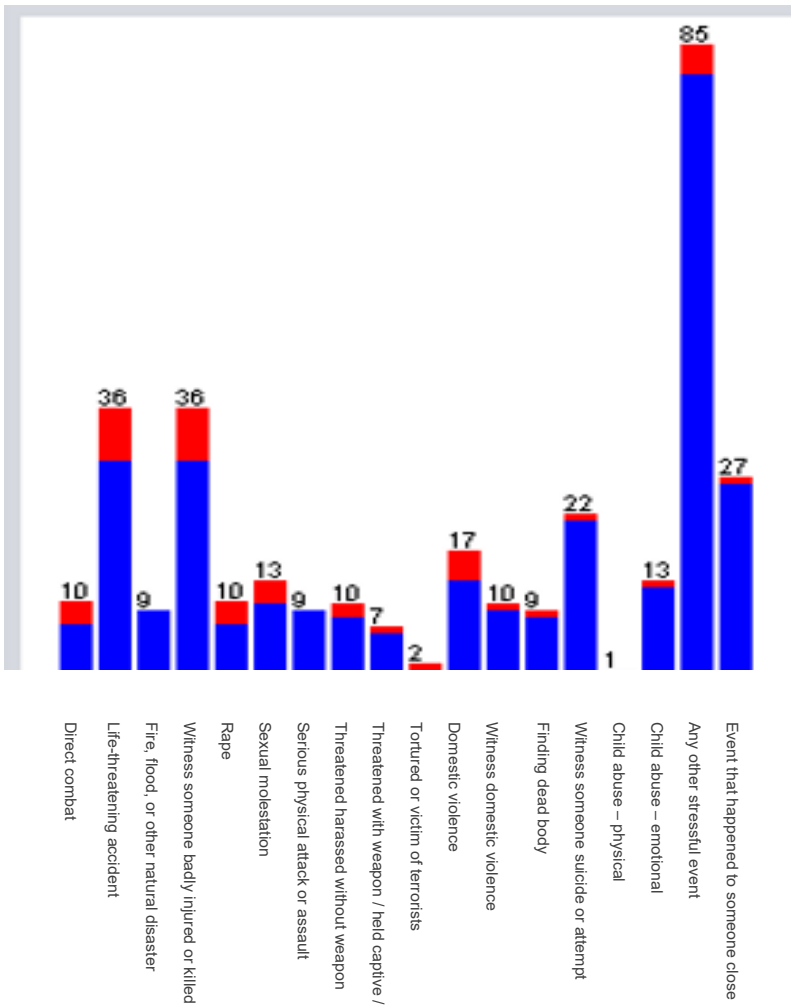


Figure 2_Feature Selection Distribution for item_ Lifetime trauma identified as the 'worst event'

* the number above each bar indicates the number of respondents who endorsed this item

** red indicates the proportion who also had endorsed the suicide 'action' questions, and blue indicates the proportion who did not endorse the suicide 'action' items

The other high-ranking variables from this analysis in identifying those who would progress from ideation only in 2010 to suicide behaviours in 2015 included: "How often do members of your workplace make you feel supported?" (from Schuster Social Support Scale) (Figure 3); "I am adequately recognised and rewarded for my work by verbal recognition" (Figure 4), "In the last four week, how often have you been bothered by trouble falling asleep or staying asleep" (from PHQ General Anxiety Scale) (Figure 5); and "Please rate your current (i.e., last 2 weeks) sleeping pattern: difficulty falling asleep" (from Insomnia: Sleep Index) (Figure 6).

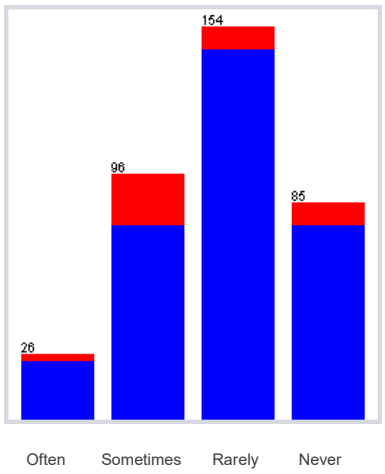


Figure 3_Feature Selection Distribution for item_ How often do members of your workplace make you feel supported

* * the number above each bar indicates the number of respondents who endorsed this item
** red indicates the proportion who also had endorsed the suicide 'action' questions, and blue indicates the proportion who did not endorse the suicide 'action' items

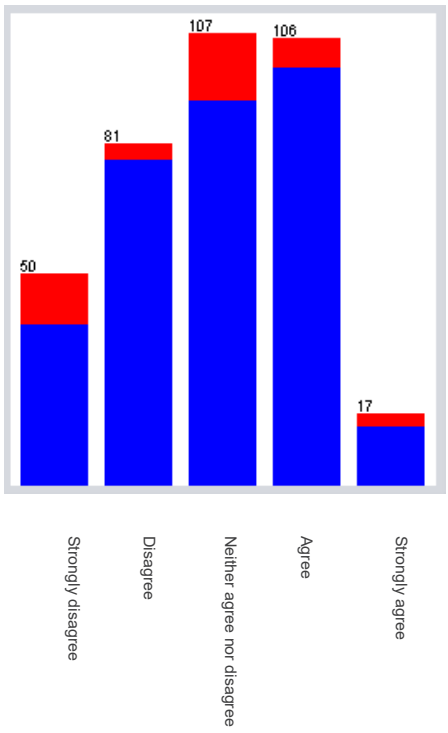


Figure 4_Feature Selection Distribution for item_ Adequately recognised and rewarded for work by verbal recognition

* the number above each bar indicates the number of respondents who endorsed this item
** red indicates the proportion who also had endorsed the suicide 'action' questions, and blue indicates the proportion who did not endorse the suicide 'action' items

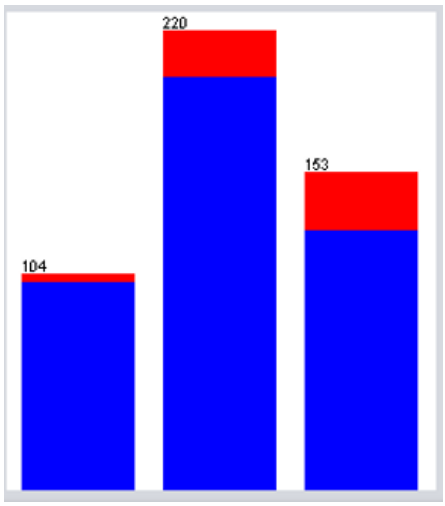


Figure 5_Feature Selection Distribution Table_ Trouble falling asleep or staying asleep

* the number above each bar indicates the number of respondents who endorsed this item
** red indicates the proportion who also had endorsed the suicide 'action' questions, and blue indicates the proportion who did not endorse the suicide 'action' items

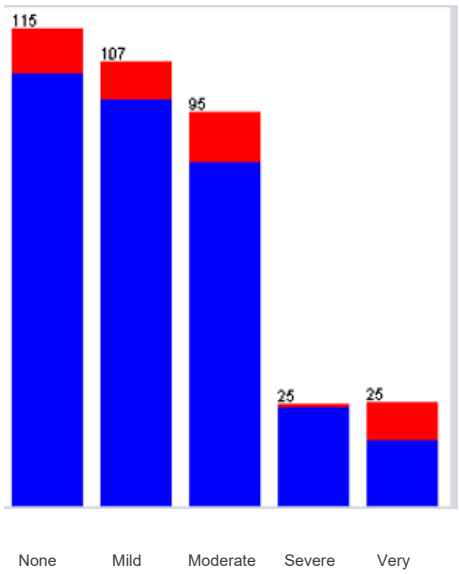


Figure 6_Feature Selection Distribution Table_ Sleep Index – difficulty falling asleep

* the number above each bar indicates the number of respondents who endorsed this item
** red indicates the proportion who also had endorsed the suicide 'action' questions, and blue indicates the proportion who did not endorse the suicide 'action' items

Predictive modelling

Predictive modelling (Random Forest) was attempted to examine the power of these features to accurately predict from those who reported ideation in 2010, those who would report suicide planning and or suicide attempt (with or without ideation) in 2015. However, the results did not improve prediction beyond the baseline classification measure (random chance). It is possible that the dataset size (n= 66) was insufficient, or that there was too much variance in the longitudinal results to generate predictive results. Furthermore, in the longitudinal analysis, only the 2010 survey items were analysed, and the cross-sectional analysis had illustrated that there were items which contributed to prediction which were only included in the 2015 survey.

In summary, when examining the longitudinal data, endorsing an event experienced during their lifetime as the 'worst traumatic event experienced' was the key variable to identify those who would progress from ideation only to suicide behaviour across the two time points. Other variables of interest related to sleep behaviour and how well they felt supported or recognised/rewarded at work. Due to the small sample size, and the inability to generate a predictive model from these features, the findings on the longitudinal data should be interpreted with caution. However, the results still provide an indication that trauma exposure, perceived lack of support or recognition in the workplace and sleeping problems should be considered as areas of interest for this population when identifying risk over time for increasing suicidality.

Analysis 3 – Validation of Machine Learning techniques

Data Analysis

Step-wise logistical regressions (forward, left to right) were undertaken on the 18 top-ranking selected features from Dataset T1-2010 and Dataset T2-2015 (removing suicide_3 and suicide_4) identified in Analysis 1. This was to determine how much variance each of these items accounted for and to identify items of significance using more traditional statistical methods. This provided a point of comparison for assessing the utility of ML techniques for predictive modelling for these types of research questions, which was the secondary aim of this exploratory research.

Step-wise logistical regressions are used to identify the most important independent variables to predict a binary outcome. Variables are systematically selected or removed from a logistical regression model based on their statistical significance. In forward stepwise logistical regressions the model initially contains no independent variables and systematically adds variables to the model until the final model is achieved.

At each step of the logistical regression, variables were chosen based on their p-values with a p-value threshold of < 0.05. Due to differences in how missing data was managed between the two statistical techniques, the sample size for the logistical regressions was considerably smaller than for the ML analysis.

Step-wise logistical regressions were completed using SPSS version 28.

Results – Analysis 3

From the T1-2010 dataset the forward step-wise logistic regression model reduced the 18 items to three themes of interest: active suicidal ideation (suicide_2), avoiding reminders of a past stressful experience (pcl_7), and loss of interest in activities that they used to enjoy (pcl_9) (Table 9). From the T2-2015 dataset the forward step-wise logistic regression model reduced the 18 items to three items of interest: active suicide ideation (suicide_2 and phq_9) and sleeping problems ("how noticeable to others do you think your sleeping problem is in terms of impairing the quality of life?") (Table 10).

The model created from the 2010 dataset (n=585) accurately predicted cases within the dataset in 87% (unexplained variance of 0.5%) of cases (baseline of 86.5% with unexplained variance of 13.5%), representing a reduction in error of prediction of 3.7% (0.5/13.5) (Table 11). The model created from the 2015 dataset (n=495) accurately predicted cases within the dataset in 77.4% (unexplained variance of 3.1%) of cases (baseline of 74.3% with unexplained variance of 22.6%), representing a reduction in error of prediction of 13.7% (3.1/22.6) (Table 12).

Table 9_Results of forward step-wise logistical regressions on top variables from ML predictive modelling T1-2010

				95% CI for Odds Ratio		
	Variables included	*B*	SE	Lower	Odds Ratio	Upper
Step 1	Suicide_2	2.442*	0.406	5.187	11.491	25.455
	Constant	-3.641	0.383		0.026	
Step 2	Suicide_2	2.353*	0.410	4.705	10.513	23.492
	pcl_7	0.490*	0.098	1.347	1.633	1.979
	Constant	-4.698	0.460		0.009	
Step 3	Suicide_2	2.280*	0.412	4.361	9.774	21.905
	pcl_7	0.323*	0.114	1.106	1.382	1.727
	Pcl_9	0.322*	0.115	1.100	1.379	1.729
	Constant	-5.129	0.493		0.006	

*P < .05

Table 10_Results of forward step-wise logistical regressions on top variables from ML predictive modelling T1-2015

					95% CI for Odds Ratio	
	Variables included	*B*	SE	Lower	Odds Ratio	Upper
Step 1	Suicide_2	2.843*	0.468	6.856	17.17	43.002
	Constant	-3.414	0.455		0.033	
Step 2	Suicide_2	2.703*	0.471	5.925	14.929	37.615
	Sleep_index_6	0.426*	0.099	1.262	1.531	1.857
	Constant	-4.145	0.498		0.16	
Step 3	Suicide_2	2.469*	0.478	4.623	11.807	30.153
	Phq_9	0.342*	0.119	1.115	1.407	1.777
	Sleep_index_6	0.341*	0.103	1.150	1.407	1.721
	Constant	-4.128	0.497		0.16	

*P < .05

Table 11_Classification Table_Forward step-wise logistical regressions on T1-2010 data

			Predicted		
			SU		Percentage
	Observed		.00	1.00	Correct
Step 1	SU	.00	506	0	100.0
		1.00	79	0	.0
	Overall Percentage				86.5
Step 2	SU	.00	497	9	98.2
		1.00	70	9	11.4
	Overall Percentage				86.5
Step 3	SU	.00	497	9	98.2
		1.00	67	12	15.2
	Overall Percentage				87.0

The cut value is .500

Table 12_Classification Table_Forward step-wise logistical regressions on T2-2015 data

			Predicted		
			SU		Percentage
	Observed		.00	1.00	Correct
Step 1	SU	.00	368	0	100.0
		1.00	127	0	.0
	Overall Percentage				74.3
Step 2	SU	.00	356	12	96.7
		1.00	101	26	20.5
	Overall Percentage				77.2
Step 3	SU	.00	340	28	92.4
		1.00	84	43	33.9
	Overall Percentage				77.4

The cut value is .500

Therefore, the themes of interest identified through the step-wise logistical regressions were largely consistent with those identified through the ML techniques. Although the techniques are not directly comparable, with the ML techniques assessing validation accuracy (the ability of the model to predict cases in a previously unseen component of the dataset) and the step-wise logistical regressions assessing the ability to accurately predict cases from the known dataset (training accuracy), arguably the ML approaches performed better than the logistical regressions. Particularly when taking into consideration that the ML approaches were building the predictive models from previously 'unseen data' (the 20% of the dataset used to test the model). When analysing the 2015 data, the ML techniques were able to correctly predict those who would progress from suicide ideation only to suicide-related behaviours in more cases than the logistical regressions (ML model predictive accuracy of 81.3% (see Table 6) versus logistical regression predictive accuracy of 77.4% (see Table 12)). When analysing the 2010 dataset, the ML techniques were able to correctly predict those who would progress from suicide ideation only to suicide-related behaviours at least as well as the logistical regressions (ML model predictive accuracy of 86.1% (see Table 6) versus logistical regression predictive accuracy of 86.1% (see Table 11)) .

Discussion

To our knowledge, this study is the first to apply ML techniques to examine predictors of the progression from suicidal ideation to action in an Australian military cohort and demonstrates the potential value of ML in developing predictive, data-driven models to identify those at increased suicide risk within Australian military and veteran populations.

The primary aim of this exploratory study was to use ML techniques (feature analysis) to identify which variables (survey items) best distinguished those who reported suicidal ideation only versus those who reported action (planning and or attempts), with or without ideation at a given point in time and across time. Predictive modelling ML techniques (Random Forest) were then applied to assess which of the identified variables were most important in accurately predicting cases (those at risk of progressing from ideation to behaviours) in previously unseen components of the dataset.

In the cross-sectional analyses undertaken, the key themes most strongly associated with contemporary serving and transitioned ADF members reporting suicide-related behaviours in both 2010 and 2015 were a mixture of active and passive suicidal ideation, lowered mood and reporting impacts on general functioning. Amongst the additional measures included in the 2015 Transition and Wellbeing Research Programme sample, key themes emerged regarding the perceived negative impact of the individuals' ADF service on their mental health, and disruptions to functioning, including ability to work and sleep disturbances. The ML predictive modelling revealed the variables which are the strongest differentiators of those who ideate only versus those who make plans or attempts among current serving ADF members in 2010 were related to reporting active suicide ideation, and to a lesser degree, passive suicide ideation, symptoms negatively impacting current ability to work, and lowered mood. In 2015, the variables which are the strongest

differentiators of those who ideate only versus those who make plans or attempts, related to active suicide ideation, and to a lesser extent passive suicide ideation, restlessness, sleep problems impacting quality of life, reporting that symptoms were negatively impacting current ability to work/meet responsibilities/sleep, and reporting that ADF service had negatively impacted their mental health.

There were different but generally complementary themes found in those still serving in 2015 and those who had transitioned out of full-time ADF service in 2015. In the transitioned cohort, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and then to a lesser extent passive suicide ideation, reporting that symptoms were negatively impacting ability to function (work, meet responsibilities, sleep), a belief that ADF service had negatively impacted their mental health, and feelings of worthlessness. In those still serving in 2015, the variables making the highest contribution to suicide-related behaviours were active suicide ideation, and then to a lesser extent feeling restless and depressed, and reporting that symptoms were negatively impacting ability to function (work, meet responsibilities).

The longitudinal analysis highlighted the diverse trajectories across time in self-reported suicidality, including shifts into no longer reporting any suicidality, as well as progression from reporting ideation only into reporting suicide-related behaviours. This is consistent with other research findings of the diverse nature of suicidal ideation, which may remain stable, intensify, remit over time, or fluctuate as stressors change (Baca-Garcia et al., 2011). This reinforces the importance of ongoing monitoring for changes in suicidality across time, including following transition out of full-time service. In the sub-group of interest in this analysis (those who had reported ideation only in 2010 and progressed to reporting suicide-related behaviours in 2015, with or without ideation), endorsement of having experienced a lifetime trauma ‘worst event’ was most strongly associated with the progression from ideation only to suicide-related behaviours over time. The variables of sleep behaviour and how well one felt supported or recognised/rewarded in the workplace also contributed to progression from ideation only to suicide-related behaviours, which are complementary with the themes identified in the ML analysis on the cross-sectional data. As the size of this group was small and a predictive model could not be generated using ML approaches from the identified features, the findings from the longitudinal data should be interpreted with caution. There are various reasons which may have contributed to the inability to generate a predictive model, including the small sample (n=66). However, the identified factors are still considered to be meaningful, and trauma exposure, perceived lack of support or recognition in the workplace and sleeping problems should be considered as areas of interest for this population when identifying risk over time for increasing suicidality.

A secondary aim of the study was to assess how well the ML techniques performed in building predictive models from the available data, compared to more traditional statistical methods. The themes of interest from the logistical regressions – active suicidal ideation, avoidance of reminders of a past stressful experience, and impact on sleep – were largely complementary with the themes identified from the ML analysis. This provides general confidence that both statistical approaches provide valuable information in addressing the research questions. However, overall, the ML techniques appeared to outperform the logistical regression results (noting the potential impact of the different sample sizes) and performed at least

as well on the 2010 dataset and more strongly on the 2015 dataset than the logistical regressions in predicting those who would progress from suicide ideation only to suicide-related behaviours while using previously 'unseen' data (the 20% 'test' data). This demonstrates the potential value of incorporating ML approaches into studies examining these types of research questions, particularly as it enables atheoretical approaches to discovering potential themes of interest in large, multi-domain datasets.

Although the findings from the cross-sectional and longitudinal analyses are exploratory, there are consistencies with other research findings and theories relating to those at increased risk of progressing from ideation to action in military and veteran populations. Themes of particular interest are active suicide ideation, mental health symptoms (particularly lowered mood), trauma exposure, beliefs about the negative impact of ADF service on mental health, and disturbances in functioning.

Active suicide ideation

Reporting active suicidal ideation had a direct association with the progression from reporting suicide ideation only to also reporting suicide-related behaviours amongst both current serving and transitioned ADF personnel. Research has indicated higher rates of suicidal ideation in military populations than in community samples, including in serving and transitioned ADF personnel (Van Hooff et al., 2018), the Canadian Armed Forces (Sareen et al., 2016) and ex-serving members (VanTil et al., 2018). Notably, a US study which applied ML techniques to assess risk factors for the transition from suicide ideation to suicide attempt within the Army STARRS dataset, similarly found that the most powerful predictors were related to suicidal ideations, including recent onset of ideation, low controllability of suicidal thoughts, and presence and recent onset of a suicide plan (Nock et al., 2018). Recent analysis of available data on ADF males who had suicided reported nearly 3 in 10 (29%) had previously identified as having suicidal ideation (AIHW, 2022).

As suicidal behaviour is on a continuum, it is expected that suicidal ideation would be a predictor of those who are at higher risk of plans or attempts. Other researchers have noted the utility of being able to separately examine the impact of passive versus active ideation on other suicide-related behaviours (Kimbrel et al., 2015). In this study, the active ideation question that asked more directly about suicide ('felt so low thought about committing suicide') was a stronger predictor than the less direct or passive ideation question ('felt that your life was not worth living'). Other researchers have proposed that suicide ideation alone may not be a key predictor of future suicide attempt, but rather that identification of 'worst-point suicidal ideation' – the individual's most intense instance of suicide ideation – is more predictive of future suicide attempt (Rozek et al., 2020; Nock et al., 2018). Arguably in this study, the second suicide ideation (have you ever felt so low that you thought about committing suicide?) item is a closer approximation to a more intense experience of ideation (referred to as active ideation), accounting for its key role in the predictive model, above that of the other suicide ideation item (the passive suicide item). Notably, a recent systematic review and meta-analysis of the relationship between passive and active suicidal ideation concluded that both are clinically significant and associated with risk, and passive ideation should still be considered in research and clinical contexts (Liu et al., 2020).

The results highlight that consideration should be given to routinely including items assessing not only suicide ideation, but both passive and active suicide ideation in screening for military populations, including for those who have transitioned out of full-time service. Reporting active suicide ideation should be considered an indication of a higher level of risk of the individual progressing to suicide-related behaviours, even if they are not currently reporting suicide-related plans or attempts.

Mental health symptoms

Arguably the most studied (O'Connor & Nock, 2014) and strongest established risk factor for completed suicides and suicidality is the presence of a mental disorder (Joiner et al., 2005), and this is consistent across genders and age groups (Cavanagh et al., 2003), as well as within military populations (Nock et al., 2014). In the current study, the mental health characteristics of the participants in both the cross-sectional and logistical datasets, who had endorsed at least one suicidality item, indicated that at least a third were also experiencing medium to high levels of mental health symptoms at the time the survey was conducted. Notably, about half of those who had endorsed the suicide planning and / or suicide attempt items were experiencing high to severe levels of mental health symptoms. Further, the ML analysis on the cross-sectional data indicated that reporting mental health symptoms, and particularly lowered mood (e.g., reporting including feeling depressed, worthless and / or restless) were factors of interest in predicting who would progress from suicide ideation only to suicide behaviours.

This is consistent with other research findings derived from these ADF datasets which highlight the link between mental health symptoms and suicidality. Previous analysis of the 2010 ADF data reported that the rate of psychiatric disorder in ADF personnel who attempt suicide was 90%, when assessed using a structured diagnostic interview (Van Hooff et al., 2013). Similarly, previous analysis of the ADF 2015 data indicated that as the severity of self-reported mental health symptoms increased, so did the level of risk for suicidality in both the current serving and transitioned ADF populations (Sadler et al., 2021; Bryant et al., 2018). Analysis of the longitudinal dataset revealed that endorsing any item on the suicide scale (12-month any suicidality) in 2010 also predicted a shift from no disorder (defined as below screening cut-off on the K-10 and the PCL-C in 2010) to 30-day probable mental disorder (above the epidemiological cut-off on either the K-10 or PCL-C) in 2015.

Analysis of data from ADF members who had died by suicide between 1997 and 2020, also highlights the role of mental health, with almost half (49%) of all ADF males who died by suicide and 66% of all ADF females who died by suicide identified as having mood (affective) disorders (AIHW, 2022). Similar findings have been reported internationally with a US psychological autopsy study of Army soldiers who had died by suicide in the past decade (Nock et al., 2017) reporting almost 80% had a prior mental disorder; further, the presence of an internalising disorder, such as depression, and comorbidity of mental disorders showed promise for differentiating between suicidal ideators and suicide completers. Similarly, a systematic review of 52 studies assessing suicide risk in US veterans found depression to be more strongly associated with

increased risk of suicide ideation, suicide attempts, and death by suicide than other comorbid psychiatric disorders (Athey & Overholser, 2018).

These results highlight the importance of undertaking suicide risk screening with those reporting or exhibiting mental health symptoms, including those still serving or who have transitioned out of military service. Accurate diagnosis and the provision of effective treatments for those with psychiatric disorders, as well as those reporting sub-syndromal symptoms, are also critical components of suicide prevention in this population.

Trauma exposure

There were also indications within this study of the potential predictive role of trauma exposure in the progression from ideation to suicide-related behaviours. This is consistent with previous analysis undertaken on the ADF 2010 dataset which revealed a link between 12-month mental disorder and suicidal thoughts, plans and attempts, with the risk for experiencing suicidality increasing if there were co-morbid mental conditions, particularly in those also reporting a lifetime history of interpersonal trauma (Van Hooff et al., 2013). Another Australian study which analysed the ADF 2015 data, revealed that 12-month suicidality was associated with childhood anxiety and childhood interpersonal trauma (Sheriff et al., 2019). Other research also suggests that posttraumatic stress symptomatology is a core predictor of suicidality. One study of Australian ex-serving members suggests that suicide attempt risk escalates by 2% for every point increase in PTSD symptom severity scores on the Clinician-Administered PTSD Scale for Diagnostic and Statistical Manual of Mental Disorders (CAPS-IV; Kerr et al., 2018). This is supported by findings from the US active military population which found that Army members who died by suicide were 13 times more likely to have a PTSD diagnosis than the rest of the Army population (Hyman et al., 2012).

Collectively these findings support the idea that co-morbid mental health conditions, particularly depressive and trauma-related disorders, are important risk factors to consider in the progression from ideation only to suicide-related behaviours in this population.

Mental health impacts of military service and on domains of functioning

This current exploratory study also lends support to previous research highlighting that it is not merely the presence of mental health conditions that constitutes a risk factor for suicidality, but also the impact of mental health conditions on the individuals' perceived ability to function in professional and/ or social environments. Perceived impairment from symptoms is an indication of the severity of the reported symptoms. Amongst current-serving and transitioned ADF members, the individuals' beliefs that the ADF had negatively impacted their mental health and that their mental health symptoms were negatively impacting their functioning, contributed to predicting progression to suicide-related behaviours.

This aligns with previous research which has demonstrated that inability to function adequately in core life domains – either in the occupational role during military service, or in other social and life domains post-service – is associated with greater risk of suicidality. Impairments in physical functioning resulting from

military service constitute one form of functionality-related risk factor, with evidence suggesting that chronic pain and physical disability may predict higher rates of suicidal ideation and attempts in military populations (Blakey et al., 2018; Legarreta et al., 2018; Andoulakis et al., 2021; Nichter et al., 2021).

Disturbances in sleep have been linked to increased risk of suicidal thoughts and behaviours (Liu et al., 2020) including in military samples (e.g., McCarthy et al., 2022; McCarthy et al., 2019). Additionally, the mental health impacts of not being able to adequately function in the occupational role and the consequent financial outcomes are well documented in military populations. Previous analysis of the ADF 2015 data exploring psychosocial factors associated with psychological distress and functional difficulties reported that the odds of belonging to the highly distressed/impaired group were greatest among those reporting insomnia (OR 18.53) (Hansen et al., 2020). Another Australian research study (Kerr et al., 2017) of 229 ex-service personnel from a PTSD outpatient program linked a history of suicide attempt with PTSD, psychopathology severity, unemployment, and a permanent incapacity to work. Similarly, another study found that veterans with comorbid PTSD and alcohol use disorders exhibited higher suicide risk and poor psychosocial functioning across vocational, interpersonal and daily living domains (Blakey et al., 2022).

Further, an analysis of electronic health record data of 293,872 US veterans indicated that rates of suicidal ideation and attempts were greater amongst veterans experiencing adverse social determinants of health relating to social and occupational functioning, such as employment issues (with 9.9% reporting suicidal ideation and 1.0% reporting suicide attempts), and social and familial problems (8.1% and 1.1% respectively; Blosnich et al., 2019). Consequent financial strain as a result of occupational difficulties may also form a close indication of risk for suicidality, with evidence from a study of US National Guard personnel suggesting that rates of financial strain and recent loss of income are nearly twice as high in those experiencing suicidality relative to those with no history of suicidality (Bryan & Bryan, 2019). This collectively supports the proposal that impairments in functioning in occupational and other life domains, emerging both during or post-military service, can be significant contributors to suicidality in military members.

In this study, general negativity towards the impact of their ADF service on mental health and not feeling well supported or recognised in the workplace, emerged as potentially important in predicting progression to suicide-related behaviours. Although the exact nature of the negativity towards the ADF cannot be derived from the available data, one area for future investigation is exposure to potentially morally injurious events. Moral injury refers to the enduring psychosocial, spiritual, and ethical harms that may result from exposure to high-stakes events that are starkly incongruent with individual moral beliefs. It is an emerging concept, but available research in military populations indicates associations with mental disorders and suicidality (Nichter et al., 2021), and even low-level moral distress can impact performance and organisational commitment (Phelps et al., 2022).

In relation to not feeling well supported in the workplace, a longitudinal examination of mental health outcomes in early career ADF members found that negative social interactions and perceived lack of social support from ADF peers and superiors was a key predictor of worsening psychological distress and

posttraumatic stress symptoms over time (Dell et al., 2022). Higher levels of feeling well supported and connected within the military unit may reflect a protective factor against the mental health impacts of service-related and other psychosocial stressors; and conversely, low levels of these factors may constitute a vulnerability (Jones et al., 2019; Dell et al., 2022). This may therefore represent a factor amenable to intervention which could be targeted by programs aiming to increase team cohesion amongst current-serving members, or by increasing efforts to facilitate connection and community amongst ex-serving members. Further, exploration of attitudes towards the perceived role of ADF service on mental health symptoms, as well as disturbances in functioning may be useful in clinical setting when assessing for suicide risk in this population, including following transition out of full-time service.

Application of findings and way forward

Suicide risk is dynamic and multifactorial, making it difficult to predict who will or will not attempt suicide. As identification and appropriate intervention remain important goals for clinicians and organisations such as the military, the identification of any themes or factors which may guide assessment and decision-making is of interest and value.

Over recent years ML techniques have been increasingly used in an attempt to enhance prediction and classification models for suicide-outcomes. These techniques have the advantage of being able to analyse complex relations between independent variables and outcomes in a data-driven way, including in large datasets. However, there is continued debate as to whether these more complex modelling techniques are sufficiently superior to simpler models of analysis that are easier to conduct, interpret and apply findings to clinical settings (Littlefield et al., 2021; Cox et al., 2020). Some researchers have instead proposed the potential benefits of amalgamating theory and data driven approaches (Cox et al., 2020), with ML viewed as a tool to complement, not replace, clinical judgement (Kirtley, 2022). Despite the limitations of ML techniques, this study demonstrates the potential value of ML to assist in creating predictive data-driven models that are relevant to the target population and that may be useful in identifying those at increased risk, potentially supplementing clinical decision making.

While it could be argued that no new or unexpected factors were derived from the ML analysis, the findings highlight themes or areas for examination that may not be routinely considered or included in assessments for escalating suicide risk but appear to be relevant for this population. The datasets analysed contained information across a range of domains, providing information on psychosocial variables (psychological and social aspects of human behaviour, e.g., social support, coping strategies, experiences of stressors), symptomatic (experience of a particular condition or disease e.g., duration, severity, triggers), and phenomenological (e.g., how the individual perceives and interacts with the world around them) information. As ML takes an atheoretical approach to data analysis, it independently weighs each piece of information on its ability to answer the research question, enabling the most important information from across the datasets to be identified. The results demonstrate that important information regarding escalating suicide risks is

derived across these categories – and that identification of people of increased risk requires consideration of multiple factors through a thorough clinical assessment.

The findings from this study provide information on which items may be useful for inclusion in ADF and veteran screening protocols, including items that have already been used in this population for screening or research purposes, or ones that could be easily inserted or modified for inclusion. This includes items directly related to suicidality, and in particular active suicide ideation, as well sleep disturbances and other indicators of disturbance of ability to function adequately in work, social and personal domains. These additional questions or themes could supplement current screening and provide additional information to clinicians on who may benefit from additional assessment, even though they may not be actively disclosing suicidality. Findings also highlight that for military personnel, including those who have transitioned out of full-time military service, it is important to consider not only current suicidal ideation and mental health status, but also the perceived role of ADF service in negatively impacting their mental health and ability to function and meet responsibilities.

The clinical reliability of applying the findings of ML techniques remains tempered given that the low prevalence of suicidal ideation, plans and attempts poses significant challenges for prediction in ML analysis. This means there are only a small number of cases from which the model can learn, and that the data is likely to be unbalanced so that the positive predictive value will always be low (as it is for structured clinical judgement; Whiting et al., 2019). However, this low positive predictive power does not mean that the model is devoid of practical value. For example, the benefits of identifying one person as being at higher risk of suicide, arguably outweighs the negligible costs of implementing an additional or modified screening or assessment protocol to an individual who was falsely identified by the model as being at high-risk. This principle is similarly employed in clinical setting examples where intervention is routinely incorporated despite low positive prediction values, such as primary prevention of breast cancer and stroke, because the relative benefits of intervention are still favourable (Kirtley, 2022).

Clinicians, and others who may interact with potentially suicidal military members and veterans need some guidance for markers of increased risk, even if they are inexact, particularly in a climate where health care needs can exceed available resources. Further, there is a small but significant group of people at risk of suicide who do not interact with the medical system (Tucker et al., 2018; Ursano et al., 2018), but there are others, including military leaders and those in administrative and judiciary roles, who may be able to play an important part in identifying these people and being a pathway to care. The factors that may be of relevance to a range of health and allied health service providers, both within and external to the military, as well those in military leadership, administrative or judiciary roles or providers of services to ex-serving members, could include guidance in identifying those individuals who may benefit from a more thorough suicide risk assessment (including those reporting or exhibiting active ideation, lowered mood, disturbances in functioning, as well as negative perceptions about the impact of military service on their mental health and functioning). Alongside the delivery of evidence-based treatments for any mental health conditions, additional areas clinicians could consider targeting include therapeutic interventions to address the impact of

negative beliefs surrounding military service on mental health and wellbeing, and the development of safety plans for those who are reporting active suicide ideation (Chu et al., 2020), and ensuring the impact of significant lifetime traumas are explored.

The finding that items not directly inquiring about suicide can provide insight into increased risk for suicide related behaviours is also notable. A proportion of those who die by suicide deny having suicidal ideation, and therefore, alternative approaches or screening questions for identifying those at risk is also of great interest. A Canadian study of military and police veterans utilized ML analysis to detect self-harm and suicidal ideation in self-report questionnaire variables, where ten items, none of which asked about suicide, were identified as predicting self-harm and ideation with an accuracy of over 75% (Colic et al., 2022). As such, the findings of the present study also support the idea that suicide risk assessments should not focus purely on direct suicidality questions – this is particularly relevant for current serving members, who may be concerned about the potential implications for their career if they disclose suicidal thoughts or behaviours. While it was beyond the scope of this paper, it is possible that having negative perceptions about the role of the military in impacting their mental health and functioning may also impact help seeking either within military health services or with services designed for ex-serving ADF members.

Limitations

In addition to the limitations of ML techniques outlined earlier, there are other limitations of this study. The samples used in this exploratory study are the largest currently available on this population, however the numbers of those reporting suicidality are relatively small, and in particular, suicide attempts are a relatively rare event. Therefore, results should be interpreted with some caution. Due to some differences in measures used across the two study datasets utilised in this project, models were estimated separately for each of the samples. The lack of ability to validate results on an independent sample may restrict the generalisability of the results. The way the suicide ideation items were analysed may have also impacted the results, with endorsement of the passive suicide ideation item used to create the ‘ideation only’ group, without also removing those who had endorsed active suicide ideation. Although this would have severely reduced the sample size, it is acknowledged that it could have impacted results, particularly given the key role of active suicide ideation in increasing the risk of progressing to suicide-related behaviours.

Another limitation is that the data collected was in the context of a larger scale self-report survey administered by a research group external to either the Departments of Defence or Veterans’ Affairs. It is unknown if serving or ex-serving ADF personnel would disclose suicidality or related factors in the same way in identifiable settings, such as in mental health screening or clinical settings. It should also be noted that the risk factors identified within the present study are limited to measures and constructs collected as part of the 2010 ADF Mental Health Prevalence and Wellbeing Study and the 2015 Transition and Wellbeing Research Programme, and other empirical and theoretical literature identifies additional factors which potentially contribute to suicide risk that were not included in this research.

The overall response rate to the Transition and Wellbeing Research Programme was low, particularly for the transitioned cohort. The overall response rate was 18 percent and responders were more likely than non-responders to be female, Officers or Non-Commissioned Officers and Air Force members (Van Hooff et al., 2018). In this current study – which only analysed those who reported any suicidality – the sample tended to be male, older, members of the Army and Non-Commissioned Officers who had served in the military for many years, and the variables identified as relevant predictors of suicide ideation and behaviours may not be representative of the broader cohort of contemporary current serving and transitioned ADF members. Finally, it is possible that some of the highest risk individuals in 2010 may have completed suicide prior to 2015.

Conclusion

Suicide risk is dynamic and multifactorial, making it difficult to predict who will or will not attempt suicide. As identification and appropriate intervention remain important goals for clinicians and organisations such as the military, the identification of any themes or factors which may guide assessment and decision-making is of interest and value.

To our knowledge, this study is the first to apply ML techniques to examine predictors of the progression from suicidal ideation to action in a contemporary Australian military cohort. It demonstrates the potential value of ML in developing predictive, data-driven models to identify those at increased suicide risk within this population, particularly in large multi-domain datasets. Although the findings are exploratory, there are consistencies with other research findings and theories relating to those at increased risk of progressing from ideation to action in military and veteran populations, indicating potential opportunities to supplement clinical decision making and to enhance current programs and services for serving and ex-serving ADF members, as well as opportunities for further research. Themes of particular interest are active suicide ideation, mental health symptoms (particularly lowered mood), trauma exposure, beliefs about the negative impact of ADF service on mental health, and disturbances in functioning.

While it could be argued that no new or unexpected factors were derived from the ML analysis, the findings highlight themes or areas for examination that may not be routinely considered or included in assessments for escalating suicide risk but appear to be relevant for this population. The datasets analysed contained information across a range of domains (psychological and social, symptoms of mental and physical disorders and disease, as well as phenomenological - how the individual perceives and interacts with the world around them). As ML takes an atheoretical approach to data analysis, it independently weighs each piece of information on its ability to answer the research question. The results demonstrate that important information regarding escalating suicide risks is derived across these categories, and that identification of people with increased risk requires consideration of multiple factors, for example through the conduct of a thorough clinical assessment. These assessments may be conducted by a range of health and allied health service providers, both within and external to the military. The results also indicate other areas that could be targeted

in services and supports for serving and transitioned ADF members, including by those in military leadership, administrative or judiciary roles or by providers of services to ex-serving members.

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Annex A - Demographic and background measures included in T1-2010 and T2-2015 surveys

Table A.1_Demographic and background measures included in T1-2010 and T2-2015 surveys

T1-2010 study: 2010 ADF Mental Health and Wellbeing Prevalence Study (McFarlane et al., 2011)		T2-2015 study: 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018).	
Construct	**Response options, reference(s)**	**Construct**	**Response options, reference(s)**
Gender	Male, female	Gender	Male, female
Age	Date of birth	Age	18-27, 28-37, 38-47, 48-57, 58+
Highest Education level	Primary school, secondary school, certificate, diploma, bachelor degree, post -graduate qualifications	Highest Education level	Primary school, secondary school, certificate, diploma, bachelor degree, post -graduate qualifications
Service	Navy, Army, Air Force	Service	Navy, Army, Air Force
Rank	Other Rank, Junior Non-Commissioned Officer, Senior Non-Commissioned Officer, Commissioned Officer, Senior Commissioned Officer	Rank	Other Rank, Junior Non-Commissioned Officer, Senior Non-Commissioned Officer, Commissioned Officer, Senior Commissioned Officer
		Military specialty/role	Navy – primary qualification, category, ship type (if serving at sea); Army – Corps, Employment Category Number; Air Force – specialisation/mustering (Australian Bureau of Statistics (ABS, 2008); 2011 Australian Defence Force Exit Survey (Shirt, 2012)).
Length of ADF service	To nearest year: Regular and Reserve service	Length of ADF service	Years and months: Regular and Reserves
Time intended to stay in the ADF	Years and months		
Total months on operational deployment (or at sea) in the past three years	Country, operational name, year(s) deployment(s) started, number of times deployed in a year, total time deployed (months)		
Deployment history (war-like peacekeeping, peace-monitoring or humanitarian)	Country, operation name, year deployment started, number of times deployed in a year, total times deployed	Deployment history (war-like/active service, non-warlike (e.g. peacekeeping, peace-monitoring, UN assistance missions), Humanitarian / Disaster relief (international), Defence aid to the civil community, border protection)	Country, operation name, years, number of times deployed, total number of months delayed, if in a combat role

Deployment exposures	Deployment exposures and number of times (0 to 10+) e.g. exposure to 'hazardous materials), 'handled or saw dead bodies' (MEAO Census Study (Dobson et al., 2012))	Deployment exposures	Deployment exposures and number of times (0 to 10+) e.g. exposure to 'hazardous materials), 'handled or saw dead bodies' (MEAO Census Study (Dobson et al., 2012))
Current significant relationship	Single, married/defacto, divorced, separated, other		
		Length of significant intimate relationship	Years, months
		ADF status of partner	Current or ex-serving ADF member, Regular or Reserve, Defence civilian, Other civilian
		Household and family structure	Relationship status, relationship satisfaction, household structure and children (Timor-Leste Family Study (McGuire et al., 2012); Household, Income and Labour Dynamics in Australia (HILDA) Survey (Watson & Wooden, 2002); 2014 Vietnam Veterans Family Study (Forrest et al., 2014)).
		Financial status	Financial status, financial hardship (Watson & Wooden, 2002; Health and Wellbeing Survey of Serving and Ex-Serving Personnel of the UK Armed Forces: Phase 2 (Fear et al., 2010)).
		Housing and housing instability	Residential postcode, housing arrangements, lifetime and recent episodes of homelessness and length and reasons for any homelessness (2010 ABS General Social Survey, ABS, 2011).
		Organisational commitment	Allen and Meyer's Affective Commitment Scale (Allen, 1990) and items devised for this study.
		Additional questions for Transitioned ADF	
		Employment status	Full-time work, home duties, unemployed/looking for work, volunteering, studying, retired. If not working / unemployed reasons for unemployed status (Young and Well Cooperative Research Centre, 2013; Fear et al., 2010).
		Current civilian employment	Number of hours worked per week, industry, main source of income (Fear et al., 2010; Shirt, 2012; Watson & Wooden, 2002); Australian Gulf War Veterans' Health Study 2011 (Sim et al., 2015)).
		Reservist status (as relevant)	Average number of hours worked per month (Soldier Wellbeing Survey (Riviere, 2011; Thomas et al., 2010).
		Transition	Year and type of transition and reasons for transition (Sim et al., 2015; Fear et al., 2010; Shirt, 2012).
		Changes in relationship status since transition	Marriage/ new partner, separation/divorce, widowed (Sim et al., 2015)

Annex B - Measures of psychological and physical wellbeing and lifestyle behaviours utilised across T1-2010 and T2-2015 surveys

Table B.1_Measures of psychological and physical wellbeing and lifestyle behaviours utilised across T1-2010 and T2-2015 surveys

T1-2010 study: 2010 ADF Mental Health and Wellbeing Prevalence Study (McFarlane et al., 2011)			T2-2015 study: 2015 Transition and Wellbeing Research Programme (Van Hooff et al., 2018)	
Construct	**Measure**	**Reference(s)**	**Measure**	**Reference(s)**
Suicidality	Four self-report items	Questions adapted from the National Survey of Mental Health and Wellbeing (ABS, 2008) and the MilHOP studies	four self-report items	Questions adapted from the National Survey of Mental Health and Wellbeing (ABS, 2008) and the MilHOP studies
Psychological distress	Kessler Psychological Distress 10-item scale (K10)	(Kessler & Ustun, 2004)	K10	(Kessler & Ustun, 2004)
PTSD symptoms	17 item Post Traumatic Stress Disorder Checklist – civilian version (PCL-C)	Weathers et al., 1993	Post Traumatic Stress Disorder Checklist – civilian version (PCL-C)	Weathers et al., 1993
Alcohol use and dependence	10 item Alcohol Use Disorders Identification Test (AUDIT – modified version)	Babor et al, 2001	Alcohol Use Disorders Identification Test (AUDIT – modified version)	Babor et al, 2001
Depressive symptoms	Patient Health Questionnaire 9-item depression module (PHQ-9)	Kroenke et al., 2001	Patient Health Questionnaire 9-item depression module (PHQ-9)	Kroenke et al., 2001
Generalised Anxiety symptoms	Generalised Anxiety Disorder 7-item scale (GAD-7)	Spitzer et al., 2006	Generalised Anxiety Disorder 7-item scale (GAD-7)	Spitzer et al., 2006
Somatic symptoms	The Patient Health Questionnaire - 15 item somatic module (PHQ-15);	Kroenke et al, 1998		
Panic disorder	PHQ – Panic Disorder module	Spitzer, RL et al, 1999	PHQ – Panic Disorder module	Spitzer, RL et al, 1999
Anger	Dimensions of Anger Reactions Scale	Novaco, 1975	Dimensions of Anger Reactions 5-item scale (DAR-5)	Forbes et al., 2004
Quality of life – overall	SF-12 Version 2 (Question 1 only)	Ware et al, 2002	SF-12 Version 2 (Question 1 only)	Ware et al, 2002
Quality of life – health outcomes	Five items on satisfaction with life, eyesight, memory, teeth and gums, hearing	45 and Up Study www.45andup.org.au; Sim et al., 2015	Five items on satisfaction with life, eyesight, memory, teeth and gums, hearing	45 and Up Study www.45andup.org.au; Sim et al., 2015
Resilience	2 items from the Connor-Davidson resilience scale	Connor, KM & Davidson, JRT, 2003	Ohio State University Brief Resilience Scale	Smith et al., 2008
Satisfaction with marriage	One item on satisfaction with marriage	Near North Area of Influence study (Bleier, J et al, 2009)		

Impact of military on family	Impact of career on relationship and on children	Near North Area of Influence study (Bleier, J et al, 2009)		
Sleep	Four items from the Sleep Impairment Index	Smith & Trinder, 2001	7 item Insomnia Severity Index (self-perceived insomnia)	Bastien et al., 2001
Physical Violence	Two items assessing frequency of threatened or actual past-month physical violence	AG21-US Army Screening measure (Cardona RA & Ritchie EC, 2007)	Two items assessing frequency of threatened or actual past-month physical violence	AG21-US Army Screening measure (Cardona RA & Ritchie EC, 2007)
Substance use	Use of tobacco (8 items), caffeine (1 item) and other supplements (1 items)	Millennium Cohort Study (Ryan et al, 2007)	Past and present tobacco usage, and for Transitioned ADF only, 12-month and lifetime drug use	2013 National Drug Strategy Survey (Australian Institute of Health and Welfare, 2011)
Social strain/support	Social strain or support from family, peers and supervisors	Schuster, Kessler & Aseltine, 1990		
Disability associated with general psychological distress	Supplementary to K-10, asked to consider in the last 4 weeks the number of days (1) totally unable to or (2) partially unable to cut down on work, study or manage day-to-day activities due to psychological distress	(Kessler RC et al, 2002)		
Lifetime trauma exposure	Self-report lifetime trauma exposure (modified list of Criterion A1 events from the CIDI version 2.1 PTSD module).	WHO, 1998	Self-report lifetime trauma exposure (modified list of Criterion A1 events from PTSD module of the CIDI 3.0)	Haro et al., 2006
Worst Lifetime traumatic event	Participants identified which traumatic events they had experienced during their lifetime, and of these, which was their 'worst event'	McFarlane AC & Van Hooff M, 2009	Participants identified which traumatic events they had experienced during their lifetime, and of these, which was their 'worst event'	McFarlane AC & Van Hooff M, 2009
Mild traumatic brain injury	Self-report mild traumatic brain injuries	Pietrzak et al, 2009	Self-report head injuries	Items modified from the Ohio State University Traumatic Brain Injury Identification Method (Corrigan & Bogner, 2007); Post-concussion Syndrome Checklist (Gouvier et al., 1992).
Occupational issues	Items devised for study on general occupational issues - whether they felt adequately recognised/rewarded for work through renumeration, verbal recognition and or awards/honours/medals; experiences of bullying; if bullying is adequately handled by Defence.			
Functioning			5-item Sheehan Disability Scale	Sheehan, 1983
General health			First item of the Short Form 36 Health Survey (SF36) and satisfaction with health	Ware, 1992; Sim et al., 2015
Recent life events			Modified 15-item version of the List of Threatening Experiences	Brugha et al., 1985
Physical activity			Short Last 7 Days Self-Administered version of The International Physical Activity Questionnaire, 2002	International Physical Activity Questionnaire, 2002

Pain			Pain intensity and disability	Sim et al., 2015
Physical injuries			Injuries sustained during military career requiring time off work	Items developed by researchers (Van Hooff et al, 2015)
Respiratory health			Respiratory health	European Community Respiratory Health Survey 1 (Burney et al., 1994)
Physical health			Physical health symptoms and severity	Sim et al., 2015
Diagnosed medical conditions			Doctor diagnosed medical conditions (44 items)	Sim et al., 2015
Risk taking behaviours - gambling			Nine-item Problem Gambling Severity Index (PGSI)	Stinchfield, 2007
Risk taking behaviours – risky driving			Items on risky driving	Australian Institute of Family Studies (Smart, 2005)
Experiences with the law			Items on experiences with the law (e.g., whether they had ever been arrested, convicted of a crime in a court of law or sent to prison)	Sim et al., 2015
Help-seeking	Six items devised for this study on help-seeking for mental health concerns and stigmas and barriers to help seeking	McFarlane et al., 2011	Items investigated help-seeking relating to mental health; ways in which people maintained their mental health; preferred means of receiving information; barriers and stigmas to care; concerns about mental health; assistance sought and received and pathways into care; satisfaction with services received; doctor diagnosed conditions, including year of diagnosis and medication use, and undiagnosed conditions; help seeking latency; and reasons for seeking care.	Section developed by study investigators with specific knowledge and experience within the field. Items also derived from ABS (2008), the CIDI 3.O (Haro et al., 2006), 2010 Mental Health Wellbeing Prevalence Study (McFarlane et al., 2011), Canadian Air Forces Recruit Mental Health Service Use Questionnaire (Fikretoglu et al., 2014) and the Solider Wellbeing Survey (Riviere, 2011; Thomas et al., 2010).
Use of technology to support mental health			Use of the internet and other emerging technologies (e.g. wearable devices) in improving the mental health and wellbeing of participants	Young and Well National Survey (Burns, 2013).
Family support and strain			Items assessing family support and strain	Schuster Social Support Scale (Schuster et al., 1990)
Satisfaction with relationship			Items assessing satisfaction with relationship	Watson & Wooden, 2002
Quality of relationship with partner			Items assessing quality of relationship with partner, including arguments and abuse	McGuire et al., 2012
Contact with other family members			Contact with other family members	Forrest et al., 2014
Impact of military service			Items assessing impact of military service on participants' relationships, employment, physical health, mental health and financial situation	Forrest et al., 2014
Conflict during childhood			Items assessing conflict during childhood, parental mental health and parental substance abuse	The Longitudinal Study of Australian Children (Gray, 2005)
Parental self-efficacy			Items assessing global parental self-efficacy	The Longitudinal Study of Australian Children (Gray, 2005)
Parental warmth			Parental warmth	Child Rearing Questionnaire (Paterson & Sanson, 1999)

Parental anger			Parental anger	National Longitudinal Study of Children & Youth (Statistics Canada, 2003)
Social support and strain			Modified Schuster Social Support Scale	Schuster et al., 1990
Contact with friends			Contact with friends not living with them	Forrest et al., 2014
Satisfaction with friendships			Satisfaction with friendships	Watson & Wooden, 2002
Associations with Ex-Service Organisations			Associations with Ex-Service Organisations	Sim et al., 2015.

Annex C - Data pre-processing of cross-sectional and longitudinal datasets

1) Open in SPSS
2) Export to Microsoft Excel (.xlsx)
3) Create outcome variable in final column:
    a. Longitudinal dataset analysis
        i. Create su_2010 variable based on su_1, su_2, su_3 and su_4
        ii. Create su_2015 variable based on suicide_1, suicide_2, suicide_3 and suicide_4
        iii. Remove all records where su_2010 is not equal to 'ideation_only'
        iv. Create outcome variable: 1 (su_2015 = action), 0 (otherwise)
    b. Cross-sectional datasets (2010 and 2015) analysis
        i. If su_3 = 1 OR su_4 = 1, set su = 1 (i.e., action), regardless of the response to su_1 and su_2
        ii. If (su_3 = 0 AND su_4 = 0) AND (su_1 = 1 OR su_2 = 1), set su = 0 (i.e., ideation only)
        iii. Remove all remaining records (e.g., missing values, or all su_1, …, su_4 equal to 0)
4) Remove special characters:
    a. '
    b. " (do not select final column with output variable formula)
    c. #NULL!
    d. _ (do not select row with variable names)
5) Remove columns that have no responses at all
6) Replace empty cells with 0 where #NULL! does not mean missing (e.g., variables starting with "op_")
    a. compute countif(blank) + countif(1), compared to countif(0)
    b. sort columns based on name or result from (a)
    c. CTRL + h from blank to 0, format as General
7) Classify columns as text, numeric and categorical variables
    a. Identify text entries by sorting on max() value per column. Text variables identified from subset where max = 0
    b. Identify numeric variables using keywords in variable name (=IFERROR(FIND("year",KQ7),IFERROR(FIND("hours",KQ7),IFERROR(FIND("age",KQ7),IFERROR(FIND("mins",KQ7),IFERROR(FIND("months",KQ7), IFERROR(FIND("days",KQ7),FIND("times",KQ7)))))))):
        i. year
        ii. months
        iii. days
        iv. hours
        v. mins
        vi. age
        vii. times
    c. Identify numeric variables by using sum() value per column and sort descending. Search for numeric variables within largest sum() values
    d. Check that all remaining variables are categorical
8) Sort columns in following order: categorical, numeric, text, response (y)
9) Some values for numeric variables are stored as text. Sort numeric columns based on sum() and investigate where sum = 0. Use Text to Column to convert text to numbers, without adding zeros (also for main_postcode)
10) Remove text variables, except

a. As text variable “first_concerned” ranked highly (initially), rather than removing it, the year was extracted and coded as numeric variable. This way, it could still be used for calculating mutual information.
b. As text variable “other_cond_1” ranked highly (initially), a new variable “other_cond” was created, based on “other_cond_1”, “other_cond_2” and “other_cond_3”. This variable has values: “PTSD”, “Depression”, “Other”. (the first two values occurred frequently)

11) Load in Weka and apply the following filters:
    a. all: NumericToNominal -R last
    b. 2010: NumericToNominal -R 1-289
    c. 2010: Discretize 290-465, bins=4, useEqualFrequency=True
    d. 2015: NumericToNominal -R 1-1331
    e. 2015: Discretize 1332-1679, bins=4, useEqualFrequency=True
    f. longitudinal: NumericToNominal -R 1-309
    g. longitudinal: Discretize 325,326, bins=5, useEqualFrequency=True
    h. longitudinal: Discretize 310-324,327-463, bins=4, useEqualFrequency=True
12) InfoGainAttributeEval, set missingMerge to False