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Predicting Skilled Workforce Retention: A Machine Learning Approach with Royal Australian Navy Sailors

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ABSTRACT

Skilled workers can be difficult and expensive to recruit, train, and retain. This is particularly true for military organizations, such as the Royal Australian Navy (RAN). Retention of both technical and nontechnical sailors is critical to future manning continuity and capability of the RAN. This research employs machine learning to analyze RAN exit survey data collected between 1999 and 2018 to predict the attitudes and behaviors of technical and nontechnical sailors voluntarily leaving the service. We find that machine learning can accurately detect differences in the attitudes and behaviors of senior technical and nontechnical sailors, as well as identify differences in sentiment across periods covering key career milestones. Our results inform current and future retention policies, both military and civilian.

INTRODUCTION

Skilled workers are in higher demand than ever before, and the shift toward service and professional jobs that we associate with white-collar work continues in the United States (Spohrer and Maglio, 2008) as well as globally (Forrester Research, 2019) and with varying sentiments toward a propensity to serve (Zais and Zhang, 2016), retention of military skilled workers is a significant challenge. Like any other firm, the Royal Australian Navy (RAN) faces this challenge, especially in the technical sailor community, whose skills transfer well to white-collar work and are in high demand in the civilian sector. Consequently, the RAN has difficulty retaining sailors with the right technical skillsets at the right seniority levels and in sufficient numbers. We build upon the operations-oriented study of managing white-collar workers, a subfield with several identified research gaps (Hopp et al., 2009), in the defense context.

Whatever the prevailing economic conditions in the civilian market driving the supply of and demand for these sailors, policymakers have various options to impact outflow of talent. Insights from traditional labor economics and manpower research have shown that various monetary and nonmonetary factors can be effective in inducing

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APPLICATION AREA: Resources: Reliability and Maintainability Manpower and Personnel

OR METHOD: Multivariate Analysis

soldiers, sailors, and airmen to remain in the service.[a] However, many of these measures are expensive, require legal and/or regulatory changes, and may be wasteful, as broad policy changes benefit those who are not on the margin of separating.

In contrast to these well-studied "classical" policy reforms, there has been a dearth of economics or operations research into systematically leveraging the opinions expressed by the members of the military through surveys. This is surprising, as personnel and workforce recruitment, assignment, and retention are traditional topics of study in operations management and research, both in civilian and defense contexts. For example, Kao and Rowan (1959) analytically model the minimum cost strategy for optimal personnel recruitment and selection given turnover in firms, while Maurer (1985) develops an analytic model for personnel rotation in the U.S. Navy. Wood (1991) examines family factors that drive enlisted soldiers to leave the army. Indeed, the defense sector is apt for applications of operations research for personnel management, such as aiding soldiers in career development through the army (Thie and Lorbeer, 1976), matching sailors to Naval duty stations (Blanco and Hillery, 1994; Holder, 2005), or even identifying entire military bases for closure (Ewing et al., 2006).

Understanding attitudes, sentiment, and behaviors displayed by both technical and nontechnical sailors can be critical to identifying (1) sailors who may be at risk of separating in the near future, as well as (2) characteristics of their jobs that elicit strong attachment to the RAN. Similar research has been conducted in the civilian workforce from an operational perspective. Ødegaard and Roos (2014) study the contribution of workplace environment and labor quality to total firm production. In the manufacturing sector, Kathuria and Davis (2001) argue that effective workforce management encourage higher product quality and consumer satisfaction.

In this research, we use data from a novel exit survey conducted by the Australian Defence Force (ADF) and several machine learning models, with a focus on support vector machine (SVM) models, as well as classical econometric models, to identify predictors of early exit from the RAN workforce, both in the technical and nontechnical communities based upon responses to exit survey questions answered by those that have separated. By highlighting and mitigating these predictors, personnel managers can reduce costly separation.

We identify key differences between technical and nontechnical sailors, especially among more senior sailors. These differences should be taken into consideration when shaping both technical and nontechnical sailor retention policy. Exiting senior technical sailors express a desire for more challenging work, and a lack of opportunities to use their skills in their jobs, especially due to civilianization of technical positions. Their attention is outward facing, looking at opportunities available in the civilian sector that values their skillset. Conversely, senior nontechnical sailors highlight concerns with pay, service time at sea, and recognition when leaving. These sailors' focus is more inward, concentrating on the perceived negative characteristics of the job that induce separation. In addition, we identify linear SVMs as particularly useful in predicting the correlation between attitude, opinions, and exit decisions. This is surprising because it implies the data are highly separable in feature space, further suggesting a strong bifurcation in opinions shared by technical versus nontechnical sailors, allowing policymakers to tailor retention incentives for the two groups. Lastly, we also examine our predictions using several algorithms and model specifications to test for robustness.

Ultimately, our findings provide a short-term and a long-term benefit. In the immediate future, understanding the factors and attitudes that are most strongly correlated with voluntary separation will allow for timely interventions by immediate supervisors to encourage at-risk sailors to remain in the RAN. Over the long run, the leadership will be able to institute systematic changes to improve job satisfaction, increase retention, and prevent critical gaps in technical skills needs. In particular, even if technical and nontechnical sailors' sentiments look similar early in their careers, leaders should not wait to introduce differentiated retention interventions in the form of counseling, professional advancements, and/or monetary and nonmonetary incentives because sentiments diverge extremely fast.

The paper proceeds as follows. To provide context for our study, we next describe the background of the RAN, current sailor retention efforts, and describe the data. Then, we present our main predictive results using a linear SVM. Robustness checks are mostly presented in the appendices for conciseness. Finally, we conclude with some recommendations on how these results should be interpreted and used by decision makers.

BACKGROUND ON THE ROYAL AUSTRALIAN NAVY

The RAN is manned by approximately 14,100 officers and sailors. Within the RAN, sailors are organized into communities based on their trade or skill. For example, the technical communities are Engineering, Aviation, Health services, Logistics & Administration, and Warfare. Each community is then further separated into subcommunities; the Engineering community is further broken down into Marine Technician, Electronics Technician, and Aviation Technician, each with its own specializations as well. This type of breakdown within workgroups is common across all sailor workgroups.

Traditionally, technical trades receive a higher level of qualification following completion of their in-service trade training than their nontechnical counterparts. The RAN uses the Australian Qualifications Framework to set the qualification standard. In addition to qualification differences, there are differences in the service incentives associated with technical and nontechnical sailors. These incentives are largely based upon three areas: pay, retention bonuses, and qualifications. In general, nontechnical sailors are paid a lower rate across equivalent career progression points; a difference of one to two pay grades exists between most nontechnical sailor and technical branches. Overall, the whole sailor population has a separation rate of 8.7% per year.

Even as recently as August 2019, reports in Australia show a shortage of technically qualified and skilled personnel in the civilian technical industries (Robertson, 2019). The RAN seeks innovative ways to incentivize technical personnel to remain in service, and the ADF exit survey provides sailors' feedback on such incentives. Given the large number and types of variables within the exit survey data, traditional methods of analysis such as ordinary least squares or logistic regression may give unreliable results. A high degree of collinearity among variables yields uninterpretable results when all variables or indiscriminately chosen subsets of variables are used as independent variables. SVM and the associated family of SVM models can be used for classification or regression using the value of the linear combination of features present in the RAN data.

DATA

The ADF exit survey began in 1999 and is delivered to all personnel leaving the service sometime after they apply to separate and before the point of actual separation. The survey is delivered electronically, respondents remain anonymous, and completion is noncompulsory. The dataset consists of 4,864 observations and covers a question set equivalent to 255 variables. The data contains variables corresponding to sailors who voluntarily left the RAN between 1999 and 2018, with an average response rate of 29.5%.

The data contains the following traditional demographic variables: branch category, worn rank, state, years of service (YOS), years in current rank, age group, gender, and dependent status. The remaining variables consist of responses to an exhaustive set of questions seeking to understand the nature of the reasons for separation. Examples of questions and responses are contained in Table 1, with the full list of questions in Appendix A. The analysis concentrates on the Able Seaman (AB) and Leading Seaman (LS) rank groups who have between four and eight YOS. These ranks were chosen as they present the greatest loss of technical skills at these ranks in that period when reviewing the whole of career average length of service profile. Table 2 provides summary statistics for survey respondents, with demographic information on gender, age, education, and YOS. Table 3 compares survey respondents' demographics with demographics of all RAN

Table 1. Example of ADF exit survey questions and responses.

Questions	Responses
Demographics	
Worn rank	**Service rank**
Age group	<24 years/25–44 years/45–54 years/>55 years
Reasons for leaving	
Issues with day-to-day unit management of personnel matters	Not/slightly/moderately/very/extremely important
Lack of confidence in senior leadership	Not/slightly/moderately/very/extremely important
Career questions	
How many years have you spent at your current rank?	Integer
Did you enjoy your career in the ADF?	Yes/No
How long were you deployed on your most recent deployment?	<2 weeks/2–4 weeks/1–3 months/4–6 months/7–12 months/ >12 months

personnel. Given the similarities between male to female ratios and age, we have confidence that survey respondents are representative of the larger RAN population.

ALGORITHM/MODEL SELECTION

To assess the efficacy of machine learning algorithms in predicting technical and nontechnical sailor separation behavior, we compared performances of random forest, chi-square automatic interaction detector (CHAID), K-means, and linear SVM algorithms.[b] Results are summarized in Table 4. The ability of each algorithm in predicting the separation behavior of RAN sailors is evaluated. The numbers in each cell in the table represent the percentage of the sample that the machine learning algorithm is correctly able to predict as a "stayer" or a "leaver." Note that due to the nature of our data sample, all service members eventually exit the RAN and take the exit survey. A stayer is classified as a sailor who has not exited the service by a certain milestone (four YOS, six YOS, or eight YOS). This is of particular interest to military scholars as well as commanders; we would like to identify factors that cause early attrition of service members when the armed forces have not had a chance to recoup its investment in human capital.

Overall, we see that performance of linear SVM, random forest, and CHAID are roughly comparable. However, both random forest and CHAID algorithms have wide variation in the number of valid predictors as the target variable (stay in the RAN for varying number of years) changes slightly, from four to six to eight years. In some samples, only five predictors are used, and in others, more than 10 variables are important in making accurate predictions. We interpret this fragility in the algorithms as indicative of their poor fit for making robust predictions. The K-means algorithm performs poorly compared to the other algorithms.

We stratify our samples by career longevity due to the nature of naval enlisted careers in the RAN. The two- to seven-year period in a sailor's career generally coincides with career milestones and conforms to general economic theory of job matching. That is, separation in the very early years of a naval career (within the first two years) is likely due to poor individual-to-organization matching. Sailors early in the career path may choose to separate for any combination of professional, personal, attitudinal, and cultural reasons. Beyond the two years-of-service point performance, individual preference, career milestones such as qualification and promotion, and pay and recognition factors help to better explain an attitude shift toward separation. Key milestones that helped shape the final selection of greater than or equal to four and less than six years of service and greater than or equal to six and less than eight years of service were the periods post matching, achievement of qualifications, initial minimum period of service, and promotion. We see that the longer a sailor's career, the greater the predictive accuracy of all algorithms. Indeed, at eight YOS or above, linear SVM, random forest, and CHAID display over 89% accuracy.

Table 2. Summary statistics of survey respondents as a percentage of total sailor sample.

Statistic	All sailors	Nontech sailors	Tech sailors
Total sample	3,901	1,765	2,136
Total as a percentage of sample/totals	100%	53.81%	46.19%
Gender			
Male	77.73%	76.37%	79.17%
Female	18.13%	20.45%	16.85%
Not answered	4.13%	3.17%	3.98%
Age groups			
24 or less	13.43%	17.17%	14.89%
25 to 44	69.26%	70.48%	73.55%
45 to 54	9.85%	7.31%	6.74%
55 or older	3.35%	1.70%	0.98%
Not answered	4.11%	3.34%	3.84%
Level of education			
Year 9	1.69%	1.42%	2.48%
Year 10	2.86%	2.55%	3.65%
Year 11	0.43%	0.79%	0.33%
Year 12	3.50%	4.53%	3.98%
Trade/vocational certificate	4.26%	4.14%	4.45%
Diploma/advanced diploma	1.91%	0.57%	0.80%
Bachelor's degree	3.08%	0.45%	1.31%
Postgraduate award	0.00%	0.00%	0.00%
Not answered	82.28%	85.55%	83.01%
Years of service			
2 or less	2.57%	3.34%	2.01%
3 to 4	35.16%	39.49%	39.89%
5 to 6	24.90%	26.29%	25.00%
7 to 8	23.85%	20.91%	21.86%
9 to 10	1.97%	2.10%	1.83%
11 to 12	1.79%	1.47%	1.87%
Greater than 12	8.86%	6.06%	7.12%
Not answered	0.90%	0.34%	0.42%

Linear SVM performs better than (or at least is comparable to) other machine learning algorithms that allow for a more complicated hypersurface bisecting the data. It is relatively simple and robust, and its ability to make accurate predictions is most likely due to the nature of the data, which is our second insight from our experimentation. The large number of questions and breadth of coverage of topics in the exit interview allows for a relatively simple algorithm like linear SVM to have good predictive properties. In particular, the extremely large feature space yields linear separation in high-dimensional space as predicted by Cover's Theorem (Cover, 1965). This points to the limited usefulness of parsimonious traditional personnel data in making accurate predictions about sailor attrition, even with sophisticated machine learning algorithms. Therefore, we select linear SVM for our primary analysis. Next, we run the analysis with two partition ratios for training and testing. The training and test ratios used were 50:50 and 70:30, selected as commonly utilized ratios. Model prediction accuracies by partition ratio are shown in Table 5. We use the partition ratio that provides the highest prediction accuracy for each sample, though results are qualitatively similar using either partition.

Table 3. HR and exit survey demographic comparison.

	Female/male % ratio	Average age female to age croup	Average age male to age group
HR data	20.8% to 79.92%	38.3 years	42.34 years
ADF exit survey data	19.4% to 80.6%	*25–44 years	*25–44 years

Note: *75.46% of ADF exit survey respondents fall into the age category 25–44 years.

Table 4. Model prediction accuracy table.

Target group	Technical sailors	Nontechnical sailors
YOS => 4 years		
Linear SVM	63.13%	59.52%
Random forest	61.60%	59.80%
CHAID	67.47%	63.13%
K-means	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 42.4%
YOS => 6 years		
Linear SVM	75.66%	72.53%
Random forest	75.80%	74.20%
CHAID	82.41%	77.35%
K-means	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 42.6%
YOS => 8 years		
Linear SVM	92.29%	91.08%
Random forest	91.70%	89.40%
CHAID	91.08%	90.84%
K-means	Silhouette = 0.1 poor Largest cluster 29.6%	Silhouette = 0.1 poor Largest cluster 42.6%
All YOS		
Linear SVM	63.61%	62.41%
Random forest	57.80%	60.90%
CHAID	68.43%	68.43%
K-means	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 29.1%

RESULTS

Our main results of the top 10 predictors of sailor separation are shown in Figures 1 and 2, with other model specifications presented in Appendix B. Figure 1 shows top predictors of technical sailor separation for the four to five YOS group and the senior six to seven YOS group. Figure 2 shows the same information for nontechnical sailors. We categorize each predictor into civilian facing, RAN facing, or other, such as housing or spousal concerns, and we summarize the results in Figure 3. First, we note that the technical and nontechnical sailor groups behave differently at the senior level. The senior technical sailor community shows strong sentiments for exploring their market value in the civilian sector and the availability of work opportunities. Moreover, this community expressed strong sentiments about the lack of opportunity to use their skills due to civilians in the military monopolizing opportunities. Conversely, the nontechnical sailor community's sentiments related to separation were prominently based on pay and recognition of effort and commitment, and this sentiment holds for four to five YOS and six to seven YOS groups.

Perhaps unsurprisingly, senior technical sailors understand they are in demand in the civilian market. At four years of service, sailors qualify for the RAN's superannuation payments from their small pensions, and it is the strongest predictor of sailor separation at that stage. However, many other prominent predictors uncovered by linear SVM are civilian focused: greater integration into the civilian workforce, attractiveness of civilian jobs, and standing employment offers in the civilian sector. Of

Table 5. Linear SVM final analysis model prediction accuracy.

Target variable structure	Linear SVM prediction accuracy with 50:50 data partition ratio	Linear SVM prediction accuracy with 70:30 data partition ratio
All sailors, 4 and 5 total YOS	68.43%	67.9%
Nontechnical sailor, 6 and 7 YOS	68.92%	70.37%
Technical sailor, 6 and 7 YOS	72.77%	72.84%

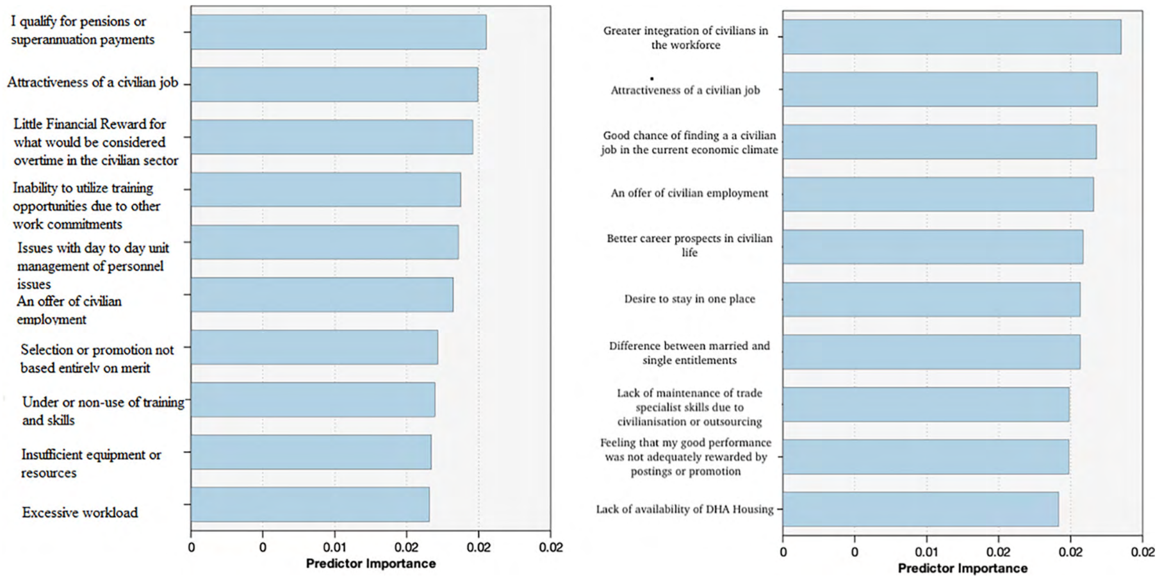

Figure 1. Top 10 predictors of technical sailors separating with four to five (left) and six to seven (right) total YOS.

the top 10 predictors for separation for technical workers, three are civilian focused for sailors with four to five YOS and six are civilian focused for sailors with six to seven YOS. The draw of civilian life is not necessarily due to dissatisfaction with the RAN, but a desire to better utilize their skillset to advance their career and receive professional and intellectual satisfaction.

Nontechnical sailors, on the contrary, express general dissatisfaction with life in the RAN. This difference is clearest among the sailors with six to seven YOS. The nontechnical sailor separating in years six and seven display sentiment in two main areas: pay and the amount of sea service. The top five predictors in this case are related to these two themes. Pay is the strongest sentiment among three of the top five predictors, which include "little financial reward for what would be considered overtime in the civilian community," "more attractive salary package available in civilian employment," and "dissatisfaction with pay." The next strongest prediction sentiment is associated with time at sea, in general, and on operations, with "too much time spent on operational

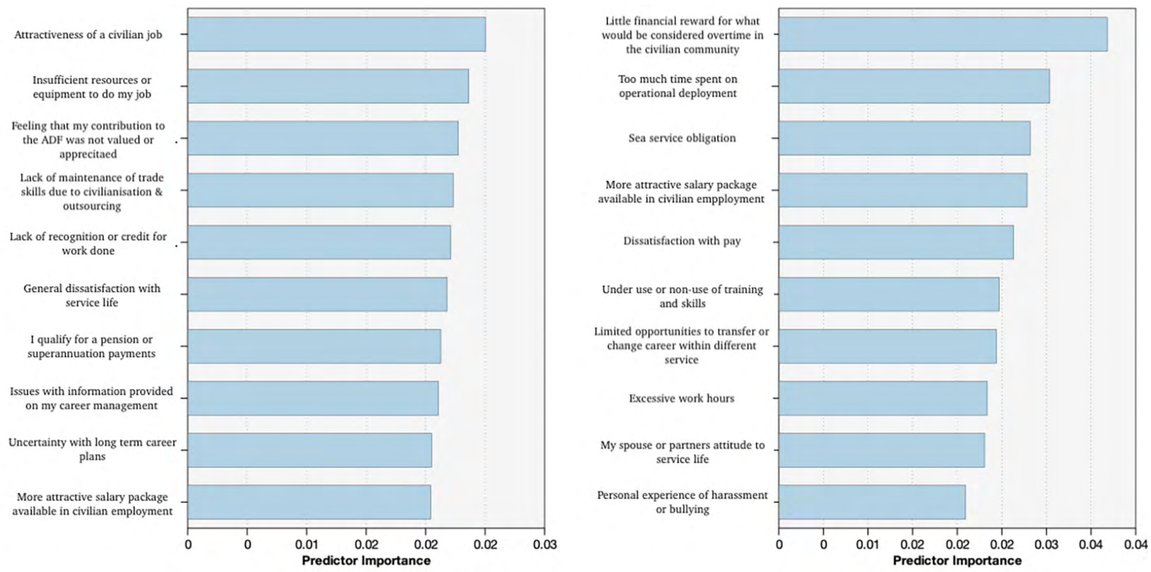

Figure 2. Top 10 predictors of nontechnical sailors separating with four to five (left) and six to seven (right) total YOS.

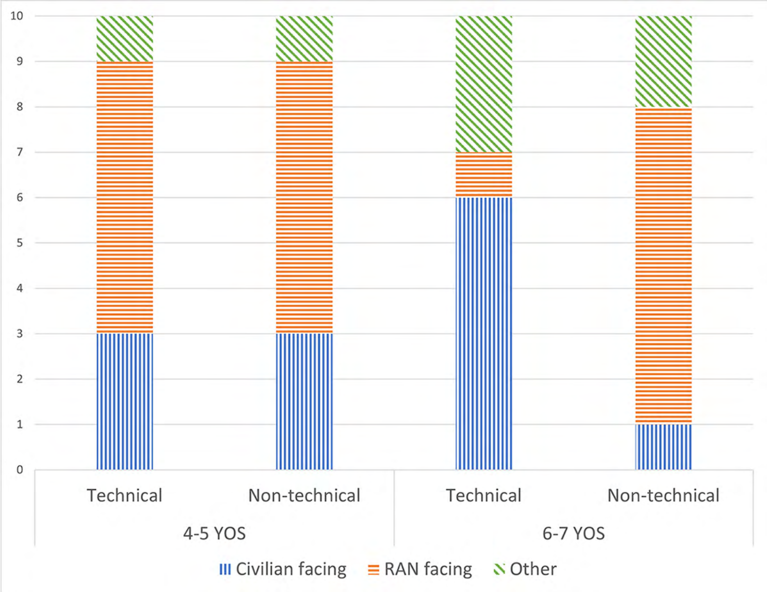

Figure 3. Civilian facing vs. RAN-facing factors for exiting.

deployment" and "sea service" being the remaining two of the top five predictors. Another predictor "excessive work hours" may be related to the sentiment of too much time at sea, as sea service and deployments are generally linked to high workloads. With the fixed salary of RAN sailors, this predictor may also indirectly point to dissatisfaction with low per-hour pay. Here, predictors diverge with senior technical sailors in that many do not report the existence of better outside options in the civilian sector. Only one of the top 10 predictors are civilian focused for the senior nontechnical sailor group. The rest are mainly focused on dissatisfaction with current working conditions within the RAN. Due to their more limited options outside the RAN, the reasons for considering separation are necessarily turned inward toward their job experience in the service.

Looking across time, nontechnical sailors change in sentiment is gradual, with RAN-facing reasons for exiting increasing from six to seven. On the other hand, the change for technical sailors is much more abrupt, with RAN-facing reasons for exiting decreasing from six to one, and civilian-facing reasons for exiting increasing from three to six. While both groups' sentiments evolve with additional years of experience, there is a clear and sharp divergence as junior sailors grow into more senior positions. While we lack more detailed administrative personnel data to be certain, we speculate this divergence arises from increased technical capabilities leading to increased attention from outside the RAN.

Machine learning may be able to support profiling of sailors more effectively during divisional interviews when displaying known separation attitudes, behaviors, and sentiment. The profile of the sailor, including those sentiments among high predictors of separation, can then shape suitable intervention measures as required, such as more specific career management, incentives, postings, and training.

CONCLUSION

In this paper, we studied the ability of machine learning algorithms to quantify the behaviors and characteristics of technical and nontechnical sailors in the RAN in choosing to separate from their military service. Our results suggest predicting sailor separation is possible with high accuracy, especially among sailors with high years of service, who are the most valuable in terms of retention. The findings in our study expand the literature on personnel economics and policy in two important ways.

First, we make a technical contribution by demonstrating the efficacy of the judicious use of machine learning algorithms along with detailed survey data to make accurate predictions about individual decisions to leave the RAN. Linear SVM is shown to have good prediction and robustness properties above classical regression techniques (such as logit models) and more complicated machine learning algorithms. We speculate that this surprising ability to accurately cleave the sample into stayers and leavers is in part due to the nature of the data. The 200+ questions across a myriad of professional, personal, psychological, and emotional domains of the exit interview allows linear SVM to unpack a complex, interwoven decision to stay or separate as a result of the high dimension of the feature space.

Second, we identify and differentiate the decisions of senior technical and nontechnical sailors to separate. Technical sailors look outward and evaluate the outside options available in the civilian sector. Nontechnical sailors, on the other hand, have fewer strong options outside the RAN and generally look inward to examine aspects of their career they find undesirable or unsatisfying. This implies both a short-term and a long-term policy prescription for decision makers at the RAN. The insights from this study can be used by the sailors' immediate superiors to identify those at high risk for leaving and intervene with whatever local resources are available. More systemically, leadership at RAN can use the findings to alter various monetary and nonmonetary characteristics of the job to make it more attractive to sailors. Especially for senior technical sailors, while higher pay and better benefits will induce more to stay, offering more opportunities to apply their training into their jobs and linking them to career advancement prospects may also lead to higher job satisfaction and ultimately, higher retention.

Finally, the analysis yields insights on the necessary timing of such interventions to retain high-quality sailors for the RAN, and the civilian labor market in general. Figure 3 serves as a warning of sorts to management in retaining high-value employees: be proactive and preemptive to increase ties to employees who are expected to command attention from competitors, perhaps even before the employees themselves advocate for rewards or promotions. The speed with which sentiments of technical sailors change at six to seven YOS implies that modest interventions initiated beyond five YOS will be unsuccessful.

While traditional retention policies focus on higher pay and better benefits as a one-size-fits-all policy, our exploration of machine learning algorithms and their ability predict separation behavior of individual sailors may open more avenues to target intervention tailored to each specific person, increasing efficacy and lowering cost. Exploring other nontraditional data sets and machine learning techniques appears promising for future research.

AUTHOR STATEMENT

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NOTES

[a]See Daula and Moffitt (1995) and Carrell and West (2005), for example. See Asch et al. (2007) for a comprehensive review of the literature.

[b]Concise definitions of each algorithm are presented in Appendix B. For more in-depth descriptions, the reader is referred to Duda et al. (2012).

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APPENDIX A. VARIABLES TABLE ADAPTED FROM THE EXIT SURVEY QUESTION SET DATA

Question/variable	Response value
Demographic	
Technical (dummy variable created)	0/1 Indicator
Nontechnical Technical (dummy variable created)	0/1 Indicator
YOS Greater than or equal to 2, 4, 6, and 8 years Technical (dummy variable created)	0/1 Indicator
Interaction Variables Technical*YOS Greater than or equal to 2, 4, 6, and 8 years (dummy variable created)	0/1 Indicator
Interaction Variables Technical*YOS Greater than or equal to 4 and less than 6, & Greater than or equal to 6 and less than 8 (dummy variable created)	0/1 Indicator
Interaction Variables Nontechnical*YOS Greater than or equal to 2, 4, 6, and 8 years (dummy variable created)	0/1 Indicator
Interaction Variables Nontechnical*YOS Greater than or equal to 4 and less than 6, & Greater than or equal to 6 and less than 8 (dummy variable created)	0/1 Indicator
Interaction Variables AB*YOS Greater than or equal to 4 and less than 6, & Greater than or equal to 6 and less than 8 (dummy variable created)	0/1 Indicator
Interaction Variables LS*YOS Greater than or equal to 4 and less than 6, & Greater than or equal to 6 and less than 8 (dummy variable created)	0/1 Indicator
Year Surveyed	E.g., 2018
What is your Category?	E.g., Maritime Logistics
Worn rank	SMN/AB/LS/PO/CPO
State (derived from locality)	NSW/ACT/SA/QLD/WA/NT/VIC
How many years have you spent at your current rank? (If less than one year write 0)	integer
In total, how many years of service have you completed with the RAN (If less than one year write 0)	Integer
Age Group	24 years and under/25 to 44 years/45 to 54 years/55 years and over
Do you identify as?	Male/Female/Prefer not to say
What are your family/living arrangements? (Note, if a dependent child/child lives with you some of the time please select living with you)	Couple – living together, no dependent child / children
	Couple – living apart, dependent child / children living away from you / Single, no dependent child / children/ Single, dependent child / children living away from you/other
Economic	
How will the salary of your new job compare to your Defence job? -	*Less than Defence/ More than Defence/ About the same as Defence*
What sector is your new job in?	Public Sector/Private Sector/Unsure
Service related	
How long were you deployed on your most recent deployment?	Less than 2 weeks/2-4 weeks/1-3 months/4-6 months/7-12 months/ More than 12 months

Question/variable	Response value
Where did you serve on your most recent overseas operational deployment or United Nations mission? – Note MEAO encompasses Afghanistan	I have not served on an operation/ Solomons/East Timor/ Christmas Island/Afghanistan/MEAO/ Other middle east/Other/ Bouganville/Gulf
During the last 12 months, how many months were you away due to operational time at sea?	*Less than 1 month/1-3 months/ 3-5 months/5-7 months/ 7-10 months/10-12 months*
During the last 12 months, how many months were you away due to domestic disasters or civil emergencies?	
During the last 12 months, how many months were you away due to unit training or field exercises?	
During the last 12 months, how many months were you away due to foreign humanitarian missions?	
During the last 12 months, how many months were you away due to military education?	
During the last 12 months, how many months were you away due to non-deployed time at sea?	
During the last 12 months, how many months were you away due to other work-related travel?	
During the last 12 months, how many months were you away due to Peacekeeping ops?	
During the last 12 months, how many months were you away due to warlike ops?	
How long is it since you returned from your most recent deployment?	*Currently deployed/Less than 3 months/3 months or more but less than 6/6 months or more but less than 1 year/I year or more but less than 2 years/2 years or more but less than 3 years/3 years or more ago*
Attitudinal or sentiment based (what was important in your decision to leave)	
Is there anything the ADF could have done that would have encouraged you to alter your decision to leave?	No/Yes
Did you enjoy your career in the ADF?	Yes/No
Responses to following questions = N/A/Not Important/Slightly Important/Moderately Important/ Very Important/Extremely Important	
Issues with day-to-day unit management of personnel matters -	Lack of maintenance of trade / specialist skills due to civilianization / outsourcing of functions -
Lack of confidence in senior Defence leadership	Lack of ongoing / advanced trade or specialist training opportunities -
Inability to access Long Service Leave or Leave Without Pay -	Inability to utilize training opportunities due to other work commitments / demanding work schedule -
Dissatisfaction with pay -	General dissatisfaction with service life -
Little financial reward for what would be considered overtime in the civilian community -	Excessive workload -
More attractive salary package available in civilian employment -	Excessive work hours -
Need for spouse / partner to get stable employment to supplement family income -	Insufficient equipment or resources to do my job -
Ineligibility for a retention bonus or allowance -	Sea service obligation -
Dissatisfaction with job-related allowances and benefits -	Desire for less separation from family -

Question/variable	Response value
Difference between single and married entitlements -	Impact of job demands on family / personal life -
Attractiveness of a civilian job supplemented by a pension	My spouse's / partner's attitude to service life -
Lack of provision for a Defence Force pension under MSBS	Too much time spent away from home because of military duties -
I qualify for a pension or superannuation payments -	The nature of the work in future postings -
Better career prospects in civilian life	A desire for more challenging work -
To make a career change while still young enough -	Desire to stay in one place -
Good chance of finding a civilian job in the current economic climate	Desire to return to my home location -
An offer of civilian employment -	Probable location of future postings -
Limited opportunities in my present Category	Posting conflicts with spouse's / partner's career -
Limited opportunities to transfer / change career within SAME Service -	Effect of postings on children's education -
Limited opportunities to transfer / change career into a DIFFERENT Service -	Effect of postings on family life -
Issues with promotion prospects -	Lack of recognition or credit for work done -
Issues with information provided on my career management -	Feeling that my contribution to the ADF was not valued or appreciated -
Feel there is a lack of opportunities for career development -	Little appreciation of the personal sacrifices made during my time in the ADF -
Lack of skills accreditation for civilian employment -	Lack of availability of DHA housing -
Desire to pursue further education that is not available through or relevant to Defence -	Adequacy of rental assistance -
Favoritism in the allocation of postings -	Uncertainty with long-term career plans -
Selections or promotions not based entirely on merit -	Ongoing difficulties with spouse employment -
Posting preferences appear not to be considered -	To look after children -
Feeling that my good performance was not adequately rewarded by postings or promotion -	Lack of adequate child care -
Underuse or non-use of training and skills -	Difficulty managing work and family commitments as a single parent
Insufficient personnel in units to do the work -	Greater integration of women in the Service
Too much time spent on operational deployment -	Traumatic incident/s related to work -
Not enough opportunities for overseas deployments -	Personal experience of harassment or bullying -
Inability to secure back to back postings during a critical stage of family / personal life -	I have satisfied my goals in the Service -
Lack of 'respite' posting opportunities -	Lack of job satisfaction -
Greater integration of civilians in the work environment -	Insufficient personnel in units to do the work -

Note: Cells in italics indicate variables that were omitted once all missing values had been accounted for.

APPENDIX B. COMPARISON OF RANDOM FOREST, K-MEANS, LINEAR SVM, AND CHAID, RESULTS FOR MODEL DOWN SELECTION

Table B.1. Model test and selection for final model results comparison table.

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
YOS => 4 years			
YOS => 4 years Linear SVM	Top 10 behavior predictors N/A model does not work with missing values	Top 10 behavior predictors 1. Limited opportunities in my current category 2. The nature of work in future postings 3. General dissatisfaction with service life 4. Desire to pursue further education not available in Defence 5. Worn rank 6. Too much time spent on operational deployment 7. Greater integration of civilians in the work environment 8. Age group 9. Desire for less separation from family 10. Too much time spent away from home because of military duties	Top 10 behavior predictors 1. The nature of the work in future postings 2. Limited opportunities in my present category 3. Age group 4. Lack of skills accreditation 5. I have satisfied my goals in service 6. My spouse's or partner's attitude to service life 7. I qualify for pension or superannuation payments 8. Not enough opportunities for overseas deployments 9. Feel there is a lack of opportunities for career development 10. Dissatisfaction with job-related allowances and benefits

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
Model accuracy		63.13% prediction accuracy	59.52% prediction accuracy
Random forest	1. Worn rank	1. Lack of confidence in SLG	1. Worn rank
	2. Family living arrangements	2. How long deployed	2. Where deployment
	3. Where deployment	3. Worn rank	3. Family living arrangements
	4. State	4. Inability to access LSL or LWOP	4. Issues with day-to-day unit management of personnel issues
	5. Last 12 months at sea operational domestic disasters civil emergencies	5. Family living arrangements	5. Dissatisfaction with pay
	6. Age group	6. Little financial reward for what would be considered overtime in civilian sector	6. Lack of confidence in SLG
	7. Last 12 months away unit training field exercises	7. Issues with day-to-day unit management of personnel issues	7. How long deployed
	8. Do you identify as	8. Is there anything else the ADF could have done after the decision to leave?	8. Inability to access LSL or LWOP
	9. How salary compares to Defence job	9. Dissatisfaction with pay	9. Do you identify as
		10. Age group	10. Is there anything else the ADF could have done after the decision to leave?

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
Model accuracy	79.6% prediction accuracy	61.6% prediction accuracy	59.8% prediction accuracy
K-Means (unsupervised)	1. Difficulty managing work and family commitments as a single parent 2. Dissatisfaction with job-related allowances and benefits 3. Feeling that my contribution to the ADF was not valued or appreciated 4. Feeling that my good performance was not adequately rewarded by postings or promotion 5. Inability to utilize training opportunities due to other work commitments and demanding work schedule 6. Lack of confidence in SLG 7. Lack of ongoing advanced trade or specialist training opportunities	1. Feeling that my contribution to the ADF was not valued or appreciated 2. Favoritism in the allocation of postings 3. Posting preferences appear to not be considered 4. Feeling that my good performance is not adequately rewarded by postings or promotion 5. Inability to utilize training opportunities due to other work commitments and demanding work schedule 6. Little appreciation of the personal sacrifices made during my time in the ADF 7. Lack of respite posting opportunities	1. Feeling that my contribution to the ADF was not valued or appreciated 2. Posting preferences appear to not be considered 3. Favoritism in the allocation of postings 4. Inability to utilize training opportunities due to other work commitments and demanding work schedule 5. Feeling that my good performance is not adequately rewarded by postings or promotion 6. Little appreciation of the personal sacrifices made during my time in the ADF 7. Lack of ongoing advanced trade or specialist training opportunities

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
	8. Little appreciation of the personal sacrifices made during my time in ADF 9. More attractive salary package available in civilian employment 10. Uncertainty with long-term career plans	8. Lack of ongoing advanced trade or specialist training opportunities 9. Lack of recognition or credit for work done 10. Issues with day-to-day unit management of personnel issues	8. Lack of respite posting opportunities 9. Lack of recognition or credit for work done 10. Lack of maintenance of trade specialist skills due to civilian outsourcing
Model accuracy	Silhouette = 0.1 poor Largest cluster 32.1%	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 42.4%
Model accuracy Chi-square automatic interaction detector (CHAID)	1. Last 12 months at sea operational domestic disasters civil emergencies 2. Last 12 months at sea operational domestic disasters civil emergencies 3. Issues with promotion prospects 4. Effect of postings on children's education	10.36% prediction accuracy 1. Worn rank 2. Need for spouse or partner to get stable employment to supplement income 3. Lack of maintenance of specialist skills due to civilian outsourcing 4. Posting preferences appear to not be considered 5. Age group	1. Lack of maintenance of specialist skills due to civilian outsourcing 2. An offer of civilian employment 3. Underuse or non-use of training and skills 4. Limited opportunity to transfer change career in different service 5. Posting conflicts with spouse's or partner's career

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
	5. Desire to return to my home location 6. Desire for more challenging work 7. Age group 8. How long since returned from most recent deployment 9. Worn rank 10. Year surveyed	6. General dissatisfaction with service life 7. Do you identify as 8. Too much time spent on operational deployment 9. Little financial reward for what would be considered 10. Personal experience of harassment or bullying	6. Year surveyed 7. Where deployment 8. Issues with promotion prospects 9. Not enough opportunity for overseas deployment 10. How long deployed
Model accuracy	58.4% prediction accuracy	67.47% prediction accuracy	63.13% prediction accuracy
YOS => 6 years			
YOS => 6 years Linear SVM	Top 10 behavior predictors N/A	1. Desire to pursue further education not available in Defence 2. Desire for more challenging work 3. General dissatisfaction with service 4. Greater integration of civilians in the workforce	1. The nature of the work in future postings 2. Desire to pursue further education not available in Defence 3. Where deployment 4. Lack of recognition or credit for work done 5. Desire for less separation from family

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
		5. Insufficient equipment or resources to do job 6. Limited opportunities to transfer within same service 7. The nature of the work in future postings 8. Feeling that my good performance was not adequately rewarded by postings or promotion 9. Attractiveness of a civilian job 10. Desire for less separation from family	6. Greater of integration of women into service 7. More attractive salary package 8. Limited opportunities to transfer within same service 9. Insufficient equipment or resources to do job 10. Little financial reward for what would be considered overtime in civilian sector
Model accuracy Random forest	N/A 1. Worn rank 2. Where deployment 3. State 4. Age group 5. Family living arrangements 6. How salary compares to Defence job	75.66% prediction accuracy 1. Family arrangements 2. Worn rank 3. Lack of confidence in SLG 4. Is there anything else the ADF could have done after the decision to leave? 5. Age group	72.53% prediction accuracy 1. Where deployment 2. Family arrangements 3. Lack of confidence in SLG 4. Worn rank 5. Dissatisfaction with pay 6. Age group

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
	7. How long deployed 8. Last 12 months at sea operational domestic disasters civil emergencies 9. Last 12 months away unit training field exercises 10. Do you identify as	6. Issues with day-to-day unit management of personnel matters 7. How long deployed 8. Inability to access LSL or LWOP 9. More attractive salary pack in civilian sector 10. Little financial reward for what would be considered overtime in the civilian sector	7. Is there anything else the ADF could have done after the decision to leave? 8. Do you identify as 9. Inability to access LSL or LWOP 10. Issues with day-to-day unit management of personnel matters
Model accuracy K-Means (unsupervised)	82% prediction accuracy 1. Difficulty managing work and family commitments as a single parent 2. Dissatisfaction with job-related allowances and benefits 3. Feeling that my contribution to the ADF was not valued or appreciated	75.8% prediction accuracy 1. Posting preferences appear to not be considered 2. Feeling that my contribution to the ADF was not valued or appreciated 3. Inability to utilize training opportunities due to other work commitments and demanding work schedule	74.2% prediction accuracy 1. Feeling that my contribution to the ADF was not valued or appreciated 2. Posting preferences appear to not be considered 3. Favoritism in the allocation of postings

Target group	All sailors	Technical	Nontechnical
Data target variable/model	<3,000 missing values	No missing values	No missing values
	4. Feeling that my good performance was not adequately rewarded by postings or promotion	4. Favoritism in the allocation of postings	4. Inability to utilize training opportunities due to other work commitments and demanding work schedule
	5. Inability to utilize training opportunities due to other work commitments and demanding work schedule	5. Under use or non-use of training and skills	5. Little appreciation of the personal sacrifices made during my time in the ADF
	6. Lack of confidence in SLG	6. Lack of respite postings	6. Feeling that my good performance is not adequately rewarded by postings or promotion
	7. Lack of ongoing advanced trade or specialist training opportunities	7. Dissatisfaction with job-related benefits and allowances	7. Lack of ongoing advanced trade or specialist training opportunities
	8. Little appreciation of the personal sacrifices made during my time in the ADF	8. Feeling that my good performance is not adequately rewarded by postings or promotion	8. Lack of respite posting opportunities
	9. More attractive salary package available in civilian employment	9. Little appreciation of the personal sacrifices made during my time in the ADF	9. Lack of recognition or credit for work done
	10. Uncertainty with long-term career plans	10. Lack of ongoing advanced trade or specialist training opportunities	10. Dissatisfaction with job-related benefits and allowances

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
Model accuracy	Silhouette = 0.1 poor Largest cluster 31.1%	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 42.6%
Chi-square automatic interaction detector (CHAID)	1. Worn rank 2. Years at current rank 3. I qualify for a pension or superannuation 4. Lack of provision of a Defence force pension 5. A desire for more challenging work 6. Feel there is a lack of opportunities for career development 7. Year surveyed 8. Age group 9. Issues with promotion prospects 10. Lack of recognition or credit for work done	1. Worn rank 2. Year surveyed 3. Dissatisfaction with pay 4. I qualify for a pension or superannuation payments 5. How long deployed 6. Greater integration of women into service 7. Ineligibility for retention bonus or allowance 8. Limited opportunity to transfer change career within different service 9. Lack of provision for Defence force pension under MSBS 10. Posting preferences appear not to be considered	1. Worn rank 2. Year surveyed 3. Traumatic incidents related to work 4. Greater integration of women into service 5. Inability to utilize training opportunities due to other work commitments 6. More attractive salary package available in civilian sector 7. Lack of maintenance of specialist skills due to civilian outsourcing 8. Where deployment 9. Posting conflicts with partner's or spouse's career 10. To make a career while still young enough

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
Model accuracy **YOS => 8 years**	80.6% prediction accuracy	82.41% prediction accuracy	77.35% prediction accuracy
YOS => 8 years Linear SVM	Top 10 behavior predictors N/A	Top 10 behavior predictors 1. Too much time spent on operational deployment 2. Desire to pursue further education not available in Defence 3. General dissatisfaction with service life 4. Adequacy of RA 5. The nature of work in future postings 6. Too much time spent away from home because of military duties 7. Favoritism in the allocation of postings 8. Ongoing difficulties with spouse's employment 9. Lack of provision for a Defence force pension under MSBS	Top 10 behavior predictors 1. Effect of postings on children's education 2. Too much time spent on operational deployment 3. The nature of work in future postings 4. Desire to pursue further education not available in Defence 5. Need for spouse or partner to get stable employment to supplement income 6. Dissatisfaction with job-related benefits and allowances 7. Personal experience of harassment. 8. Lack of skills accreditation 9. Where deployment

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
		10. Posting preferences appear to be not considered	10. Lack of recognition or credit for work done
Model accuracy Random forest	N/A 1. Worn rank 2. Family living arrangements 3. Where deployment 4. Age group 5. How long deployed 6. State 7. Last 12 months at sea operational 8. Do you identify as 9. How salary compares to Defence job 10. Last 12 months at sea operational domestic disasters civil emergencies	92.29% prediction accuracy 1. Family arrangements 2. How long deployed 3. Issues with day-to-day unit management of personnel matters 4. Inability to access LSL or LWOP 5. Worn rank 6. More attractive salary pack in civilian sector 7. Lack of confidence in SLG 8. Little financial reward for what would be considered overtime in the civilian sector 9. Dissatisfaction with pay 10. Age group	91.08% prediction accuracy 1. Dissatisfaction with pay 2. Do you identify as 3. Family arrangements 4. Dissatisfaction with pay 5. How long deployed 6. Worn rank 7. More attractive salary pack in civilian sector 8. Lack of confidence in SLG 9. Where deployment 10. Inability to access LSL or LWOP

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
Model accuracy	92.1% prediction accuracy	91.7% prediction accuracy	89.4% prediction accuracy
K-Means (unsupervised)	1. Difficulty managing work and family commitments as a single parent 2. Dissatisfaction with job-related allowances and benefits 3. Feeling that my contribution to the ADF was not valued or appreciated 4. Feeling that my good performance was not adequately rewarded by postings or promotion 5. Inability to utilize training opportunities due to other work commitments and demanding work schedule 6. Lack of confidence in SLG	1. Posting preferences appear to not be considered 2. Inability to utilize training opportunities due to other work commitments and demanding work schedule 3. Favoritism in the allocation of postings 4. Feeling that my contribution to the ADF was not valued or appreciated 5. Under use or non-use of training and skills 6. Lack of respite postings 7. Dissatisfaction with job-related benefits and allowances	1. Feeling that my contribution to the ADF was not valued or appreciated 2. Posting preferences appear to not be considered 3. Favoritism in the allocation of postings 4. Inability to utilize training opportunities due to other work commitments and demanding work schedule 5. Feeling that my good performance is not adequately rewarded by postings or promotion 6. Little appreciation of the personal sacrifices made during my time in the ADF

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
	7. Lack of ongoing advanced trade or specialist training opportunities 8. Little appreciation of the personal sacrifices made during my time in the ADF 9. More attractive salary package available in civilian employment 10. Uncertainty with long-term career plans	8. Feeling that my good performance is not adequately rewarded by postings or promotion 9. Little appreciation of the personal sacrifices made during my time in the ADF 10. Lack of ongoing advanced trade or specialist training opportunities	7. Lack of respite posting opportunities 8. Lack of ongoing advanced trade or specialist training opportunities 9. Lack of recognition or credit for work done 10. Dissatisfaction with job-related benefits and allowances
Model accuracy	Silhouette = 0.1 poor Largest cluster 31.7%	Silhouette = 0.1 poor Largest cluster 29.6%	Silhouette = 0.1 poor Largest cluster 42.6%
Chi-square automatic interaction detector (CHAID)	1. Worn rank 2. Years at current rank 3. Impact of job demands on family personal life 4. Feeling that my contribution to the ADF is not valued or appreciated 5. Feeling there is a lack of opportunities for career development	1. Too much time spent on operational deployment 2. Selections or promotions not based entirely on merit 3. Difficulty managing work and family commitments as a single parent 4. Attractiveness of a civilian job supplemented by a pension	1. Year surveyed 2. Lack of skills accreditation for civilian employment 3. Worn rank 4. Did you enjoy ADF career 5. Good chance of finding a civilian job in the current economic climate

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
		5. Lack of provision of a Defence force pension under MSBS 6. Difference between married and single entitlements	
Model accuracy	89.3% prediction accuracy	91.08% prediction accuracy	90.84% prediction accuracy
YOS => 4 years			
All YOS Linear SVM	Top 10 behavior predictors N/A	Top 10 behavior predictors 1. Lack of maintenance of trade specialist skills due to civilian outsourcing 2. The nature of work in future postings 3. Feeling that my good performance is not adequately rewarded by postings or promotion 4. Age group 5. Limited opportunities in my present category 6. Dissatisfaction with pay 7. Attractiveness	Top 10 behavior predictors 1. The nature of work in future postings 2. Lack of maintenance of trade specialist skills due to civilian outsourcing 3. Age group 4. Feeling that my good performance is not adequately rewarded by postings or promotion 5. Limited opportunities in my present category 6. General dissatisfaction with service

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
		8. of a civilian job supplemented by a pension 9. General dissatisfaction with service 10. Lack of skills accreditation	7. Lack of skills accreditation 8. Dissatisfaction with pay 9. Attractiveness of a civilian job supplemented by a pension 10. Desire for less separation from family
Model accuracy	N/A	63.61% prediction accuracy	62.41% prediction accuracy
Random forest	N/A	1. How long deployed 2. Do you identify as 3. Family arrangements 4. Issues with day-to-day unit management of personnel matters 5. Dissatisfaction with pay 6. Worn rank 7. Little financial reward for what would be considered overtime in the civilian sector 8. Is there anything else the ADF could have done after the decision to leave 9. Inability to access LSL or LWOP	1. Where deployment 2. Issues with day-to-day unit management of personnel matters 3. Family arrangements 4. Do you identify as 5. Dissatisfaction with pay 6. Worn rank 7. Lack of confidence in SLG 8. Inability to access LSL or LWOP 9. Is there anything else the ADF could have done after the decision to leave 10. Age group

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
		10. Lack of confidence in SLG	
Model accuracy K-Means (unsupervised)	41.5% prediction accuracy 1. Difficulty managing work and family commitments as a single parent 2. Dissatisfaction with job-related allowances and benefits 3. Feeling that my contribution to the ADF was not valued or appreciated 4. Feeling that my good performance was not adequately rewarded by postings or promotion 5. Inability to utilize training opportunities due to other work commitments and demanding work schedule 6. Lack of confidence in SLG	57.8% prediction accuracy 1. Feeling that my contribution to the ADF was not valued or appreciated 2. Favoritism in the allocation of postings 3. Posting preferences appear to not be considered 4. Feeling that my good performance is not adequately rewarded by postings or promotion 5. Inability to utilize training opportunities due to other work commitments and demanding work schedule 6. Lack of respite postings	60.9% prediction accuracy 1. Posting preferences appear to not be considered 2. Feeling that my contribution to the ADF was not valued or appreciated 3. Inability to utilize training opportunities due to other work commitments and demanding work schedule 4. Favoritism in the allocation of postings 5. Under use or non-use of training and skills 6. Lack of respite postings 7. Dissatisfaction with job-related benefits and allowances 8. Feeling that my good performance is not

Target group Data target variable/model	All sailors <3,000 missing values	Technical No missing values	Nontechnical No missing values
	7. Lack of ongoing advanced trade or specialist training opportunities 8. Little appreciation of the personal sacrifices made during my time in the ADF 9. More attractive salary package available in civilian employment 10. Uncertainty with long-term career plans	7. Little appreciation of the personal sacrifices made during my time in the ADF 8. Lack of ongoing advanced trade or specialist training opportunities 9. Lack of recognition or credit for work done 10. Dissatisfaction with job-related benefits and allowances	adequately rewarded by postings or promotion 9. Lack of ongoing advanced trade or specialist training opportunities 10. Little appreciation of the personal sacrifices made during my time in the ADF
Model accuracy	Silhouette = 0.1 poor Largest cluster 31.7%	Silhouette = 0.1 poor Largest cluster 42.6%	Silhouette = 0.1 poor Largest cluster 29.1%
Chi-square automatic interaction detector (CHAID)	1. Years at current rank 2. Worn rank 3. Age group 4. Feeling there is a lack of opportunities for career development 5. Lack of provision for a Defence force pension under MSBS 6. Did you enjoy career ADF	1. Lack of maintenance of specialist skills due to civilianization of workforce 2. Do you identify as 3. Traumatic incidents related to work 4. Impact of job demands on family life	1. Lack of maintenance of specialist skills due to civilianization of workforce 2. Do you identify as 3. Traumatic incidents related to work 4. Impact of job demands on family life

Target group	All sailors	Technical	Nontechnical
Data target variable/model	<3,000 missing values	No missing values	No missing values
	7. Desire to pursue further education that is not available in Defence 8. A desire for more challenging work 9. Attractiveness of a civilian job supplemented by a pension 10. More attractive salary package available in civilian employment	5. Greater integration of women in then service 6. Need for spouse or partner to get stable employment to supplement family income 7. Feeling that my good performance is not adequately rewarded by postings or promotion 8. Adequacy of rental assistance 9. Lack of job satisfaction 10. To make a career change while still young enough	5. Greater integration of women in then service 6. Need for spouse or partner to get stable employment to supplement family income 7. Feeling that my good performance is not adequately rewarded by postings or promotion 8. Adequacy of rental assistance 9. Lack of job satisfaction 10. To make a career change while still young enough
Model accuracy	85.4% prediction accuracy	68.43% prediction accuracy	68.43% prediction accuracy