ORANGA TAMARIKI
Ministry for Children

Social Impact and Research

New Zealand Government

Measuring Case Complexity

Part 2 Model

Development of a model to measure complexity of care and protection cases using operational data

The Oranga Tamariki Social Impact and Research team works to build the evidence base that helps us better understand wellbeing and what works to improve outcomes for New Zealand's children, young people and their whānau.

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Executive Summary

Historically, the workload of Oranga Tamariki frontline staff has been assessed by examining the number of tamariki allocated to social workers. This ‘tamariki per social worker’ measure has been criticised over the years as it only focuses on quantity and therefore provides an inaccurate picture of true workloads since it does not account for differences between the complexity of cases.

This report outlines the development of a model to measure the complexity of care and protection cases using operational data. It forms part of a broader initiative to address the gap in assessing and comparing workloads by developing a more sophisticated, data-informed approach to understanding and improving social worker caseload management.

Methodology

The model was developed, using structured data from Oranga Tamariki’s case management system (CYRAS), to predict the complexity of cases as rated by social workers in a national survey (Part 1). In the survey, social workers ranked the complexity of tamariki and whanau they have been working with using a 5-level scale (i.e., from ‘Not at all Complex’ to ‘Extremely Complex’).

Complexity was examined separately at three key phases of social work: Intake/Investigation/Partnered Response, Intervention, and Placement. Different machine learning models (specifically XGBoost and Random Forest machine learning algorithms) were applied, focusing on best predicting tamaiti complexity for each of the three phases.

To achieve an acceptable level of accuracy for prediction of complexity, the final model was refined from a 5-level scale (i.e., as collected in the survey) down to a 2-level scale (Low/Medium vs High Complexity). From this point onwards, when referring to a complex tamariki/case, it is meant that the case was predicted to be highly complex.

Generally, the balanced accuracy of the final selected models was approximately 64 – 78% for predicting the correct type of complexity across the phases. The ability of the model to predict the rarer event of high complexity (the true positive rate) was highest for the Placement phase at 70% of the time, then Intervention phase 47%, and lowest in the Intake/Investigation/Partnered Response phase at 35%.

This performance of the final models was in-line with the broader literature. Our models performed best in phases where more information about the tamariki tends to be available (such as the Placement phase), as well as being better at correctly predicting when cases were *not* complex (84-93% of the time) than correctly predicting when they were complex (35-70% of the time).

After selecting the most favourable models, we then used them to predict case complexity for all tamariki who were on the national care and protection caseload (including unallocated cases) around the time the survey was run (September 2023). At this time there were around 18,700 tamariki across the various care and protection phases of social work assigned to approximately 1,100 kaimahi. The findings discussed next, are based on these predictions.

Key Model Findings

National Tamaiti Complexity

Application of the model to all tamariki on the care and protection caseload nationally showed that:

- Overall tamaiti complexity was lowest in the Intake/Investigation/Partnered Response phase and increased for the later phases.
- Complexity tended to increase with age and was more likely in older tamariki, particularly those aged 14 – 18. However, those aged 0 – 1 years old were more likely to be predicted as complex compared to their slightly older peers.
- The Intervention phase generally had the highest proportion of predicted tamaiti complexity when examined across age group, ethnicity and region separately.
- South Auckland had the most complex Intervention phase, and the most complex Placement phase was in Taranaki-Manawatu.

National Caseload Complexity

The 2-level prediction of complexity does not allow for a graduated scoring of complexity of caseloads. However, it can be used to create a dual axis caseload complexity measure, by combining 'the number of tamariki on a social workers caseload' with 'the proportion of those cases predicted to be complex'.

This dual measure can provide insight into social worker caseloads and identify potentially unmanageable situations where caseloads have both an above average number of tamariki *and* an above average proportion of high complexity cases. Thresholds for potentially unmanageable caseloads were chosen as the national average for each measure, although an acceptable practice threshold could be set instead. Predicted caseload complexity and application of the dual measure showed that:

- Approximately 17% of social workers nationally were found to be carrying both an above-average number of tamariki *and* an above-average proportion of complex cases.
- Wellington had the highest proportion of social workers with caseloads at potentially unmanageable levels (18.5%) followed by Canterbury (17.3%) and South Auckland (16.9%).
- On average the predicted complexity for social workers caseloads was highest in the Placement phase, followed by Intervention, and lowest in Intake/Investigation/Partnered Response phase.
- Generally social workers with a higher number of tamariki on their caseload tend to have a lower share of complex cases (and vice versa). This caseload number to complexity trade-off differs by phase. Social workers in the

Placement phase were most sensitive to this trade-off with those in Intake/Investigation/Partnered Response phases the least.
- More experienced social workers tended to have fewer tamariki on their caseloads, although caseloads were not necessarily less complex on average. However, more experienced social workers caseloads were less likely to be adjusted based on how complex they were.

Limitations and Recommendations

The case complexity model could be used as a tool for better understanding workload pressures, informing workforce planning, resource allocation, and regional support strategies. However, due to the current level of its accuracy, the model should *only* be used at an aggregate level, with its prediction *not* suitable for individual case allocation decisions.

For next steps, application of the model to caseload management and planning needs to be considered, the model should be periodically recalibrated to reflect changes in practice and data quality. Specifically, staff surveys (i.e., as in Part 1 of this project) should be routinely repeated to ensure the model's predictive capability remains accurate. In addition, future improvements to the model could include integrating additional structured and unstructured data sources to enhance predictive accuracy.

Background

This report summarises the approach and findings from development of a model to measure the complexity of cases held by Oranga Tamariki. This report is part of a broader initiative, intended to improve social worker caseload management.

Currently, caseloads are assessed by measuring the number of children allocated to a social worker. This measure has long been acknowledged to be incomplete in the sense that it does not reflect the complexity of the cases or provide reliable indication about the time (or resources) required to deliver quality services. As a result, subsequent reports have recommended developing better, more sophisticated measures to assist with identifying pressures and improve planning for resource allocation. For example, the Ministerial Advisory Board report 'Te Kahu Aroha'[1] noted that:

> *"As a critical part of strengthening the capacity and capability of social workers, it is clear that there is a need to improve the sophistication of workload monitoring beyond that of the average number of tamariki per social worker. This may take the form of a suite of related indicators, or a single workload indicator that reflects complexity of cases and can account for workload pressures or the capacity of staff. We have consistently heard that far too many (often care and protection) social workers are overloaded and stretched to breaking point, often work long hours, and with limited confidence that the load can be shared in the immediate future, or that national office has noticed their predicament."*

The report further recommended Oranga Tamariki develop an approach to account for the complexity of cases and enable effective social work:

> *"Begin work to improve the sophistication of workload management beyond that of the current averaging by number of tamariki per social worker, to an approach that recognises and accounts for the complexity of cases and enables an equitable workload allocation across social workers and sites, and across Oranga Tamariki functions."*

Following this, work aimed at developing a complexity measure was begun by Oranga Tamariki. Part 1 of this project surveyed Care and Protection Social Workers from across the motu to collate their reported (i.e., subjective) complexity level of each case allocated to them at the time. [2] In Part 2 of this project, a model utilising operational data to predict the reported complexity of a given case was developed. This report presents the approach used to develop this model, summarise key findings, and make recommendations for improvements and next steps.

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[1] Oranga Tamariki Ministerial Advisory Board. (2021). Hipokingia ki te Kahu Aroha Hipokingia ki te Katoa. Wellington, New Zealand: Oranga Tamariki—Ministry for Children.

[2] For more information about the survey see previous report *Measuring Case Complexity, Part 1 Survey.*

Benefits to understanding case complexity

In more detail, understanding case complexity could benefit the business in several ways:

Determine which aspects of a case are fixed and which aspects are fluid

- help us understand what elements of a case make it more complex or less complex and how these might change over time.

Improve understanding and aid in resourcing, case allocation and staff wellbeing

- help us understand why, for example, some social workers might have 10 children on their caseload while others have 20.
- help workforce planning and allocation of cases for sites and regions (taking complexity into account as opposed to just counting the number of children assigned to social workers).
- assist in making sure case allocation is fair and reasonable nationally.
- help identify areas which require support and potentially what supports are required.

Determine which aspects of a case social workers are involved in, how it impacts their workload, and where time is spent

- assist the future organisational strategy in terms of where time and effort are currently spent, what we want to focus on in the future, and where shifts need to be made to achieve this.

Determine/justify the cost of a case

- contribute to service mapping to estimate cost.
- justify the changes in costs in relation to the complexity of cases rather than the number of cases.

Accountability

- contribute to intentions of the organisation to develop a model to inform allocation and resourcing decisions at regional and national levels.
- provide information and monitor progress around the identified gap in managing workload for Te Riu, the Ministerial Advisory Board, PSA and other external monitors.

Out of scope

The project does not aim to:

- **Tell individual social workers how complex their cases are.** Social workers will always know their case best.

- **Determine the appropriate level of cases a social worker should be working on.** A measure of case complexity will show the relative caseload complexity for social workers but will not be able to determine the right level of cases they should be working on.

- **Determine how cases should be allocated at an individual level**. Measurement of case complexity through a model is based on structured data available in the system. The model can provide insight at an aggregate level but will lack the full contextual information appropriate for allocation of each case.
- **Determine the amount of time a social worker spends on a case**. A model will determine the complexity of people involved in a case and working with social workers, but not the amount of time various social worker tasks might take. The complexity of a case could indicate how the expected timeliness of casework tasks might change, but this aspect itself will not be covered by the model.

Methodology

Develop potential measures for case complexity

Part 1 of this project outlined the conceptual approach to complexity in the care and protection system and initial feedback gathered from several experienced frontline practitioners to identify contributing factors to complexity.

We identified from the collated factors a list of potential measures available in structured data that could be developed and allocated to three main cohorts of interest across the care and protection social work process (active Intakes/Investigation/Partnered Response phases, Intervention phases, and Placement phases).

To better reflect how operational data is structured in the system and may represent complexity, potential measures were framed at the level they are relevant to building a model (Figure 1):

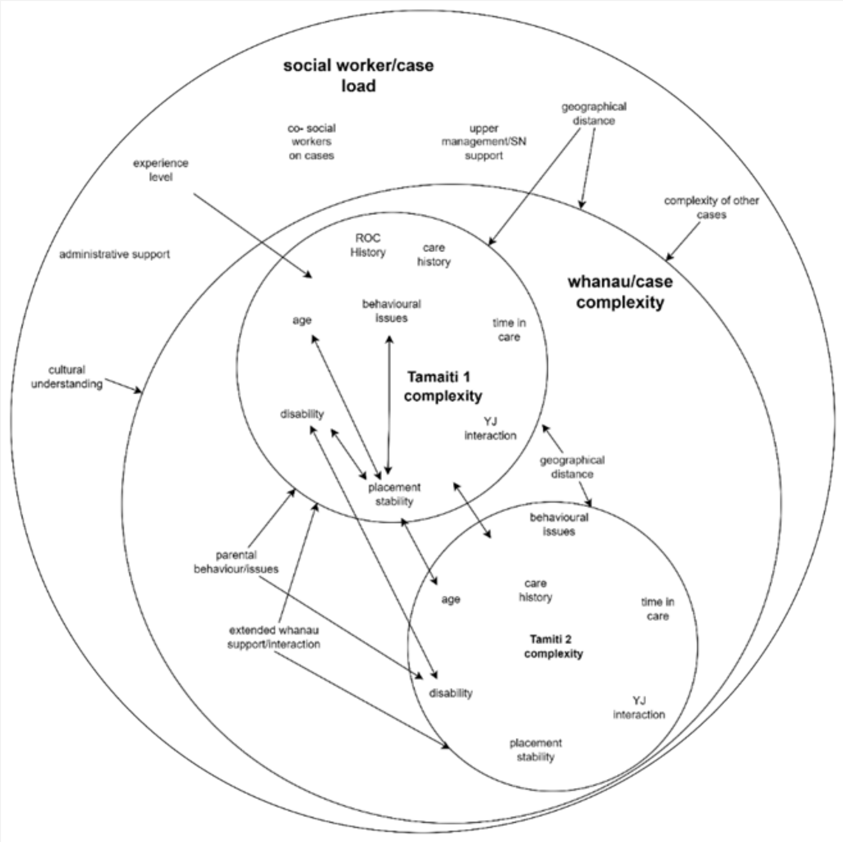
- complexity that occurs at the tamaiti level (individual aspect)
- complexity that occurs at the whanau or case level (case aspect)
- complexity that occurs at the level of the "system" or social worker level (caseload aspect)

Some measures may interact across and contribute to multiple levels of complexity. For example, individual aspects can impact the case aspects and caseload aspects, while case aspects can also impact individual aspects and caseload aspects. Considering the contribution of all levels of potential measures when developing a model of case complexity is necessary to fully capture such interactions.

Numerous measures were also developed into several versions representing different aspects of complexity (for example, the number of Reports of Concern the client has ever received or has received within the last year or received prior to the current active phase or during the current phase or received from multiple notifier types etc.). In total, there were several hundred versions of measures developed to test their ability to measure the complexity of a case.

In this framework, a few factors were added with our system in mind, including experience of social worker, differences among staff sites and phases within a case. All measure information was extracted from our internal case management system CYRAS.

Figure 1. A framework of case complexity



Note*: Factors that potentially contribute to complexity can be grouped into three levels – complexity that occurs at the tamaiti level, complexity that occurs at the whanau or case level, and complexity at the system or social worker level.*

Finally, to produce meaningful results, any model of complexity must be applied to the entirety of caseloads held nationally. Therefore, only measures that were based in structured data, and available at sufficient levels of coverage and quality were included in the model. Table 1 summarises a list of such measures used to test the prediction of complexity in the model, themed by key areas, for the three cohorts.

Table 1. Potential types of measures of case complexity identifiable in structured data across the three cohorts representing the significant phases of care and protection social work

	Cohort		
Theme	**Intake/Investigation/PRP** Active Intake/Investigation/Partnered Response phase	**Intervention** Active Intervention phase	**Placement** Active Placement phase (indicative of care and protection custody)
Age of the child	Younger than 10, likely linked to family issues Older than 10, likely linked to behavioural issues and subsequently harder to place		
Youth Justice involvement	Current and historical Youth Justice (YJ) Family Group Conferences (FGC), referrals and plans		

<table>
<tr><td></td><td colspan="3">Current and historical YJ custody episodes, remand episodes, and supervision or supervision with activity orders

Current and historical YJ involvement (phases)</td></tr>
<tr><td>Disability, mental health and/or behavioural issues</td><td></td><td colspan="2">Needs split into domains of functioning from Gateway assessments (both child and parent aspects) and CYRAS alerts

Behavioural and relationship issues identified from substantiated finding

The number of Kessler, SACS (Substance and choices scale), SKS (combined SACS, Kessler, Suicide screens) assessments[3]

Results of SKS, SACs, Kessler assessments</td></tr>
<tr><td>Substance use</td><td></td><td colspan="2">The number of Kessler, SACS, SKS assessments

Results of Kessler, SACS, SKS assessments

Needs identified from Gateway assessment (both child and parent aspects) and CYRAS alerts</td></tr>
<tr><td rowspan="2">Multiple report of concerns</td><td colspan="3">History of Reports of Concern (ROC)

Complexity of reports (such as from different notifier types, with abuse findings)

Severity (outcome with ‘Further Action Required’ (FAR), Family violence incidents, abuse findings)</td></tr>
<tr><td></td><td colspan="2">Reports of Concern received and abuse found while in care or before FGCs</td></tr>
<tr><td rowspan="2">Care and FGC experience</td><td colspan="3">History of care and FGCs

History and stability of placements

History of prior FGCs

Geographical separation issues identified in a case through differences in sites of staff and phases</td></tr>
<tr><td></td><td></td><td>Current placement at residence or a Family Home/Supervised Group Home for long term (90 days and more)</td></tr>
<tr><td>Number of social workers on a case</td><td colspan="3">Current or historical number and churn of Key social worker of a case

Number of co-social workers during the period (intensive staffing)

Experience of Key social worker</td></tr>
</table>

[3] The substances and choices scale (SACS) assesses and monitors the use and impact of alcohol and drugs. The Kessler screen gives an indication of psychological distress and possible mental health issues. The suicide screen helps to identify whether tamaiti or rangatahi have active thoughts of suicide. The screen does not determine the risk level but assists in deciding whether further investigation is needed. Together these screens are known as the SKS screens.

		Churn of FGC coordinators Churn of YJ social workers	
			Total staff allocated to the phase Churn of FGC coordinators while in care Concurrent key social workers or open phases
Siblings in care elsewhere		Indicative of separation issues perhaps and visitation difficulties if siblings are not placed together Geographical separation identified in a case	

Model Development

This section outlines how we examined and tested whether using structured operational data from CYRAS can predict the complexity of cases as ranked by social workers.

As discussed, in Part 1 of this project, we surveyed a sample of social workers to record their ratings of case complexity for tamaiti and whanau on their current caseloads. All potential measures from our structured data were extracted from our case management system at the time of the survey and joined to the relevant cases and survey responses to enable testing of various models on their predictive power of rated complexity.

To test the model, we randomly assigned all survey responses into *training* (75% of responses) and *testing* (25% of responses) sub-groups. Next, we used applied models, using each to estimate the relationship between the various predictors (i.e., structured operational data) and complexity for the *training* sub-group. Then, we predicted the complexity levels for the *testing* sub-group using the estimated relationships from each model (i.e., the estimates established from the *training* sub-group).

We then examined the aspects of models predicted. To select our preferred model, we compared each model's accuracy, true positive (specificity), true negative (sensitivity), and balanced accuracy rates.

Before discussing these findings, note that we introduced changes following our initial analysis:

- Only predicting tamaiti complexity (i.e., and not also whanau complexity) since the nature of numerous predictors were tamaiti specific, and doubts regarding the feasibility of models accurately predicting two different complexity ratings, where contributing measures may be overlapping.

- Changing complexity from a five-value scale to two-value, as this significantly improved the ability of the models to accurately predict complexity to an acceptable level. As shown in Table 1Table 2, cases either had a Low/Medium or High predicted level of complexity.[4]

Table 2. Survey complexity ratings and grouped levels for model testing

Survey complexity	Three-level complexity	Two-level complexity
Not at all complex	Low complexity	Low/Medium complexity
Somewhat complex	Medium complexity	Low/Medium complexity
Moderately complex	Medium complexity	Low/Medium complexity
Very complex	High complexity	High complexity
Extremely complex	High complexity	High complexity

- Modelling each phase separately (i.e., Intake/Investigation/Partnered Response, Intervention, and Placement), resulted in better prediction for all models (i.e., compared to modelling all phases jointly). For tamaiti with different phases open within the same case the highest level phase currently open was used.
- Removing highly correlated predictors (i.e., from the operational measures) improved the performance of all models. This required estimating the models twice, once in order to detect all highly correlated predictors (with correlation of 95% or higher), and a second time while excluding these predictors.[5]
- Implementing a Boruta algorithm for all relevant variables improved the performance of all models.[6]

Overall, the two models which performed best were Random Forest and XGBoost (Extreme Gradient Boosting). Briefly, Random Forest fits the data (i.e., over the *training* sub-group) by building multiple decision trees in parallel. Each tree is trained using a random subset of the available predictors, and a random subset of the training data. This randomness helps to address overfitting by ensuring that the trees are diverse, where the final prediction is the aggregation of all predictions from all trees, classifying the complexity of each case using a majority vote. On the other hand, XGBoost builds regression trees sequentially, where the model overall

[4] The two-level variation also outperformed a three-level measure (which in turn, outperformed the five-level measure).
[5] We also tested this approach setting a lower (80%, 90%) and higher (99%) correlation threshold, with the 95% leading to the best results.
[6] The Boruta algorithm addresses instances where too many variables are fed into a machine learning model, and as a result, decrease the accuracy of the model. The algorithm iteratively removes measures that are statistically less relevant than others by using a wrapper around a random forest classification that compares the relevance of real features to that of random probes. For more information, see: [Feature Selection with the Boruta Package | Journal of Statistical Software]

performance is improved incrementally, by correcting the prediction errors found by previous trees (i.e., when creating each subsequent tree).[7]

Table 3 summarises the performance of the two models for each phase/cohort. Overall, the models correctly predict complexity between 73% and 85% of the time (i.e., accuracy). However, given that having a complex case is less common than having a non-complex one, the accuracy measure overstates the performance of the models. For example, in the survey, social workers ranked 18% of all tamaiti in Intake/Investigation/Partnered Response phases as complex (i.e., Very or Extremely Complex). Therefore, using a model that *always* predicts a non-complex value will record an accuracy measure of 82% (since this will be true 82% of the time).

Next, the table shows that the true positive rate, or the share of complex cases that were *correctly* predicted as complex is relatively low. The models correctly predicted complexity for 40-47% of all Interventions, about one third of Intake/Investigations/Partnered Responses, and 61-69% of Placement phases. Speculatively, the greater rate of prediction in the Placement phase may be a result of having more information about these tamariki and rangatahi given their higher involvement in the system (which are used by the model as predictors). In all phases, the XGBoost model has recorded a greater true positive rate than the Random Forest model.

In contrast, when examining the true negative rate, or share of non-complex cases that were *correctly* predicted as non-complex, these were relatively greater, with the random forest model showing better rates. Finally, the balanced accuracy (average of the two), suggests that different models are better at predicting different phases.

Table 3. Accuracy, true positive, true negative, and balanced accuracy rates for Random Forest and XGBoost models across phase cohorts

Phase	Model	Accuracy	True positive	True negative	Balanced accuracy
Intake/ Investigation/ PRP	XGBoost	82.6%	34.7%	93.0%	63.9%
	Random Forests	84.5%	33.3%	95.6%	64.5%
Intervention	XGBoost	72.6%	47.4%	83.7%	65.6%
	Random Forests	78.2%	39.5%	95.3%	67.4%
Placement	XGBoost	80.2%	69.8%	85.2%	77.5%
	Random Forests	80.2%	60.5%	89.8%	75.2%

***Note**: predictive results for the testing sub-group, after removing predictors that have a 95% (or higher) correlation with one another.*

Following this comparison, we selected XGBoost as our preferred model. Despite recording a lower true negative and balanced accuracy rate (in two of the three phases), XGBoost is preferred as it more accurately predicts high complexity, which is the focus of this analysis. A full list of the selected predictive measures under each of the final phase cohort XGBoost models is available in Appendix 1: Contributing measures underlying the complexity models – generally across the phases these

[7] It also includes advanced features to ensure regularisation to prevent model overfitting, for tree *pruning*. Other models that were considered included neural networks, multiple nearest neighbour, and Multinomial Logistic Regression models.

covered historical and recent counts of various care and protection interactions (ROC, FAR, FGC, placement types), phase history, case staffing levels, clients on case, indications of abuse and mental health/behavioural issues.

The model is likely to understate the actual share of highly complex cases because it records a low true positive rate in some phases. But, it has utility if the extent of the error is similar across dimensions (e.g., location, age group, gender, ethnicity), then the model can be used to compare the complexity levels of one such group *relative* to all others (e.g., males versus females). This is the assumption when discussing the predicted complexity levels in the upcoming sections.

Complexity Model Results

Following the testing process, we went on to use the XGBoost models to predict the two-level complexity (Low/Medium or High) of the entire caseload nationally (including unallocated cases) at the time the survey was rolled out (September 2023). Using a two-level measure of complexity as a score in the section below effectively identifies the proportion of tamariki in a caseload that are predicted to be highly complex.

National Caseload Tamariki Demographic

National caseload numbers decrease as the phases progress

The cohorts of interest from the national caseload had 10,533 (56%) tamariki from Intake/Investigation/Partnered Response, 4,633 (25%) tamariki from Intervention and 3,577 (19%) tamariki from Placement phases.

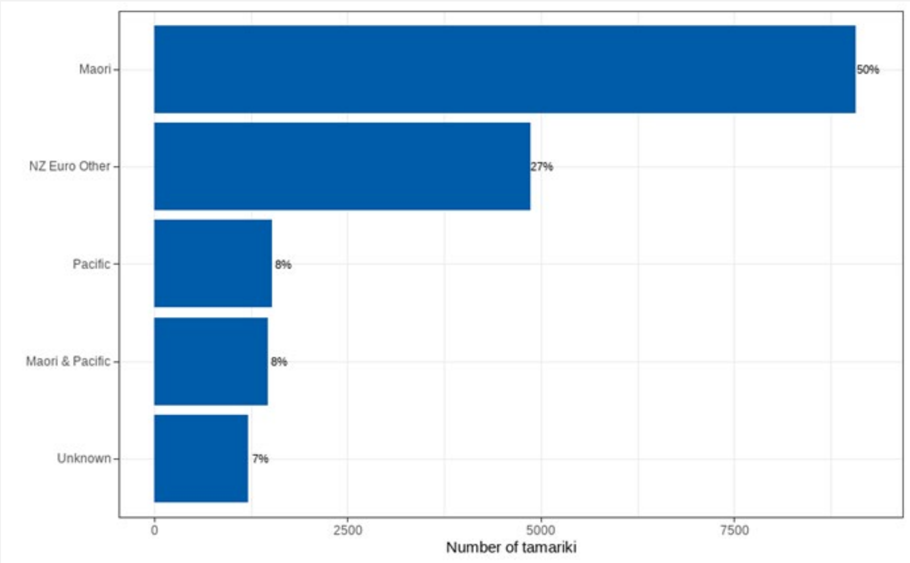
Table 4. Number of tamariki on care and protection caseloads nationally across the three cohorts of interest and proportions by prioritised ethnicity and age group

Cohort	Intake/ Investigation/PRP	Intervention	Placement	Total
Total	10,533	4,633	3,577	18,743
Māori	47%	54%	57%	50%
Māori & Pacific	6%	10%	10%	8%
Pacific	10%	7%	6%	8%
NZ Euro Other	27%	25%	27%	27%
Unknown	10%	4%	0%	7%
<0	2%	1%	0%	1%
0-1	11%	13%	4%	10%
2-5	22%	25%	15%	21%
6-9	21%	22%	20%	21%
10-13	24%	22%	27%	24%
14-15	12%	10%	16%	12%
16-18	7%	6%	16%	9%
19+	0%	1%	1%	1%
Unknown	1%	0%	0%	1%

Māori account for the highest proportion of tamariki on caseloads and increases as phases progress

Māori account for 50% of tamariki on caseloads nationally with a further 8% being Māori & Pacific. The proportion of tamariki Māori in each phase cohort increases with involvement level, being the highest for the Placement phase as seen in Table 4.

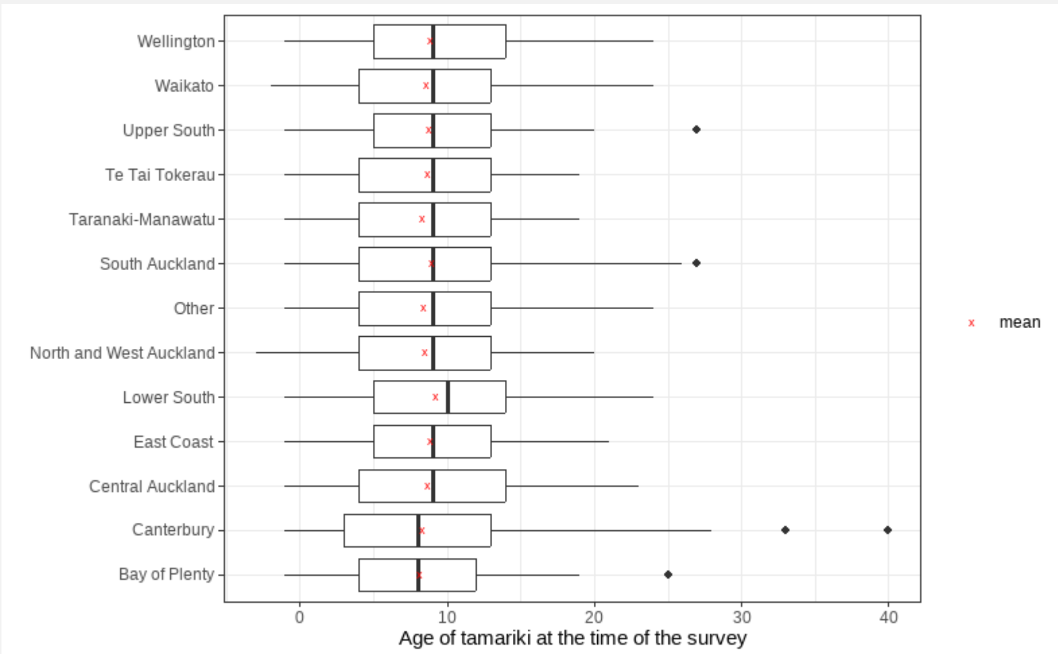
Figure 2. Number and proportion of tamariki on national care and protection caseloads by ethnicity



Most tamariki in cases are aged 13 and under, with over half usually under 10, across regions. Those in the Placement cohort tend to be older with 60% over 10 years old

Across the regions generally over 75% of tamariki are aged 13 and under, with over half under 10 years old. Across cohorts, the Placement cohort is notably older with only 39% being under 10, compared to 55 – 61% for the other two cohorts. Some tamariki were reported to be outside the target age range for interaction with Oranga Tamariki. This can be due to legitimate practice reasons on occasion or potential data entry errors such when a parent is labelled as a client, a case/client is not closed off, or when siblings age out of a case containing younger clients and are not closed off as current clients.

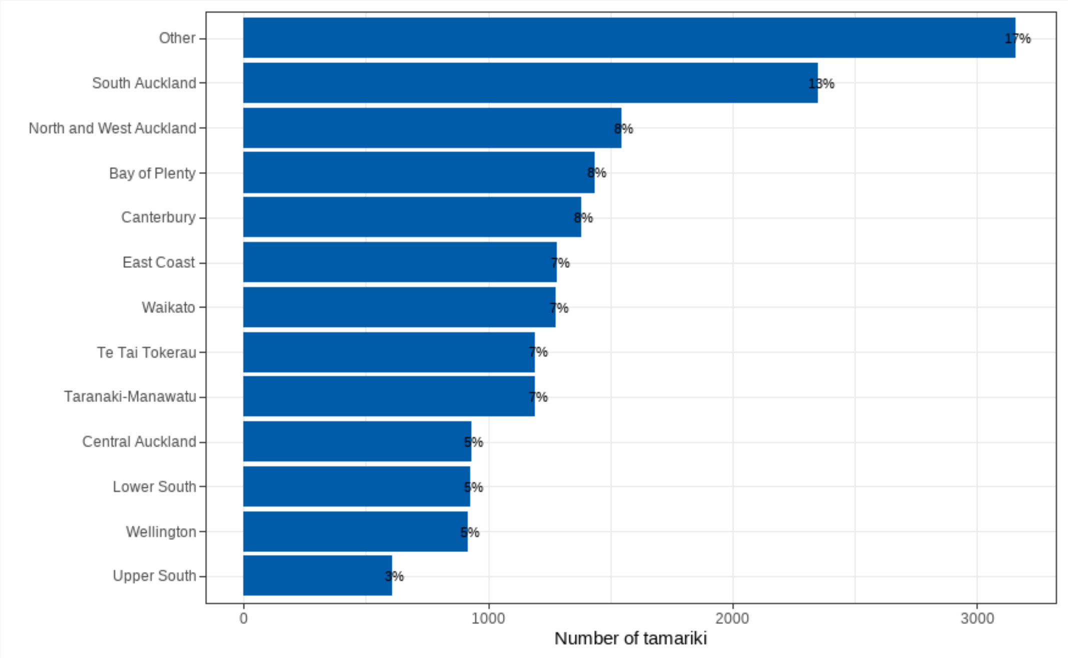
Figure 3. Distribution of tamariki ages on care and protection caseloads by region



Most tamariki are assigned to the ‘Other’ region due to unallocated cases, followed by South Auckland and North and West Auckland

A significant proportion of tamariki (17%) on care and protection cases are based within the ‘Other’ regional category. This is due to a high number of unallocated tamariki within the full cohort, mostly within the Intake phase. 13% of tamariki within the full cohort are allocated within the South Auckland region followed by 8% in North and West Auckland.

Figure 4. Number and proportion of tamariki in national care and protection cases by region



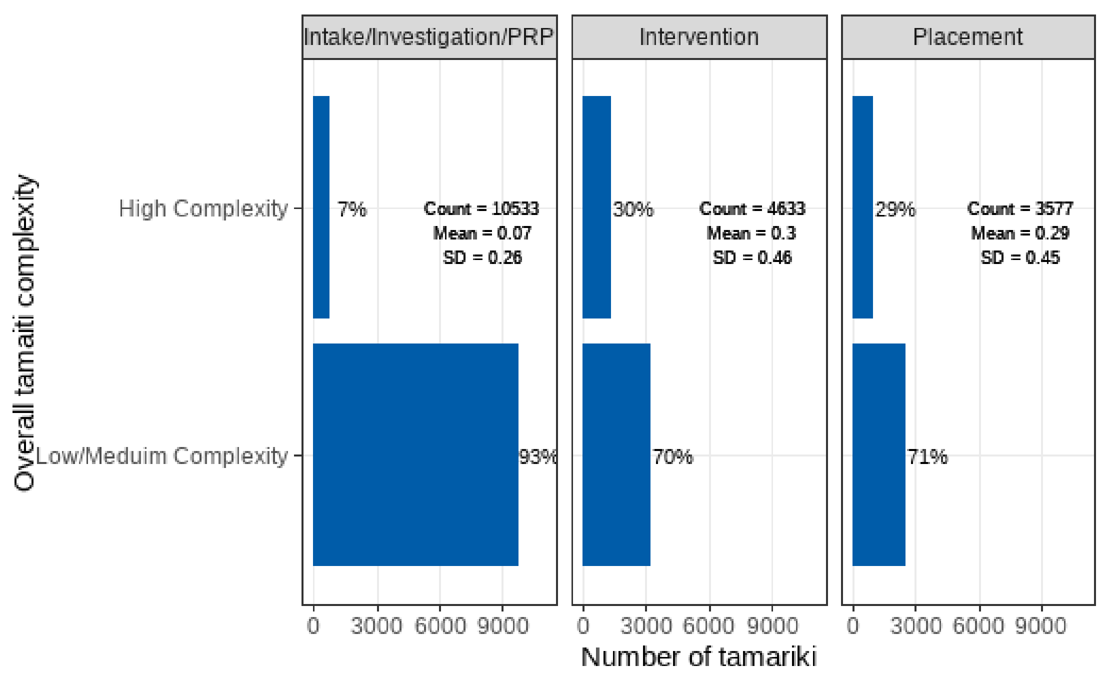
Predicted Tamaiti Complexity Nationally

Tamaiti complexity is lowest in the Intake/Investigation/Partnered Response phase and increased for the higher phases

Predicted tamaiti complexity is lowest in the Intake/Investigation/Partnered Response phase with only 7% rated with high complexity, a lower proportion than the 18% found in the survey sample with similar complexity. The model for this phase cohort had the lowest accuracy at predicting complex tamariki which could explain this lower predicted proportion.

The proportion of tamaiti rated with high complexity increased with the higher phases to approximately similar levels of 30% for Intervention and 29% for Placement phases, closely mirroring the proportions in the survey sample of 31% and 33% respectively.

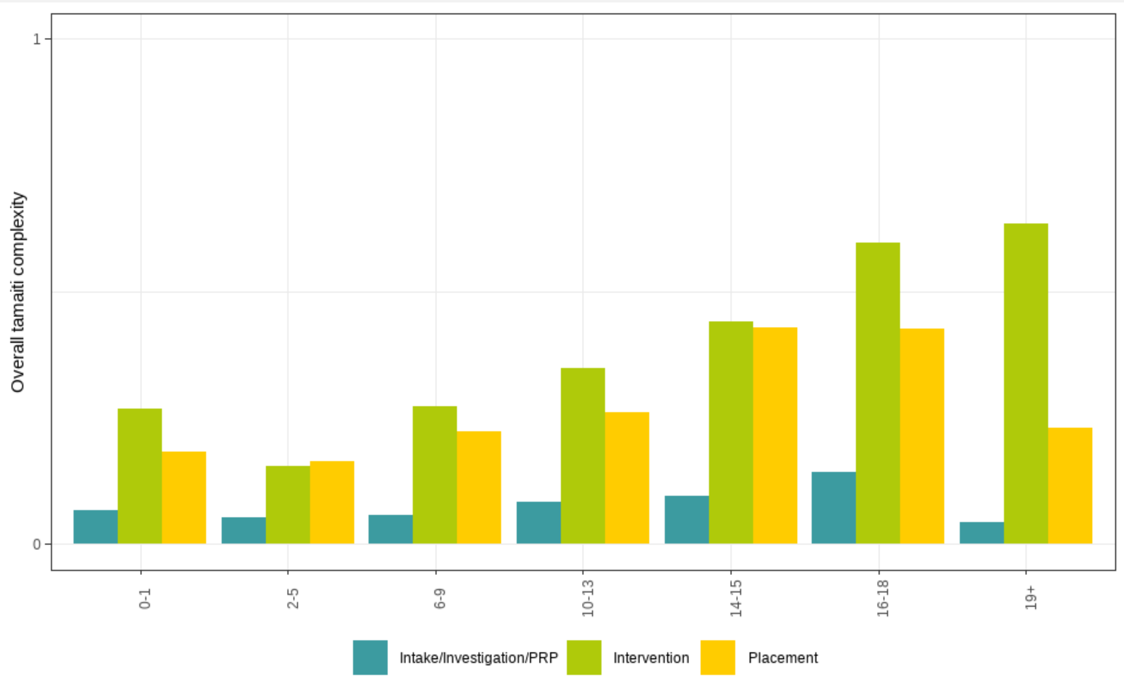
Figure 5. Proportion of predicted complexity in each phase cohort



Complexity tended to increase with age in each phase. 0 – 1 year olds were more complex compared to slightly older tamariki

Overall, complexity tended to increase with age, peaking at ages 16 – 18 for the Intake/Investigation/Partnered Response cohort, and at 14 – 15 for the Placement cohort. Rates for those aged 19+ are greatest for the Intervention phase. However, rates for this age group should be treated with caution due to the small numbers (since most 19+ year olds should have aged out of the system).

Figure 6. Average predicted tamaiti complexity across phase cohorts by age groups

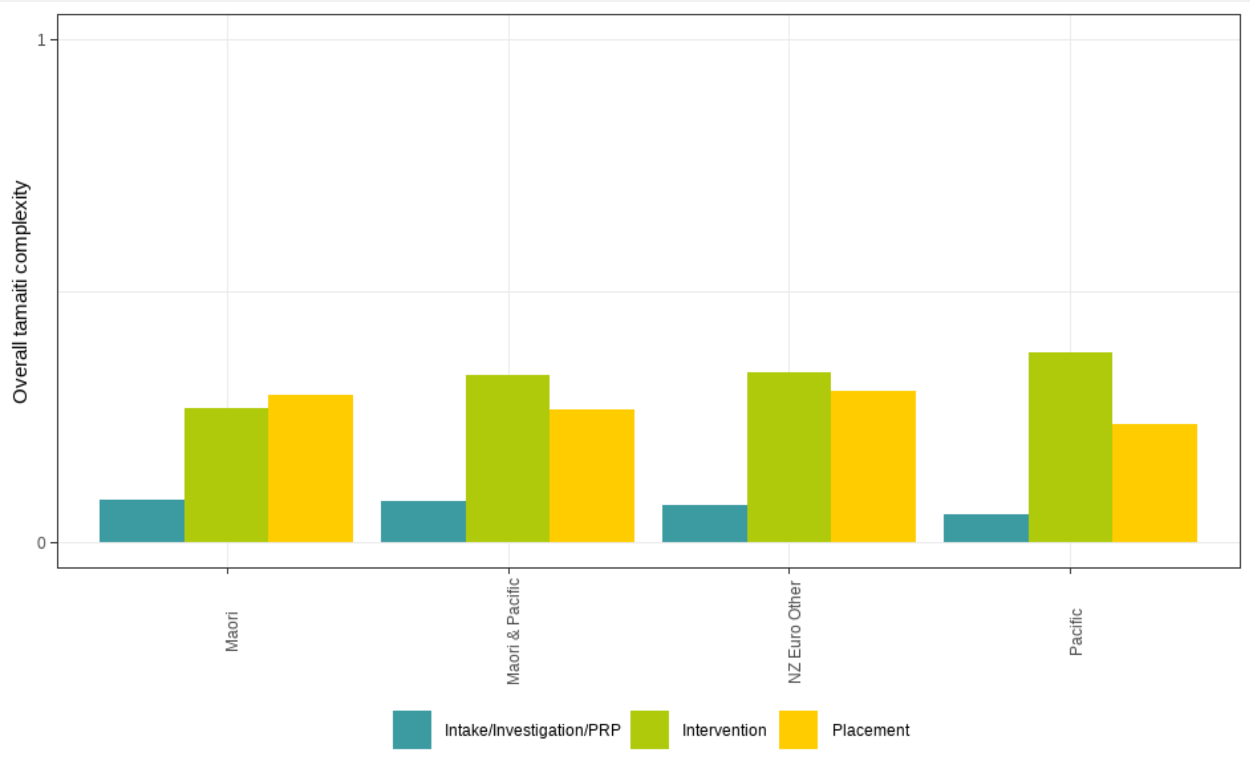


Interestingly, the proportion complex of 0 – 1 year olds was noticeably higher in all phases than the proceeding 2 – 5 year old group. This potentially indicates that cases with such young tamaiti may be more challenging to work with. In-line with the survey findings, complexity levels in the Intake/Investigation/Partnered Response phase were much lower than for the other two cohorts, with the Intervention phase tending to be the most complex across most age groups.

Complexity was highest in the Intervention phase across most ethnicities, being highest for Pacific

Complexity was highest in the Intervention phase for all ethnicities except for Māori, where the Placement phase showed a slightly higher rate. Pacific had the highest complexity in the Intervention phase and also the lowest complexity in the Placement phase.

Figure 7. Average predicted tamaiti complexity across phase cohorts by ethnicity



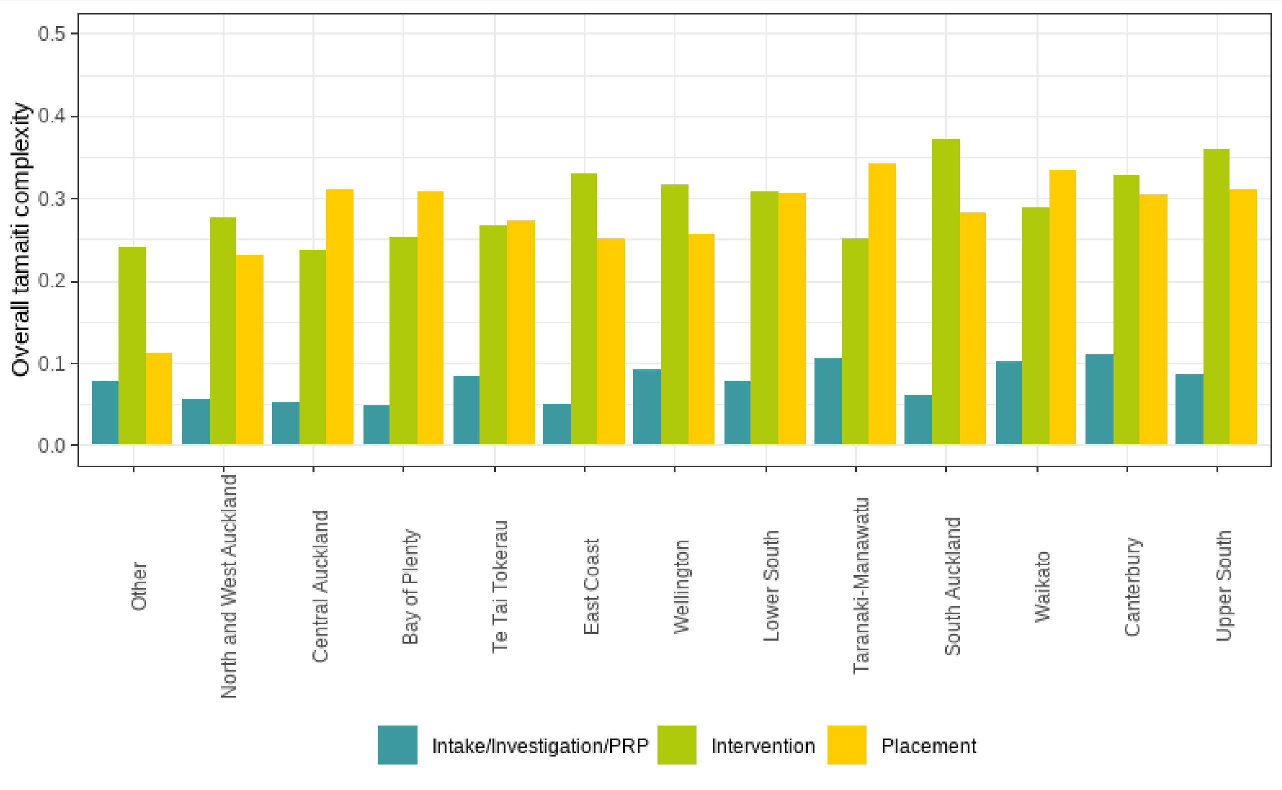
In general, the Intervention phase was rated the most complex across many regions with a few notable exceptions. South Auckland had the most complex Intervention phase with the most complex Placement phase in Taranaki-Manawatū

The Intervention phase is generally the most complex across many regions except for Central Auckland, Bay of Plenty, Taranaki-Manawatū and Waikato where the Placement phase is noticeably more complex. South Auckland had the most complex Intervention phase while Taranaki-Manawatū had the most complex Placement phase. Interestingly, all the South Island regions (Upper South, Canterbury and Lower South) recorded some of the highest levels of complexity across most of their phases.

As can be seen a large proportion of care and protection regions have complexity scores higher at the Intervention phase than in the Placement phase. This was also observed with the survey results and may be due to:

- The nature of the work involved with implementing a Family Group Conference usually conducted in this phase
- The coordination level required at this phase
- Intervention social workers perspectives of workload

Figure 8. Average predicted tamaiti complexity across phase cohorts by care and protection region



Social Worker Caseload Complexity

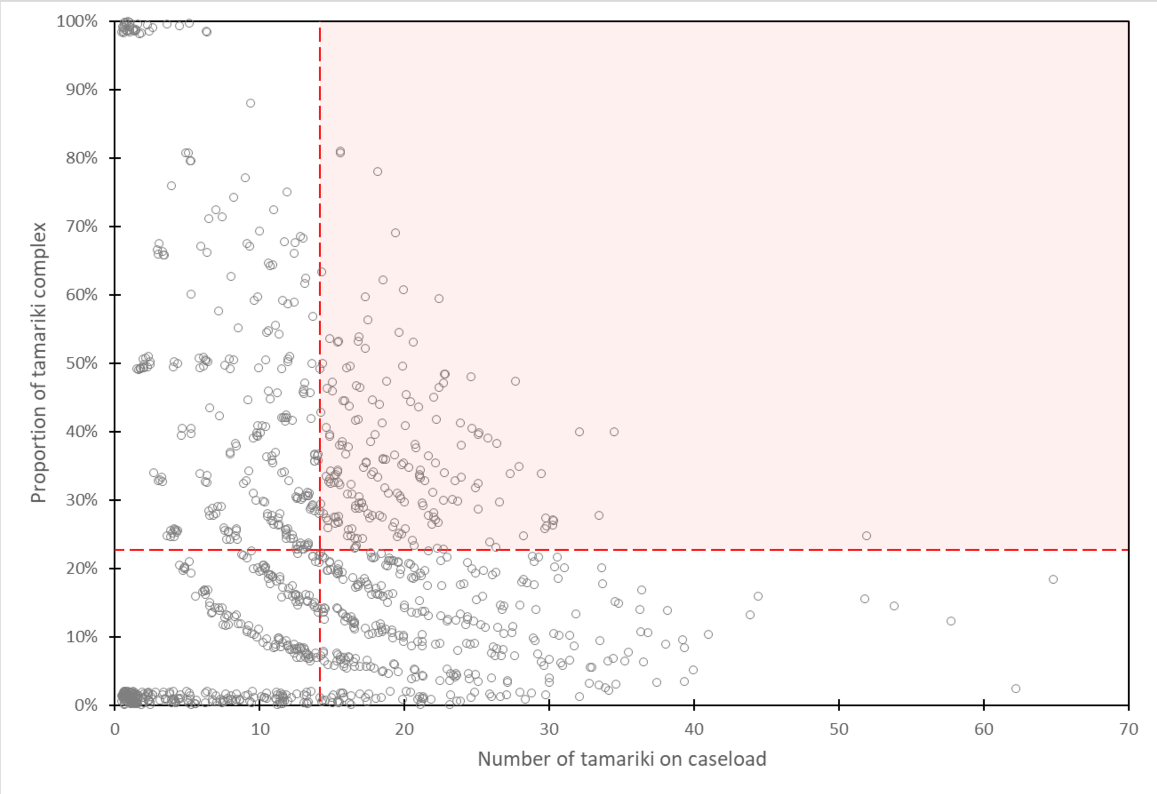
A two-level measure of complexity allows determination of the proportion of tamariki predicted to be complex alongside the number of tamariki on a caseload illustrating the natural trade-off for case allocation and providing an indication of potentially unmanageable levels for a caseload

Ultimately, development of a model that could predict complexity was intended to provide a more nuanced measure of a social worker's caseload, one that is beyond merely counting the number of tamariki they were working with.

Ideally, a graduated measure of complexity such as the 5-levels ('Not at all complex' up to 'Extremely Complex') collected in the survey would have provided a potential scoring mechanism to represent a complexity adjusted caseload number (i.e. a 'Not at all complex' tamaiti could be a 1 whereas an 'Extremely complex' tamaiti could be a 5 on their caseload). As has been detailed in the methodology section sufficient accuracy for complexity prediction was only possible with a two-level measure (Low/Medium vs High) which is too broad a categorisation to allow for an effective scoring of caseload complexity. However, a two-level measure of tamaiti complexity does provide an additional piece of information by illustrating what proportion of a social worker's caseload is considered to be highly complex.

One possible application of the model could be to combine the share of high complexity cases for each social worker, with the number of tamariki they are working with. Figure 9 illustrates this by plotting each social worker holding a care and protection caseload nationally.

Figure 9. All social workers nationally by number of tamariki on their caseload and the proportion of them predicted to be complex



***Note**: Each circle represents one social worker and their caseload that they are assigned to in a Key Social Worker role. The red lines indicate the national average for social worker caseloads. The top right quadrant indicates social workers carrying both an above average number of tamariki and above average proportion predicted to be complex.*

Each circle represents a kaimahi plotted by the number of tamariki they are an allocated key social worker for by the proportion of them that are predicted to be complex. The dotted red lines indicate the average number of tamariki on caseloads nationally (14) and the average proportion predicted to be complex (23%). A clear curve can be seen illustrating the general trade off social workers make (i.e., as a group) between the number of tamariki on caseload, and the share that are complex. This trade-off is to be expected for a manageable allocation of cases to a social worker. For instance, if a social worker has many tamariki on their caseload fewer of them tend to be complex (lower right quadrant) whereas if many of the tamariki are complex the total number of tamariki on the caseload is lower to likely compensate (upper left quadrant). The red shaded area of Figure 9 indicates social workers who are carrying both an above average number of tamariki on their caseload and an above average proportion which are complex (16.7% of kaimahi nationally). Social workers in this quadrant are potentially at risk of holding an unmanageable caseload, even more so depending on how far their caseload is in this quadrant. Therefore, examining both measures in tandem can be used as an indication of risk for unmanageable caseloads.

Note, the boundary for the quadrant in this Figure 9 was set to equal the national averages. This was done for illustrative purposes, and a different threshold may be required for more meaningful practical applications.

Caseload complexity is highest for the Placement phase, followed by Intervention, with Intake/Investigation/Partnered Response being lowest. Caseload numbers are also most sensitive to the addition of complex tamariki in the same order.

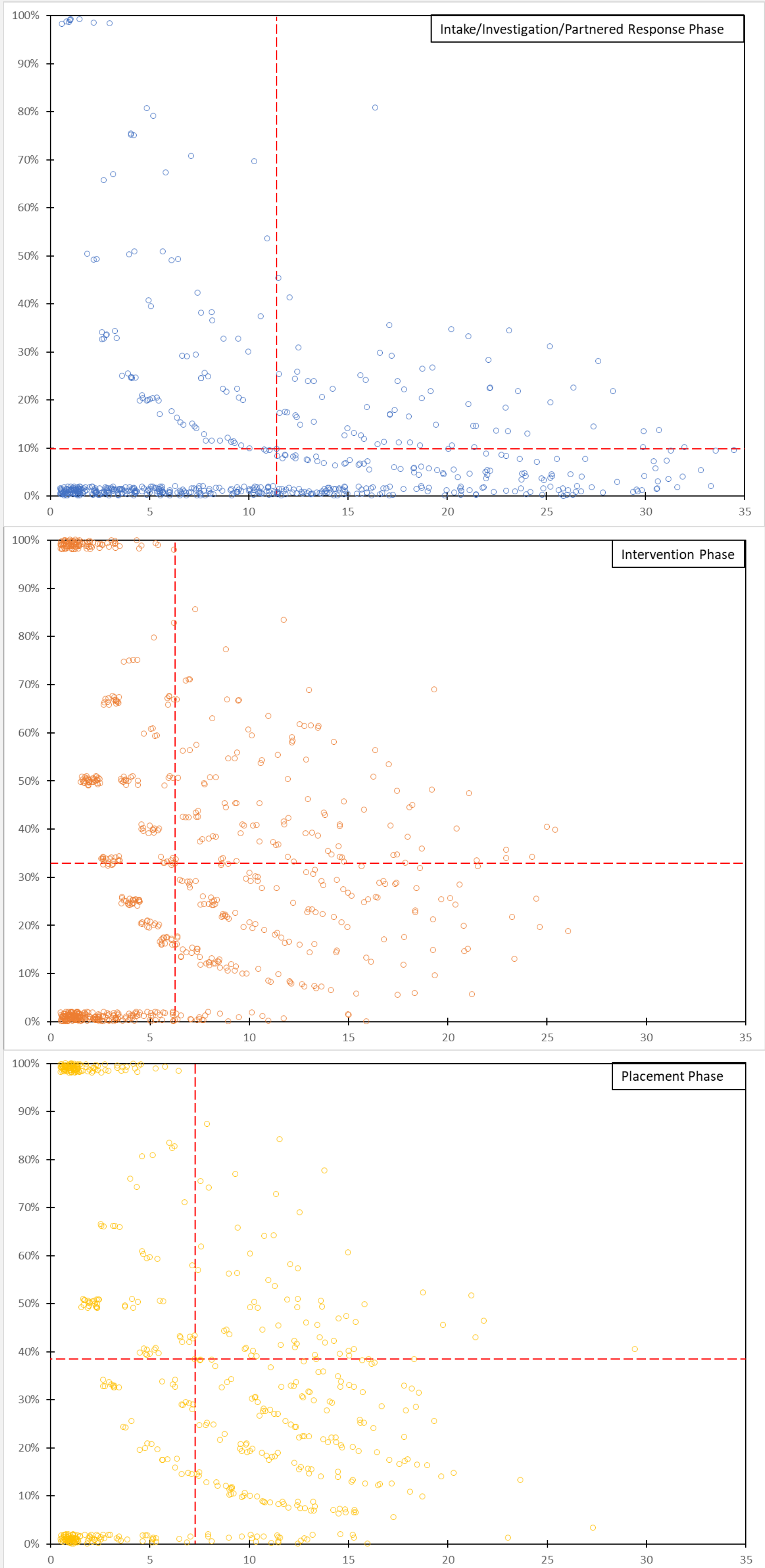
Figure 10 illustrates the dual caseload measure of number of tamariki and proportion complex as split for each phase. The highest average number of tamariki on a social workers caseload are in the Intake/Investigation/Partnered Response phase (11), followed by Placement (7) and then Intervention phases (6). Social workers had the highest average proportion complex on their caseloads in the Placement phase (39%), followed by Intervention (33%) and then Intake/Investigation/Partnered Response phases (10%).

In addition, the figure suggests that while the quantity-complexity trade-off is present in all phases, the magnitude of this (inverse) relationship varies. For example, the caseloads in the Intakes/Investigation/Partnered Response phase have a flatter slope generally than the other phases, illustrating that in this phase social workers require a relatively smaller reduction in work-volumes (i.e., number of children) when taking on an additional complex tamaiti. While this may reflect differences in how complexity is defined in this phase (compared to the other phases) it may also reflect the possibility that complexity in this phase has less influence on social worker capacity. Potentially, this may result from complex tamaiti not adding much additional work to a social workers caseload for this particular phase.

The Intervention phase has a generally steeper curve indicating complexity has a greater effect on social worker caseload capacity with the Placement phase having the steepest curve in general and greatest sensitivity of complexity to caseload numbers.

Social workers often specialise by phase wherein they work primarily within one phase. However, it is important to note social workers can and do work across several phases to varying levels depending on their given areas practice approach which can cause limitations when splitting results by phase such as underrepresenting total caseloads.

Figure 10. All social workers nationally by number of tamariki on their caseload and the proportion of them predicted to be complex split by phase



Note: *Each circle represents one social worker and their caseload that they are assigned to in a Key Social Worker role. The red lines indicate the national average for social worker caseloads of that* *phase. Note, scale for number of tamariki has been limited to 35 for comparability of phases although there are some outliers above this limit.*

More experienced social workers hold fewer tamariki on their caseloads on average although the proportion considered complex does not change much with experience generally. However, more experienced social workers' caseloads are less likely to be adjusted based on how complex they are

Nationally, approximately 1,100 kaimahi held care and protection cases at the time of the survey. To explore the relationship between work experience with the caseload and complexity measures, social worker experience was proxied using the difference in time between the date of the survey, and the earliest date recorded in the system for being assigned a social worker role for a care and protection case.

Of the 1,100 kaimahi holding cases nationally, 38% had 0 – 2 years experience, 29% 3 – 5 years, 17% 6 – 10 years and 16% with over 10 years' experience. Table 5 shows how the average number of tamariki on a caseload tends to reduce with experience, while share of complex cases does not differ significantly. One exception is the 6 – 10 year experience group, which shows a lower share of complex cases.

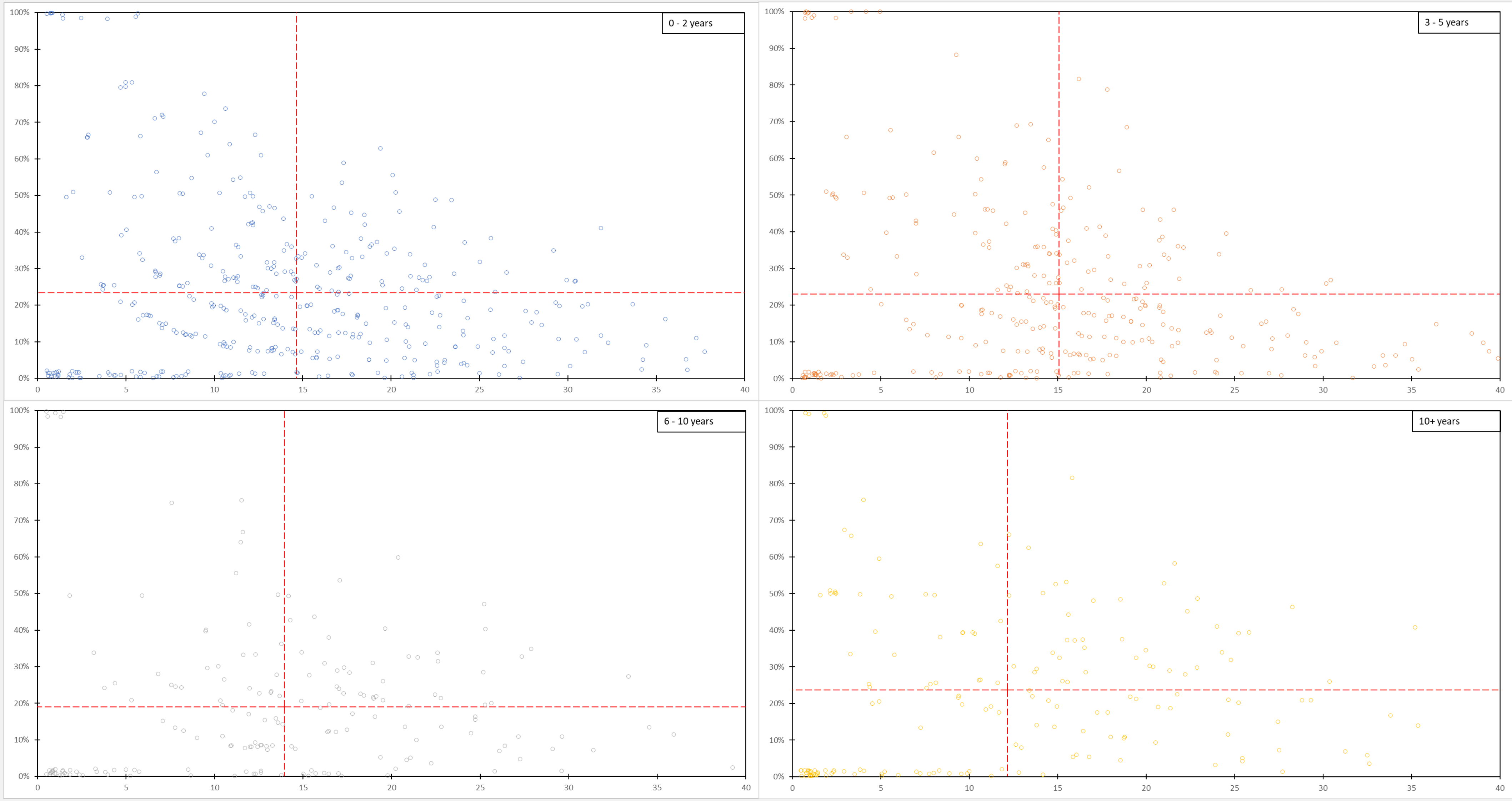
Table 5. Breakdown of kaimahi workloads by the number of years experience since being assigned their first Social Worker Role

Years of social work experience	Proportion of national kaimahi	Average number of tamariki on caseload	Average proportion predicted with High Complexity
0 – 2 years	38%	14.7 *(std. 9.0)*	23.4% *(std. 22.1%)*
3 – 5 years	29%	15.1 *(std. 9.4)*	23.0% *(std. 23.6%)*
6 – 10 years	17%	13.9 *(std. 9.1)*	19.0% *(std. 21.2%)*
Over 10 years	16%	12.2 *(std. 9.0)*	23.7% *(std. 21.1%)*

***Note**: The table presents the distribution of kaimahi by years of experience. For each group, the table also shows the average and standard deviation (in brackets) number of tamariki on caseload and proportion predicted with High Complexity.*

Whilst average proportions of caseloads predicted to be complex were not appreciably different for most social worker experience groups, we do see from Figure 11 how the distribution of cases provides some further insight into trade-offs between the number of tamariki and the proportion complex on a caseload.

Figure 11. All social workers nationally by number of tamariki on their caseload and the proportion of them predicted to be complex split by years of social work experience



***Note**: Each circle represents one social worker and their caseload that they are assigned to in a Key Social Worker role. The red lines indicate the national average for social worker caseloads of that experience group. Scale for number of tamariki has been limited to 40 for comparability of groups although there are some outliers above this limit.*

In social worker groups with over 6 years experience the trade-off is less evident and tend to have much flatter slopes generally, indicating greater tolerance for additional complex tamaiti (i.e., in terms of reducing the number of tamariki on their caseloads). Additionally, for social workers with over 10 years experience there is a greater spread of social worker caseloads into the potentially unmanageable upper right quadrant, with many that hold above national-average numbers of tamariki *and* proportion complex. Potentially, this could be indicating that very experienced social workers are receiving complex tamaiti without much adjustment to the number of tamariki assigned to their caseload.

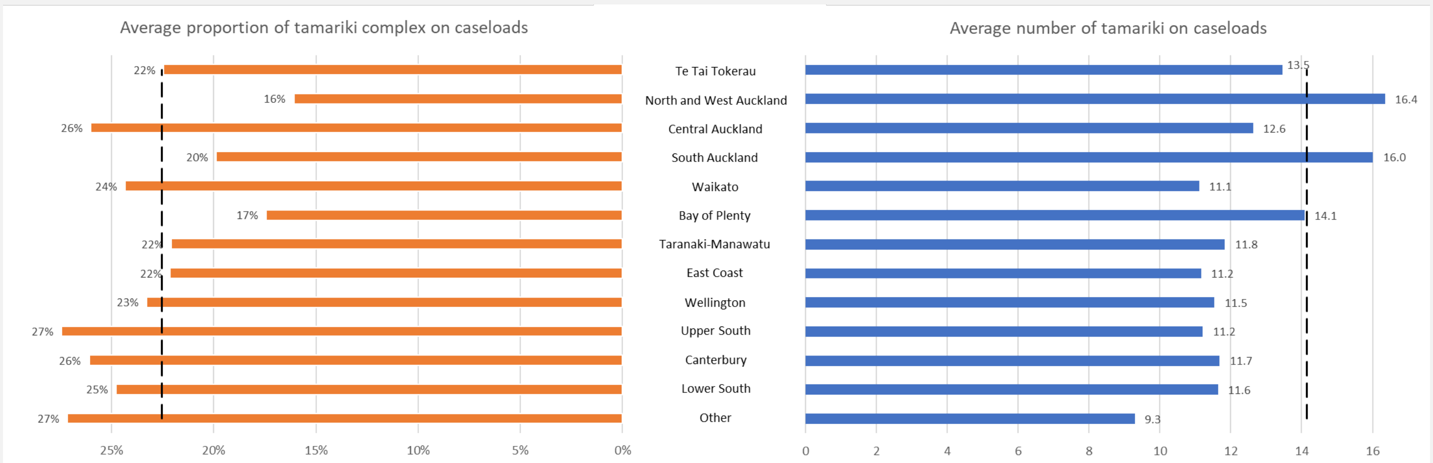
The 0 – 2 and 3 – 5 year experience groups had similarly steeper slopes generally indicating the trade-off between the number of tamariki and the proportion complex on a caseload is strongest for these social workers.

Importantly, it is worth noting that given the predictions of complexity are based on three separate phase dependent models that an overall view of all cases on a social worker caseload may be subject to variable accuracy depending on the mix of phases for the tamaiti they are working with.

No regions had both the average number of tamariki and proportion complex on caseloads above the national average. However, several regions had complex caseloads above the national average with Upper South, Other, Canterbury and Central Auckland being the highest

Figure 12 shows the dual measure for average numbers on caseloads and average proportion of caseloads predicted to be complex within each region compared to the national averages.

Figure 12. Regional breakdown of dual caseload measure



***Note**: Chart shows the average number of tamariki on social worker caseloads (blue, right) and the average proportion of them predicted to be complex (orange, left) in each region. The black dotted line indicates the national caseload averages.*

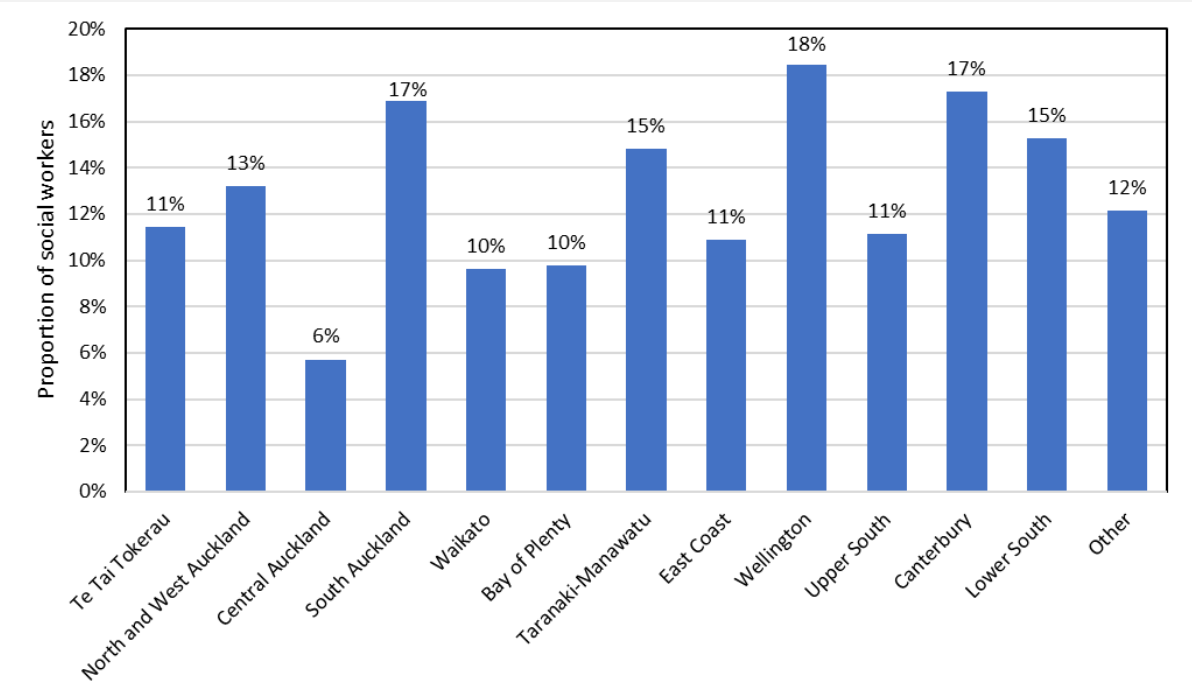
No regions had the average of both measures above the national average meaning none were in the potentially unmanageable caseload quadrant on average. North and West Auckland and South Auckland were the only two regions with above average caseload numbers. However, several regions were above the national average in terms of proportions of caseloads predicted to be complex with Upper South the highest followed by other notably high regions of Other, Canterbury, Central Auckland, Lower South, and Waikato. The South Island regions all feature above average on complexity of caseloads similar to Figure 8 where average tamaiti complexity was highest across multiple phases for them. As can be seen a large proportion of care and protection regions have complexity scores higher at the Intervention phase than in the Placement phase. This was also observed with the survey results and may be due to:

- The nature of the work involved with implementing a Family Group Conference usually conducted in this phase
- The coordination level required at this phase
- Intervention social workers perspectives of workload

Wellington has the highest proportion of caseloads at potentially unmanageable levels followed by Canterbury and South Auckland

Whilst averages do not indicate any region is falling into the potentially unmanageable caseload quadrant of both high caseload numbers and proportions complex, each region does still have a number of social workers operating in this quadrant. A more meaningful measure to account for this distribution is calculating the proportion of a region's social workers in this quadrant to provide a better indication of potential risk that may require attention.

Figure 13. Proportion of social workers with potentially unmanageable caseloads by region



Note*: Potentially unmanageable caseloads are those with both an above-average number of tamariki and above-average proportion considered complex compared to the national average.*

Figure 13 shows how the proportion of social workers in this potentially unmanageable caseload quadrant varies across the regions. Wellington has the highest proportion of social workers with a potentially unmanageable caseload at almost 1 in 5 social workers (18.5%) followed by Canterbury (17.3%) and South Auckland (16.9%).

It is important to note that caution should be taken if extending this dual measure and focusing down to the site level as the number of social workers within each site becomes much smaller. Given the accuracy of the models, it is best used at an aggregate level to provide meaningful insight and if utilised at too small a scale can introduce a fair degree of inaccuracy to the predictive results. The model should be used at the aggregate scale and not for application of caseload decisions at the individual social worker level as practitioners will always know more contextual information about cases than the model given it is trained off a subset of that information which has been entered as structured data into the case management system.

Conclusions and recommendations

A model for measuring complexity of tamaiti in care and protection cases nationally was developed. In order to achieve an acceptable level of accuracy for prediction of complexity, the model was split by phase of social work and the categorisation of complexity was refined from a 5-level scale (as collected in the survey) down to a 2-level scale (Low/Medium vs High Complexity).

Generally, the balanced accuracy of the selected models was of an acceptable level at approximately 64 – 78% for predicting the correct type of complexity (Low/Medium vs High Complexity). The ability of the model to predict the rarer event of high complexity (the true positive rate) was highest for the Placement phase at 70% of the time, then Intervention phase 47%, and finally lowest in the Intake/Investigation/ Partnered Response phase at 35%. Potentially, the ability of models to predict high complexity improves with the higher involvement phases as naturally more structured data is likely available to inform its capability.

Application of the model to the entire care and protection caseload nationally (at the time the survey was conducted) showed that overall tamaiti complexity was lowest for the Intake/Investigation/Partnered response phase and increased for the higher phases. In addition, tamaiti complexity tended to increase with age across the phases, often predicting highest in the Intervention phases overall, and when examined by age group, ethnicity, and region separately.

While the performance of the model and the usage of a 2-level measure are not sufficient for providing a graduated score for complexity of caseloads, these findings could be used in other applications. For example, by examining the number of tamariki on a social workers caseload, alongside the proportion of such cases predicted to be complex, the model's output could be used to provide an indication of when caseloads are falling within a potentially unmanageable quadrant, wherein they have both above average numbers of tamariki on their caseload and an above average proportion complex. The thresholds were chosen as the national averages although an acceptable practice threshold could also be set to determine the bounds of this unmanageable caseload quadrant.

When applied, the dual measure showed a general trade-off between the number of tamariki on a caseload and what proportion were complex as might be expected to allow a manageable caseload. Placement phases were most sensitive to the addition of another complex tamaiti affecting numbers on a social workers caseload, while Intake/Investigation/Partnered Response the least. Similarly, more experienced Social Workers exhibited a low sensitivity to this trade-off, possibly indicating their caseloads are less likely to be adjusted based on addition of more complex tamaiti. Regions with the highest proportion of caseloads at potentially unmanageable levels were Wellington, Canterbury and South Auckland.

Again, it is important to note that due to the limited accuracy of the models for predicting complexity, it is *not* advisable to examine the prediction at the individual social worker level for case allocation. The model is best used to provide indicative results that are useful at the aggregate level for identifying potential areas where further support, resource allocation, investment, or further attention should be directed. At the individual tamaiti or social worker caseload levels, more will always be known about the context and particulars of a case than what the model is likely to indicate.

In addition, note that the performance of the model is expected to deteriorate over time – as data entry in the system changes, as practice approaches change, as the view of what complexity is changes. The model was trained on data gathered from a survey at a point in time and is subject to all the factors defining social work and the state of structured data available then. It is recommended to repeat a similar process periodically to recalibrate and potentially improve predictive capability of the model in future. This process would entail running a similar survey over numerous social workers to gather further training data on rated complexity of tamaiti to retrain the model accounting for any changes in practice and quality of data entry over time.

Finally, model performance could be improved by incorporating further structured data that was not originally available at the time such as:

- contextual information from other sources within Oranga Tamariki (e.g., HR data)
- contextual information from data shares with other organisation (health, education, etc) about surrounding circumstances and needs
- structured data sources newly created in the case management system
- rich unstructured data in the case management system (case notes, documents, etc) themed up into structured indicators using large language model machine learning techniques.

Appendix 1: Contributing measures underlying the complexity models

The development process of the model resulted in several hundred measures being tested against their ability to predict the rated complexity of tamaiti, gathered from the survey as detailed in the Model Development section. The best accuracy for prediction was achieved by splitting the models by phase, each phase model had its own set of contributing measures utilised to determine a prediction which are listed below. It is important to note that each variable is important to the models performance yet how it contributes is not specified. The presence of one of the variables does not mean a tamaiti is complex for example, it may simply be considered important in regards to the presence of other indicators or may simply help refine the predicted complexity from a model.

Table 6. Contributing structured data variables for the Intake/Investigation/Partnered Response phase complexity model

Intake/Investigation/PRP Variables	Description
GW_REF_YN	Binary flag for whether client ever had a referral for a Gateway Assessment
GW_REF_PRIOR_YR_YN	Binary flag for whether client had a referral for a Gateway Assessment within prior year leading up to period end
CASE_ALL_PHS_STAFF_SEP_CUR	Binary flag for potential geographic separation of case work (calculated from mismatch between counts of all distinct sites for staff on case and all distinct sites associated with phases currently on case)
HIGHEST_PHASE	Highest phase a client has within a case (intake phase being lowest and placement phase being highest)
CLIENT_COUNT_CASES_CUR	Count of all distinct cases client is involved in at that point in time (includes both care and protection and youth justice cases)
ABUSE_COUNT	Count of all substantiated findings of abuse (including physical, emotional, sexual abuse and neglect)
ABUSE_COUNT_1YP	Count of all substantiated findings of abuse (including physical, emotional, sexual abuse and neglect) within prior year leading to period end
SCREEN_MAX_COUNT	The maximum number of screens in either the SACS, SUIC or SKS screens (whichever is highest) that they

	have ever had (i.e. if client had 3 SACS, 1 SUIC and 5 SKS screens this variable would equal 5)
COMB_TOTAL_NEEDS_COUNT	Count of all relevant Gateway Assessment or CYRAS alert need codes for client
CASE_CP_PHASE_ACTIVE_CUR	Count of distinct care and protection phases currently open on case
CASE_ALL_PHASE_ACTIVE_CUR	Count of all distinct phases currently open on case
CASE_ALL_CLIENTS_CUR	Count of distinct clients in all phases currently on case
CASE_ALL_STAFF_CUR	Count of distinct staff in all phases currently on case
CASE_CLI_CP_KEY_SW_EXP_YRS_SW	For the most experienced care and protection Key Social worker currently attached to client in a case, the number of years since their first allocation to any social worker role
CASE_CLI_ALL_PHASE_ACTIVE_CUR	Count of all distinct phases currently allocated to a client within the case
CASE_CLI_CP_KEY_SW_COUNT_1YP	Count of distinct care and protection Key social workers allocated over the last year to a client within the case
CASE_CLI_CP_TOTAL_STAFF_1YP	Count of distinct staff in the care and protection phases allocated over the last year to a client within the case
CASE_CLI_ALL_STAFF_1YP	Count of distinct staff in all phases allocated over the last year to a client within the case
CASE_CLI_ALL_PHASE_HIST	Count of all distinct phases allocated over entire history to a client within the case
CASE_CLI_ALL_STAFF_HIST	Count of distinct staff in all phases allocated over entire history to a client within the case
CASE_CLI_ALL_PHASE_SITE_HIST	Count of distinct sites associated with all phases allocated over entire history to a client within the case
CLI_ALL_STAFF_HIST	Count of distinct staff in all phases allocated ever to a client (regardless of case)
COHORT_ALL_CP_REVIEW_FGC_HELD	Count of all care and protection Review Family Group Conferences ever held
CP_FGC_HELD_1YP	Count of all care and protection Family Group Conferences held in prior year leading up to period end
COHORT_ALL_CP_NEW_FGC_HELD	Count of all New care and protection Family Group Conferences ever held

COHORT_CP_REVIEW_FGC_HELD_1YP	Count of all care and protection Review Family Group Conferences held in prior year leading up to period end
ALL_CP_FGC_PRIOR_TO_CUR_PHASE	Count of all care and protection Family Group Conferences held before the earliest start date of the currently active phases
ROC_TYPE_COUNT	Count of different types of notifiers for all Reports of Concern ever received for a client
ROC_COUNT_BEFORE_CUR_PHASE	Count of Report of Concerns before earliest start date of currently open phases.
ROC_COUNT_IN_CUR_PHASE	Count of Reports of Concern during currently open phase.
ROC_1YP	Count of Reports of Concern received for a client within year leading up to period end.
ROC_TYPE_COUNT_1YP	Count of different types of notifiers for Reports of Concern received for a client within year leading up to period end.
ROC_1Y_PHS	Count of Report of Concerns within the year prior to the earliest start date of currently open phases.
ROC_COUNT_BEFORE_FGC	Count of Reports of Concern received before their first care and protection Family Group Conference
ROC_COUNT_AFTER_FGC	Count of Reports of Concern received after their first care and protection Family Group Conference
FAR	Count of Reports of Concern received for a client with an outcome of "Further Action Required"
FAR_1YP	Count of Reports of Concern received for a client with an outcome of "Further Action Required" within last year leading to period end.
FAR_1Y_PHS	Count of Reports of Concern received for a client with an outcome of "Further Action Required" within the year prior to the earliest start date of currently open phases
CASE_YJ_CLIENTS_CUR	Count of distinct clients in youth justice phases currently on case
CASE_CLI_CP_CO_SW_HIST	Count of distinct staff with care and protection Co social worker roles allocated over entire history to a client within the case
CASE_CLI_CP_CO_SW_1YP	Count of distinct staff with care and protection Co social worker roles allocated over the last year to a client within the case
CLI_CP_CO_SW_HIST	Count of distinct staff with care and protection Co social worker roles allocated ever to a client

Table 7. Contributing structured data variables for the Intervention phase complexity model.

Intervention Variables	Description
GW_COUNT_DOMAINS	Count of domains of functioning flagged with a Gateway Assessment need code
GW_MNTL_HLTH_YN	Binary flag for any Gateway Assessment need code in the Mental Health domain of functioning
GW_ABUSE_YN	Binary flag for any Gateway Assessment need code in the Abuse Indication domain of functioning
CRA_COUNT_DOMAINS	Count of domains of functioning flagged by a CYRAS alert code
CRA_MNTL_HLTH_YN	Binary flag for any CYRAS alert code in the Mental Health domain of functioning
CRA_NEURO_DEV_HLTH_YN	Binary flag for any CYRAS alert code in the Neurological/Developmental Health domain of functioning
COMB_MNTL_HLTH_YN	Binary flag for any Gateway Assessment need or CYRAS alert code in the Neurological/Developmental Health domain of functioning
COMB_ABUSE_YN	Binary flag for any Gateway Assessment need or CYRAS alert code in the Abuse Indication domain of functioning
COMB_COUNT_DOMAINS	Count of domains of functioning flagged with a Gateway Assessment need or CYRAS alert code
CLIENT_AGE_AT_PERIOD_END	Age of client at point in time of interest (period end)
BEHAVIOUR_COUNT	Count of all substantiated findings of behavioural and relationship difficulties
GW_ABUSE_COUNT	Count of all Gateway Assessment need codes in the Abuse Indication domain of functioning
GW_NEURO_DEV_HLTH_COUNT	Count of all Gateway Assessment need codes in the Neurological/Developmental Health domain of functioning
CRA_TOTAL_NEEDS_COUNT	Count of all relevant CYRAS alert need codes for client
CRA_MNTL_HLTH_COUNT	Count of all CYRAS alert need codes in the Mental Health domain of functioning
CRA_NEURO_DEV_HLTH_COUNT	Count of all CYRAS alert need codes in the Neurological/Developmental Health domain of functioning
COMB_TOTAL_NEEDS_COUNT	Count of all relevant Gateway Assessment or CYRAS alert need codes for client

COMB_ABUSE_COUNT	Count of all Gateway Assessment or CYRAS alert need codes in the Abuse Indication domain of functioning
COMB_NEURO_DEV_HLTH_COUNT	Count of all Gateway Assessment or CYRAS alert need codes in the Neurological/Developmental Health domain of functioning
CASE_CLI_CP_PHASE_ACTIVE_CUR	Count of distinct care and protection phases currently allocated to a client within the case
CASE_CLI_ALL_PHASE_ACTIVE_CUR	Count of all distinct phases currently allocated to a client within the case
CASE_CLI_CP_KEY_SW_COUNT_1YP	Count of distinct care and protection Key social workers allocated over the last year to a client within the case
CASE_CLI_ALL_PHASE_HIST	Count of all distinct phases allocated over entire history to a client within the case
CLI_ALL_PHASE_HIST	Count of all distinct phases allocated ever to a client
COHORT_ALL_CP_NEW_FGC_HELD	Count of all New care and protection Family Group Conferences ever held
ALL_CP_FGC_HELD	Count of all care and protection Family Group Conferences ever held
ALL_CP_FGC_PRIOR_TO_CUR_PHASE	Count of all care and protection Family Group Conferences occurring before the earliest start date of the currently active phases
ROC_COUNT_BEFORE_CUR_CARE	Count of Reports of Concerns before current care custody episode
ROC_COUNT_BEFORE_CUR_PHASE	Count of Report of Concerns before earliest start date of currently open phases
ROC_COUNT_IN_CUR_PHASE	Count of Reports of Concern during currently open phase
ROC_1YP	Count of Reports of Concern received for a client within year leading up to period end
ROC_TYPE_COUNT_1YP	Count of different types of notifiers for Reports of Concern received for a client within year leading up to period end.
ROC_COUNT_BEFORE_FGC	Count of Reports of Concern received before their first care and protection Family Group Conference
ROC_COUNT_AFTER_FGC	Count of Reports of Concern received after their first care and protection Family Group Conference
FAR	Count of Reports of Concern received for a client with an outcome of "Further Action Required"

Table 8. Contributing structured data variables for the Placement phase complexity model.

Placement Variables	Description
FAM_SGH_DURATION_90DAYS	Binary flag for whether a client was in family home or supervised group home placements cumulatively for more than 90 days altogether. 90 days serves as an indication of 'long term' in what should be a transitional placement option.
CUR_FAM_SGH_DURATION_90DAYS	Binary flag for whether a client is currently in a family home or supervised group home placement for more than 90 days. 90 days serves as an indication of 'long term' in what should be a transitional placement option.
FAM_SGH_CURRENT	Binary flag for whether a client is currently in a family home or supervised group home placement.
CRA_COUNT_DOMAINS	Count of domains of functioning flagged by a CYRAS alert code
CRA_MNTL_HLTH_YN	Binary flag for any CYRAS alert code in the Mental Health domain of functioning
CRA_BEHAV_ATTCH_YN	Binary flag for any CYRAS alert code in the Behavioural/Attachment Issues domain of functioning
CUR_PLACEMENT_CHURN	Count of all placements within the current care episode open at period end
CUR_UNQ_PLACEMENT_CHURN	Count of all unique placements within the current care episode open at period end. Unique placement is identified based on placement resource.
TOTAL_FAM_SGH_DURATION	Count of total days a client has ever been in a family home or supervised group home placement cumulatively.
CUR_FAM_SGH_DURATION	Count of days a client has been in a currently open family home or supervised group home placement.
CONT_INCIDENT_COUNT	Count of continuous incidents of Reports of Concern. A continuous incident is defined as multiple Reports of Concern received within 60 days of each other as likely related to similar issues so considered one incident of reports. The incident is considered not continuous if a Report of Concern is received after 60 days of the previous Report of Concern.
BEHAVIOUR_COUNT	Count of all substantiated findings of behavioural and relationship difficulties
ABUSE_COUNT_1YP	Count of all substantiated findings of abuse (including physical, emotional, sexual abuse and neglect) within prior year leading to period end

ABUSE_DURING_CARE	Count of all substantiated findings of abuse (including physical, emotional, sexual abuse and neglect) during the current care episode.
BEHAVIOUR_DURING_CARE	Count of all substantiated findings of behavioural and relationship difficulties during current care episode.
SKS_COUNT	Count of SKS (combined SACS, Kessler and SUIC screens) screens applied to a client.
SCREEN_MAX_COUNT	The maximum number of screens in either the SACS, SUIC or SKS screens (whichever is highest) that they have ever had (i.e. if had 3 SACS, 1 SUIC and 5 SKS screens this variable would equal 5)
CRA_TOTAL_NEEDS_COUNT	Count of all relevant CYRAS alert need codes for client
CRA_MNTL_HLTH_COUNT	Count of all CYRAS alert need codes in the Mental Health domain of functioning
CRA_BEHAV_ATTCH_COUNT	Count of all CYRAS alert need codes in the Behavioural/Attachment issues domain of functioning
CASE_CP_TOTAL_STAFF_CUR	Count of distinct staff allocated to the care and protection phases currently on case
CASE_ALL_STAFF_CUR	Count of distinct staff allocated in all phases currently on case
CASE_CLI_CP_TOTAL_STAFF_CUR	Count of distinct staff allocated to the current care and protection phases for a client within the case
CASE_CLI_ALL_STAFF_CUR	Count of distinct staff allocated to all phases currently for a client within the case
CASE_CLI_CP_TOTAL_STAFF_1YP	Count of distinct staff allocated to the care and protection phases over the last year for a client within the case
CASE_CLI_ALL_STAFF_1YP	Count of distinct staff allocated to all phases over the last year for a client within the case
CLI_CP_KEY_SW_COUNT_CARE	Count of distinct care and protection Key social workers allocated over current care episode to a client
CLI_CP_CO_SW_CARE	Count of distinct care and protection Co social workers allocated over current care episode to a client
CLI_ALL_PHASE_CARE	Count of all distinct phases allocated over current care episode to a client
CLI_ALL_STAFF_CARE	Count of distinct staff allocated in all phases over current care episode to a client
CLI_CP_KEY_SW_COUNT_HIST	Count of distinct care and protection Key social workers allocated ever to a client

CLI_ALL_STAFF_HIST	Count of distinct staff allocated in all phases ever for a client (regardless of case)
BEHAVIOUR_BEFORE_PHASE	Count of all substantiated findings of Behavioural and Relationship Difficulties before earliest start date of currently open phases.
ROC	Count of Reports of Concern ever received for a client
ROC_TYPE_COUNT	Count of different types of notifiers for all Reports of Concern ever received for a client
ROC_COUNT_BEFORE_CUR_CARE	Count of Reports of Concern received for client before current care episode.
ROC_COUNT_IN_CUR_CARE	Count of Reports of Concern received for client during current care episode.
ROC_COUNT_BEFORE_CUR_PHASE	Count of Reports of Concern received for a client before earliest start date of currently open phases.
ROC_COUNT_IN_CUR_PHASE	Count of Reports of Concern received for client during currently open phases.
ROC_1YP	Count of Reports of Concern received for a client within year leading up to period end.
ROC_TYPE_COUNT_1YP	Count of different types of notifiers for Reports of Concern received for a client within year leading up to period end.
ROC_COUNT_AFTER_FGC	Count of Reports of Concern received after their first care and protection Family Group Conference
FAR	Count of Reports of Concern received for a client with an outcome of "Further Action Required"
FAR_1YP	Count of Reports of Concern received for a client with an outcome of "Further Action Required" within last year leading to period end.
ABUSE_DURING_PHASE	Count of all substantiated findings of abuse (including physical, emotional, sexual abuse and neglect) during currently open phases.
CASE_CP_CPC_SW_CUR	Count of distinct care and protection coordinators currently on case
CASE_CP_CO_SW_CUR	Count of distinct care and protection Co social workers currently on case
CASE_CLI_CP_CO_SW_CUR	Count of distinct care and protection Co social workers currently allocated to a client within the case
CASE_CLI_YJ_YJC_SW_CUR	Count of distinct youth justice coordinators currently allocated to a client within the case

CASE_CLI_CP_CO_SW_1YP	Count of distinct staff with care and protection Co social worker roles allocated over the last year to a client within the case
CASE_CLI_YJ_YJC_SW_1YP	Count of distinct youth Justice coordinators allocated over the last year to a client within the case
CLI_CP_CPC_SW_HIST	Count of distinct care and protection care coordinators allocated ever to a client
CLI_YJ_PHASE_HIST	Count of distinct youth justice phases allocated ever to a client