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Identifying risk of poor physical and mental health recovery following a road traffic crash: An industry-specific screening tool

Esther Smits[a,*], Charlotte Brakenridge[a], Elise Gane[a], Jacelle Warren[a,b], Michelle Heron-Delaney[c,d], Justin Kenardy[e], Venerina Johnston[a]

[a] The University of Queensland, RECOVER Injury Research Centre, 288 Herston Road, Herston, Queensland, 4006, Australia
[b] Jamieson Trauma Institute, Royal Brisbane & Women's Hospital, Metro North Hospital and Health Service, Cnr Butterfield St and Bowen Bridge Rd, Herston, Queensland, 4029, Australia
[c] Australian Catholic University, School of Psychology, 1100 Nudgee Road, Banyo, Queensland, 4014, Australia
[d] The Queensland Centre for Mental Health Learning, The Park Centre for Mental Health, West Moreton Health, Cnr Ellerton Drive and Court Road, Wacol, Queensland, 4076, Australia
[e] The University of Queensland, School of Psychology, McElwain Building, St Lucia, Queensland, 4072, Australia

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ABSTRACT

This study aimed to develop an industry-specific tool to identify risk of poor physical and mental recovery following minor to moderate injuries sustained in a road traffic crash (RTC). Existing tools are often designed for implementation by health professionals rather than insurer case managers who may not have a background in health. This study is a secondary analysis of a longitudinal cohort study using data collected at 2–6 months and 24 months post-RTC. Participants were claimants (n = 254; Mean age = 50 years; 65% female) with mild-moderate injuries recruited through the common-law 'fault-based' compulsory third party scheme in Queensland, Australia. Sociodemographic, functional and psychological health factors were collected at baseline (2–6 months post RTC) and used as potential predictors for physical and mental health-related quality of life (Short Form 36 v2) at the 2-year follow-up. The LASSO (Least Absolute Shrinkage and Selection Operator) analysis identified six disability items (from the World Health Organization Disability Assessment Schedule 2) to predict poor physical and one item to predict poor mental health-related quality of life. Logistic regressions of these items in addition to age and gender were used to develop a screening tool. Using the tool, 90% of those at risk of poor physical and 80% of those at risk of poor mental health-related quality of life were identified correctly. To conclude, this study presents an 8-item, context-specific tool to help injury managers identify individuals at risk of poor physical and mental health recovery following mild-moderate RTC-related injuries. The tool requires validation in a new cohort and confirmation of acceptability by end-users.

1. Introduction

Although deaths from road traffic crashes (RTCs) have plateaued, the number and cost of injuries sustained remains unabated with up to 50 million non-fatal injuries occurring worldwide each year (World Health Organization, 2018). By 2020, it is anticipated that RTC injuries will be the third leading cause of disability-adjusted life years lost worldwide (World Health Organization, 2001). In Australia, the annual costs of RTCs is estimated at AU$29 billion (Australian Automobile Association, 2017). Interestingly, the majority of compensation claims

Abbreviations: AIS, Abbreviated Injury Scale; AUC, Area Under the Curve; CTP, Compulsory Third Party; LASSO, Least Absolute Shrinkage and Selection Operator; MAIC, Motor Accident Insurance Commission; MCS, mental component summary; OMPQ, Orebro Musculoskeletal Pain Questionnaire; OMPQ-SF, OMPQ short form; PCS, physical component summary; PTSD, post-traumatic stress disorder; ROC, receiver operator characteristics; RTC, road traffic crash; RTW, return to work; SF36, Short Form 36; TRIPOD, Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis; UQ SuPPORT, University of Queensland Study of Physical and Psychological Outcomes; WAD, whiplash associated disorders; WHODAS-II, World Health Organization Disability Assessment Schedule 2

* Corresponding author at: RECOVER Injury Research Centre, The University of Queensland, Level 7, UQ Oral Health Centre, 288 Herston Road, Herston, QLD, 4006, Australia.

E-mail addresses: E.Smits@uq.edu.au (E. Smits), C.Brakenridge@uq.edu.au (C. Brakenridge), E.Gane@uq.edu.au (E. Gane), Jacelle.Warren@health.qld.gov.au (J. Warren), Michelle.Delaney@acu.edu.au (M. Heron-Delaney), J.Kenardy@uq.edu.au (J. Kenardy), V.Johnston@uq.edu.au (V. Johnston).

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following injury tend to be for minor to moderate injuries, which contribute substantially to the overall costs of Compulsory Third Party (CTP) insurance schemes (Motor Accident Insurance Commission, 2016). Not all of these injuries will require interventions, but in an environment of fixed resources, it is essential to ensure that appropriate resources are provided to those most in need. A challenge for insurers responsible for approving rehabilitation funding is to identify those at greater risk of poorer outcomes or protracted recovery.

Several tools have been developed to assist health professionals to identify those at greater risk of delayed recovery (Hill et al., 2008; Linton and Boersma, 2003; Linton and Halldén, 1998; Ritchie et al., 2013). However, these are not entirely suitable for the CTP environment. The focus of tools such as the STarTback tool for patients with non-specific back pain (Hill et al., 2008) or the clinical prediction tool for whiplash associated disorders (WAD) (Ritchie et al., 2013) are for specific body regions or disorders. However, RTC-related injuries usually involve several body regions (e.g. neck-pain and orthopaedic injury) and may not fit the diagnostic criteria of currently available tools. An alternative to condition or body region-specific tools are generic tools like the Orebro Musculoskeletal Pain Questionnaire (OMPQ) which focuses on psychosocial barriers (Linton and Boersma, 2003). The OMPQ was originally developed to identify patients four to 12 weeks following injury at risk of long-term back pain problems (Linton and Boersma, 2003; Linton and Halldén, 1998) but its utility has also been demonstrated in individuals with other musculoskeletal conditions (Dunstan et al., 2005; Hockings et al., 2008; Margison and French, 2007). For example, scores on the OMPQ short form (OMPQ-SF) have been associated with persistent pain (Gopinath et al., 2015b) and delayed return to work (Gopinath et al., 2015a) in participants with RTC-related mild/moderate musculoskeletal injures. However, it was designed for implementation by health professionals rather than insurer case managers who may not have a background in health.

The current trend is to apply a screening tool as early as four weeks following an injury, with a recent study showing that such tools could identify injured workers at risk of delayed return to work (RTW) when administered within 15 days of a soft tissue injury to any body region (Nicholas et al., 2018). Nevertheless, there is no consensus for the optimal time to administer a screening tool, with suggestions that barriers to recovery will vary with time since injury (Nicholas et al., 2018; Waddell et al., 2003). Given that the average time from RTC to claim lodgement is between 2–6 months (Motor Accident Insurance Commission, 2017), administering a tool within the first 15 days, though ideal, is not feasible in the CTP industry.

Another limitation of current tools is the variation in purpose and endpoint. For instance, there are tools designed to identify claimants at risk of compensation related stress (Spittal et al., 2018); risk of chronicity (Ritchie et al., 2013); or risk of delayed RTW (Dunstan et al., 2005; Linton and Boersma, 2003). In CTP schemes, insurers have a legal obligation to support rehabilitation to "(1) *restore, as far as reasonably possible, physical or mental functions lost or impaired through personal injury; and (2) optimise, as far as reasonably possible, the quality of life of a person who suffers the loss or impairment of physical or mental functions through personal injury*" (Motor Accident Insurance Commission, 2012). Therefore, a CTP industry-specific tool is needed that enables insurers to identify claimants at risk of poor recovery regarding physical and mental functioning and quality of life.

Prospective cohort studies, such as The University of Queensland Study of Physical and Psychological Outcomes (UQ SuPPORT) study (Kenardy et al., 2014), are important resources for developing tools which identify individuals at greater risk of poorer outcomes in the long term. A secondary analysis of the UQ SuPPORT study dataset was undertaken to contribute further to our knowledge of recovery from predominantly minor injuries up to 2 years post-RTC. This study aims to develop an industry-specific screening tool to identify claimants at risk of poorer physical and mental recovery that could be administered by insurer case managers within the first six months of injury. A secondary aim is to compare its performance with the OMPQ-SF in this cohort.

2. Methods

2.1. Study design

The UQ SuPPORT study was a longitudinal cohort study with data collected at approximately 6, 12 and 24 months (Wave 1, 2 and 3) post-RTC. The full protocol has been described elsewhere (Kenardy et al., 2014). The initial UQ SuPPORT study (#20090000035) and this secondary analysis (#2018000490) were approved by the Medical Research Ethics Committee at The University of Queensland in Australia. The study followed the "Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) statement" (Moons et al., 2015).

2.2. Participants

Participants were recruited from the Motor Accident Insurance Commission (MAIC) database between April 2009 and September 2010. MAIC is the regulatory authority responsible for the ongoing management of the CTP scheme in Queensland, Australia, and participants were claimants within this common-law "fault-based" CTP motor vehicle insurance scheme. Eligible claimants were individuals who: sustained predominantly minor physical injury with an Abbreviated Injury Scale (AIS) score of 1–3 (Association for the Advancement of Automotive Medicine, 2019; Gennarelli and Wodzin, 2006); were a driver/passenger of a car/motorbike, a cyclist, or a pedestrian involved in an RTC; were 18 years or older; had good English-speaking ability; had their RTC date within 3 months of claim notification date; and were an Australian resident. The exclusion criteria included cognitive impairment and severe physical conditions preventing the patient from completing the survey. In total, 3146 eligible claimants were invited by a letter from MAIC to participate, with 372 (12%) accepting the invitation and participating in wave 1. A flowchart of recruitment and sample sizes at each wave has been published elsewhere (Kenardy et al., 2014). Informed consent was obtained from all 372 participants. Claimants who declined to participate (N = 2723) were significantly younger (mean(SD) age = 39.7(14.5) versus 48.6(14.9)) and had a lower percentage with an Injury Severity Score (ISS) ≥ 4 (18% versus 35%) compared to those participating in the study. The ISS relates to the severity of the combination of physical injuries of the individual (Baker et al., 1974). The participating sample consisted of predominantly whiplash injury (56%). Other injuries included soft tissue contusion, abrasion, haematoma, or laceration; strains with no fracture or dislocation; and, fractures (e.g. rib or ankle).

2.3. Outcome measure

Following the MAIC guidelines for CTP rehabilitation providers (Motor Accident Insurance Commission, 2012), poor recovery was determined by poor physical and mental health-related quality of life, measured with the Short Form 36 (SF36-v2) (Ware, 2000) two years post-injury (Wave 3). The SF36 is commonly used as a measure of recovery following an RTC (Rissanen et al., 2017). The physical (PCS) and mental component summary scores (MCS) were calculated using established methods (Ware, 2000). Participants who scored more than one standard deviation (SD) lower than the Australian population norm (Hawthorne et al., 2007) on the PCS and MCS were categorised as having a 'poor physical health-related quality of life outcome' or 'poor mental health-related quality of life outcome'. One SD difference is considered a clinically important distance from the mean on this questionnaire (Hawthorne et al., 2007).

Table 1
Independent measures considered as potential predictors.

Items	Number of items	Variable type	Scoring
Socio-demographics			
Age	1	continuous	years
Gender	1	binary	male/female
Education	1	binary	Up to year 12 / More than year 12
Has a partner	1	binary	yes/no
In paid employment	1	binary	yes/no
Are your days occupied with paid/unpaid activities	1	binary	yes/no
Crash-related			
Injury severity (ISS)	1	binary	minor / moderate-serious
Driver status	1	binary	driver or passenger / pedestrian or cyclist
Perception of CTP insurance process	8	continuous	5-point scale; 'not at all' to 'a lot'
Psychological health-related			
Prior diagnosis of mental illness	1	binary	yes/no
Perceived threat to life	1	binary	not at all or slightly / moderately to very strongly
Post-traumatic stress (IES-R)	22	continuous	5-point scale; 'not at all' to 'extremely'
Depression and Anxiety (HADS)	14	continuous	4-point scale; 'very little' to 'a great deal of the time'
Physical or functional health-related			
Disability (WHODAS II)	12	continuous	5-point scale; 'none' to 'extremely difficult'
Interference of difficulties with life	1	continuous	5-point scale; 'none' to 'extreme'
Days difficulties present	1	binary	no-some days with difficulties / all 30 days difficulties
RTC-related health care utilization	1	categorical	up to 1 visit / 1-2 visits / 2 or more visits per week
Non RTC-related health care utilization	1	categorical	up to 1 visit / 1-2 visits / 2 or more visits per week
Function and pain (OMPQ-SF)	10	continuous	11-point scale; 'not at all' to 'extremely'
Health Status (EQ5D3L)	5	binary	no problems / some problems or cannot do
Psychosocial			
Social Support (MSPSS)	12	continuous	7-point scale; 'very strongly disagree' to 'very strongly agree'
Other			
Alcohol use (AUDIT 1-8)	8	categorical	5-point scale; 'never' to 'almost daily'
Alcohol use (AUDIT 9-10)	2	categorical	3-point scale; 'no' to 'yes, during last year'

Abbreviations: ISS = Injury Severity Scale; CTP = Compulsory Third Party; IES-R = Impact of Event Scale - Revised; HADS = Hospital Anxiety and Depression Scale; WHODAS II = World Health Organization - Disability Assessment Schedule; OMPQ = Orebro Musculoskeletal Pain Questionnaire Short Form; EQ5D3L = European Quality of Life – 5 Dimensions – 3 Levels; MSPSS = Multidimensional Scale of Perceived Social Support; AUDIT = Alcohol Use Disorders Identification Test.

2.4. Independent measures

Sociodemographic, functional and psychological health factors were collected at Wave 1. Data regarding injury severity, based on AIS-coded (Association for the Advancement of Automotive Medicine, 2019; Gennarelli and Wodzin, 2006) injury data, was supplied by MAIC. Injury Severity Scores (ISS) were calculated from the AIS data. Table 1 provides an overview of all measures used in the current analysis. Details and properties of the measures are described previously (Kenardy et al., 2014). Only self-report measures were included to ensure the tool can be used by non-health professionals such as insurer case managers.

2.5. Statistical analysis

Complete cases analyses[a] were undertaken using those patients who completed the SF36 at Wave 3. Two models were developed to: (1) predict poor physical health-related quality of life outcome with the PCS score as dependent variable (Poor = PCS $<$ 39.5); and (2) poor mental health-related quality of life outcome with the MCS score as dependent variable (Poor = MCS $<$ 40.1). The statistical analyses consisted of several steps:

2.5.1. Predictor selection

Due to the large number of initial predictors (n = 106) and high amount of multicollinearity between predictors (Variance Inflation Factor of up to 6), the LASSO (Least Absolute Shrinkage and Selection Operator (Tibshirani, 2018)) technique was used to identify a set of predictors for each outcome separately. The LASSO technique allows entering all individual items simultaneously and is well-suited for models showing high levels of multicollinearity (Hartmann et al., 2009; Van der Kooij and Meulman, 2006). The LASSO technique also minimizes the risk of over-fitting. The error in predicting future observations was estimated by 5-fold cross validation. The LASSO selects two models: the optimal model with minimum expected prediction error and a parsimonious model with an expected prediction error that is within one standard error of the optimal model. According to the rule of parsimony, predictions should be kept as simple as possible, i.e. using the fewest number of predictors that provides the best prediction within an acceptable margin of error (Vandekerckhove et al., 2015).

2.5.2. Logistic regression analysis

Bivariate logistic regressions were used to build the prediction models with the items identified by the LASSO. Prediction models were built for the optimal and parsimonious LASSO models, and for the OMPQ-SF. Age and gender were always included as potential predictors in the LASSO models.

2.5.3. Predictive value

The predictive value of the models was assessed by receiver operating characteristic (ROC) curves. The predicted probabilities saved in the previous step were used to create the ROC curves. For all models, the following parameters were calculated: sensitivity; specificity; positive predictive value (PPV); negative predictive value (NPV); and percent correctly classified. The purpose of the screening tool was to identify as many individuals as possible who were at risk of having a poor outcome. Therefore, cut-off scores were selected to generate the highest sensitivity, with reasonable specificity.

2.5.4. Screening tool development

The logistic regression equations corresponding to the parsimonious

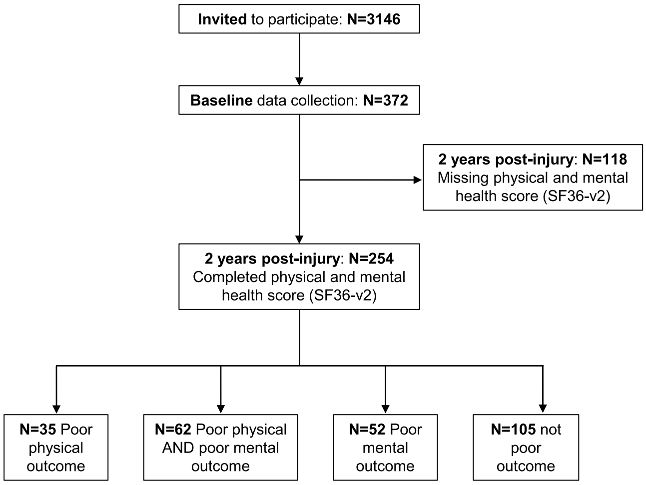

Fig. 1. Flow chart of participants included in this study.

models and the selected cut-off scores were used to create a tool[b] to identify risk of both poor physical and mental health-related quality of life (two risk-scores).

3. Results

In total, 254 participants completed the SF36 at the 2 year follow-up (see Fig. 1), and were therefore used for analysis. Of these, 97 (= 35 + 62, see Fig. 1) met the criteria for poor physical health-related quality of life (i.e. more than 1SD lower than the Australian norm for the PCS score: mean(SD) = 49.8(10.3)) and 114 (= 52 + 62, see Fig. 1) met the criteria for poor mental health-related quality of life outcome (Australian norm MCS: mean(SD) = 50.0(9.9) (Hawthorne et al., 2007)). The average duration between RTC and baseline data collection was 5 months. Participant characteristics are shown in Table 2. Participants who were lost to follow-up and therefore did not complete Wave 3 (n = 118) differed from those participants who completed Wave 3 in two variables: they were younger by 5.4 years ($t_{(370)} = 3.3$, $p < 0.01$) and had a smaller proportion of injuries with ISS ≥ 4 (25.4% vs 39.8%, $t_{(251)} = 2.8$, $p < 0.01$).

3.1. Predictor selection

The optimal LASSO model for predicting poor physical health-related quality of life consisted of 17 items and the parsimonious model of 6 items (Table 3). The optimal and parsimonious LASSO models for predicting poor mental health-related quality of life were identical with one item selected (see Table 3).

3.2. Prediction models

Three regression models to predict poor physical health (optimal; parsimonious; and OMPQ-SF model) and two for poor mental health-related quality of life (parsimonious and OMPQ-SF model) were built. The predictive performance of the 18-item model (optimal model + gender) for physical health-related quality of life was higher (Area Under the Curve; AUC = 0.93, 95%CI: 0.90-0.96, $p < 0.001$) than the 8-item model (parsimonious model + age and gender) (AUC = 0.91, 95%CI: 0.87-0.94, $p < 0.001$) and both were higher than the OMPQ-SF model (AUC = 0.80, 95%CI: 0.74-0.86, $p < 0.001$). Predictive performance of the 3-item model (parsimonious model + age and gender) for mental health-related quality of life (AUC = 0.75, 95% CI: 0.68-0.81, $p < 0.001$) was lower than the OMPQ-SF model (AUC = 0.81, 95%CI: 0.75-0.86, $p < 0.001$).

3.3. Predictive value

Table 4 shows the cut-off score from the ROC analysis, sensitivity, specificity, PPV, NPV and percent correctly classified for all models. If the predicted probability of a participant was higher than the cut-off scores, this participant was indicated as 'high risk' of a poor health outcome. The selected cut-off scores resulted in high sensitivity (≥0.8), and moderate to high specificity for the different models. The newly developed tool demonstrated higher sensitivity and specificity for predicting poor physical health-related quality of life and similar performance for poor mental health-related quality of life (parsimonious models in Table 4) compared with the OMPQ-SF. Fig. 2 shows the predicted probabilities for poor physical health-related quality of life for each individual plotted against their predicted probability for poor mental health-related quality of life (based on the parsimonious models in Table 4), indicating their classifications based on the selected cut-off scores.

Table 2
Characteristics of participants who had complete score on the SF36v2 at Wave 3 (2 years post injury) and who were lost to follow-up at Wave 3.

	Complete cases (n = 254) Age: mean(SD) = 49.9(14.6), range 19-94		Cases lost to follow-up (n = 118) Age: mean(SD) = 44.5(15.0), range 19-81	
	N	%	N	%
Gender				
Male	90	35.4	50	42.4
Female	164	64.6	68	57.6
Education				
Up to year 12	66	26.0	39	33.1
More than year 12	175	68.9	72	61.0
Current Partner Status				
Living with partner	159	62.6	68	57.6
Not living with partner	83	32.7	43	36.4
Employment status				
Employed in paid work	155	61.0	69	58.5
Not employed in paid work	78	30.7	39	33.1
Road User Type				
Pedestrian/Cyclist	52	20.5	22	18.6
Driver/Passenger	202	79.5	96	81.4
Injury Severity*				
ISS 1-3	151	59.4	87	73.7
ISS ≥ 4	101	39.8	30	25.4

* Based on the Injury Severity Score (ISS): an ISS of 1–3 generally includes superficial injuries, such as whiplash or soft tissue abrasions and an ISS of ≥ 4 includes non-life-threatening injuries, such as lower limb and rib fractures, or a combination of superficial and other minor injuries.

Table 3
Items selected by LASSO method for predicting health outcomes 2 years following a road traffic crash.

	Predicting poor physical health outcome		Predicting poor mental health outcome	
	Optimal model (17 items)	More Parsimonious model (6 items)	Optimal model (1 item)	More Parsimonious model (1 item)
Age	X			
Household (WHODAS)*	X	X		
Learning (WHODAS)	X	X		
Emotional (WHODAS)	X	X		
Concentrating (WHODAS)	X			
Walking (WHODAS)	X	X		
Getting dressed (WHODAS)	X	X		
Day work (WHODAS)	X			
Overall interference (WHODAS)	X	X	X	X
Work expectations (OMPQ)*	X			
Talk about problems with friends (MSPSS)*	X			
Slowed down feeling (HADS)*	X			
Frightened feeling (HADS)	X			
Lost interest appearance (HADS)	X			
How often alcohol (AUDIT)*	X			
Feeling guilt after drinking (AUDIT)	X			
Involved in CTP* claim management	X			

* WHODAS II = World Health Organization - Disability Assessment Schedule; OMPQ = Orebro Musculoskeletal Pain Questionnaire; MSPSS = Multidimensional Scale of Perceived Social Support; HADS = Hospital Anxiety and Depression Scale; AUDIT = Alcohol Use Disorders Identification Test; CTP = Compulsory Third Party.

3.4. Screening tool development

Based on the parsimonious models, the screening tool was developed and is available in the supplementary documentation as an Excel macro file. Fig. 3 shows a screenshot of the tool. Introductory statements, based on information included in the originating questionnaires, have been included to ensure each question is answered as originally intended. Two versions of the tool are created and available in the supplementary documentation to allow self-report and screening over the phone.

4. Discussion

The purpose of this study was to develop a tool to identify individuals at risk of poor recovery following minor/moderate injuries sustained in RTCs that could be administered by case managers in the CTP industry. The developed tool estimates the risk of poor physical and mental health-related quality of life separately. Providing two prediction outcomes is advantageous for guiding treatment. For example, if poor physical health-related quality of life is predicted, the rehabilitation process might need to involve an exercise physiologist or physiotherapist, whereas if poor mental health-related quality of life is predicted, a psychologist might be involved. The tool will also indicate if an individual is at risk of both poor physical and mental recovery, which could suggest that an integrated inter-professional approach to the rehabilitation should be employed.

The developed tool is short, easy to administer and clearly identifies an individual at risk of poor physical and/or mental health-related quality of life at two years post-RTC. Performance of the tool for predicting both physical and mental health-related quality of life is considered acceptable (AUC ≥ 0.7), with the prediction for physical health-related quality of life being excellent (AUC ≥ 0.9) (Hosmer and Lemeshow, 2000). It is important that the tool correctly identifies as many individuals as possible who are at risk of poor recovery following RTCs so that resources can be directed to those most in need. Our tool has high sensitivity for predicting poor physical (0.90) and mental health-related quality of life (0.80), meaning that 90% of those at risk of poor physical health-related quality of life and 80% of those at risk of poor mental health-related quality of life were identified correctly. In comparison with the predictive value of the OMPQ-SF in this cohort, our tool performed better for predicting poor physical health-related quality of life, and similarly for predicting poor mental health-related quality of life. Until the newly developed tool has been validated, the OMPQ-SF could be considered a suitable alternative.

Individual items of several questionnaires were used as potential predictors in contrast to other studies which used the summary scores

Table 4
Predictive accuracy of the different models for predicting health outcomes 2 years following a road traffic crash.

	cut-off score (ROC analysis)*	Sensitivity (95% CI)	Specificity (95% CI)	PPV†	NPV†	Correctly classified
Predicting poor physical health						
Optimal model (18 items)‡,‖	0.26	0.89 (0.82-0.96)	0.81 (0.74-0.88)	74%	92%	84%
Parsimonious model (8 items)‡,‖	0.26	0.90 (0.83-0.96)	0.75 (0.68-0.82)	69%	92%	81%
OMPQ short form (10 items)	0.31	0.81 (0.72-0.89)	0.60 (0.51-0.68)	56%	83%	68%
Predicting poor mental health						
Parsimonious§ model (3 items)‡,‖	0.45	0.80 (0.72-0.87)	0.63 (0.55-0.71)	64%	79%	71%
OMPQ short form (10 items)	0.38	0.80 (0.72-0.88)	0.66 (0.57-0.74)	66%	80%	72%

* Cut-off score was selected for optimal sensitivity and reasonable specificity.
† PPV = Positive Predictive Value; NPV = Negative Predictive Value.
‡ These models include the items age and gender.
§ The optimal and parsimonious model selected by the LASSO analysis were identical.
‖ 18-item model was based on 196 complete cases (58 missing baseline predictors); 8-item model on 233 complete cases (21 missing baseline predictors) and 3-item model on 239 complete cases (15 missing baseline predictors).

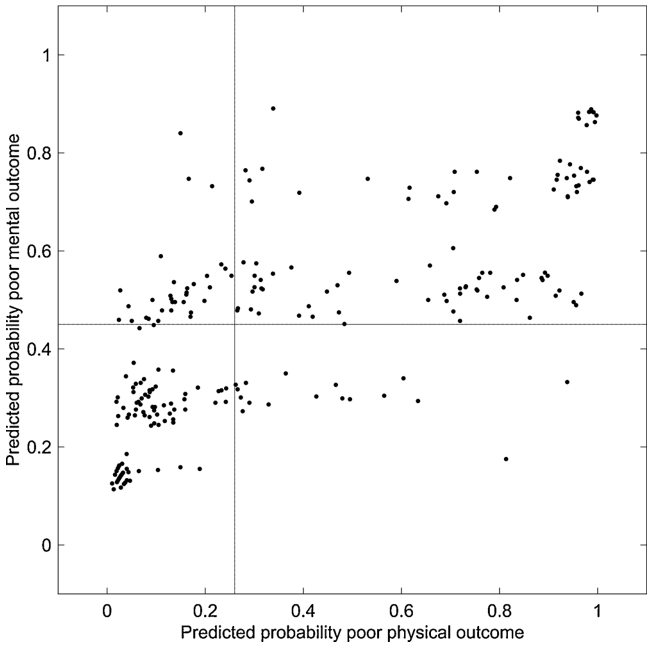

Fig. 2. Predicted probabilities of the parsimonious models for predicting poor physical and mental health. The dashed lines correspond to the selected cut-off values used for to develop the screening tool (vertical line: cut-off = 0.26; horizontal line: cut-off = 0.45): The upper right quadrant indicates those at risk of both poor physical and mental health, and the bottom left quadrant indicates those not at risk of either poor physical or mental health.

of questionnaires (Rissanen et al., 2017; Ritchie et al., 2013; Samoborec et al., 2018; Spittal et al., 2018). Consequently, comparing our results to previous literature is not straightforward. Comprehensive overviews of previous literature on recovery following a road traffic crash and associated risk factors have been published in two systematic reviews recently (see Rissanen et al. (2017) and Samoborec et al. (2018)). These reviews show that predictors of poor physical and mental-health related quality of life following an RTC include high pain levels, pre-accident physical and mental health status, pain catastrophizing, lower socio-economic status, diagnosis of post-traumatic stress disorder (PTSD) and injury severity (Rissanen et al., 2017; Samoborec et al., 2018). Although our analysis did include most of these variables as potential predictors, they were not selected for the final model. Our analysis did not include a diagnosis of PTSD as a potential predictor, because this is not a self-report measure and only a health specialist (e.g. a registered psychologist) can make this diagnosis. However, a measure of trauma-related stress (the Impact of Event Scale) was included, but not selected in our analysis. We aimed at only including self-report measures that a non-health professional could administer. The differences between our study and previous literature could be explained by the fact that the research to date has been highly heterogeneous regarding aims and tools used for assessment, including the method of selecting predictors (Rissanen et al., 2017; Samoborec et al., 2018).

The items selected for our tool were several disability-related items of the WHODAS-II. In a previous analysis of the UQ SuPPORT data, disability level also appeared to be a strong predictor of non-return to work (Heron-Delaney et al., 2017). Additionally, the clinical prediction tool for recovery following whiplash, also includes initial disability level as an important risk factor for developing chronic moderate/severe disability (Ritchie et al., 2013) although disability was assessed with the Neck Disability Index and not with a generic measure like the WHODAS-II. On the contrary, initial disability levels were not mentioned as important predictors of poor recovery following an RTC in two recent systematic reviews (Rissanen et al., 2017; Samoborec et al., 2018). This may be because disability was not measured or included as a potential predictor (but rather as an outcome) in most of the studies included in the reviews (Rissanen et al., 2017; Samoborec et al., 2018). Furthermore, our analysis only selected one item (in addition to age and gender) to predict poor mental health-related quality of life recovery. Although the predictive value of the mental component of our tool is good, it could be further optimized by including additional items, such as number of prior traumatic events or discharge location, which were selected for a recently published prediction model of stress (Spittal et al., 2018).

The greatest strength of this study is that it provides a tool specifically developed for the CTP industry. The tool identifies risk of poor physical and mental health-related quality of life recovery following an RTC and can be readily used by non-health professionals such as insurer case managers. Previous studies (Atherton et al., 2006; Heron-Delaney et al., 2017) have suggested that the predictors found in their studies could be used for predictive screening, but they did not provide an actual tool. We have collated the equation and cut-off values to calculate future risk scores into an Excel macro file to increase utility of research findings for practical implementation.

The provided screening tool is brief and easy to administer and not condition specific or time limited. Thus, this tool can be applied to any

Screening tool to identify risk of poor physical and/or mental health recovery following minor and moderate injuries sustained in a road traffic crash (self-report version)

1. Age	**50**	In years
2. Gender	**2**	1 (female) - 2 (male)
The next questions are about difficulties people have because of health conditions. Health conditions include diseases or illnesses, other health problems that may be short or long lasting, injuries, mental or emotional problems and problems with alcohol or drugs. Think back over the past 30 days and answer the following questions, thinking about how much difficulty you had doing the following activities (e.g. increased effort, discomfort or pain, slowness and changes in the way you do the activity)		
3. Taking care of your household responsibilities?	**3**	1 (no difficulty) - 5 (severe difficulty)
4. Learning a new task, for example, learning how to get to a new place?	**2**	1 (no difficulty) - 5 (severe difficulty)
5. Walking a long distance such as a kilometre?	**2**	1 (no difficulty) - 5 (severe difficulty)
6. Getting dressed?	**3**	1 (no difficulty) - 5 (severe difficulty)
7. How much have you been emotionally affected by your health problems?	**2**	1 (none) - 5 (extreme)
Other difficulties include difficulties with standing for a longer time, joining community activities, concentrating for more than 10 minutes, washing your body, dealing with new people, maintaining friendships and your day to day work. Think about the these and the above difficulties when answering the next question.		
8. Overall, how much do these difficulties interference with your life?	**2**	1 (none) - 5 (extreme)
Probability poor physical health-related quality of life outcome	0.37	**AT RISK of poor physical health recovery**
Probability poor mental health-related quality of life outcome	0.32	**NOT AT RISK of poor mental health recovery**

Fig. 3. Screenshot of the screening tool.

injury type. Although the outcome of the screening tool is not yet linked to a certain treatment or intervention, it does provide two risk scores, one for physical and one for mental health-related quality of life. These risk scores could, for example, help indicate which type of rehabilitation approach is needed.

4.1. Study limitations

A limitation is that baseline was not measured immediately following the RTC. The time between RTC and baseline measures varied between two and six months. This has implications for the delivery of this screening tool. It may be less valid to use immediately following an RTC, however, it recognises the environment in which insurer case managers operate and the time lag between injury occurrence and claim submission (Motor Accident Insurance Commission, 2017). It is possible that the predictors identified vary over time, so to confirm the usefulness of this tool, it should be tested for its predictive value soon after injury. The screening tool should also be tested for those with more severe injuries, since the current analysis was based on a cohort with predominantly minor injuries.

Another potential limitation of the study is the high rate of individuals who were invited to participate and declined (N = 2723) (Kenardy et al., 2014). Differences between this sample and the participating sample may have an impact on generalizability of the study results. Even though there were two significant differences in demographics between the participating and non-participating sample, non-participants being on average nine years younger (within a wide range for both samples) and having a proportion of 82% with an ISS ≥ 4 (versus 65% for the participants) are not anticipated to have had a large impact on the results of this study and development of the tool. Nevertheless, these differences should be noted when considering the generalizability of the results for the wider population with mild-moderate RTC-related injuries and results should be confirmed in larger future cohorts.

5. Conclusion

This study presents the development of a brief and simple 8-item tool that can be used to identify, with high sensitivity, those individuals with mild to moderate RTC-related injuries who are at risk of poor physical and/or mental health-related quality of life recovery at two years post-injury. Importantly, this tool can be administered by non-health professionals and is not condition specific. The tool requires validation in a new cohort and acceptability by end-users (i.e. insurance representatives) should be confirmed.

Suppliers

a. Statistical Package for the Social Sciences (SPSS) version 25
International Business Machines Corporation (IBM)
IBM Australia Limited
Level 13, IBM Centre
601 Pacific Highway
St Leonards NSW 2065

b. Microsoft Excel 2016
Microsoft Headquarters
One Microsoft Way
Redmond, WA 98052
United States of America

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2019.105280.

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