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Predicting relative need for urgent dental care

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Objective**:** To develop prediction models of the relative need for care to differentiate between urgent and not urgent individuals presenting for emergency dental care. ***Design and Methods*****:** Data were collected from 839 adults presenting to public dental clinics across South Australia (SA) and New South Wales (NSW) for emergency dental care. Prediction of the urgency of emergency dental care was based on the assessment of two binary logistic regression models - Model 1: urgency of care=<48 hours vs. 2+ days, Model 2: urgency of care=2–7 days vs. 8+ days. Subsequently predictive equations for urgency of emergency dental care were developed using binary logistic regression analysis. The models incorporated subjective oral health indicators (i.e., experience of pain or other oral symptoms) and measures of psychosocial impact of oral disorders (i.e., difficulty sleeping and being worried about the appearance/health of one's teeth or mouth). ***Results*****:** The cut-off point for the prediction of urgency was defined as a probability value ≥0.40 and ≥0.50 for Model 1 and Model 2 respectively. These cut-off values were chosen as they produced test results that were consistent with the proportions of patients falling into various urgency categories derived from dentist's assessment of urgency. Model 1's sensitivity was 58%, specificity 77% and positive predictive value (PPV) 59%. Model 2's sensitivity was 75%, specificity 65% and PPV 71%. ***Conclusions*****:** These models of relative need may be useful tools for the screening of urgent dental care and for allocating priority among patients presenting for emergency dental care.

Key words: Emergency dental care, prediction, urgency

Introduction

The Australian state and territory governments play a major role in providing public dental services to disadvantaged segments, for example low-income adults, of the Australian population. Eligibility is means-tested so users are required to hold a government concession card. Approximately one-third of the Australian population is eligible to use public dental hospitals and community dental services. Dental care is provided to these adults by a limited workforce, with only approximately 16 per cent registered practising dentists in Australia working in public dental services (Tuesner and Spencer, 2003). As a result, insufficient resources within the public sector make it difficult to provide timely and appropriate dental care to this eligible population.

Overwhelming demand for emergency dental care has been given priority, leading to the allocation of most resources to emergency care, and away from general dental care (Ziguras and Moore, 2001).

Consequently, long waiting lists for general dental care have developed. This situation has a detrimental impact on the oral health of eligible adults, with patients either cycling through emergency care or spending longer on waiting lists for general dental care (Auditor General Victoria, 2002; SADS, 2003). This situation in public dental services requires new approaches to managing demand for emergency dental care. As demand for care increases it becomes important to explicitly identify people who are most at need and allocate care on a priority basis in a transparent and consistent manner (Adams, 1999; Ubel, 2000).

Further, for good oral health outcomes, care within the public dental system should be more oriented toward providing general dental care rather than emergency dental care, restorations rather than extractions, and prevention of oral disease rather than treatment (Spencer, 2001). High demand for emergency care within clinics places pressure on clinics to provide services that are aimed at immediate treatment to relieve the problem rather than maintenance of teeth and prevention of future disease. A decrease in the provision of emergency dental care would enable clinics to devote resources to restorative and preventive care that would lead to improvements in the oral health of adult cardholders.

As Spencer (2001) described, in order to achieve public dental care that is aimed at prevention and maintenance, various strategies are required. One such strategy is to reduce the number of eligible adults receiving emergency dental care. Each day a considerable number of adults contact the public dental service for emergency care. A small proportion of these adults require emergency care for an acute dental problem. Somewhat larger proportions require palliative treatment for dental problems causing pain or discomfort which impact on daily living. However, many adults are using the emergency dental service as a way of avoiding the long waiting periods associated with waiting lists for general dental care. It is these adults who should be moved from the emergency dental care stream into general dental care. Various demand management strategies are in place and range from denying emergency care to levying a co-payment for an emergency visit. Strategies such as these are blunt and indiscriminant, and not long-term solutions. Strategies that take into

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consideration a patient's need for care or the urgency with which the care is required are a far more direct, explicit and equitable approach to rationing dental care. Systems that give priority to patients with the greatest need first are deemed more equitable (Spencer et al., 2002) and are consistently favoured by the public when asked to choose between allocative systems for health care (Ubel, 2000).

The aim of this study, therefore, was to develop prediction models to assist in the differentiation of urgent and not urgent individuals presenting for emergency dental care.

Methods

To assess the urgency of patients seeking emergency dental care, a random selection of eligible adults presenting to public dental clinics in South Australia (SA) and New South Wales (NSW) for emergency care was used. Participants had to be a holder of a current government concession card, be aged 18 years or older, and be dentate with six or more natural teeth. More comprehensive details of sampling methodology and selection are provided in another publication (Luzzi et al., 2009) which identified those subjective oral health indicators and psychosocial impacts of oral diseases and disorders associated with urgency of emergency dental care.

Participants completed a structured interview on subjective oral health indicators (i.e., symptom-based measures of disease and social and psychological consequences or oral diseases and disorders) and then underwent a clinical oral examination in order to obtain a clinical assessment of urgency of care. In the clinical examination patient urgency was measured on an ordinal scale represented by the categories <48 hours, 2–7 days, 8–13 days and 14+ days for emergency dental care.

Subjective oral health indicators and psychosocial impacts of oral diseases and disorders were examined as potential predictors of urgency of care. In a multivariate analysis, subjective oral health indicators and psychosocial impacts were combined as predictor variables in a regression model predicting the urgency of patients seeking emergency dental care (outcome). Data were analysed using binary logistic regression analysis. A general linear logistic regression model was specified. It provides an estimate of a patient's likelihood of being judged as requiring urgent emergency dental care expressed as a probability between 0.0 and 1.0 (i.e., predicted probability of being urgent). Probabilities generated from the linear function were used to classify patients into various emergency care urgency categories.

Two models were developed to assess urgency for emergency dental care. This was done by dichotomising the four categories of the dependent variable. The first model examined patients categorised by the assessing dentist as requiring care within 48 hours or two plus days and the second model examined patients categorised as requiring care in two to seven days or in eight or more days time. The second model excluded all patients who were given an urgency rating of <48 hours by the assessing dentist. The predictive ability of the subjective indicators was assessed using the sensitivity, specificity and predictive values from a standard contingency table approach. Sensitivity was defined as the proportion of patients predicted to be urgent who were judged as urgent by the dentist (true positive test result) and specificity as the proportion of patients predicted not to be urgent and who were also judged as not being urgent by the dentist (true negative test result). Positive predictive value (PPV) was defined as the percentage of patients with a positive test result who actually are urgent and negative predictive value (NPV) as the percentage of patients with a negative test result who actually are not urgent (Table 1).

Probability of being urgent: varying the probability cut-off

Each prediction was represented by a predicted probability (since the results of the logistic regression analysis were in terms of the probability of being urgent); however the probability cut-off that differentiates between 'urgent' and 'non-urgent' individuals could be varied. For example, suppose a cut-off of 0.5 was chosen. When the probability being 'urgent' as calculated by Model 1 was ≥0.5, then the individual was expected to be 'urgent'. This probability can be altered to be ≥0.25, ≥0.4, ≥0.6 and so forth thus generating a series of outcomes which can be described by their sensitivities and specificities. The relation of sensitivity and specificity for possible cut-off points is presented as a receiver operating characteristic (ROC) curve, constructed by plotting sensitivity (true positive rate) against the false positive rate (1–specificity) over a range of cut-off values. Generally the best cut-off point is at or close to the shoulder of the ROC curve, where substantial gains can be made in specificity with only modest reductions in sensitivity. ROC curves show the performance of a predictive test over all possible decision points, and the area under the curve (AUC) can be used as a measure of the discriminant ability of the prediction test. The AUC can be interpreted as meaning that an individual who actually is urgent will have a higher test score than someone who is not urgent on (AUC*100)% of occasions (Nuttall and Deery, 2002). The optimal cut-off value for a positive test depends on the presence or severity of oral disease and symptom experience. The criteria used to select cut-off points for this study were based on those that conform with the observed prevalence of the gold standard, i.e., the distribution of persons according to the dentist's clinical assessment of urgency.

Results

A total of 839 adults requesting emergency dental care were recruited across SA (n=427) and NSW (n=412).

According to the assessing dentist, 35.8% of respondents required emergency care within 48 hours, a further 34.8% required care within two to seven days and the remaining 29.4% were deemed able to wait eight or more days for treatment.

Model 1: <48 hours versus 2+ days

For Model 1, data on nine oral health indicators and psychosocial impacts of oral diseases and disorders of 750 patients were considered predictive of being urgent

Table 1. Relationship between a diagnostic test result and clinical assessment of urgency

		Clinical assessment of urgency		
		urgent **+ve**	**not urgent** **-ve**	Total
Test result	**urgent** **+ve**	a (true +ve)	b (false +ve)	a + b
	not urgent **-ve**	c (false -ve)	d (true -ve)	c + d
	Total	a + c	b + d	N

where Sensitivity=a/(a+c), Specificity=d/(d+b), PPV=a/(a+b), NPV=d/(c+d), a+b+c+d=N
Source: Fletcher, Fletcher and Wagner, 1996

Table 2. Independent predictor variables for Model 1 - <48 hours vs. 2+ days: response categories, logistic regression beta coefficients and standard errors

i	*Independent variable*	*Response category* (x_i)	*Beta coefficient* (b_i)	*SE(Beta)*
0	Model constant***	N/a	-1.436	0.266
1	Pain in teeth with cold food/fluids	Yes	-0.352	0.187
		No†		
2	Pain in jaw opening mouth wide***	Yes	0.882	0.219
		No†		
3	Shooting pain in face or cheeks	Yes	0.399	0.210
		No†		
4	Bleeding gums*	Yes	-0.411	0.197
		No†		
5	A broken filling*	Yes	0.501	0.200
		No†		
6	A loose tooth***	Yes	0.855	0.240
		No†		
7	Difficulty sleeping***	All the time***	1.575	0.259
		Very Often**	1.057	0.323
		Often	0.143	0.334
		Sometimes**	0.659	0.226
		Never†		
8	Worried about the health of teeth or mouth**	All the time	-0.454	0.294
		Very Often	0.507	0.314
		Often	0.137	0.331
		Sometimes	0.186	0.305
		Never†		
9	Dental anxiety*	DAS‡ score≥13	0.418	0.204
		DAS score<13†		

Analysis used n = 750 patients with complete data on all variables
N/a Not applicable
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
† Reference category
‡ DAS=Dental Anxiety Scale (Corah, 1969)
Model fit statistics: Hosmer-Lemeshow GOF test: χ^2 (df)= 3.647 (8); p -value=0.887
–2 LL ratio test: Model χ^2 (df)= 134.108 (15); p -value=<0.0001; Calibration slope=(Model χ^2- (df-1))/ Model χ^2=1.12

Table 3. Independent predictor variables for Model 2 - 2–7 days vs. 8+ days: response categories, logistic regression beta coefficients and standard errors

i	*Independent variable*	*Response category (x_i)*	*Beta coefficient (b_i)*	*SE(Beta)*
0	Model constant***	N/a	-1.213	0.248
1	Toothache***	Yes	0.967	0.253
		No†		
2	Pain in teeth with hot food/fluids**	Yes	0.651	0.219
		No†		
3	Pain worse in the middle of the day	Yes	0.633	0.352
		No†		
4	Bleeding gums**	Yes	0.698	0.235
		No†		
5	Broken filling**	Yes	0.732	0.265
		No†		
6	Difficulty sleeping**	All the time**	1.079	0.393
		Very Often*	1.072	0.499
		Often*	0.981	0.398
		Sometimes	0.156	0.272
		Never†		
7	Worried about appearance of teeth or mouth*	All the time	-0.407	0.276
		Very Often**	-1.189	0.394
		Often	0.270	0.400
		Sometimes	-0.586	0.306
		Never†		

Analysis used n = 476 patients (limited to patients found by dentists to need care within 2–7 days or 8+ days) with complete data on all variables
N/a Not applicable
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
† Reference category
Model fit statistics: Hosmer-Lemeshow GOF test: χ^2 (df)= 4.929 (6), p -value=0.765; and
–2 LL ratio test: Model χ^2 (df)= 106.309 (13), p -value=<0.0001, Calibration slope=(Model χ^2- (df-1))/ Model χ^2=0.89

(i.e., requiring treatment within 48 hours). The logistic regression equation to estimate the probability of being 'urgent' for Model 1 was:

p('urgent') =

$$\frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4+b_5x_5+b_6x_6+b_7x_7+b_8x_8+b_9x_9)}}$$

where e=natural logarithm base, b_0=model constant, b_k=regression coefficient of the k^{th} predictor variable (k=1 to 9), x_k=value of the k^{th} predictor variable (k=1 to 9). Table 2 presents the logistic regression model for prediction of patients needing urgent dental care (i.e., within 48 hours). For each of the nine predictor variables in Model 1, response categories, beta coefficients and standard errors are provided.

To illustrate how this can be used to generate the probability of being urgent which can subsequently be used to prioritise patients for emergency dental care, suppose an individual contacts a public clinic for emergency dental care and responds to the battery of question asked (Figure 1 - Response - #1). Based on these responses, and using a cut-off probability of 0.4, the logistic regression equation generates a probably of being urgent of 0.7, and so, the individual is deemed to require care within 48 hours (i.e., p('urgent')=0.75>0.4).

Model 2: 2–7 days versus 8+ days

For model 2, data on seven oral health indicators and psychosocial impacts of oral diseases and disorders of 476 patients were considered predictive of being urgent (i.e., requiring treatment in 2–7 days). The logistic regression equation to estimate the probability of being 'urgent' for Model 2 was:

p('urgent') =

$$\frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4+b_5x_5+b_6x_6+b_7x_7)}}$$

where e=natural logarithm base, b_0=model constant, b_k=regression coefficient of the k^{th} predictor variable (k=1 to 7), x_k=value of the k^{th} predictor variable (k=1 to 7). Table 3 presents the logistic regression model for prediction of patients needing care within 2–7 days. For each of the seven predictor variables in Model 2, response categories, beta coefficients and standard errors are provided.

	Response - # 1	Response - # 2
In the last week, have you had…		
• pain in teeth with cold food or fluids	Yes	Yes
• pain in jaw when opening mouth wide	Yes	No
• shooting pain in face or cheeks	No	No
• bleeding gums	No	Yes
• a broken filling	No	No
• a loose tooth	No	No
• a toothache	Yes	Yes
• pain in teeth with hot food/fluids	No	No
• pain which is worse in the middle of the day	No	No
During the last week, how often has pain, discomfort or other problems with your teeth, mouth or dentures caused you to have…		
• difficulty sleeping	Very often	Sometimes
During the last week, how often have you…		
• worried about the health of your teeth or mouth	Very often	Sometimes
• worried about the appearance of your teeth or mouth	Sometimes	Never
Dental Anxiety Scale (DAS)		
• Imagine you had an appointment to go to the dentist tomorrow, how would you feel about it?	I would be afraid that it would be unpleasant and painful	I would be a little uneasy about it
• Imagine you are waiting in the dentist's waiting room for your turn in the chair, how would you feel?	Tense	A little uneasy
• Imagine you are in the chair waiting while the dentist gets the drill ready to begin working on your teeth, how would you feel?	Tense	Tense
• Imagine you are in the dentist's chair to have your teeth cleaned. While you are waiting and the dentist is getting out the instruments to be used to scrape your teeth around the gums, how would you feel?	Tense	A little uneasy
URGENCY:	**<48 hours**	**2-7 days**

Response - #1 (Model 1):
DAS score = sum of responses = 13 (=4+3+3+3)

$$\text{Predicted probability:}\quad P(\text{'urgent'}) = \frac{1}{1+e^{-(-1.436+(-0.352\times1)+(0.882\times1)+(0\times0)+(0\times0)+(0\times0)+(0\times0)+(1.057\times1)+(0.507\times1)+(0.418\times1))}} = 0.75$$

Response - #2 (Model 2):

$$\text{Predicted probability:}\quad P(\text{'urgent'}) = \frac{1}{1+e^{-(-1.213+(0.967\times1)+(0\times0)+(0\times0)+(0.698\times1)+(0\times0)+(0.156\times1)+(0\times1))}} = 0.65$$

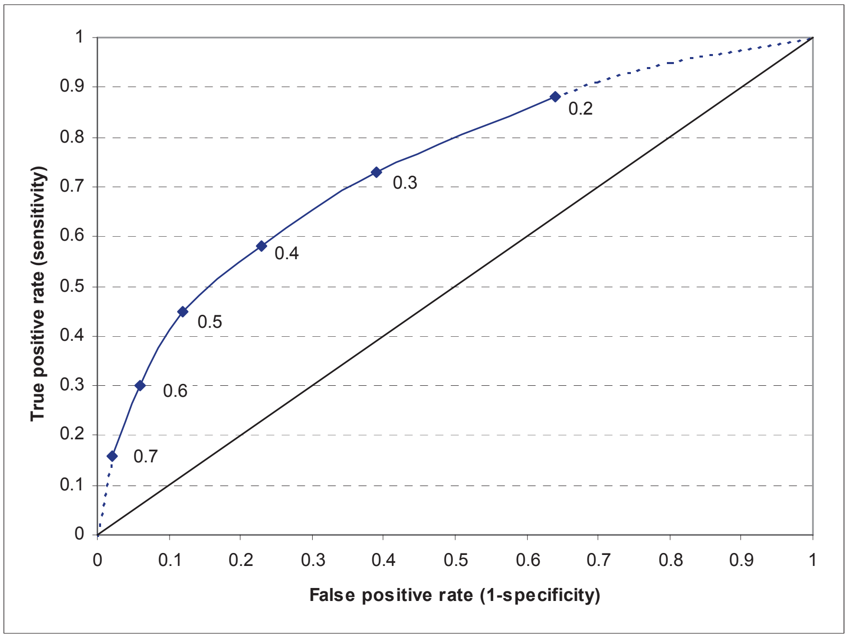
Figure 1. *Patient responses to battery of questions used to determine urgency of care required*

Figure 1 (Response - #2) illustrates a pattern of responses which generates a probably of being urgent of 0.65. Hence, when using a cut-off probability of 0.5, the individual is deemed to require care in 2-7 days (i.e., p('urgent')=0.65>0.5).

The ROC curve for Model 1 is shown in Figure 2. If we require that the probability of needing care within 48 hours be greater than 0.7 to diagnose urgent cases, all of the people diagnosed as "urgent" would certainly be urgent, but many other urgent people would be missed using this definition of urgency. The test would be very specific at the expense of sensitivity. At the other extreme, if anyone with a probability of less than 0.2 is used to diagnose urgent cases, very few urgent people would be missed, but most non-urgent people would be falsely labelled as being urgent. The test would then be very sensitive, but non-specific.

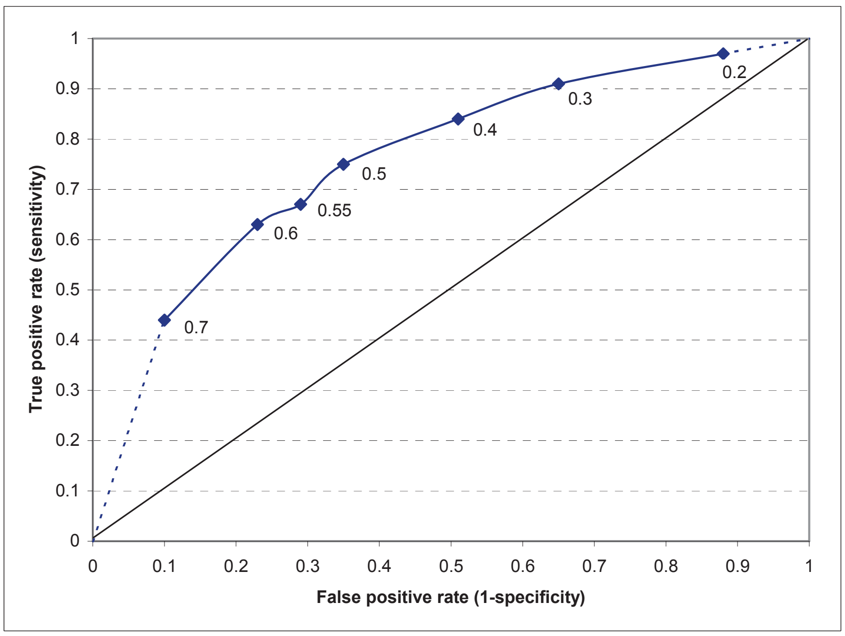
The ROC curve for Model 2 examining urgency of 2–7 days versus 8+ days is shown in Figure 3. The cut-off values on the curve represent the probability of needing treatment in 2–7 days. If we want to ensure that more urgent patients are not missed then a low cut-off should be chosen. If we want to have fewer false positives (i.e., correctly identify more non-urgent patients) then a higher cut-off value should be considered.

The area under the curve was 0.74 (Figure 2) and 0.76 (Figure 3) for Model 1 and Model 2 respectively, indicating reasonable discriminant ability of the test. This means that for Model 1, in 74% of all possible pairs of subjects in which one has urgency < 48 hours and the other urgency ≥ 2 days, this model will assign a higher probability to the subject with urgency < 48. For Model 2, a subject who actually is urgent (i.e., urgency = 2–7 days) will have a higher test score than someone who is not urgent on 76% of occasions.



Note: Area under the ROC curve=0.739, 95%CI=(0.701, 0.776)

Figure 2. *ROC curve for Model 1: care required within 48 hours*



Note: Area under the ROC curve=0.764, 95%CI=(0.722, 0.806)
† Limited to n=476 patients found by dentists to need care within 2–7 days or 8+ days

Figure 3. *ROC curve for Model 2*†*: care required in 2–7 days*

To determine how well the models were able to predict urgency of care, sensitivity, specificity, positive predictive values (PV+) and negative predictive values (PV–) were calculated for Model 1 and Model 2 at varying cut-off values.

Tables 4 and 5 show the results of using different cut-off levels for the predicted probability of being urgent for Model 1 and Model 2 respectively. When a probability of 0.4 was chosen as the cut-off level, the percent predicted with Model 1 to require care within 48 hours approximated that of the clinician's assessment of urgency in our patient sample. For example, suppose there are 100 patients presenting for emergency dental care. According to the gold standard, 36% were urgent and 64% were not urgent. Using a cut-off level of 0.4, the model sensitivity was 58% and specificity was 77% (Table 4) indicating that of those 36 patients actually requiring care within 48 hours, 21 (58% of 36) will be correctly identified as urgent and will therefore be seen within 48 hours, but 15 will be misclassified and receive care in 2+ days time (i.e., 15 patients end up with false negative results). Of the 64 patients who are considered able to wait 2+ days for treatment, 49 (77% of 64) without urgent need will actually test negative but 15

Table 4. Model 1 - <48 hours vs. 2+ days: Sensitivity, specificity and predictive values for possible cut-off values

	Sensitivity (%)	*Specificity (%)*	*PPV (%)*	*NPV (%)*	*Urgent patients (%)*
≥ 0.0	100	0			100.0
≥ 0.2	88	36	43	84	72.7
≥ 0.3	73	61	51	81	51.2
≥ 0.4	58	77	59	77	35.1
≥ 0.5	45	88	67	74	24.1
≥ 0.6	30	94	75	71	14.1
≥ 0.7	16	98	78	68	7.3

Table 5. Model 2 - 2–7 days vs. 8+ days: Sensitivity, specificity and predictive values for possible cut-off values

	Sensitivity (%)	*Specificity (%)*	*PPV (%)*	*NPV (%)*	*Urgent patients (%)*
≥ 0.0	100	0			100.0
≥ 0.2	97	12	56	79	92.9
≥ 0.3	91	35	62	76	78.6
≥ 0.4	84	49	66	73	68.7
≥ 0.5	75	65	71	69	56.3
≥ 0.6	63	77	76	64	44.5
≥ 0.7	44	90	84	58	28.2

will be misclassified (i.e., 15 patients end up with false positive results) and receive care within 48 hours.

Consider now what happens to the 64 patients not classified as needing to be seen immediately when Model 2 is used. To determine how many of these 64 patients are classified as needing to be seen in the period 2–7 days or in 8+ days, a cut-off for Model 2 needs to be selected. To illustrate this, Model 2 is interpreted for a cut-off of 0.5, the threshold at which the proportion predicted to need care in 2–7 days was similar to the proportion assessed by the dentist as needing care in 2–7 days. At this threshold of 0.5, the model sensitivity was 75% and specificity was 65% (Table 5). Thus, 28 of the 64 patients initially presenting for emergency care were classified as able to wait 8 or more days for dental care.

Discussion

These models and their application are only appropriate in similar groups of patients and the context of public dental services. In addition, one must also take into account changing disease patterns of a population which will influence the applicability of the models, even within the public dental care setting. However, the underlying explicit rationing of emergency dental care based on predictive models built upon subjective oral health indicators and psychosocial impacts of oral conditions may have wider relevance.

Currently there are no systematic and validated priority systems in place for persons presenting for public-funded dental care. Therefore, there are no validated cut-off points to define a positive test for urgency of dental care in adults presenting for public-funded emergency dental care. Highly sensitive screening tests minimise the number of false negative results, but increase the number of false positive test results. On the other hand, highly specific screening tests minimise the number of false positive results but increase the number of false negative results. A decision regarding acceptable levels of sensitivity and specificity involves weighting the consequences of leaving ‘urgent’ individuals untreated (false negatives) and classifying ‘non-urgent’ individuals as ‘urgent’ (false positives).

The prediction rule is a practical and simple tool for prioritising patients presenting for emergency dental care. To obtain the probability of being urgent for a particular patient, information is needed on the oral health indicators and psychosocial impacts for Model 1 and Model 2 respectively; this information can be readily obtained when a patient contacts the dental clinic to arrange an appointment. One key issue that may arise from trying to implement a prioritising tool of this nature would be patients anticipating a desired response set. Patients who currently access public dental services for emergency dental care understand that they are required to indicate that they are in pain in order to receive emergency dental care. However, with a screening tool such as this one, priority is based on a pattern of responses to the set of questions asked. Some questions require a ‘Yes/No’ response while others have five response categories (e.g., all the time, very often, often, sometimes, or never). There would be many permutations patients would have to work through before they can understand which responses hold the greatest weighting. Thus, it would be difficult for patients to work out what combinations of responses will give them a higher priority classification. However, there are ways to minimise this potential problem. For example, unexpected response categories being more important, or key indicators can be masked by using a range of questions in the models that do not contribute to overall priority allocation. However, the practical and ethical implications of these approaches have not been explored.

The multivariate logistic regression equations offer a scientific approach to prioritising care within the public dental system and improve on current methods used to allocate care which basically involve offering care on a 'first come, first served basis' to all those requesting dental care for a specific dental problem or for the relief of dental pain. Predictive models take the pressure away from reception staff to allocate appropriate appointment times to patients and eliminate the subjective nature of the way in which care is currently offered. They can be easily implemented within the public dental clinics by installing a computer algorithm on clinic computers, incorporating the formula of the logistic regression equation and beta coefficients presented in the results section, which generates the predicted probability of being urgent, and hence priority, of persons requesting emergency dental care.

Before introduction on a wide scale these models must be tested further to establish whether their predictions are valid in other settings. This validation research is currently underway. To validate the equations for each of the models, they are being applied to data that have not been used to generate the equations. Predictive equations rarely perform as well with new data as with the data with which they were developed because during development, the equation maximises the probability of predicting the values in the original dataset. When testing the models, the important factor is the size of the decrement in performance, i.e., the size of the change in sensitivity and specificity in the test phase. However, what size is considered to be too much has not been agreed upon in the literature.

In efforts to reform emergency dental care, public dental services should consider putting into place a system that allocates priority based on need as this would be more equitable and just in the delivery of dental care. Consistent with other research, this need is defined as relief of pain and restoration of quality of life, which the general public also view as acceptable criteria when allocating care on the basis of need (Ubel, 2000; Edwards et al., 2003). The priority models developed in this research offer options for reform in the delivery of emergency dental services, and have the potential to improve the allocative efficiency and effectiveness of public dental services. This, in turn, may enable dental care to be fairly distributed and delivered to low income and disadvantaged Australians. Reform efforts within the public dental sector should focus on the provision of preventive dental care services and access to appropriate and timely treatment when dental problems do arise. Priority tools such as this one may assist in achieving this goal by enabling a reallocation of funding from emergency dental care to general dental care, and by offering timely access to emergency dental care only to those with an urgent dental need.

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