Annals of Epidemiology 36 (2019) 5–14

Contents lists available at ScienceDirect

Annals of Epidemiology

Review article

Effect of comorbidity on injury outcomes: a review of existing indices

D. Tharanga Fernando, BSc [a,*], Janneke Berecki-Gisolf, PhD [a],
Stuart Newstead, BSc (Hons), MSc, PhD, AStat [a], Zahid Ansari, PhD, MS, MPH, MBBS [b]

[a] *Monash University Accident Research Centre, Victoria, Australia*
[b] *Health Intelligence Unit, Victorian Agency for Health Information, Melbourne, Victoria, Australia*

A R T I C L E I N F O

Article history:
Received 12 February 2019
Accepted 16 June 2019
Available online 21 June 2019

Keywords:
Chronic disease
Trauma
Charlson
Comorbidity
Elixhauser
Index
Injury
Outcome

A B S T R A C T

Purpose: Accounting for comorbidity in predicting outcomes for patients is vital in clinical care, epidemiological research, and health service planning. The aim of this study was to review published literature to compare the performance of existing comorbidity indices and their use in injury populations.
Methods: A thematic literature search for comorbidity indices and/or injury outcomes was conducted. Methods, results, and recommendations from selected articles were abstracted, documented, and compared; comparisons of results were made in terms of the indices' ability to predict outcomes, using the C-statistic, R^2, and odds ratios.
Results: Fifty-two articles relating to the derivation and/or validation of comorbidity measures were found. The most commonly used measures were the Charlson Comorbidity Index (CCI) and the Elixhauser Comorbidity Measure (ECM). The ECM was found to outperform the CCI in terms of predictive ability, although the CCI was more widely used. Derivation of study-specific weights to the CCI added more predictive power to the index.
Conclusions: Existing literature that compared the predictive abilities of the ECM and CCI favors the ECM. This literature review did not identify a measure specifically designed for general injury populations. Development of an injury-specific comorbidity measure will be timely and assist future research in injury epidemiology.

Introduction

Injury and comorbidity are both associated with adverse health outcomes such as mortality, hospital stay, and use of critical health care services. Accounting for comorbidity will affect a patient's natural clinical course and change the expected outcomes compared with nonconsideration of comorbidity [1]. Comorbidity also plays a vital role in epidemiological research (e.g., in calculating mortality rates or fatality rates for a specific condition) and health and social services planning (compounding effects of comorbidity can inflate resource needs) [1,2].

Both injury and chronic noncommunicable disease (NCD) have been recognized globally as major sources of disease burden, resulting in mortality, loss of functional health, disability in individuals, and costs to health and social service systems. The Global Burden of Disease (GBD) Report—2004 Update [3] showed that NCDs accounted for nearly half of the GBD among all age groups in low- and middle-income countries, and this proportion was much greater in high-income countries. Another GBD report stated that NCDs accounted for 71.3% of deaths globally in 2015 and injuries accounted for 8.5% of deaths [4]. In certain patients, mostly older adults, injury and chronic NCDs are likely to co-occur, with co-occurrence of chronic disease increasing the likelihood of adverse injury burden and mortality outcomes. This substantiates the need for appropriately quantifying comorbidity in establishing prognostic outcomes for injury patients.

To quantify the effect of comorbid conditions, a comorbidity index can be used. A comorbidity index can be used to predict outcomes for patients or adjust for the presence of these conditions in other research and clinical care. A review of these measures,

The study was approved by the Monash University Human Research Ethics Committee (Project no: 1256). The study was literature based and the research is low risk in that there was no discomfort or risk of harm to the participants.

The data that support the findings of this study were accessed from publicly available publications databases and can be accessed via the relevant websites.

The authors declare that they have no competing interests, financially, or otherwise.

* Corresponding author. Monash University Accident Research Centre, Monash University, Clayton Campus, 21 Alliance Lane, Clayton, Victoria 3800, Australia. Tel.: +61-3-9905 1805.
E-mail address: tara.fernando@monash.edu (D.T. Fernando).

https://doi.org/10.1016/j.annepidem.2019.06.004
1047-2797/© 2019 Published by Elsevier Inc.

especially those used in injury settings, will be informative for injury epidemiology. Measures that are adequate and appropriate in quantifying the effect of comorbidity on health outcomes for injury patients will be beneficial in clinical settings, epidemiological research, and health care planning.

Two systematic reviews have been conducted to date, to evaluate the performance of some of the existing comorbidity indices [5,6]. These two reviews, however, did not evaluate this from an injury perspective. The presence of comorbidities varies between injury and noninjury patients [7,8] and comorbidities may not be the key predictors of outcomes for injury patients [9]. Mortality Risk Score for Trauma (MoRT) was an injury-specific comorbidity index derived by Thompson et al. in 2010 [10]. This was based on a cohort of serious injury patients. Serious injury patients account for around 15% of all injury patients [11], and therefore, the MoRT needs further validation to be considered robust for use in general injury populations. Hence, it is still not clear if a specific comorbidity index needs to be derived for use in this population. A preliminary assessment of existing comorbidity measures and their use and utility in injury populations will shed light on their capabilities to account for comorbidities in predicting outcomes and inform if there should be a need for a more specific index for injury patients.

A narrative review of published research was conducted to summarize existing comorbidity measures (indices and alternatives) that have been commonly used to adjust for or test the effect of co-occurring chronic conditions on outcomes. The aim was to assess the capabilities of these measures to predict outcomes for general medical patients and more specifically, for injury patients.

The focus of this review was on commonly assessed health outcomes such as mortality [10,12–15], development of complications [15], additional use of critical care services such as intensive care unit (ICU) stay and mechanical ventilator (MV) use [16], need for long-term nursing care [16], extended length of hospital stay [14], increased likelihood of readmission to hospital [14], and costs [17].

The aim of this study was to review past literature to (1) describe published indices and their evolution, (2) assess the overall performance of the existing main comorbidity indices in terms of predicting health outcomes, and (3) explore their use in injury populations.

The study was approved by the Monash University Human Research Ethics Committee.

Materials and methods

Search strategy

The literature search was conducted using Google, Google Scholar, PubMed, and the Monash University Library (with access to over 4 million articles via platforms such as Ovid) between September 2016 and August 2017. The following terms and their derivations were used to search titles and contents: injury, outcome, comorbidity, pre-existing condition, comorbidity index, Charlson index, Elixhauser, and outcome-related terms such as death, mortality, readmissions, length of stay (LOS), complications, cost, ICU, ventilator, and discharge destination, with the term comorbidity. PubMed was also searched using the medical subject headings (MeSH) terms “comorbidity” and the selected outcome terms as a double check.

Inclusion/exclusion of literature

After an initial screening of abstracts, journal articles relating to development and validation of comorbidity indices (such as the Charlson Comorbidity Index [CCI] and Elixhauser Comorbidity Measure [ECM]) or other measures such as the count of comorbidities, presence/absence of certain comorbidities, or the presence of at least one comorbidity were retained. Articles relating to the development and/or validation of other comorbidity measures such as medication-based indices (chronic disease score and RxRisk) and ICU scoring systems that use severity of diseases classifications (e.g., acute physiology and chronic health evaluation II, simplified acute physiology score II) were excluded. The aforementioned data sources were less commonly available compared with hospital admission administrative data, and this review was more focused toward comorbidity indices that can be applied to the latter form of data. The literature retained for further review were limited to those related to specific injury outcomes such as in-hospital death, mortality, readmissions, LOS, complications, cost, ICU, and MV use and discharge destination. Two systematic literature reviews were also used to identify relevant literature and compare conclusions. Key literature referred to in the chosen articles if it was not picked up initially was included for review. Articles were organized by themes, (1) outcome being studied and (2) study population (injury vs. noninjury), and ordered chronologically in terms of published year.

Data extraction and reporting

Data were abstracted using a tailored data collection form. Abstracted data included information on the study population, comorbidity measure, data source, health outcome measure, predictive ability (C-statistics, R^2, and odds ratios) and final recommendations. The C-statistic measures the ability to discriminate those with and without the outcome, using the area under the receiver operating characteristic curve. The C-statistic ranges from 0 to 1 where 0.5–0.7 represents poor discrimination and anything greater than that considered good discrimination: the larger the C-statistic, the better the predictive ability of the model. Furthermore, using the extracted information and chronologically ordering them based on the studies from which they were sourced, flow charts were drawn to understand the evolution of the widely used comorbidity indices. The extracted information was also tabulated (1) by the more commonly used comorbidity indexes, outcome measures, and predictive ability and (2) by type of comorbidity measures and their use in injury outcome studies. The derivation and use of empirical weights for the commonly used indices were also reviewed.

Results

Abstracts of 188 articles, including two systematic literature reviews pertaining to comorbidity index validation, were screened and 36 were found to derive or validate comorbidity measures and were retained for further review. An additional fourteen articles identified in the two systematic reviews were also retained. Eighteen from the total of 50 articles were based on injury populations. Figure 1.

Main comorbidity indices and their evolution

The most commonly used measures for quantifying comorbidity were (1) the presence of at least one comorbidity; (2) the count of comorbidities; (3) CCI and its variations; and (4) the ECM and its updates.

Charlson Comorbidity Index and Elixhauser Comorbidity Measure

This review focuses on the two indices most commonly used and evaluated for performance, namely the CCI [18] and the ECM

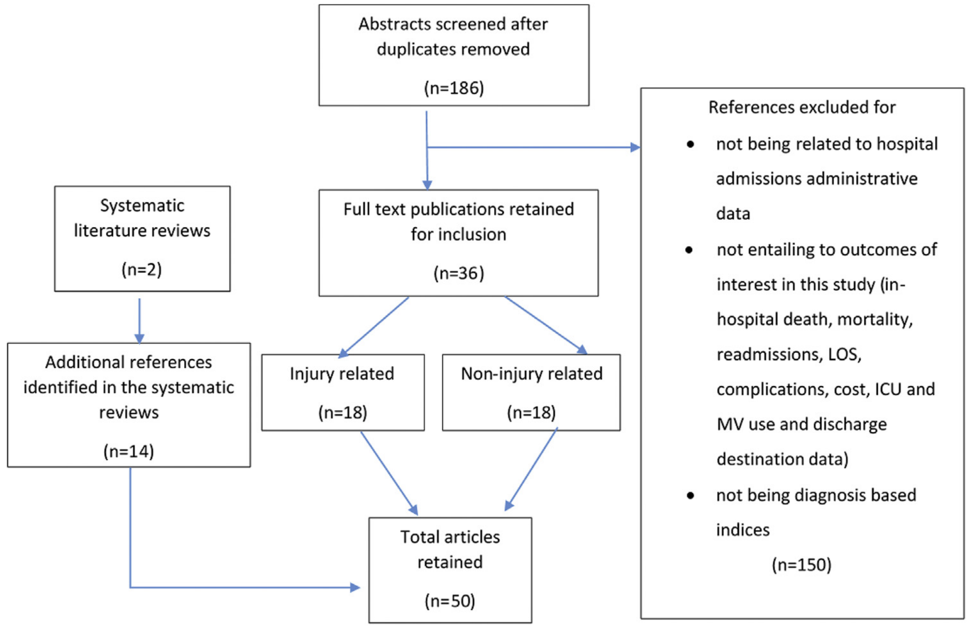

Fig. 1. Flow chart representing the article selection process for this study.

[19]. Both indices are diagnosis-based and are derived from a list of comorbidities (19 comorbidities for the CCI and 30 for the ECM), which are related to a particular health outcome. Figure 2 shows the evolution of these two comorbidity indicators since the early 80s (starting with the initial development of the CCI). The most recent update to the CCI is the new weights derived by Quan et al. in 2011 for twelve comorbid conditions, and for the ECM, it is the weighted score derived by van Walraven et al. in 2009 for twenty-one conditions.

The original ECM used a binary representation of the presence of each considered comorbidity as its measure, whereas the original CCI allocated a weight to each comorbidity and calculated a weighted summed score as the index. The CCI was developed in 1987 using a general cohort of patients admitted to a hospital during a one-month period and then followed up over a course of one year to assess mortality [18]. According to Google Scholar, the CCI has also been cited 26,353 times (9 October 2018) by papers that developed indices as well as those that used the index. The ECM developed in 1998 [19] identified a set of 30 distinct comorbidity groups based on the International Classification of Diseases, Ninth Revision, Clinical Modification codes. The ECM and its variations have all been described as good predictors for in-hospital death [5,20,21].

Seven of the 50 studies used both the CCI and ECM, 3 studies used only the ECM, and 26 studies used only the CCI, whereas 12 used other measures such as the count of or the presence of at least one condition. The CCI and the ECM are discussed in detail next.

Studies that derived empirical weights

Some studies in the past derived empirical weights for comorbid conditions using the CCI list and/or conditions specific to the study population. All of them concluded that study-specific weights outperformed the original CCI weights for assessing mortality outcomes [26,30–33], while Holman et al. (2005) further concluded that, although the empirical weights outperformed the original CCI weights, the ability to predict 30-day readmission and LOS was poor [32]. A comparison of the original CCI weights and the Quan updates of 2011 revealed that conditions such as peptic ulcer disease appear to have no impact on 1-y mortality, whereas conditions such as HIV/AIDS, renal disease, and diabetes have relatively lower impact than they used to, and liver diseases and dementia have acquired relatively higher weights in the updates [29]. These changes could partly be attributed to advances in medical science and changes in disease epidemiology and in part to improvements in comorbidity recording in administrative data sets over time. This emphasizes the need for updating comorbidity measures to select conditions relevant to a specific population and allocating weights that are currently appropriate.

Assessing the overall performance of the main indices in terms of predicting outcomes

Articles that used the CCI and ECM and their variations and updates in quantifying comorbidity are presented in Table 1. The performance of the CCI (and its variations) and the ECM (and its variations) in terms of their ability to predict outcomes are presented for noninjury and injury populations, respectively. The table presents results of studies evaluating the index admission and excludes results of lookback periods. Studies that conclude good predictive ability either found a significant gain in the C-statistic [37,41,44] or R^2 [48] when moving from the baseline model to a model that includes a comorbidity indicator, or found an odds ratios $\geq$1.3 [40,52]. Some of the studies did not discuss this change, instead drew conclusions based on the overall C-statistic. They concluded good predictive ability if the C-statistic for the model with the comorbidity indicator was $\geq$0.7 [20,21,27–29,43], whereas those concluding a weak predictive power of the index found the C-statistic to be in the range of 0.5–0.7 [42]. Li et al. (2010) (validated both CCI and ECM) and Holman et al. (2005) (validated CCI) made no specific conclusion of the predictive ability of the indices they tested, but the C-statistic was less than 0.7, which implies weak predictive power. It should be noted that a measure such as the C-statistic is highly dependent on the study population. It is also dependent on the model adjustment for other variables; that is, the number and type of model covariates drive the C-statistic, and therefore, C-statistics from different studies are not always comparable. A number of studies used the CCI for adjusting for comorbidity in modeling the effect of other variables on health outcomes (e.g., effect of injury on long-term mortality,

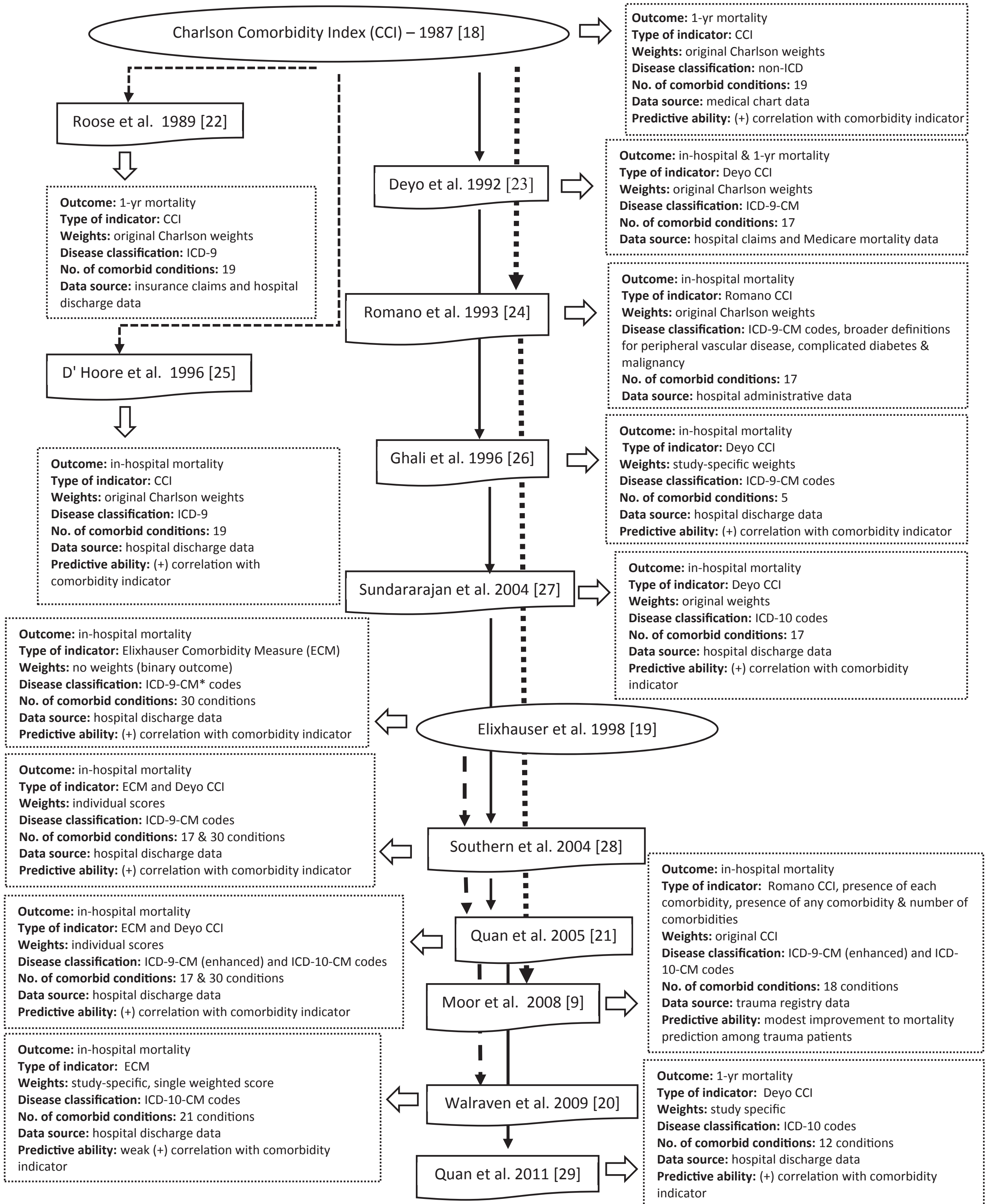

Fig. 2. Evolution of comorbidity indices for short-term mortality [9,18–29].

adjusted for pre-existing comorbidity [8]). For the purposes of this review, they have not been included, as this review focused on establishing the effect of comorbidity on the outcomes rather than adjusting for them. One such study [Kuwabara et al. (2010)] [51] was retained as it was based on an injury population and looked at LOS and costs; such outcomes were not often assessed among injury populations.

The CCI and its variations have been used more often than the ECM (Table 1). Eight studies that compared the performance of the CCI and ECM concluded in favor of the ECM for predictive ability [20,28,35,38,39,42,43,50], which is similar to conclusions drawn by Yurkovich et al. [5]. Studies that found the ECM to perform better than the CCI maintained that comorbidities have independent effects on outcomes and they differ for patient groups [19,24],

Table 1
Performance of existing comorbidity indices for selected outcomes among injury and general patient populations

Outcome measure	Noninjury populations				
	Article	Comorbidity measure	Prediction ability basis	Value of statistic	Author conclusion on predictive ability
In-hospital death	Librero et al. (1999) [34]	CCI (OA)	Standardized-death-rate increment with CCI	Not available	Good
	Stukenborg et al. (2001) [35] ‡,§	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01–0.04 (C-statistic = 0.61–0.72)	Weak
	Stukenborg et al. (2001) [35] ‡,§	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.07–0.09 (C-statistic = 0.66–0.77)	Weak, but better than the CCI
	Sundararajan et al. (2004) [27]	CCI (OA)	C-statistic	0.86	Good
	Southern et al. (2004) [28] ‡	CCI (OA)	C-statistic	0.7	Good
	Southern et al. (2004) [28] ‡	ECM (OA)	C-statistic	0.79	Good and better than the CCI
	Quan et al. (2005) [21]	CCI (OA)	C-statistic	0.86	Good
	Quan et al. (2005) [21]	ECM (OA)	C-statistic	0.87	Good
	Nuttall et al. (2005) [36] ‖	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.02 and 0.04 (C-statistic = 0.71 and 0.73)	Weak
	Zhu and Hill (2008) [37]	ECM (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.14 (C-statistic = 0.72)	Good
	van Walraven et al. (2009) [20] ‡	CCI (OA)	C-statistic	0.75	Good
	van Walraven et al. (2009) [20] ‡	ECM (U)	C-statistic	0.76	Good and better than the CCI
	Li et al. (2010) [38] ‡	CCI (OA)	C-statistic	0.65	No specific conclusion
	Li et al. (2010) [38] ‡	ECM(OA)	C-statistic	0.76	Better than the CCI
	Yu-Tseng et al. (2010) [39] ‡,¶	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.01 (C-statistic = 0.71 and 0.71)	Weak
	Yu-Tseng et al. (2010) [39] ‡,¶	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.041 (C-statistic = 0.74 and 0.74)	Weak, but better than the CCI
	Quan et al. (2011) [29]	CCI (OA)	C-statistic	0.88	Good
	Quan et al. (2011) [29]	CCI (U)	C-statistic	0.88	Good and similar predictive ability to the original CCI
1-y mortality	Goldstein et al. (2004) [40]	CCI (OA)	Statistically significant gain in odds of outcome from model with CCI <2 to CCI ≥2	OR = 1.72	Good
	Holman et al. (2005) [32] #	CCI (OA)	C-statistic	0.88 and 0.74	No specific conclusion
	Preen et al.(2006) [41] **	CCI (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.05 and 0.06 (C-statistic = 0.89 and 0.92)	Good
	Livingston EH (2007) [42] ‡	CCI (OA)	C-statistic	0.52	Weak
	Livingston EH (2007) [42] ‡,††	ECM (OA)	C-statistic	0.72	Good and better than the CCI
	Yu-Tseng et al. (2010) [39] ‡,¶	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.02 (C-statistic = 0.75 and 0.68)	Weak
	Yu-Tseng et al. (2010) [39] ‡,¶	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.03 (C-statistic = 0.77 and 0.70)	Weak, but better than the CCI
	Mnatzaganian et al. (2011) [43] ‡	CCI (OA)	C-statistic	0.72	Good
	Mnatzaganian et al. (2011) [43] ‡	ECM (OA)	C-statistic	0.75	Good and better than the CCI
	Quan et al. (2011) [29]	CCI (OA)	C-statistic	0.89	Good
	Quan et al. (2011) [29]	CCI (U)	C-statistic	0.90	Good and similar predictive ability to the original CCI
	Stavem et al. (2017) [44]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.66 (C-statistic = 0.78)	Good
Readmission within 30 d	Librero et al. (1999) [34]	CCI (OA)	Standardized-readmission-rate increment with CCI	NA	Good
	Parker et al. (2003) [45]	CCI (OA)	Wald X^2	$P < .0001$	Good
	Holman et al. (2005) [32] #	CCI (OA)	C-statistic	0.67 and 0.61	No specific conclusion
	Preen et al.(2006) [41] **	CCI (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.02 (C-statistic = 0.64 and 0.62)	Weak
LOS	Librero et al. (1999) [34]	CCI (OA)	Standardized LOS increment with CCI	NA	Good
	Melfi et al. (1995) [46]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 (C-statistic = 0.65)	Weak
	Parker et al. (2003) [45]	CCI (OA)	F-statistic	$P < .0001$	Good
	Holman et al. (2005) [32] #	CCI (OA)	R^2	0.17 and 0.03	No specific conclusion
	Atalay et al. (2009) [47]	CCI (OA)	X^2	NA	Weak

(continued on next page)

Table 1 (*continued*)

Outcome measure	Noninjury populations				
	Article	Comorbidity measure	Prediction ability basis	Value of statistic	Author conclusion on predictive ability
			Injury populations		
In-hospital death	Gabbe et al. (2005) [13]	CCI (OA)	Gain in C-statistic from baseline model (including injury severity) to model with comorbidity added	0.03 (C-statistic = 0.86)	Weak
	Moor et al. (2008) [9] *	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.00 (C-statistic = 0.94)	Weak
	Thompson et al. (2012) [48]	ECM (OA)	C-statistic	0.47	Weak
	Neuhaus et al. (2013) [49]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.62 (C-statistic = 0.77)	Good
	Neuhaus et al. (2013) [49]	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.63 (C-statistic = 0.77)	Good
	Toson et al. (2015) [14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.11 and 0.09 (C-statistic = 0.73 and 0.72)	Good
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.07 (C-statistic = 0.70)	Good
1-y mortality	Kurichi et al. (2007)[50] ‡,§§	CCI (OA)	C-statistic	0.65–0.68	Weak
	Kurichi et al. (2007)[50] ‡,§§	ECM (OA)	C-statistic	0.69–0.70	Weak, but better than CCI
	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.06 and 0.16 (C-statistic = 0.69 and 0.71)	Good
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.08 (C-statistic = 0.71)	Good
Readmission within 30 d	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.01 (C-statistic = 0.55 and 0.55)	Weak
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.00 (C-statistic = 0.54)	Weak
LOS	Kuwabara et al. (2010)[51] ‖‖	CCI (OA)	Beta coefficient for log LOS	0.09 and 0.12	Good
	Thompson et al. (2012)[48]	ECM (OA)	Gain in R^2 from baseline model to model with comorbidity added	Values not provided	Weak
	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in R^2 from baseline model to model with comorbidity added	0.00 & 0.01 (R^2 = 0.01 and 0.01)	Weak
	Toson et al. (2015)[14] †	CCI (U)	Gain in R^2 from baseline model to model with comorbidity added	0.01 (R^2 = 0.01)	Weak
Discharge destination	Chen et al. (2012)[52]	CCI (OA)	Significant gain in odds of outcome from model with CCI <2 to CCI ≥2	1.29 ≤ OR ≤ 3.65	Good
Costs	Kuwabara et al. (2010)[51] ‖‖	CCI (OA)	Beta coefficient for log cost	0.08 and 0.12	Good
ICU LOS	Thompson et al. (2012)[48]	ECM (OA)	Gain in R^2 from baseline model to model with comorbidity added	0.04	Good

CCI (OA) = original CCI or adaptation (Deyo/Romano); CCI (U) = updated CCI, weights per Quan et al. (2011); ECM (OA) = ECM or adaptations; ECM (U) = updated ECM with scores per van Walraven et al. (2009).
* Count was better.
† Individual presence was better.
‡ Compared CCI and ECM.
§ C-statistic range provided as study tested the index performance on 5 populations.
‖ C-statistic for the Charlson Deyo and Charlson Dartmouth-Manitoba adaptations.
¶ C-statistic for patients with index disease = acute myocardial infarction and index disease = chronic obstructive pulmonary disease.
# C-statistic for patients with index disease = asthma and index disease = acute myocardial infarction.
** C-statistic for medical patients and procedural patients.
†† Limited to 5 ECM conditions.
‡‡ Study used two algorithms; Sundararajan (2004) and Quan (2005).
§§ C-statistic range provided as study tested the index performance on 3 populations.
‖‖ CCI reference = 0, beta reported for CCI 1 and CCI ≥ 2.

thereby discouraging the use of summary indices. It should, however, be noted that the ECM requires adjusting for 30 binary parameters. This could result in overfitting, and furthermore, this may be impractical when sample sizes are small, resulting in many empty cells. A weighted index with fewer parameters may be more practicable in small samples. Decisions on which index to use are dependent on the data and objective of the study. Overall, the CCI has been praised for its reliability and good correlation with mortality, whereas the drawbacks are that it is limited to 19 conditions and likely to underdetect nonfatal adverse outcomes [53].

Table 1 also shows that the CCI and ECM have been used more often to assess mortality outcomes than resource use. Fewer studies have validated the CCI and ECM on injury populations than general medical populations. Among injury populations, the count or individual presence of comorbidities performed equally well or outperformed the CCI in terms of predictive ability [9,14] (Table 1). Outcomes such as long-term mortality, use of the ICU and MV, and complications have not been assessed for the effect of comorbidity using these indices; ICU and MV use were commonly assessed using individual disease presence [54–56] (not shown in tables). Studies that used the CCI and ECM for nonmortality-related outcomes such as readmission to hospital, LOS, and costs were also fewer in number than studies of mortality-related outcomes (Table 1).

Use of comorbidity indices in injury populations

This review assessed the use of comorbidity measures in predicting outcomes among injury populations, assessing what measures have been used most frequently and how such measures performed in terms of predictive ability. Studies related to injury populations in general were few compared with the number of studies in general clinical populations as seen in Table 1, although the relative proportions of each study type have not been reported as this was not a systematic review and therefore is not an exhaustive list of studies.

Four studies found the CCI good at predicting outcomes among injury patients [14,49,51,52] (Table 1). Kurichi et al. (2007) compared the CCI and ECM for predicting 1-y mortality among elderly veterans with lower extremity amputations, reporting that the ECM only slightly outperformed the CCI [50], and that overall the indices were weak predictors of the outcome. Moor et al. (2008) concluded that a count of comorbidities was as good as the CCI in quantifying the effect of comorbidity on in-hospital death [9] among high-level trauma patients, whereas Toson et al. (2015) suggested that the individual presence of seventeen CCI conditions was better than the weighted score in predicting mortality [14] among older patients with hip fracture. The latter also concluded that the CCI was not suitable for predicting resource utilization.

Table 2 summarizes some of the studies on injury-specific patient cohorts and the use of comorbidity indicators for predicting outcomes. The general consensus from these studies is that the CCI is a good predictor of mortality but not a good predictor for burden-related outcomes. Conversely, the CCI has been recommended as good at predicting discharge destination and disability outcomes [52,59]. The table also shows the absence of studies assessing the CCI for complications.

Indicators of the individual presence of comorbidities has been found to be equally effective or better at predicting health outcomes compared with the CCI by Moor et al. and Toson et al. [9,14] (Table 2). Overall, among injury patients, age and injury severity were better predictors of outcome than comorbidity measures [10,13,49,51,55]. Validation of the CCI or other comorbidity measures on general injury cohorts was scarce (Table 2).

The only study identified that derived empirical weights for an injury population was by Thompson et al. in 2010 [10]. They derived the MoRT using a cohort of patients with serious injury. The MoRT performed just as well as the CCI in predicting mortality, but better predictive ability was gained by adding age, gender, and injury severity to the model. Injury severity, age, and gender were found to add more predictive power in other studies also [13,49,55]. The MoRT was a more parsimonious index, as it used only six comorbid conditions: severe liver disease, myocardial infarction, cerebrovascular disease, cardiac arrhythmias, dementia, and depression. They concluded that in the context of injury, eliciting information on past comorbidity is not always possible and therefore an index with a fewer number of conditions would be more practical.

Discussion

We studied the performance of existing comorbidity indices in terms of predicting outcomes and explored how they have been used for assessing outcomes among injury patients whose data were often sourced from administrative databases.

This review found that of the diagnosis-based indices, the CCI and ECM were the most commonly used comorbidity measures for predicting outcomes among hospital-admitted patients. These two indices were compared for performance in terms of predictive power: the ECM outperformed the CCI, although the CCI was the more commonly used measure [5,6]. The more common use of the CCI could also be due to the fact that it preceded the ECM and had been around for over 11 y before the ECM. Two adaptations of the CCI are available, namely the Deyo and Romano versions; both of which have been proven to have good predictive ability for mortality by certain studies. Several studies explored the derivation of empirical weights for the Charlson list of conditions as opposed to using the original Charlson weights, which had improved the predictive ability of the index [26,30–33,36]. Weights, however, should be reflective of current medical practice and disease prevalence. Many decades have passed since the development of the CCI and eight years since the latest update by Quan et al. [29]. Although regular updates have been made, the scale in its original form is still commonly used. Due to advances in medical science and changes in chronic disease epidemiology, the derivation of new empirical weights at regular time intervals to reflect current medical advances is justified.

This review has brought to light suboptimal use of general comorbidity measures, for example, the use of older versions rather than the updated CCI in specific injury populations. It also found that injury outcomes research tended to focus on subgroups of populations, such as older age groups or specific-injury groups such as traumatic brain injury or hip fractures; only one study focused on all injury patients [57]. Although most injury outcome studies concluded that injury characteristics and age best predict outcomes [9,12,13,55,57], relevant adjustments for comorbidity improved predictive power and so are still necessary. Therefore, appropriate comorbidity measures are required for this group. The only study we found that derived an index based on empirical weights using an injury population did so to assess mortality outcomes. However, this study was based on a cohort of serious injury patients only [10], and we found no validation studies for this index.

This review also found that specific comorbidity measures have so far not been developed for burden-related outcomes such as LOS, readmission, MV use, ICU stay, costs, and complications among injury or general clinical patients. Development of comorbidity measures relating to burden, mortality, and complications for all injury patients, be they weighted summed scores, individual presence of conditions, counts of comorbidities, or the presence of at least one comorbidity, with conditions significant to the outcome, needs to be explored. Such measures can be utilized in a number of settings; in evaluating and comparing treatments, predicting outcomes, and identifying comorbidities that are relevant to a specific outcome. They are useful in teasing out the risk of outcomes from injury-related processes adjusting for comorbidity which is a competing risk. For example, when assessing the risk of noncancer mortality, a weighted-index adjustment accounts for noncancer (comorbidity-related) mortality, where other methods such as survival analysis would use "competing risks" imposed by comorbidities to assess cancer survival.

This study is not without limitations. First, it was not a systematic literature review, and therefore may have missed relevant literature; although based on the retrieval of relevant publications cited in the captured literature, we believe that key literature has been included. Second, the focus of this review was research that used administrative data for creating and validating comorbidity indices and excluded studies based on medical chart review and self-report. Some studies have found chart reviews to better capture comorbidity, which may improve the predictive ability of indicators [44,64]. Given that other studies have found the contrary, the difference in comorbidity capture may not be significant [65,66]. Both data sources have limitations: self-reporting introduces respondent bias whereas administrative data can lack information on comorbidities not treated or actively observed during the hospital episode [39,41–43,48].

Table 2
Comorbidity measures used in injury studies and details of conclusions drawn by authors

Comorbidity measure	Article	Study population	Conclusion
General injury population			
CCI	Kuwabara et al. (2010)[51]	All injury patients	Higher odds of mortality for higher CCI scores but not so much for LOS; CCI was used to adjust for comorbidity rather than establish association
Count	Morris et al. (1990)[57]	All injury (patients ≥15 y of age)	Higher number of conditions associated with higher odds of mortality; risk greater among patients with less severe injuries
	Mc Gwin et al. (2004)[12]	All injury (patients ≥50 y of age)	Higher risk of death for older trauma patients with comorbidity and minor injuries than those without
Individual presence of each condition	Morris et al. (1990)[57]	All injury (patients ≥15 y of age)	Certain conditions associated with higher odds of mortality
	Bochicchio et al. (2005)[54]	Critically ill trauma patients	Selected conditions, age, and comorbidity associated with LOS, MV use, and mortality. Also supports findings from Mc Gwin et al. that mortality is greatly influenced by the injuries.
	Kao et al. (2006)[55]	Mostly high-level trauma centers	Diabetes is a weak factor in predicting mortality, LOS and ICU stay, whereas age and injury severity are stronger factors
	Ahmad et al. (2007)[56]	All injury	Diabetes mellitus associated with ICU stay, ventilator use, and complications, but not mortality and LOS
Specific injury population			
CCI	Gabbe et al. (2005)[13]	Serious injury	CCI is associated with mortality but does not add more predictive power to models with other predictive variables such as age
	Kurichi et al. (2007)[50]	Elderly veterans with lower extremity amputations	
	CCI was weak at predicting 1-y mortality		
	Camilloni et al. (2008)[58]	Home and road injury (patients ≥65 y of age)	CCI predicts mortality best among mild and moderately severely injured patients
	Moor et al. (2008)[9]	High level trauma center patients	CCI no better than the count of conditions
	Thompson et al. (2010)[10]	Patients 18–84 y, 3 or higher on the Abbreviated Injury Scale	CCI and MoRT performs equally; better predictability achieved by adding injury severity, age, and gender
	Chen et al. (2012)[52]	Traumatic brain injury patients	CCI predicts discharge destination well
	Neuhaus et al. (2013)[49]	Patients ≥ 18 y with hip fractures	Three forms of the CCI; original 1987 CCI, the 1994 age-adjusted CCI, and the 2011 updated and reweighted CCI. All indices good at predicting mortality after adjusting for age and other variables
	Gabbe et al. (2013)[59]	Orthopedic injury patients after surgery	CCI predicts disability well
	Toson et al. (2015)[14]	Patients ≥ 65 y with hip fractures	CCI, a good predictor for mortality but not resource utilization. Presence of individual conditions better than CCI and a lookback period for comorbidity improves prediction of long-term mortality
Count	Moor et al. (2008)[9]	High-level trauma center patients	CCI no better than count of conditions
	Senn-Reeves and Jenkins (2015)[15]	Patients ≥15 y with blunt thoracic trauma	Comorbidities associated with complications and discharge destination; used 10 selected comorbidities
Individual presence of each condition	Gabbe et al. (2005)[60]	High-level trauma center patients	Comorbidity not an independent predictor of mortality
	Kurichi et al. (2007)[50]	Elderly veterans with lower extremity amputations	
	ECM was only slightly better than the CCI at predicting 1-y mortality		
	Moor et al. (2008)[9]	High-level trauma center patients	CCI no better than individual disease presence
	Thompson et al. (2012)[61]	Traumatic brain injury patients ≥55 y of age	ECM poor at predicting in-hospital mortality, and LOS, but a good predictor for ICU LOS
	Lustenberger et al. (2013)[16]	Traumatic brain injury patients	Diabetes mellitus associated with mortality and discharge destination but not ventilator use, ICU stay, or LOS
	Morris et al. (2014)[62]	Admissions after trauma resuscitation	Obstructive pulmonary disease and diabetes mellitus associated with readmission, although the more important predictors were ICU stay and surgical site infections
	Hwabejire et al. (2014)[63]	Patients ≥90 y of age in a high-level trauma center	Comorbidity has no effect on mortality, based on 6 baseline comorbid conditions
	Toson et al. (2015)[14]	Patients ≥ 65 y of age with hip fractures	CCI good for predicting mortality but not resource utilization. Presence of individual conditions better than CCI and a lookback period for comorbidity improves prediction of long-term mortality

Conclusions

Binary representation of individual comorbidities, such as used in the ECM, outperformed weighted indices and other comorbidity measures in predicting health outcomes as per the studies included in this review. However, the performance ability of an index is dependent on the data, study population, and objectives of the research. The ECM although has not been validated enough on injury populations. Most existing comorbidity indices have proven to be good predictors of mortality outcomes but not of resource use or complications. Weighted indices were found to benefit from regular updating of weights using empirical methods to better represent current health practices. A specific comorbidity index for general injury-populations has not been derived to date. Development of measures to quantify the effect of comorbidity on specific clinical outcomes for general hospital–admitted injury patients is essential for improved quantification of the impacts of comorbidity on health outcomes in future injury epidemiology research. The measures developed should resonate with the present epidemiology of chronic diseases, their clinical relevance, and account for the effects of injury-related and demographic factors associated with outcomes. Such an index will eliminate biases introduced by outdated weights and irrelevant comorbidities found in existing indices.

Acknowledgment

This paper is part of a PhD Thesis which is supported by the Victorian Injury Surveillance Unit funded by the Victorian Government.

Authors' contributions: T.F., J.B., and Z.A. conceived the presented idea. The theory and structure was developed by T.F. and J.B. J.B., S.N., and Z.A. supervised T.F. in producing the findings of this work. All authors read and approved the final manuscript.

References

[1] Feinstein AR. The pre-therapeutic classification of co-morbidity in chronic disease. J Chronic Dis 1970;23(7):455–68.
[2] Valderas JM, Starfield B, Sibbald B, Salisbury C, Roland M. Defining comorbidity: implications for understanding health and health services. Ann Fam Med 2009;7(4):357–63.
[3] World Health Organization. The global burden of disease: 2004 update. Switzerland: WHO; 2008.
[4] Wang H, Naghavi M, Allen C, Barber RM, Bhutta ZA, Carter A, et al. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet 2016;388(10053):1459–544.
[5] Yurkovich M, Avina-Zubieta JA, Thomas J, Gorenchtein M, Lacaille D. A systematic review identifies valid comorbidity indices derived from administrative health data. J Clin Epidemiol 2015;68(1):3–14.
[6] Sharabiani MTA, Aylin P, Bottle A. Systematic review of comorbidity indices for administrative data. Med Care 2012;50(12):1109–18.
[7] Cameron CM, Purdie DM, Kliewer EV, McClure RJ. Differences in prevalence of pre-existing morbidity between injured and non-injured populations. Bull World Health Organ 2005;83:345+.
[8] Mitchell RJ, Cameron CM, McClure R. Higher mortality risk among injured individuals in a population-based matched cohort study. BMC Public Health 2017;17:150.
[9] Moore L, Lavoie A, Sage NL, Bergeron É, Émond M, Liberman M, et al. Using information on preexisting conditions to predict mortality from traumatic injury. Ann Emerg Med 2008;52(4):356–364.e352.
[10] Thompson HJ, Rivara FP, Nathens A, Wang J, Jurkovich GJ, Mackenzie EJ. Development and validation of the mortality risk for trauma comorbidity index. Ann Surg 2010;252(2):370–5.
[11] AIHW, Pointer SC. Trends in hospitalised injury, Australia 1999–00 to 2014–15 Injury research and statistics series no 110 Cat no INJCAT 190. Canberra: AIHW; 2018.
[12] McGwin Jr G, MacLennan PA, Fife JB, Davis GG, Rue III LW. Preexisting conditions and mortality in older trauma patients. J Trauma Acute Care Surg 2004;56(6):1291–6.
[13] Gabbe BJ, Magtengaard K, Hannaford AP, Cameron PA. Is the Charlson comorbidity index useful for predicting trauma outcomes? Acad Emerg Med 2005;12(4):318–21.
[14] Toson B, Harvey LA, Close JC. The ICD-10 Charlson comorbidity index predicted mortality but not resource utilization following hip fracture. J Clin Epidemiol 2015;68(1):44–51.
[15] Senn-Reeves JN, Jenkins DH. Examining the relationship between preinjury health and injury-related factors to discharge location and risk for injury-associated complications in patients after blunt thoracic trauma: a pilot study. J Trauma Nurs 2015;22(3):136–47.
[16] Lustenberger T, Talving P, Lam L, Inaba K, Bass M, Plurad D, et al. Effect of diabetes mellitus on outcome in patients with traumatic brain injury: a national trauma databank analysis. Brain Inj 2013;27(3):281–5.
[17] Farley JF, Harley CR, Devine JW. A comparison of comorbidity measurements to control for confounding in health outcomes studies. DTIC Document; 2005.
[18] Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis 1987;40(5):373–83.
[19] Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. Med Care 1998;36(1):8–27.
[20] van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. Med Care 2009;47:626–33.
[21] Hude Q, Vijaya S, Patricia H, Andrew F, Bernard B, Jean-Christophe L, et al. Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data. Med Care 2005;43(11):1130–9.
[22] Roos LL, Sharp SM, Cohen MM, Wajda A. Risk adjustment in claims-based research: The search for efficient approaches. J Clin Epidemiol 1989;42(12):1193–206.
[23] Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. J Clin Epidemiol 1992;45(6):613–9.
[24] Romano PS, Roos LL, Jollis JG. Presentation adapting a clinical comorbidity index for use with ICD-9-CM administrative data: differing perspectives. J Clin Epidemiol 1993;46(10):1075–9.
[25] D'Hoore W, Bouckaert A, Tilquin C. Practical considerations on the use of the Charlson comorbidity index with administrative data bases. J Clin Epidemiol 1996;49(12):1429–33.
[26] Ghali WA, Hall RE, Rosen AK, Ash AS, Moskowitz MA. Searching for an improved clinical comorbidity index for use with ICD-9-CM administrative data. J Clin Epidemiol 1996;49(3):273–8.
[27] Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. J Clin Epidemiol 2004;57(12):1288–94.
[28] Southern DA, Quan H, Ghali WA. Comparison of the Elixhauser and Charlson/Deyo methods of comorbidity measurement in administrative data. Med Care 2004;42(4):355–60.
[29] Quan H, Li B, Couris CM, Fushimi K, Graham P, Hider P, et al. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. Am J Epidemiol 2011;173(6):676–82.
[30] Klabunde CN, Potosky AL, Legler JM, Warren JL. Development of a comorbidity index using physician claims data. J Clin Epidemiol 2000;53(12):1258–67.
[31] Martins M, Blais R. Evaluation of comorbidity indices for inpatient mortality prediction models. J Clin Epidemiol 2006;59(7):665–9.
[32] Holman CAJ, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. J Clin Epidemiol 2005;58(10):1006–14.
[33] Schneeweiss S, Wang PS, Avorn J, Glynn RJ. Improved comorbidity adjustment for predicting mortality in Medicare populations. Health Serv Res 2003;38(4):1103–20.
[34] Librero J, Peiró S, Ordiñana R. Chronic comorbidity and outcomes of hospital care: length of stay, mortality, and readmission at 30 and 365 days. J Clin Epidemiol 1999;52(3):171–9.
[35] Stukenborg GJ, Wagner DP, Connors AF. Comparison of the performance of two comorbidity measures, with and without information from prior hospitalizations. Med Care 2001;39(7):727–39.
[36] Nuttall M, van der Meulen J, Emberton M. Charlson scores based on ICD-10 administrative data were valid in assessing comorbidity in patients undergoing urological cancer surgery. J Clin Epidemiol 2006;59(3):265–73.
[37] Zhu H, Hill MD. Stroke: the Elixhauser index comorbidity adjustment in-hospital case fatality. Neurology 2008;71(4):283–7.
[38] Li P, Kim MM, Doshi JA. Comparison of the performance of the CMS Hierarchical Condition Category (CMS-HCC) risk adjuster with the Charlson and Elixhauser comorbidity measures in predicting mortality. BMC Health Serv Res 2010;10:245.
[39] Chu Y-T, Ng Y-Y, Wu S-C. Comparison of different comorbidity measures for use with administrative data in predicting short- and long-term mortality. BMC Health Serv Res 2010;10(1):140.
[40] Goldstein LB, Samsa GP, Matchar DB, Horner RD. Charlson index comorbidity adjustment for ischemic stroke outcome studies. Stroke 2004;35(8):1941–5.
[41] Preen DB, Holman CDAJ, Spilsbury K, Semmens JB, Brameld KJ. Length of comorbidity lookback period affected regression model performance of administrative health data. J Clin Epidemiol 2006;59(9):940–6.
[42] Livingston EH. Development of bariatric surgery-specific risk assessment tool. Surg Obes Relat Dis 2007;3(1):14–20.

[43] Mnatzaganian G, Ryan P, Norman PE, Hiller JE. Accuracy of hospital morbidity data and the performance of comorbidity scores as predictors of mortality. J Clin Epidemiol 2012;65(1):107–15.
[44] Stavem K, Hoel H, Skjaker SA, Haagensen R. Charlson comorbidity index derived from chart review or administrative data: agreement and prediction of mortality in intensive care patients. Clin Epidemiol 2017;9:311–20.
[45] Parker JP, McCombs JS, Graddy EA. Can pharmacy data improve prediction of hospital outcomes? comparisons with a diagnosis-based comorbidity measure. Med Care 2003;41(3):407–19.
[46] Melfi C, Holleman E, Arthur D, Katz B. Selecting a patient characteristics index for the prediction of medical outcomes using administrative claims data. J Clin Epidemiol 1995;48(7):917–26.
[47] Atalay A, Turhan N. Determinants of length of stay in stroke patients: a geriatric rehabilitation unit experience. Int J Rehabil Res 2009;32(1):48–52.
[48] Thompson H, Dikmen S, Temkin N. Prevalence of Comorbidity and its Association with Traumatic Brain Injury and Outcomes in Older Adults. Res Gerontol Nurs 2012;5(1):17–24.
[49] Neuhaus V, King J, Hageman MG, Ring DC. Charlson comorbidity indices and in-hospital deaths in patients with hip fractures. Clin Orthop Relat Res 2013;471(5):1712–9.
[50] Kurichi JE, Stineman MG, Kwong PL, Bates BE, Reker DM. Assessing and using comorbidity measures in elderly veterans with lower extremity amputations. J Gerontol 2007;53(5):255–9.
[51] Kuwabara K, Matsuda S, Imanaka Y, Fushimi K, Hashimoto H, Ishikawa KB, et al. Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database. J Trauma Acute Care Surg 2010;68(2):463–70.
[52] Chen AY, Zagorski B, Parsons D, Vander Laan R, Chan V, Colantonio A. Factors associated with discharge destination from acute care after acquired brain injury in Ontario, Canada. BMC Neurol 2012;12(1):16.
[53] Extermann M. Measuring comorbidity in older cancer patients. Eur J Cancer 2000;36(4):453–71.
[54] Bochicchio GV, Joshi M, Bochicchio K, Shih D, Meyer W, Scalea TM. Incidence and impact of risk factors in critically ill trauma patients. World J Surg 2006;30(1):114–8.
[55] Kao LS, Todd SR, Moore FA. The impact of diabetes on outcome in traumatically injured patients: an analysis of the National Trauma Data Bank. Am J Surg 2006;192(6):710–4.
[56] Ahmad R, Cherry RA, Lendel I, Mauger DT, Service SL, Texter LJ, et al. Increased hospital morbidity among trauma patients with diabetes mellitus compared with age- and injury severity score–matched control subjects. Arch Surg 2007;142(7):613–8.
[57] Morris Jr JA, MacKenzie EJ, Edelstein SL. The effect of preexisting conditions on mortality in trauma patients. JAMA 1990;263(14):1942–6.
[58] Camilloni L, Farchi S, Rossi PG, Chini F, Borgia P. Mortality in elderly injured patients: the role of comorbidities. Int J Inj Contr Saf Promot 2008;15(1):25–31.
[59] Gabbe BJ, Harrison JE, Lyons RA, Edwards ER, Cameron PA. Comparison of measures of comorbidity for predicting disability 12-months post-injury. BMC Health Serv Res 2013;13(1):1.
[60] Gabbe BJ, Cameron PA, Wolfe R, Simpson P, Smith KL, McNeil JJ. Predictors of mortality, length of stay and discharge destination in blunt trauma. ANZ J Surg 2005;75(8):650–6.
[61] Thompson HJ, Weir S, Rivara FP, Wang J, Sullivan SD, Salkever D, et al. Utilization and costs of health care after geriatric traumatic brain injury. J Neurotrauma 2012;29(10):1864–71.
[62] Morris DS, Rohrbach J, Sundaram LMT, Sonnad S, Sarani B, Pascual J, et al. Early hospital readmission in the trauma population: Are the risk factors different? Injury 2014;45(1):56–60.
[63] Hwabejire JO, Kaafarani HA, Lee J, Yeh DD, Fagenholz P, King DR, et al. Patterns of injury, outcomes, and predictors of in-hospital and 1-year mortality in nonagenarian and centenarian trauma patients. JAMA Surg 2014;149(10):1054–9.
[64] Lee DS, Donovan L, Austin PC, Gong Y, Liu PP, Rouleau JL, et al. Comparison of coding of heart failure and comorbidities in administrative and clinical data for use in outcomes research. Med Care 2005;43(2):182–8.
[65] Nguyen TQ, Simpson PM, Braaf SC, Cameron PA, Judson R, Gabbe BJ. Comparison of the performance of mental health, drug and alcohol comorbidities based on ICD-10-AM and medical records for predicting 12-month outcomes in trauma patients. BMC Health Serv Res 2018;18:408.
[66] Price J, Estrada CA, Thompson D. Case study. Am J Med Qual 2003;18(1):38–45.