

I'm not a robot!

Do you use the Charlson Comorbidity Index and want to contribute your expertise? Join our contributor team! History of definite or probable MI (EKG changes and/or enzyme changes) Exertional or paroxysmal nocturnal dyspnea and has responded to digitalis, diuretics, or afterload reducing agents Peripheral vascular disease Intermittent claudication or past bypass for chronic arterial insufficiency, history of gangrene or acute arterial insufficiency, or untreated thoracic or abdominal aneurysm (≥ 6 cm) History of a cerebrovascular accident with minor or no residual and transient ischemic attacks Chronic cognitive deficit Connective tissue disease Any history of treatment for ulcer disease or history of ulcer bleeding Severe = cirrhosis and portal hypertension with variceal bleeding history, moderate = cirrhosis and portal hypertension but no variceal bleeding history, mild = chronic hepatitis (or cirrhosis without portal hypertension) Severe = on dialysis, status post kidney transplant, uremia, moderate = creatinine > 3 mg/dL (> 20 mmol/L) This is a COVID-19 patient? For research purposes only: wills NOT impact results Confirmed positive Suspected unlikely Confirmed negative Please fil out required fields Mary Charlson, MD, is the William Foley Professor of Medicine, Chief of General Internal Medicine and the Program Chairperson for the Master of Science Program in Clinical Epidemiology and Health Services Research at Cornell Medical College. She is also a clinical epidemiologist and methodologist. Dr. Charlson has also developed new methods of improving prognostic stratification in acute and chronic illness. To view Dr. Mary Charlson's publications, visit PubMed Related CalcsqSOFAAPACHE II Score SMART-COPH Have feedback about this calculator? The present critical review was conducted to evaluate the clinimetric properties of the Charlson Comorbidity Index (CCI), an assessment tool designed specifically to predict long-term mortality, with regard to its reliability, concurrent validity, sensitivity, and predictive validity. The original version of the CCI has been adapted for use with different sources of data, ICD-9 and ICD-10 codes. The inter-rater reliability of the CCI was found to be excellent, with extremely high agreement between self-report and medical charts. The CCI has also been shown either to have concurrent validity with a number of other prognostic scales or to result in concordant predictions. Importantly, the clinimetric properties of the CCI has been demonstrated in a variety of medical conditions, with stepwise increases in the CCI associated with stepwise increases in mortality. The CCI is also characterized by the clinimetric property of incremental validity, whereby adding the CCI to other measures increases the overall predictive accuracy. It has been shown to predict long-term mortality in different clinical populations, including medical, surgical, intensive care unit (ICU), trauma, and cancer patients. It may also predict in-hospital mortality, although in some instances, such as ICU or trauma patients, the CCI did not perform as well as other instruments designed specifically for that purpose. The CCI thus appears to be clinically useful not only to provide a valid assessment of the patient's unique clinical situation, but also to demarcate major diagnostic and prognostic differences among subgroups of patients sharing the same medical diagnosis. © 2022 The Author(s). Published by S. Karger AG, Basel The term comorbidity has a Latin origin and results from the combination of two words: "co" meaning "along with" and "morbis" meaning "disease." It was Alvan R. Feinstein who provided the first clinical definition of this concept, which refers to "any distinct additional clinical entity that has existed or that may occur during the clinical course of a disease that is under study" [1]. Further, he noted that a comorbid condition has the potential not only to impact a patient's prognosis, but also to alter therapeutic plans and outcomes [1]. Prior to his paper, comparability of patients was judged primarily by similarities in age, gender, race, and anatomic stage and not on comorbid conditions. Since this resulted in comorbid conditions confounding outcomes, failure to catalog it led to the exclusion of patients with any diseases other than the index disease from studies. The term "comorbidity" has been defined in many different ways [2]. The specific reason for defining a comorbid condition is crucial and there is no universally correct answer. Most agree that comorbidity is not a measure of overall health status, self-rated health, performance status (NY Heart Association criteria, Eastern Cooperative Oncology Group), psychological well-being, or stage of disease (i.e., Tumor-Node-Metastasis - TNM classification). Some measures have counted body systems involved or medications. Central to the definition of a comorbid condition is the question: For what purpose? Co-occurrence is not sufficient to define a comorbid condition. If co-occurrence is the only criterion to define a comorbid condition, then color blindness, hangover, upper respiratory infection, an injured ankle after a car accident, pain in the thumb, and an elevated white blood cell count, would all be comorbid conditions. The definition of a comorbid condition depends on the key questions involved: diagnostic comorbidity (conditions that confound diagnosis), treatment comorbidity (conditions that alter therapy), and prognostic comorbidity (conditions that impact outcomes). Diagnostic and treatment comorbidity must be defined in the context of a specific condition(s). In medicine, most major diseases are defined by specific criteria independent of the presence of another chronic disease, although the actual criteria may differ by groups or settings. Diagnostic comorbidity is more complex in psychiatry than in medicine. In psychiatry, diagnostic comorbidity, even with the Diagnostic and Statistical Manual of Mental Disorders (DSM) handbook to improve inter-observer reliability, is a complex issue and considers a number of potential relationships between disorders: (a) one specific disorder preceding or increasing the risk for another one, (b) two coexisting disorders that may predispose to the development of another disease, (c) antecedent factors specific for different disorders, and (d) a complex interaction of one or more distinct antecedent factors [3]. This was shown in a 12-month study of 9,300 adults [4]; of the 2,500 adults who had one DSM-IV disorder, almost half (45%) had more than two more DSM-IV disorders [4]. This complexity resulted in the development and promulgation of psychometric methods of assessment of psychiatric scales. In psychiatry, psychometrics has dominated assessments of disease [5]. Psychometric analytics used strategies for assessment such as Cronbach's alpha, where more items in the scale lead to higher correlations [5]. Fava and Beech [5, 6] pointed out the difference between psychometrics and clinimetrics in psychiatry, and the clinimetric properties of existing and widely used measures were examined [7]. Fava et al. [8] raised the issue that patterns of symptoms, severity of illness, timing of disease, rate of progression, response to treatment or impact of conditions are often not considered in the usual taxonomy of psychiatry. Wright and Feinstein [9] pointed out that psychometric and clinimetric scales had different purposes. For psychometric scales, a number of homogeneous items for assessing the diagnosis of a singular condition may be important, but for measuring a phenomenon like change in status or more complex phenomena, the index cannot be homogeneous and redundant [9]. Clinimetrics is the term originally coined by Alvan R. Feinstein [10] to introduce an innovative approach that has been redefined as the science of clinical measurements [11]. Such a clinically based evaluation method is particularly useful for testing a number of measurement properties (e.g., inter-rater reliability, concurrent validity, sensitivity, incremental, and predictive validity). This paper will focus on the clinimetric assessment of prognostic comorbidity, which is a broader concept than diagnostic treatment comorbidity, and specifically on chronic conditions that impact on survival outcomes, especially long-term survival. Comorbidity has also been used to predict a variety of outcomes: functional status, quality of life, complications, readmissions, and health care utilization [12]. Kaplan and Feinstein [13] proposed an innovative method for classifying and staging comorbidity in relation to long-term survival. They focused on cogenitally comorbid conditions excluding such conditions as varicose veins and hemorrhoids, as well as completed illnesses such as previous fracture, and evaluated hypertension, congestive heart failure (CHF), or myocardial infarction (MI), stroke, pulmonary insufficiency, renal disease, chronic liver disease, gastrointestinal bleeding, amputation, cancer, alcohol, or physical impairment on a grade 1-3 scale, assigning 3 points to patients who had a 3 in any of the areas. The 5-year mortality rates for new onset diabetics range from 7% for patients with grade 0 to 69% for those with grade 3 [13]. Subsequently, the Charlson Comorbidity Index (CCI) developed in 1987 became the most widely used index, and is often considered to be the gold-standard measure to assess comorbidity in clinical research [14]. The present critical review was conducted to evaluate the clinimetric properties of the CCI, including reliability, concurrent validity, sensitivity, incremental validity, and predictive validity. Methodsin view of the amount of literature on this topic (e.g., the number of citations of the original version of the CCI exceeds 36,925 Scopus, accessed on September 30, 2021), this review cannot be systematic. We will analyze the most relevant studies conducted with its reliability, concurrent validity, sensitivity, incremental and predictive validity. Search StrategyA comprehensive search of the literature was performed using the following databases: MEDLINE, Embase, PsycINFO, Google Scholar, and Web of Science. End database was searched from inception to September 30, 2021. A manual search of the literature was also conducted, and reference lists of the retrieved articles were examined for further studies not identified. Further, all articles citing the original study [14] in the Web of Science were also considered to identify further potentially related studies. The search terms used were "comorbidity index," "reliability," "reproductive," "concurrent validity," "predictive," and "incremental validity." Eligibility CriteriaTo be included in this review, studies had to meet the following criteria: (1) English-language article published in a peer-reviewed journal; (2) the full text of the article was available; (3) the article concerned a medical study (e.g., prospective cohort study); (4) the article concerned the clinimetric properties of the CCI for use in different populations. The CCI is a composite index (I.C.P., C.G., and M.E.C.) independently performed the search, screened titles and abstracts, selected studies, evaluated the full text of articles appearing potentially relevant, and extracted data from studies meeting the eligibility criteria. In case of disagreement, a consensus was reached through discussion. ResultsThe initial search of the literature yielded a total of 36,925 articles, but only those studies which best displayed the clinimetric properties of the various versions of the CCI were included and analyzed in this critical review. The different versions of the CCI have been extensively used in a wide range of medical settings and were found to entail the clinimetric properties of reliability, concurrent validity, sensitivity, incremental and predictive validity. The CCIthe original version of the Comorbidity Index (Table 1) developed by Mary E. 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The CCI, the 19 item-version different Adaptations of the CCI for Use with Different Data SourcesOver the years, several adaptations of the CCI for use with different sources of data have been proposed for coding medical records, electronic health records (EHR), problem lists and ICD-9 and ICD-10 data, and different versions have been developed and come into use [15-19]. The CCI-Age-Comorbidity Index (age-CCI) was designed for use in small studies and was a highly significant predictor of mortality [14, 15]. The age-CCI has been most often used in oncology. In 5,643 patients with colorectal cancer, the age-CCI predicted survival over 5 years [20], as well as perioperative and 18-month mortality in a smaller study of 279 patients [21]. The age-CCI predicted 5-year mortality in 2,257 patients with gastric cancer [22] and 379 patients with resected pancreatic cancer [23]. 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[38] adapted the comorbidity index to ICD-9 using only the first three codes of ICD-9 and showed it predicted inpatient death in 62,456 patients with one of four medical conditions [39]. However, D'Hoore did not fare as well as the Deyo or Romano versions in direct comparison of prediction of 1-year mortality in 141,161 participants enrolled in epidemiologic studies [40]. Adaptations of the CCI Using ICD-10-Sundararajan et al. [19] adapted the Deyo version of CCI for use with ICD-10 codes, classifying the CCI for more than 400,000 patients hospitalized in each of 4 years, in comparison to 2 years of ICD-9 codes, as a predictor of in-hospital death. Using the area under the receiver operating characteristic (ROC) curve as a measure of the CCI's ability to discriminate between those subjects who experienced the outcome of interest (i.e., in-hospital mortality) and those who did not [41]. Sundararajan et al. [19] showed that ROC values for the revised CCI were found to range from 0.85 to 0.86. Halton et al. [42], using clinical judgment, also mapped the Deyo adaption to ICD-10 codes, with codes that differ somewhat from Sundararajan's to study readmission of 3,473 Swiss patients (finding that comorbidity predicted readmission). Quan et al. [43] took both the Halton and Sundararajan codes and added a third list developed by coders to formulate a new set of ICD codes in 158,805 36,925 articles, but only those studies which best displayed the clinimetric properties of the various versions of the CCI were included and analyzed in this critical review. The different versions of the CCI have been extensively used in a wide range of medical settings and were found to entail the clinimetric properties of reliability, concurrent validity, sensitivity, incremental and predictive validity. The CCIthe original version of the Comorbidity Index (Table 1) developed by Mary E. 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validated in a separate population. Desai et al. [265] developed another scale focused on conditions identified as high risk for elderly patients in 524 patients. Their resultant High Risk in Elderly Scale was validated in a population of 852 and had a c statistic for 1-year mortality of 0.69 versus 0.65 for the Deyo/Charlson [265]. The Cox model showed identical relative risks (1.9, 95% CI 1.5–2.1) [265]. There is no separate validation. Kusumastuti et al. [266] focused on 36,751 community-dwelling elderly using 7 re-weighted conditions in the CCI, predicting 1- and 3-year mortality in relation to frailty and frailty phenotype, and showed limited added value of their new estimate of comorbidity in predicting 1- and 3-year mortality. These findings were not evaluated in a separate population. Reid et al. [267] created a disease-specific comorbidity index in 9,396 head and neck cancer patients (with 4 conditions from the CCI and conditions which were complications, like pneumonia, urinary tract infection, and electrolyte imbalance) in predicting 5-year mortality and found that the CCI and their new head and neck condition had almost identical relative risks for survival: 1.5 and 1.53, respectively. The disease-specific index was not validated in a separate population. Volk et al. [268] developed a modified "Charlson" index to predict 4-year mortality in 624 patients after liver transplant using 9 re-weighted conditions and showed increased mortality with one or more conditions from the "modified" index; this was not validated in a separate population. Martins et al. [269] developed a new study-specific index to predict in-hospital death among 5640 patients admitted over a 2-year period for respiratory illnesses, with 8 of the original 19 conditions re-weighted and added to another 13 conditions including symptoms to predict in-hospital death. This was validated in a separate population of 14,622 patients with respiratory illnesses (CCI original: $c = 0.721$; 95% CI 0.701–0.740) versus Martins ($c = 0.755$, 95% CI 0.730–0.774) [269]. Baldwin et al. [270] tested a colon cancer-specific Klabinde index (no published weights) to another 13 conditions including symptoms to predict in-hospital death. This was not validated in a separate population. Toson et al. [271] conducted a study of hip fracture patients that compared the CIIH vs. Quan Charlson [235] and showed patient differences in the rates of death (14 times higher with Quan); it was found that the CIIH outperformed Quan for in-hospital mortality ($c = 0.34$ vs. 0.20) and Quan did slightly better for 1-year mortality (0.071 vs. 0.690) [271]. There is no separate validation. Appendix 30: Other Systems that Have Been Set Up to Evaluate Comorbidity to Predict Survival: Most are comorbidity indices, and none do have validation: (2) Cardiac arrest: Hallstrom et al. [272] created a comorbidity assessment to predict survival after out-of-hospital ventricular fibrillation using 10 chronic conditions and 6 recent symptoms that occurred in 282 patients pre-cardiac arrest. There was no validation (11 citations). Community-based elderly: (3) Coronary heart disease: (3) Cardiac arrest: Hallstrom et al. 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(6) Community-based elderly: (6) Coronary heart disease: (6) Cardiac arrest: Hallstrom et al. [276] developed a 3-level scale approach to 6 specific chronic conditions (i.e., diabetes, cancer, COPD) to predict 2-year survival in 375 dialysis or transplant patients. There was no validation (320 citations). End-stage renal disease: Davies et al. [277] picked seven disease areas (i.e., rheumatic disease, left ventricular dysfunction) in a three-level scale to predict 5-year survival in 303 peritoneal dialysis patients. There was no validation (403 citations). End-stage renal disease: Van Manen et al. [278] showed that the Deyo version was a better predictor of 2-year survival than Davies or Khan: Van Manen et al. [278] created their own disease-specific index, which was comprised of the β -coefficients for diseases that predicted 2-year survival in their cohort; their index had a c value of 0.75 like Deyo ($c = 0.74$) [278] (121 citations). Dialysis/transplant: Khan et al. 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[279] tested their new comorbidity dialysis-specific index in 244,651 patients with four conditions related to renal disease and 11 other conditions all weighted to predict 3-year survival; they found that the performance in the validation study was virtually identical to the CCI (dialysis index = 0.6698; CCI = 0.6623) [279] (275 citations). Adults: Riis et al. [280] selected 16 conditions (i.e., cataract, skin conditions, allergy, diabetes) weighted them on a four-point scale differently for 6,641 men and women over 40 years old in Catalonia to predict 5-year survival in 6,600 adults. There was no validation (53 citations). Lung cancer: Colinet et al. [281] created a 6 item weighted measure from an initial group of 735 with non-small cell cancer (i.e., tobacco = 7; diabetes = 5; and cancer = 1) and validated it as a predictor of 1-year survival in 136 patients with non-small cell cancer (190 citations). Hospitalized patients: Sessler et al. [282] created a Risk Stratification Index, which used between 184 and 1,096 of the 16,000 ICD-9 diagnoses and 4,500 ICD-9 procedure codes to predict in-hospital mortality, 1-year mortality, and length of stay. They evaluated 35,179,507 Medicare provider analysis and review (MEDPAR) patient stay records split into a development and a validation data set, and developed tables to calculate the risks for each of the outcomes for specific individuals in 288 studies. The new index had "almost perfect" prediction of in-hospital mortality ($c = 0.98$) than the CCI ($c = 0.65$, which is not surprising), since it was calculated from discharge diagnoses. With 1-year mortality, the new index had a slightly better c statistic ($c = 0.83$) than the CCI ($c = 0.77$) [282] (105 citations). Holman et al. [283] developed the Multipurpose Australian Comorbidity Scoring System using 102 conditions from ICD-9 (i.e., gout and cataract) that were associated with an increased risk of 1-year mortality in 1,118,989 patients admitted for medical, procedural, or psychiatric reasons. They then tested it in five smaller groups of patients from the same cohort admitted for either asthma, MI, mastectomy, TURP, or psychiatric reasons. The c statistics for CCI versus their scoring system were quite similar for 1-year mortality in the five groups (e.g., asthma, $c = 0.88$ CCI and MACSS, $c = 0.9$) [283] but the multipurpose Australian comorbidity scoring system (MACSS) did better in predicting length of stay and 30-day re-admission rates (130 citations). Older adults: Newman et al. [284] created a Physiological Index of Comorbidity from carotid ultrasound, pulmonary function tests, brain magnetic resonance scans, serum cystatin-c and fasting glucose to predict 9-year mortality in 2,928 subjects enrolled in the Cardiovascular Health Study. However, the physiological index predicted mortality only slightly more than age, race, and gender ($c = 0.726$) than the physiological index ($c = 0.735$). There was no validation (120 citations). Veterans: Among primary care patients at Veterans Affairs centers, the Seattle Index of Comorbidity was developed to predict 2-year mortality from a scale containing age, six chronic conditions (cancer, CHF, diabetes, stroke, lung disease, and prior MI), one acute condition (pneumonia), and two variables for smoking (past) and current [285]. Validated in 5,478 patients, it predicted 2-year mortality with an explanatory power identical to the PCS and MCS in the SF-36 [285] (173 citations). In 1,741 Australian veterans Byles et al. 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A total of 10,498,413 adults in Ontario were divided into a derivation and validation data set to predict 1-year mortality [287]. The final ADG model had a c statistic for 1 year of 0.917 compared to 0.906 for Charlson in the validation cohort [287] (261 citations). Diabetes: Austin et al. [288] had similar findings with incident and prevalent diabetes showing that in 1,226,146 patients the ADG had a slightly higher c statistic (i.e., ACG = 0.838 vs. CCI = 0.827) in the validation sample in the larger prevalent population (21 citations). Rheumatic disease: England et al. [289] evaluated an index designed to predict functional outcomes and 1-year mortality specifically developed in 4,765 patients with rheumatic diseases, consisting of 8 conditions all given a weight of two. There was no validation (139 citations). Australian women: In 5,217 older Australian women, Toth et al. 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