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Patient Reported vs. Claims Based Life Expectancy Tools: External Evaluation of Prediction Models in Men with Prostate Cancer

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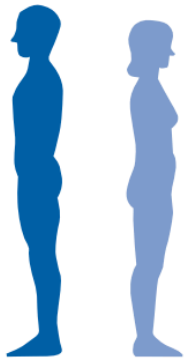
Prostate Cancer

Figure 3. Leading Sites of New Cancer Cases and Deaths – 2020 Estimates

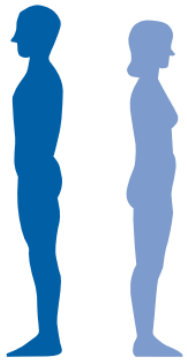
Estimated New Cases

Male			Female		
Prostate	191,930	21%	Breast	276,480	30%
Lung & bronchus	116,300	13%	Lung & bronchus	112,520	12%
Colon & rectum	78,300	9%	Colon & rectum	69,650	8%
Urinary bladder	62,100	7%	Uterine corpus	65,620	7%
Melanoma of the skin	60,190	7%	Thyroid	40,170	4%
Kidney & renal pelvis	45,520	5%	Melanoma of the skin	40,160	4%
Non-Hodgkin lymphoma	42,380	5%	Non-Hodgkin lymphoma	34,860	4%
Oral cavity & pharynx	38,380	4%	Kidney & renal pelvis	28,230	3%
Leukemia	35,470	4%	Pancreas	27,200	3%
Pancreas	30,400	3%	Leukemia	25,060	3%
All sites	**893,660**		**All sites**	**912,930**	



Estimated Deaths

Male			Female		
Lung & bronchus	72,500	23%	Lung & bronchus	63,220	22%
Prostate	33,330	10%	Breast	42,170	15%
Colon & rectum	28,630	9%	Colon & rectum	24,570	9%
Pancreas	24,640	8%	Pancreas	22,410	8%
Liver & intrahepatic bile duct	20,020	6%	Ovary	13,940	5%
Leukemia	13,420	4%	Uterine corpus	12,590	4%
Esophagus	13,100	4%	Liver & intrahepatic bile duct	10,140	4%
Urinary bladder	13,050	4%	Leukemia	9,680	3%
Non-Hodgkin lymphoma	11,460	4%	Non-Hodgkin lymphoma	8,480	3%
Brain & other nervous system	10,190	3%	Brain & other nervous system	7,830	3%
All sites	**321,160**		**All sites**	**285,360**	



Estimates are rounded to the nearest 10, and cases exclude basal cell and squamous cell skin cancers and in situ carcinoma except urinary bladder. Estimates do not include Puerto Rico or other US territories. Ranking is based on modeled projections and may differ from the most recent observed data.

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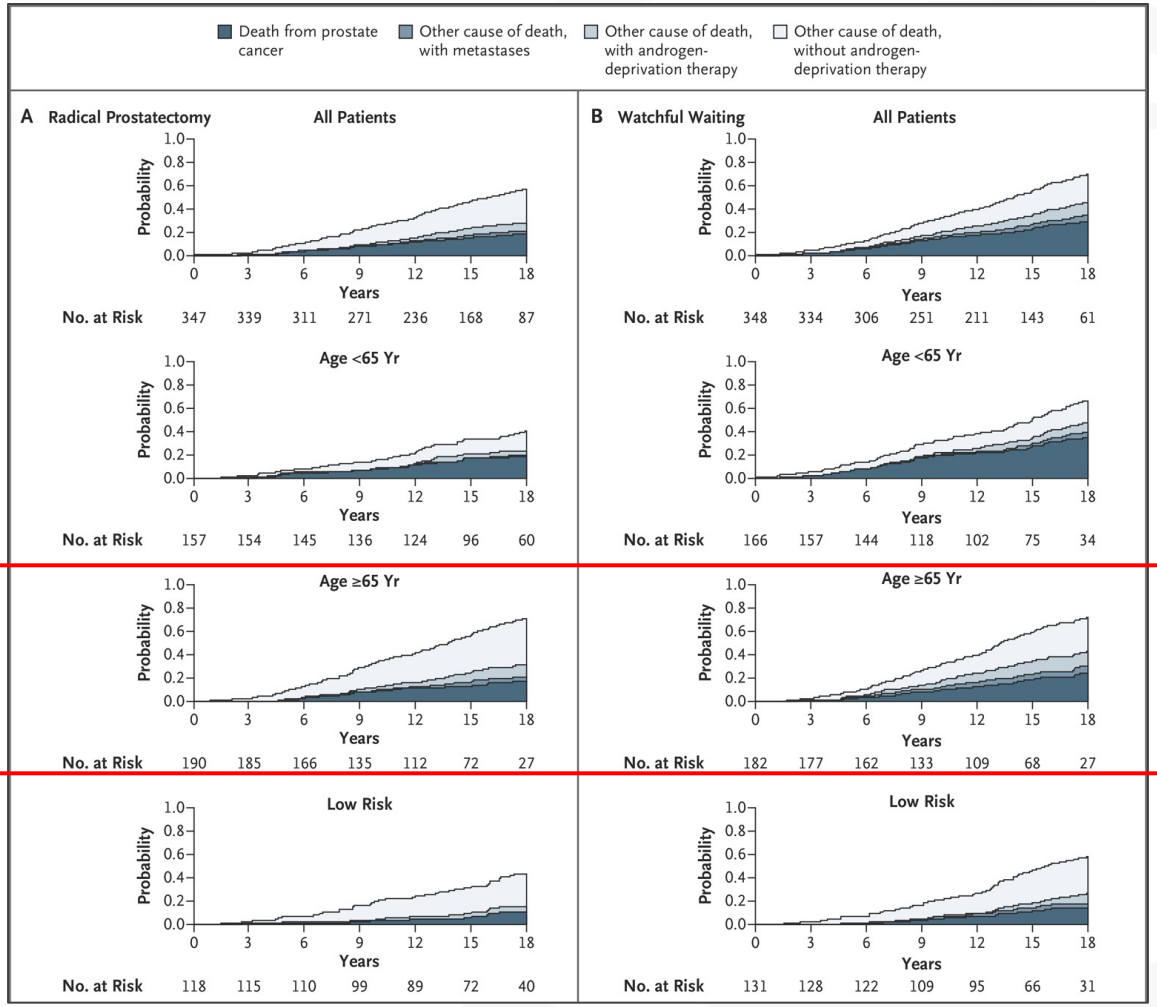
What Do Prostate Cancer Patients Die Of?



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Current Tools

- Comorbidity based Model (Cho) developed from Medicare claims
  - » Includes age, race, and Charlson Comorbidity Score
- Age Adjusted Comorbidity Model (Daskivich) developed in the VA population
  - » Includes age, race, treatment, PSA, Gleason Score, cancer stage, and the prostate cancer-specific comorbidity index
- Self Reported Health Status Nomogram (Hoffman): developed from Prostate Cancer Outcomes Study
  - » Includes age, race, and patient-reported overall health

Enthusiasm for Big Data

Front Oncol. 2016; 6: 149.
Published online 2016 Jun 14. doi: 10.3389/fonc.2016.00149
PMCID: PMC4905980
PMID: 27379211

Big Data Analytics for Prostate Radiotherapy

James Coates,[1,*] Luis Souhami,[2] and Issam El Naqa[3]

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J Am Med Inform Assoc. 2015 Nov; 22(6): 1114.
Published online 2015 Nov 9. doi: 10.1093/jamia/ocv136
PMCID: PMC5009910
PMID: 26555016

The NIH Big Data to Knowledge (BD2K) initiative

Philip E Bourne,[1,*] Vivien Bonazzi,[1] Michelle Dunn,[1] Eric D Green,[2] Mark Guyer,[1] George Komatsoulis,[3] Jennie Larkin,[1] and Beth Russell[1]

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Published in final edited form as
N C Med J. 2014 Jul-Aug; 75

Big Data for Population-Based Cancer Research

The Integrated Cancer Information and Surveillance System

Anne-Marie Meyer, PhD, research assistant professor, Andrew F.
Laura Green, MBA, project manager, Adrian Meyer, MS, director
PhD, MPH, assistant professor, Ethan Basch, MD, MSc, director,
director

JAMA. 2018 Apr 3;319(13):1317-1318. doi: 10.1001/jama.2017.18391.

Big Data and Machine Learning in Health Care.

Beam AL[1], Kohane IS[1].

Author information

PMID: 29532063 DOI: 10.1001/jama.2017.18391

Aim of the Study

To determine whether augmenting current life prediction tools with new data inputs (i.e. patient-reported or claims-based health measures) improves predictive accuracy.

Methods

- Study Sample: SEER-CAHPS data
  - » Men 65 years and older diagnosed with prostate cancer from 2004 to 2013.

- Identified 3 existing tools that estimate life expectancy:
  - » Cho Model – based on claims data
  - » Daskivich Model – based on claims data
  - » Hoffman Model – based on patient-reported health data

- Assessed incremental value of adding different data to predict **other cause mortality** using competing risk regression.

Results

- Among 3,240 men diagnosed with prostate cancer, 246 (7.62%) died of prostate cancer and 631 (19.48%) died of other causes.
- The 3 tools performed similarly well, with 10-year time-dependent AUCs ranging from 0.738 to 0.783.
- The addition of different data types modestly improved performance for all models.

Results

	Models	AIC	R^{2*}	LR Test	DF	AUC
Cho model	Original model: Age, race and comorbidity level	9188.72	0.09	304.68	8	0.749
	Original model + Overall Health + Smoking	9115.30	0.11	386.09	12	0.753
Daskivich model	Original Model: Age, Race/Ethnicity, Primary Treatment, PSA, Gleason Score, Cancer Stage, PCCI category	9115.09	0.12	400.31	19	0.783
	Original Model + Overall Health + Smoking	9043.33	0.14	480.07	23	0.796
Hoffman model	Original Model: Age, Race/Ethnicity, Overall Health	9184.58	0.10	310.81	9	0.738
	Original Model + NCIComorbidity + Frailty	9117.34	0.11	388.06	14	0.744

Limitations

- Observational study
- Accuracy of coding practices
- Limited panel of patient-reported outcomes
- Unable to compare utility of different models due to limited number of patients with 10-years of follow-up
- Generalizability to non-Medicare populations

Conclusions

- In an external cohort, current life expectancy models performed similar to their initial description, serving as further evidence of their accuracy.
- Enriching models with new data types resulted in incremental improvements, suggesting that prediction can improve with increased data capture.
- Additional research will be needed to assess what combination of inputs provides the optimal balance of performance, feasibility, and meaningfulness.

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