

Polygenic risk score with *KLK3* SNP-SNP interaction pairs for predicting prostate cancer aggressiveness

Received: 18 March 2025

Accepted: 28 April 2026

Cite this article as: Lin, H.-Y., Sarkar, I., Mazumder, H. *et al.* Polygenic risk score with *KLK3* SNP-SNP interaction pairs for predicting prostate cancer aggressiveness. *Commun Med* (2026). <https://doi.org/10.1038/s43856-026-01645-z>

Hui-Yi Lin, Indrani Sarkar, Harun Mazumder, Po-Yu Huang, Kenneth R. Muir, Johanna Schleutker, Nora Pashayan, Jyotsna Batra, David E. Neal, Henrik Grönberg, Sune F. Nielsen, Børge G. Nordestgaard, Catherine M. Tangen, Robert J. MacInnis, Alicja Wolk, Demetrius Albanes, Ruth C. Travis, Janet L. Stanford, Lorelei A. Mucci, Adam S. Kibel, Olivier Cussenot, Sonja I. Berndt, Stella Koutros, Karina Dalsgaard Sørensen, Cezary Cybulski, Eli Marie Grindedal, Josef Hoegel, Christiane Maier, Robert J. Hamilton, Barry S. Rosenstein, Ana Vega, Manolis Kogevinas, Fredrik Wiklund, Kathryn L. Penney, Manuel R. Teixeira, Hermann Brenner, Esther M. John, Radka Kaneva, Christopher J. Logothetis, Susan L. Neuhausen, Kim De Ruyck, Piet Ost, Marija Gamulin, Nawaid Usmani, Frank Claessens, Jose Esteban Castela, Paul A. Townsend, UKGPCS collaborators, APCB BioResource (Australian Prostate Cancer BioResource), Zsafia Kote-Jarai, Christopher A. Haiman, Rosalind A. Eeles, the PRACTICAL consortium & Jong Y. Park

We are providing an unedited version of this manuscript to give early access to its findings. Before final publication, the manuscript will undergo further editing. Please note there may be errors present which affect the content, and all legal disclaimers apply.

If this paper is publishing under a Transparent Peer Review model then Peer Review reports will publish with the final article.

Polygenic risk score with *KLK3* SNP-SNP interaction pairs for predicting prostate cancer aggressiveness

Hui-Yi Lin^{1,*}, Indrani Sarkar¹, Harun Mazumder¹, Po-Yu Huang², Kenneth R. Muir³, Johanna Schleutker^{4,5}, Nora Pashayan^{6,7}, Jyotsna Batra^{8,9,10}, David E. Neal^{11,12,13}, Henrik Grönberg¹⁴, Sune F. Nielsen^{15,16}, Børge G. Nordestgaard^{16,15}, Catherine M. Tangen¹⁷, Robert J. MacInnis^{18,19}, Alicja Wolk²⁰, Demetrius Albanes²¹, Ruth C. Travis²², Janet L. Stanford^{23,24}, Lorelei A. Mucci²⁵, Adam S. Kibel²⁶, Olivier Cussenot^{27,28}, Sonja I. Berndt²¹, Stella Koutros²¹, Karina Dalsgaard Sørensen^{29,30}, Cezary Cybulski³¹, Eli Marie Grindedal³², Josef Hoegel³³, Christiane Maier³⁴, Robert J. Hamilton^{35,36}, Barry S. Rosenstein³⁷, Ana Vega^{38,39,40}, Manolis Kogevinas^{41,42,43,44}, Fredrik Wiklund¹⁴, Kathryn L. Penney⁴⁵, Manuel R. Teixeira^{46,47,48}, Hermann Brenner^{49,50}, Esther M. John⁵¹, Radka Kaneva⁵², Christopher J. Logothetis⁵³, Susan L. Neuhausen⁵⁴, Kim De Ruyck⁵⁵, Piet Ost⁵⁶, Marija Gamulin⁵⁷, Nawaid Usmani^{58,59}, Frank Claessens⁶⁰, Jose Esteban Castelao⁶¹, Paul A. Townsend^{62,63}, UKGPCS collaborators, APCB BioResource (Australian Prostate Cancer BioResource), The IMPACT Study Steering Committee and Collaborators, The Profile Study Steering Committee, Zsafia Kote-Jarai⁶⁴, Christopher A. Haiman⁶⁵, Rosalind A. Eeles^{64,66}, the PRACTICAL consortium & Jong Y. Park⁶⁷

¹Biostatistics and Data Science Program, School of Public Health, Louisiana State University Health Sciences Center, New Orleans, LA 70112, USA; ²Information and Communications Research Laboratories, Industrial Technology Research Institute, Hsinchu, Taiwan; ³Division of Population Health, Health Services Research and Primary Care, University of Manchester, Oxford Road, Manchester, M13 9PL, UK; ⁴Institute of Biomedicine, University of Turku, Finland; ⁵Genomics, Laboratory Division, Turku University Hospital, PO Box 52, 20521 Turku, Finland; ⁶Department of Public Health & Primary Care, Strangeways Research Laboratory, Worts Causeway, Cambridge, CB1 8RN, UK; ⁷Department of Applied Health Research, University College London, London, WC1E 7HB, UK; ⁸School of Biomedical Sciences, Faculty of Health,

Queensland University of Technology, Brisbane, Queensland, Australia; ⁹Centre for Genomics and Personalised Health, Queensland University of Technology, Brisbane, Queensland, Australia; ¹⁰Translational Research Institute, QUT, Woolloongabba, Brisbane, Queensland, Australia; ¹¹Nuffield Department of Surgical Sciences, University of Oxford, Room 6603, Level 6, John Radcliffe Hospital, Headley Way, Headington, Oxford, OX3 9DU, UK; ¹²University of Cambridge, Department of Oncology, Box 279, Addenbrooke's Hospital, Hills Road, Cambridge CB2 0QQ, UK; ¹³Cancer Research UK, Cambridge Research Institute, Li Ka Shing Centre, Cambridge, CB2 0RE, UK; ¹⁴Department of Medical Epidemiology and Biostatistics, Karolinska Institutet, SE-171 77 Stockholm, Sweden; ¹⁵Department of Clinical Biochemistry, Herlev and Gentofte Hospital, Copenhagen University Hospital, Herlev, 2200 Copenhagen, Denmark; ¹⁶Faculty of Health and Medical Sciences, University of Copenhagen, 2200 Copenhagen, Denmark; ¹⁷SWOG Statistical Center, Fred Hutchinson Cancer Research Center, Seattle, WA 98109, USA; ¹⁸Cancer Epidemiology Division, Cancer Council Victoria, 200 Victoria Parade, East Melbourne, VIC, 3002, Australia; ¹⁹Centre for Epidemiology and Biostatistics, Melbourne School of Population and Global Health, The University of Melbourne, Grattan Street, Parkville, VIC 3010, Australia; ²⁰Institute of Environmental Medicine, Karolinska Institutet, 177 77 Stockholm, Sweden; ²¹Division of Cancer Epidemiology and Genetics, National Cancer Institute, NIH, Bethesda, Maryland, 20892, USA; ²²Cancer Epidemiology Unit, Nuffield Department of Population Health, University of Oxford, Oxford, OX3 7LF, UK; ²³Division of Public Health Sciences, Fred Hutchinson Cancer Research Center, Seattle, Washington, 98109-1024, USA; ²⁴Department of Epidemiology, School of Public Health, University of Washington, Seattle, Washington 98195, USA; ²⁵Department of Epidemiology, Harvard T. H. Chan School of Public Health, Boston, MA 02115, USA; ²⁶Division of Urologic Surgery, Brigham and Women's Hospital, 75 Francis Street, Boston, MA 02115, USA; ²⁷Sorbonne Universite, GRC n°5, AP-HP, Tenon Hospital, 4 rue de la Chine, F-75020 Paris, France; ²⁸CeRePP, Tenon Hospital, F-75020 Paris, France; ²⁹Department of Molecular Medicine, Aarhus University Hospital, Palle Juul-Jensen

Boulevard 99, 8200 Aarhus N, Denmark; ³⁰Department of Clinical Medicine, Aarhus University, DK-8200 Aarhus N, Denmark; ³¹International Hereditary Cancer Center, Department of Genetics and Pathology, Pomeranian Medical University, 70-115 Szczecin, Poland; ³²Department of Medical Genetics, Oslo University Hospital, 0424 Oslo, Norway; ³³Institute for Human Genetics, University Hospital Ulm, Albert-Einstein-Allee 11, 89081 Ulm, Germany; ³⁴Humangenetik Tuebingen, Paul-Ehrlich-Str 23, D-72076 Tuebingen, Germany; ³⁵Dept. of Surgical Oncology, Princess Margaret Cancer Centre, Toronto ON M5G 2M9, Canada; ³⁶Dept. of Surgery (Urology), University of Toronto, Canada; ³⁷Department of Radiation Oncology and Department of Genetics and Genomic Sciences, Box 1236, Icahn School of Medicine at Mount Sinai, One Gustave L. Levy Place, New York, NY 10029, USA; ³⁸Fundación Pública Galega Medicina Xenómica, Santiago de Compostela, 15706, Spain; ³⁹Instituto de Investigación Sanitaria de Santiago de Compostela, Santiago de Compostela, 15706, Spain; ⁴⁰Centro de Investigación en Red de Enfermedades Raras (CIBERER), Spain; ⁴¹ISGlobal, Barcelona, Spain; ⁴²IMIM (Hospital del Mar Medical Research Institute), Barcelona, Spain; ⁴³Universitat Pompeu Fabra (UPF), Barcelona, Spain; ⁴⁴CIBER Epidemiología Salud Pública (CIBERESP), 28029 Madrid, Spain; ⁴⁵Channing Division of Network Medicine, Department of Medicine, Brigham and Women's Hospital/Harvard Medical School, Boston, MA 02115, USA; ⁴⁶Department of Laboratory Genetics, Portuguese Oncology Institute of Porto (IPO Porto) / Porto Comprehensive Cancer Center, Porto, Portugal; ⁴⁷Cancer Genetics Group, IPO Porto Research Center (CI-IPOP) / RISE@CI-IPOP (Health Research Network), Portuguese Oncology Institute of Porto (IPO Porto) / Porto Comprehensive Cancer Center, Porto, Portugal; ⁴⁸School of Medicine and Biomedical Sciences (ICBAS), University of Porto, Porto, Portugal; ⁴⁹Division of Clinical Epidemiology and Aging Research, German Cancer Research Center (DKFZ), D-69120, Heidelberg, Germany; ⁵⁰German Cancer Consortium (DKTK), German Cancer Research Center (DKFZ), D-69120 Heidelberg, Germany; ⁵¹Departments of Epidemiology & Population Health and of Medicine, Division of Oncology, Stanford Cancer Institute, Stanford University School of Medicine, Stanford, CA 94304, USA;

⁵²Molecular Medicine Center, Department of Medical Chemistry and Biochemistry, Medical University of Sofia, Sofia, 2 Zdrave Str., 1431 Sofia, Bulgaria; ⁵³The University of Texas M. D. Anderson Cancer Center, Department of Genitourinary Medical Oncology, 1515 Holcombe Blvd., Houston, TX 77030, USA; ⁵⁴Department of Population Sciences, Beckman Research Institute of the City of Hope, 1500 East Duarte Road, Duarte, CA 91010, USA; ⁵⁵Ghent University, Faculty of Medicine and Health Sciences, Basic Medical Sciences, Proeftuinstraat 86, B-9000 Gent, Belgium; ⁵⁶Ghent University Hospital, Department of Radiotherapy, De Pintelaan 185, B-9000, Gent, Belgium; ⁵⁷Department of Oncology, University Hospital Centre Zagreb, University of Zagreb, School of Medicine, 10 000 Zagreb, Croatia; ⁵⁸Department of Oncology, Cross Cancer Institute, University of Alberta, 11560 University Avenue, Edmonton, Alberta, T6G 1Z2, Canada; ⁵⁹Division of Radiation Oncology, Cross Cancer Institute, 11560 University Avenue, Edmonton, Alberta, T6G 1Z2, Canada; ⁶⁰Molecular Endocrinology Laboratory, Department of Cellular and Molecular Medicine, KU Leuven, BE-3000, Belgium; ⁶¹Genetic Oncology Unit, CHUVI Hospital, Complejo Hospitalario Universitario de Vigo, Instituto de Investigación Biomédica Galicia Sur (IISGS), 36204, Vigo (Pontevedra), Spain; ⁶²Division of Cancer Sciences, Manchester Cancer Research Centre, Faculty of Biology, Medicine and Health, Manchester Academic Health Science Centre, NIHR Manchester Biomedical Research Centre, Health Innovation Manchester, University of Manchester, M13 9WL, UK; ⁶³The University of Surrey, Guildford, Surrey, GU2 7XH, UK; ⁶⁴The Institute of Cancer Research, London, SM2 5NG, UK; ⁶⁵Center for Genetic Epidemiology, Department of Preventive Medicine, Keck School of Medicine, University of Southern California/Norris Comprehensive Cancer Center, Los Angeles, CA 90015, USA; ⁶⁶Royal Marsden NHS Foundation Trust, London, SW3 6JJ, UK; ⁶⁷Department of Cancer Epidemiology, Moffitt Cancer Center, 12902 Magnolia Drive, Tampa, FL 33612, USA

* Correspondence: hlin1@lsuhsc.edu

Abstract

Background: Prostate cancer (PCa) is heterogeneous, making risk stratification essential for clinical care. Although polygenic risk scores (PRSs) with main effects of single-nucleotide polymorphisms (SNPs) can help identify individuals at high risk before biological and clinical onset, a PRS for predicting PCa aggressiveness remains underdeveloped. The *KLK3*, which encodes prostate-specific antigen (PSA), is linked to PCa aggressiveness. Recent findings on *KLK3* SNP-SNP interactions show promise for predicting PCa aggressiveness. The objective of this study is to develop a PRS (PRS-*KLK3*int) by examining *KLK3* SNP-SNP interaction pairs.

Methods: The PRS-*KLK3*int was developed based on a discovery set (10,836 PCa patients) and two validation sets with 14,348 and 16,584 patients of European ancestry. A total of 3,145 SNP pairs and two published PRSs were evaluated. **Results:** This study developed a PRS-*KLK3*int with 284 SNPs, combining an existing PRS with 270 SNPs and 12 SNP-SNP interaction pairs with 15 SNPs (one overlapped). All these 12 pairs were involved with at least one SNP from *KLK3*. The PRS-*KLK3*int outperformed two existing PRSs in predicting PCa aggressiveness (p-values: 3.5×10^{-18} , 9×10^{-14} , and 1.7×10^{-20} for the three sets). It effectively distinguished high-risk from low-risk groups across all datasets. The top 1% high-risk group had a higher prevalence of PCa aggressiveness than the middle 50% group (45.5% vs. 25.9%, OR=2.38, $p=2.2 \times 10^{-5}$) in the discovery set, and similar results were observed in validation sets (OR=2.56, $p=4.3 \times 10^{-6}$; OR=2.07, $p=2.1 \times 10^{-5}$). **Conclusions:** These findings support PRS-*KLK3*int as a valuable tool for PCa severity stratification, especially in identifying extremely high-risk PCa patients.

Plain language summary

Prostate cancer (PCa) can range from mild to very aggressive, so predicting severity early is important. Genetic tools called polygenic risk scores (PRS) can estimate risk before biological

signs appear, helping doctors act sooner. Current PRSs don't predict aggressiveness well. This study developed a new score, PRS-KLK3int, using genetic interactions in the KLK3 gene, which is linked to prostate-specific antigen (PSA) and cancer severity. Researchers analyzed data from over 10,000 patients and confirmed results in two large groups. PRS-KLK3int, built from 284 genetic markers, outperformed older scores in identifying aggressive cancer. PCa patients in the top 1% risk group were about twice as likely to have aggressive cancer. This tool could guide early screening and prevention before PCa progression starts.

Introduction

Precise risk classification is essential for guiding treatment or monitoring decisions for prostate cancer (PCa) patients. As a heterogeneous disease, PCa accounts for 11% of all cancer deaths, making it the second leading cause of death in American men in 2024¹. The risk of PCa and PCa-specific mortality rates are significantly different in different racial groups, likely due to a combination of environmental, biological, and genetic factors². While the 5-year survival rate for localized and regional PCa is nearly 100%, that of PCa patients with distant metastasis is only 34%³. Due to the substantial clinical heterogeneity, distinguishing between indolent and aggressive PCa at diagnosis remains challenging⁴. Depending on the nature of selected biomarkers, risk stratification tools can be utilized at different stages of PCa disease development. Most current risk stratification tools target early detection of PCa aggressiveness in the biological or clinical onset stages. D'Amico Risk Classification and the Cancer of the Prostate Risk Assessment (CAPRA) Score are based on tumor characteristics (such as prostate-specific antigen (PSA), Gleason score, and clinical stage) for early detection in the clinical onset stage of PCa aggressiveness⁵. Gene expression signatures of tumors for PCa progression (such as Oncotype-DX^{6,7}, and Decipher⁷) are suitable for early detection in both biological and clinical onset stages. However, few reliable risk stratification tools were reported to predict PCa aggressiveness before its biological onset⁸.

Genetics plays an important role in PCa development. A large-scale twin study has shown that genetics contributes to 57% of PCa development⁹. A handful of inherited genetic variants or single nucleotide polymorphisms (SNPs) for predicting PCa aggressiveness have been identified in genome-wide association studies (GWAS)^{10,11}. Due to the limited predictive power of individual SNPs, many studies developed polygenic risk scores (PRSs), which are primarily calculated as a weighted sum of allele dosages from multiple GWAS-identified SNPs^{12, 13}. However, these conventional PRSs do not consider SNP-SNP interactions. Despite this limitation, PRSs are increasingly recognized as valuable tools in precision medicine for various phenotypes, including PCa.

While many PRSs have been developed to assess PCa risk, few specifically address PCa aggressiveness. One PRS with 290 SNPs predicts age at diagnosis of aggressive PCa, defined as with Gleason score ≥ 7 , PSA ≥ 10 ng/mL, T3-T4 stage, nodal metastases, or distant metastases, based on ~72,000 men¹⁴. Another study developed a PRS of predicting age at PCa diagnosis with 166 SNPs using data from ~76,000 men¹⁵. Because age at PCa diagnosis is positively associated with PCa-specific mortality^{16, 17, 18}, these two PRSs are related to PCa aggressiveness. However, these scores' utility in predicting PCa aggressiveness may be limited as they were designed with a focus on age at PCa diagnosis rather than disease severity itself, and included both non-PCa men and PCa patients in developing these scores. Additionally, their focus on SNP main effects does not account for potential SNP-SNP interactions. This presents an opportunity for improvement.

SNP-SNP interaction is considered the key to improving prediction accuracy for PRSs. Our previous study identified 3,145 SNP-SNP interaction pairs for predicting PCa aggressiveness. The majority (98.6%) of them involved *KLK3*⁸. *KLK3* encodes the PSA, which is used for PCa

screening, diagnosis, and prognostic monitoring¹⁹. Increased levels of PSA in the bloodstream may suggest the existence of PCa or other prostate-related issues²⁰. Previous studies showed that SNPs in *KLK3* were significantly associated with PSA levels, PCa risk, and aggressiveness^{8, 21, 22, 23, 24, 25}. Given the substantial role of *KLK3* in PCa biology and the prevalence of SNP-SNP interaction pairs relating to *KLK3*, we aim to develop and validate a polygenic risk score (PRS-*KLK3*int) that integrates these interactions. The objective of this study is to assess whether this PRS-*KLK3*int can improve the prediction of PCa aggressiveness compared to existing PRSs that are based exclusively on SNP main effects.

Methods

Statistics and Reproducibility

The main statistical methods utilized in this study include the SNP Interaction Pattern Identifier (SIPI) approach, the RR3x3 method (Risk Ratio scoring based on 3×3 genotype pair combinations), and logistic models. The details and usage of these methods are listed in the following sections. For the study population, this study included 41,768 PCa patients with European ancestry and valid PCa aggressiveness data at the OncoArray cohort from the PRACTICAL consortium⁸. For this study, the SNP data in the PCa OncoArray cohort were used. For independent datasets, we excluded the PCa patients in our previous study⁸, which was used to identify the 3,145 SNP interaction pairs. For enhancing the reproducibility of the proposed genetic risk scores, the participants are divided into 3 independent sets: the United Kingdom (UK), USA/Canada/Australia (UCA), and other European countries (EU) sets. We used the UK set as the discovery set (n=10,836), the UCA set (n=14,348), and the EU set (n=16,584) as the two validation sets. PCa aggressiveness is defined as a Gleason score ≥ 8, PSA ≥ 100 ng/mL, disease-distant metastasis stage at diagnosis, or death from PCa, consistent with our previous study²⁶. This study was approved by the Louisiana State University Health

Science Center Institutional Review Board under protocol number 5543. Patient consent was not required because deidentified data were used in this study.

SNP data and quality controls

This study used both genotyped and imputed SNP data. The genotyped SNP data were generated using the Infinium OncoArray (Illumina, San Diego, CA). The imputed SNP data were generated based on the genotyped data using three panels of the 1,000 Genomes Project as reference. Imputation was performed using SHAPEIT2 and IMPUTE2. One-step imputation has also been performed for regions surrounding known susceptibility loci. Strict quality control was applied for the OncoArray studies. SNPs were excluded if they had a call rate <95% and departed from Hardy-Weinberg equilibrium at $p < 1 \times 10^{-12}$ in PCa patients. Samples were excluded with a call rate of <95%. Ancestry analysis used a principal component analysis based on 2,318 ancestry informative markers. The details of population stratification and quality control criteria for the PRACTICAL Consortium cohort were reported previously²⁶.

Selection of SNP-SNP interaction pairs

Our previous study identified 3,145 SNP-SNP pairs significantly associated with PCa aggressiveness⁸. Among them, 3121 pairs were available in the PRACTICAL OncoArray SNP dataset (Fig. 1). The SNP Interaction Pattern Identifier (SIPI) approach was utilized to test SNP-SNP interaction pairs in this study²⁷. SIPI is a machine learning method to test 45 interaction models for each SNP pair by considering three key factors: model structure, inheritance mode, and coding direction. In order to increase accuracy for detecting SNP-SNP interactions, the 2-stage 3pRule+bootstrap approach is suggested²⁸. Thus, we applied the 2-stage 3pRule+bootstrap approach for selecting SNP-SNP interaction pairs in the UK set, the

discovery set. In the 1st stage, we applied the 3 p-value rule (3pRule), which is a modified rule to define significant SNP-SNP interaction pairs based on (1) p-pair of SNP1-SNP2 < p-pair-criterion (such as Bonferroni correction), (2) p-pair < p-main of SNP1, and (3) p-pair < p-main of SNP2. The p-pair is the p-value for a SNP-SNP interaction pair, and the p-main is the p-value of the 1st SNP or 2nd SNP in a pair. In this study, we applied the SIPI approach to get p-pairs. For testing SNP main effects, p-main values were obtained based on the minimum p-value of the 3 inheritance modes (dominant, recessive, and additive). In the 2nd stage, the bootstrap approach was applied to create datasets by resampling with replacement and with the same sample size as the original dataset. In the UK set, the p-pair-criterion was 1.6×10^{-5} ($=0.05/3121$) for the 3pRule set and was 1×10^{-5} for the 500 bootstrap runs. The “SIPI,” “eval3pRule”, and “boot3p_SIPI” R functions in the SIPI package were applied ^{27, 29}.

RR3x3 scoring system for SNP-SNP interaction pairs

For scoring SNP-SNP interaction pairs, we developed RR3x3 (Risk Ratio scoring based on 3x3 genotype pair combinations). This RR3x3 scoring especially benefits in maintaining valuable signals for high-risk genotype groups, usually with a small sample size. Each SNP has 3 potential genotypes (such as GG, GA, and AA). With a pair of SNPs, a 3-by-3 (3x3) table can be constructed with 9 genotype combinations (called pair-genotypes). While SIPI is powerful in detecting SNP-SNP interactions, the SIPI-interaction patterns simplify the 9-genotype combinations for a SNP pair into a few groups (such as 2 groups of high vs. low-risk). This feature hinders the SIPI-interaction pattern’s prediction accuracy. In order to preserve a complete risk profile of a SNP pair, we used the RR3x3 scoring approach instead. In this RR3x3 scoring method, a risk ratio of a genotype combination in a SNP pair (called pair-genotype, such as AA-GG and AG-GG) is calculated using an outcome percentage in a specific pair-genotype divided by the overall outcome percentage in the study. For this study, the outcome percentage is the percentage of PCa aggressiveness (aggr%), so the RR3x3 scores were calculated based

on the aggr% for each pair-genotype divided by the overall aggr%. Pairs with a missing SNP in a pair were imputed based on the SNP main effect. For the pairs selected based on the 3pRule+ Bootstrap, the corresponding RR3x3 scores were calculated accordingly. Using the stepwise selection ($p < 0.05$) in the logistic model with the candidate pairs, the 12 pairs were selected. As shown in Equation 1, PRS-12pair was calculated based on the sum of the RR3x3-scores of these selected 12 pairs.

$$\text{PRS-12pair} = \text{RR3x3-score}_{\text{pair1}} + \text{RR3x3-score}_{\text{pair2}} + \dots + \text{RR3x3-score}_{\text{pair12}} \quad (\text{Equation 1})$$

Two PRSs with SNP main effects only

We are interested in comparing this PRS-12 pair with the 2 published PRSs, which only involved SNP main effects without considering SNP-SNP interactions. Two published PRSs with 166 SNPs¹⁵ and 290 SNPs¹⁴ were selected from the PGS catalog (PGS000742 and PGS003331)³⁰. PGS000742 and PGS003331 were developed based on age at PCa diagnosis and age at aggressive PCa (Gleason score ≥ 7 , PSA ≥ 10 ng/mL, T3-T4 stage, nodal metastases, or distant metastases), respectively, using time-to-event analyses with both controls and PCa cases. In these 2 published scores, 155 and 270 biallelic SNPs (PRS-m155 and PRS-m270) were tested in this study. The performance of the PRSs was evaluated based on the significance level of the selected PRS in logistic regression, adjusting for the first 7 principal components of population stratification as suggested by the PRACTICAL study³¹. For easy comparison, PRS-12pair, PRS-m155, and PRS-m270 were standardized. To leverage the benefits of the two PRSs, we created a PRS-KLK3int with 284 SNPs based on the weighted sum of PRS-12pair and PRS-m270. The weights were generated based on logistic regression.

In addition to testing numeric PRSs, we also tested categorical PRSs with 7 groups. For clinical usage, it is crucial to identify distinct high- and low-risk groups based on PRSs. Thus, we classified PCa patients into 7 groups based on PRS's distribution in each study set. These 7

groups are the bottom 1%, bottom 1-10%, bottom 11-25%, middle 50%, top 11-25%, top 1-10%, and top 1%, which were defined based on the PRS's percentiles of [0, 1), [1, 10), [10, 25), [25, 75), [75, 90), [90, 99), and [99, 100]. An open bracket “()” indicates the interval does not include the number itself, and a closed bracket “[]” includes the number itself. The significance was defined based on a p-value <0.05. The Area Under the Receiver Operating Characteristic Curve (AUC) values for the models were calculated. Furthermore, we were interested in evaluating PRS performance by adding age at diagnosis.

Results

Detection of SNP-SNP interaction pairs for PRS-12pair

The procedure of selecting SNP pairs based on the UK set for PRS is listed in Fig. 1. Among the 3,121 candidate SNP pairs, the 2-stage 3pRule+ bootstrap approach was applied to improve detection accuracy. By applying the 3pRule with $p\text{-pair} < 1.6 \times 10^{-5}$ ($=0.05/3121$, Bonferroni correction) as the p-pair criterion, 613 pairs satisfied the 3pRule. In the 2nd stage, 99 pairs were satisfied with the 3pRule in $\geq 75\%$ of 500 bootstrap datasets. These 99 pairs were grouped into the 6 clusters with 6 *KLK3* SNPs as a hub. The cluster is defined as several SNP pairs sharing a common or hub SNP. Among these 99 pairs, 50, 37, 15, 6, 3, and 2 pairs had rs17632542, rs2569735, rs1058205, rs174776, rs2292185, and rs266876 as the hub, respectively. Some pairs are involved with 2 *KLK3* SNPs. After excluding 16 pairs with >400 missing values, we generated the RR3X3-scores for the remaining 83 pairs for further analyses. After applying for stepwise selection with a p-value <0.05 in the logistic model, 12 pairs were selected. Finally, PRS-12pair was calculated based on the sum of the RR3x3-scores of these 12 pairs. All 12 pairs were involved with *KLK3* SNPs and consist of only 15 SNPs. These 12 pairs and their gene information are listed in Supplementary Table 1.

General results of 4 polygenic risk scores (PRSs) for PCa aggressiveness

The descriptive statistics of the 4 PRSs (PRS-12pair, PRS-m155, PRS-m270, PRS-KLK3int) are listed in Supplementary Table 2, and their distributions are shown in Supplementary Fig. 1. The distributions of the 2 PRS-main scores were close to a normal distribution. However, the distribution of PRS-12pair was skewed to the right (positively skewed), indicating that some men had a considerably high score of PCa aggressiveness. This is a desired feature for PRS to identify extremely high-risk groups. However, a small variation was observed for the low-value part of PRS-12pair; therefore, PRS-12pair may not be an ideal tool for distinguishing low-risk aggressive groups. These results inspired us to create a combined score, PRS-KLK3int, by integrating PRS-12pair and PRS-m270 to take advantage of both scores.

Comparison of PRS-12pair with the 2 PRSs with SNP main effects only

For the 2 published PRSs, the associations between these 2 PRSs with SNP main effects only and PCa aggressiveness are listed in Supplementary Table 3. PRS-m155 and PRS-m270 can predict PCa aggressiveness for all 3 data sets (all p-values <0.05). Specifically, we observed that PRS-m270 performed better than PRS-m155 for all 3 data sets, and these 2 PRSs performed better in the UK and EU sets than the UCA sets. Based on the adjusted results, the p-values for PRS-m155 were 7.5×10^{-4} , 4.4×10^{-4} , and 4.8×10^{-8} for the UK, UCA, and EU sets, respectively, while the p-values for PRS-m270 were 8.2×10^{-7} , 3.3×10^{-5} , and 9.4×10^{-11} , respectively. In addition, the performance of PRS-12pair was better in terms of significance level than PRS-m155 and PRS-m270 in all 3 sets (Supplementary Table 3). The p-values for PRS-12pair were 5.4×10^{-15} , 4.0×10^{-8} , and 1.8×10^{-13} for the UK, UCA, and EU sets, respectively.

We tested whether PRS-12pair can further improve the performance of the PRS-m270. In the model with PRS-12pair and PRS-m270 (Supplementary Table 4), PRS-12pair performed better than PRS-m270 in all 3 sets. For the UK set, the p-values for PRS-m270 and PRS-12pair were 1.4×10^{-4} and 2.9×10^{-12} . Similar conditions were observed in the UCA and EU sets. After

adjusting PRS-m270 and the 7 principal components, PRS-12pair can still better predict PCa aggressiveness than PRS-m270 ($p=1.0\times 10^{-10}$ and 6.4×10^{-11} for the UCA and EU sets, respectively). Further, PRS-m270 was still significant ($p=1.9\times 10^{-2}$ and 9.6×10^{-8} for the UCA and EU sets, respectively).

Performance evaluation of PRS-KLK3int (continuous score version)

The performance of PRS-KLK3int is shown in Supplementary Table 4. As expected, the PRS-KLK3int performed better than PRS-12pair and PRS-m270 alone for predicting PCa aggressiveness. The p-values for PRS-KLK3int were 3.5×10^{-18} , 9×10^{-14} , and 1.7×10^{-20} for the UK, UCA, and EU sets, respectively. As shown in Supplementary Table 5, the AUC values of PRS-KLK3int were 0.55, 0.58, and 0.59 after adjusting for the 7 principal components for the UK, UCA, and EU sets, respectively. Significant improvements were made by adding the 12 pairs into the PRS-m270 in all 3 sets. The p-values of the AUC comparison between PRS-KLK3int and PRS-m270 were 7.3×10^{-5} , 0.004, and 0.051 for the UK, UCA, and EU sets, respectively.

Performance evaluation of PRS-KLK3int (risk-group version)

We further identified distinct high- and low-risk groups based on PRS-KLK3int, PRS-m270, and PRS-m155. For each study set, the PCa patients were classified into 7 groups based on PRS's distribution. These 7 groups are bottom 1%, bottom 1-10%, bottom 11-25%, middle 50% (25-75%), top 11-25%, top 1-10%, and top 1%. PRS-KLK3int can distinguish high-risk PCa aggressiveness better than PRS-m270, and PRS-m155. The performance of risk classification of PCa aggressiveness for the UK, US, and EU sets in terms of PRS percentiles is listed in Fig. 2 and Supplementary Table 6.

In the UK set, PRS-KLK3int can significantly distinguish the top 1% and top 1-10% from the majority of the middle 50% group (Table 1 and Supplementary Tables 6 and 7). Based on PRS-KLK3int, the prevalence of PCa aggressiveness for the middle 50% group was 25.9%. PCa aggressiveness prevalence for the top 1% group (45.5%) was significantly higher than that in the middle 50% group (OR=2.38, $p=2.2 \times 10^{-5}$). This highlights that this PRS-KLK3int is able to categorize the top 1% of PCa patients at approximately 2-fold higher risk compared with the normal risk group. The top 1-10% group also had a significantly higher PCa aggressiveness prevalence than those in the middle 50% group (32.8% vs. 25.9%, OR=1.4, $p=2.2 \times 10^{-5}$). For detecting the low-risk groups, PRS-KLK3int did not perform well in distinguishing the extremely low score group (bottom 1%), but it can significantly distinguish the bottom 10% (OR=0.81, $p=0.010$). For the UK set, PRS-m155 and PRS-m270 cannot distinguish the top 1%, top 1-10%, and bottom 1% compared with the middle 50% group. However, PRS-m155 can distinguish the bottom 1-10% vs the middle 50% (OR=0.81, $p=0.012$), but PRS-m270 cannot.

The performance of PRS-KLK3int in terms of PCa aggressiveness risk classification in the UCA and EU sets is similar to the UK set. For the UCA and EU sets, PRS-KLK3int can significantly distinguish the top 1% and top 1-10% from the majority of the middle 50% group. For PRS-KLK3int in the UCA set, PCa aggressiveness prevalence was 26.2%, 16.9%, and 12.3% for those in the top 1%, top 1-10% and middle 50% groups, respectively (Supplementary Table 7). PCa aggressiveness prevalence for the top 1% and top 1-10% groups was significantly higher than that in the middle 50% group (OR=2.56, $p=4.3 \times 10^{-6}$ for top 1%; OR=1.45, $p=2.5 \times 10^{-5}$ for top 1-10%). For PRS-KLK3int in the EU set, PCa aggressiveness prevalence was 37.8%, 29.3%, and 23.1% for those in the top 1%, top 1-10%, and middle 50% groups, respectively. PCa aggressiveness prevalence for the top 1% and top 1-10% groups was significantly higher than those in the middle 50% group (OR=2.07, $p=2.1 \times 10^{-5}$ for top 1%; OR=1.38, $p=1.1 \times 10^{-6}$ for top 1-10%). Similarly to the UK set, PRS-m270 and PRS-m155

performance was inferior to PRS-KLK3int in the UCA and EU sets. For the UCA set, PRS-m270 could distinguish the top 1% and top 1-10% versus the middle 50% for PCa aggressiveness (OR=2.17, $p=1.2 \times 10^{-4}$; OR=1.22, $p=0.025$, respectively). This similar trend of PRS-m270 can be observed in the EU set. PCa aggressiveness prevalence was significantly higher for the top 1% and top 1-10% compared with the middle 50% (OR=1.53, $p=0.013$; OR=1.23, $p=0.001$, respectively). For PRS-m155, PCa aggressiveness prevalence was significantly higher for the top 1% (OR=2.06, $p=0.0004$) in the UCA set and was significantly lower for the bottom 1% (OR=0.41, $p=0.0003$) in the EU set compared with the middle 50%. These results demonstrate that adding 12 pairs to PRS-m270 can significantly increase prediction accuracy for PCa aggressiveness, especially for the extremely high-risk group.

PRS-KLK3int and age at PCa diagnosis for predicting PCa aggressiveness

We evaluated PRS-KLK3int performance by adding age at PCa diagnosis, a known risk factor of PCa aggressiveness, in models. As shown in Supplementary Table 8, age at diagnosis is positively associated with PCa aggressiveness for all 3 sets (UK: $p=5.0 \times 10^{-7}$; UCA: $p=8.1 \times 10^{-46}$; EU: $p=4.5 \times 10^{-116}$). The age at PCa diagnosis was positively correlated with the risk of PCa aggressiveness. After adjusting age at diagnosis in the models, PRS-KLK3int remained highly significant (UK: $p=8.0 \times 10^{-17}$; UCA: $p=2.7 \times 10^{-8}$; EU: $p=5.8 \times 10^{-14}$). Adding age at PCa diagnosis to the models increased the AUC values significantly for the UCA and EU sets but not the UK set (Supplementary Table 5). The AUC values were 0.56, 0.64, and 0.65 for the UK, UCA, and EU, respectively.

Discussion

In this study, we developed PRS-KLK3int, could significantly predict PCa aggressiveness susceptibility more accurately than the other 3 PRSs alone (PRS-12pair, PRS-m270, and PRS-m155) when we evaluated the 3 large study sets (UK, UCA, and EU). To our knowledge, this is

the first validated PRS involved SNP-SNP interactions for PCa aggressiveness. The major component of this score, PRS-12pair, contains 12 *KLK3* interaction pairs with only 15 SNPs. Notably, PRS-12pair outperformed the two other PRSs (PRS-m155 and PRS-m270) for predicting PCa aggressiveness. The PRS-*KLK3*int can improve distinguishing PCa patients with an extremely high risk (the top 1% and top 1-10%) and the bottom 10% compared with the middle-risk group of PCa aggressiveness. The p-values of PRS-*KLK3*int for comparing the top 1% with the middle-risk group are in a range of 4.3×10^{-6} to 2.2×10^{-5} for the 3 study sets. However, PRS-*KLK3*int did not perform well in differentiating the extremely low-risk group (bottom 1%) but can significantly predict the low-risk group in the bottom 10% based on its distribution. These findings demonstrated that PRS-*KLK3*int combines the advantages of both scores of PRS-12pair and PRS-m270, allowing it to differentiate between high- and low-risk groups of PCa aggressiveness.

The PRS-12 pair contains 15 SNPs in 13 genes, including *KLK3*. Among them, there are 3 *KLK3* SNPs (rs17632542, rs2569735, and rs174776). The genes linked to the 12 *KLK3* SNP pairs exhibit biological functions associated with PCa aggressiveness. *KLK3* is a gene that codes for PSA, which is a serine protease only secreted by the prostate gland³². In previous GWA studies, rs17632542 in *KLK3* was associated with various PCa phenotypes, including PSA level, PCa risk, aggressiveness, and Gleason score^{21, 33}. In addition, SNP-SNP interactions involving several *KLK3* SNPs (including rs17632542, rs2569735, and rs174776) can significantly predict PCa aggressiveness⁸. A meta-analysis study reported a significant association between rs174776 and PCa risk³⁴. Among other genes in PRS-12pair, most genes are involved in PCa and other cancers, such as *SMAD3*, *CCND1*, *EPHB1*, *DEPTOR*, *JAZF1*, *PDCD6IP*, and *TPM1:LACTB*. *SMAD3* is overexpressed in advanced prostate tumors and regulates the expression of enzymes involved in the angiogenesis pathway^{35, 36}. Moreover, rs35874463 in *SMAD3* can predict height³⁷, which is one of the known risk factors for PCa

aggressiveness³⁸. *CCND1* and *KLK3* are also included in the 8-gene expression signature to predict the survival of PCa patients. This gene signature is based on circulating tumor cells, and its performance is better than most clinical variables³⁹. *EPHB1* encodes a receptor tyrosine kinase involved in cell growth, differentiation, and apoptosis⁴⁰, and its overexpression in prostate tumors suggests it may act as a potential oncogene⁴¹. In addition, expression of *DEPTOR* in prostate tumors was downregulated and correlated positively with PCa progression⁴². Low expression of *DEPTOR* promotes cell proliferation, survival, migration, and invasion, supporting its role as a potential tumor suppressor^{43, 44}. Regarding *JAZF1*, it is associated with PCa cell growth and response to polyamine-targeted therapies⁴⁵. Moreover, the *JAZF1* rs849140 variant correlates with height⁴⁶, a known risk factor for prostate cancer risk and aggressiveness. As for *PDCD6IP*, previous studies reported a positive correlation between the expression of *PDCD6IP* and Gleason Score⁴⁷. *PDCD6IP* expression was significantly different in prostate malignant tissues when compared to indolent and normal prostate tissues⁴⁸. rs2729786 is located in the intergenic region between *TPM1* and *LACTB*. *TPM1* was identified as one of 27 genes for a PCa progression gene signature⁴⁹. This evidence highlights the potential biological role of genes linked to the 12 *KLK3* SNP pairs in PCa aggressiveness.

Although both PRS-m270 and PRS-m155 are significantly associated with PCa aggressiveness, it is important to discuss why these two PRSs showed a protective effect ($OR < 1.0$) on PCa aggressiveness. Several large-scale longitudinal studies have shown that men diagnosed with PCa at an older age have a higher risk of PCa-specific mortality, a terminal phenotype of PCa aggressiveness^{16, 17, 18}. Our study results also indicated that age at PCa diagnosis is positively associated with PCa aggressiveness across all three sets. Consequently, a higher score of PRS-m155 and PRS-m270 suggests a higher chance of a younger age at PCa diagnosis, which may correspond to a lower risk of PCa aggressiveness.

We developed a promising PRS-KLK3int by integrating 12 *KLK3* SNP-SNP interaction pairs, which can be used in clinical settings as a valuable adjunct beyond existing tools primarily based on tumor gene expression (Decipher, Prolaris, and Oncotype-DX). This is because PRS-KLK3int can be used to classify high-risk PCa patients before biological onset, which will be beneficial for a large group of PCa patients under active surveillance. It has been shown that approximately 60% of low-risk PCa patients are under active surveillance⁵⁰. Moreover, genetic scores can also play a crucial role in alleviating PCa patients' anxiety stemming from the uncertainty of long-term PCa outcomes. Studies have shown that PCa patients' anxiety and depression are common and are significantly associated with poor prognosis (such as PC progression and survival), even after treatments based on longitudinal studies^{51, 52}. The strength of this study lies in its rigorous study design and large discovery and validation datasets, which ensure the reliability and validity of the PRS findings. As shown in Fig. 1, the development of the PRS-12pair was through a solid process, including (1) the selection of candidate 3,145 SNP pairs based on our previous solid study⁸, (2) application of SIPI for testing SNP-SNP interactions²⁷, (3) the 3pRule+bootstrap SNP pair selection process to reduce false positivity and (4) the RR3x3 scoring system based on the risk of 9 genotype combinations of a SNP pair. The processes 2-4 were developed by our team.

While these study findings are promising, we are aware that there are some limitations. First, PRS-KLK3int, developed in this study to predict PCa aggressiveness, was derived from PCa patients with European ancestry. Thus, its applicability to other racial and ethnic groups remains uncertain and warrants further investigation. Notably, men with African ancestry are known to have a higher risk of incidence, aggressiveness, and poor outcomes than those with European ancestry^{53, 54}, underscoring the importance of validating and potentially adapting this genetic score in diverse populations. Second, the 12 SNP-SNP interaction pairs were selected based on SNP-SNP interactions using candidate genes in 4 major pathways⁸. A broader or

genome-wide search level will be necessary to enhance the PRS of PCa aggressiveness. Third, while PRS-KLK3int shows promising results in terms of statistical significance, its AUC performance remains limited, indicating that it is not suitable for standalone use. However, it can be added to the existing tools to improve prediction accuracy. Finally, this study focused on genetic profiles without considering other factors, such as gene expression; therefore, its application in clinical settings needs further evaluation.

In conclusion, our findings highlight the PRS-KLK3int as a more effective tool for predicting PCa aggressiveness. This PRS supports risk stratification and personalized care to improve patient outcomes. In summary, PRS-KLK3 interaction effectively leverages interaction effects among biologically relevant SNPs to improve risk prediction for PCa aggressiveness. Its unique ability to predict PCa aggressiveness or progression before biological onset offers a valuable complement to existing tools in clinical settings. By refining genetic risk stratification, this model has the potential to support early decision-making in clinical practice. Future studies should explore different models of genome-wide interactions and extend validation to various populations to enhance applicability.

Competing interests

The authors declare no competing interests.

Data availability

The data used in this project are available from the Prostate Cancer Association Group to Investigate Cancer Associated Alterations in the Genome Consortium (PRACTICAL Consortium, <https://practical.icr.ac.uk/>), but restrictions apply to the availability of these data. Data access requests should be directed to practical@icr.ac.uk.

Code availability

The SIPI function in the SIPI R package can be downloaded from the GitHub website²⁹.

Acknowledgments

This work was supported by the Department of Defense (HT9425-23-1-0438, PI: H. Lin).

We thank the high-performance computational clusters provided by the Louisiana State University Health Sciences Center and the Louisiana Optical Network Infrastructure. Additional members from the PRACTICAL consortium (<http://practical.icr.ac.uk/>) are provided in Supplementary Information.

Author contributions

H.L., I.S., H.M., and P.H. conducted data analyses. H.L. and J.Y.P. were mainly responsible for study design. H.L. drafted the initial version of the paper. H.M., I.S., P.H., and J.Y.P. were part of the writing group and were mainly responsible for the interpretation of the data and critical commenting on the initial draft versions of the paper. K.R.M., J.S., N.P., J.B., D.E.N., H.G., S.F.N., B.G.N., C.M.T., R.J.M., A.W., D.A., R.C.T., J.L.S., L.A.M., A.S.K., O.C., S.I.B., S.K., K.D.S., C.C., E.M.G., J.H., C.M., R.J.H., B.S.R., A.V., M.K., F.W., K.L.P., M.R.T., H.B., E.M.J., R.K., C.J.L., S.L.N., K.D.R., P.O., M.G., N.U., F.C., J.E.C., P.A.T., Z.K.J., C.A.H., R.A.E. were responsible for cohort-level data collection, cohort-level data analyses, and critical reviews of the draft paper. The consortium (UKGPCS collaborators, APCB BioResource, The IMPACT Study Steering Committee and Collaborators, The Profile Study Steering Committee, and the PRACTICAL consortium) also assisted with cohort-level data collection and cohort-level data analyses. All authors approved the final version of the paper submitted to the journal.

References

1. Siegel RL, Giaquinto AN, Jemal A. Cancer statistics, 2024. *CA Cancer J Clin* **74**, 12–49 (2024).
2. Berglund A, *et al.* Epigenome-wide association study of prostate cancer in African American men identified differentially methylated genes. *Cancer Med* **13**, e70044 (2024).
3. American Cancer Society. Cancer Facts & Figures 2024 In: *Survival Rates for Prostate Cancer*. Atlanta, American Cancer Society (2024).
4. Ye H, Sowalsky AG. Molecular correlates of intermediate- and high-risk localized prostate cancer. *Urol Oncol* **36**, 368–374 (2018).
5. May M, *et al.* Validity of the CAPRA score to predict biochemical recurrence-free survival after radical prostatectomy. Results from a european multicenter survey of 1,296 patients. *J Urol* **178**, 1957–1962; discussion 1962 (2007).
6. Klein EA, *et al.* A 17-gene assay to predict prostate cancer aggressiveness in the context of Gleason grade heterogeneity, tumor multifocality, and biopsy undersampling. *Eur Urol* **66**, 550–560 (2014).
7. Cui F, Tang X, Man C, Fan Y. Prognostic value of 17-Gene genomic prostate score in patients with clinically localized prostate cancer: a meta-analysis. *BMC Cancer* **24**, 628 (2024).
8. Lin HY, *et al.* KLK3 SNP-SNP interactions for prediction of prostate cancer aggressiveness. *Sci Rep* **11**, 9264 (2021).
9. Mucci LA, *et al.* Familial Risk and Heritability of Cancer Among Twins in Nordic Countries. *JAMA* **315**, 68–76 (2016).
10. Berndt SI, *et al.* Two susceptibility loci identified for prostate cancer aggressiveness. *Nat Commun* **6**, 6889 (2015).
11. Amin AI Olama A, *et al.* A meta-analysis of genome-wide association studies to identify prostate cancer susceptibility loci associated with aggressive and non-aggressive disease. *Hum Mol Genet* **22**, 408–415 (2013).
12. Lewis CM, Vassos E. Polygenic risk scores: from research tools to clinical instruments. *Genome Med* **12**, 44 (2020).
13. Choi SW, Mak TS, O'Reilly PF. Tutorial: a guide to performing polygenic risk score analyses. *Nat Protoc* **15**, 2759–2772 (2020).

14. Huynh-Le MP, *et al.* Prostate cancer risk stratification improvement across multiple ancestries with new polygenic hazard score. *Prostate Cancer Prostatic Dis* **25**, 755–761 (2022).
15. Karunamuni RA, *et al.* Additional SNPs improve risk stratification of a polygenic hazard score for prostate cancer. *Prostate Cancer Prostatic Dis*, (2021).
16. Clark R, Vesprini D, Narod SA. The Effect of Age on Prostate Cancer Survival. *Cancers (Basel)* **14**, (2022).
17. Pettersson A, Robinson D, Garmo H, Holmberg L, Stattin P. Age at diagnosis and prostate cancer treatment and prognosis: a population-based cohort study. *Ann Oncol* **29**, 377–385 (2018).
18. Bernard B, Burnett C, Sweeney CJ, Rider JR, Sridhar SS. Impact of age at diagnosis of de novo metastatic prostate cancer on survival. *Cancer* **126**, 986–993 (2020).
19. Lawrence MG, Lai J, Clements JA. Kallikreins on steroids: structure, function, and hormonal regulation of prostate-specific antigen and the extended kallikrein locus. *Endocr Rev* **31**, 407–446 (2010).
20. Penney KL, *et al.* Association of KLK3 (PSA) genetic variants with prostate cancer risk and PSA levels. *Carcinogenesis* **32**, 853–859 (2011).
21. Sullivan J, *et al.* An analysis of the association between prostate cancer risk loci, PSA levels, disease aggressiveness and disease-specific mortality. *Br J Cancer* **113**, 166–172 (2015).
22. Kotarac N, Dobrijevic Z, Matijasevic S, Savic-Pavicevic D, Brajuskovic G. Association of KLK3, VAMP8 and MDM4 Genetic Variants within microRNA Binding Sites with Prostate Cancer: Evidence from Serbian Population. *Pathol Oncol Res* **26**, 2409–2423 (2020).
23. Chen C, Xin Z. Single-nucleotide polymorphism rs1058205 of KLK3 is associated with the risk of prostate cancer: A case-control study of Han Chinese men in Northeast China. *Medicine (Baltimore)* **96**, e6280 (2017).
24. Helfand BT, *et al.* Associations of prostate cancer risk variants with disease aggressiveness: results of the NCI-SPORE Genetics Working Group analysis of 18,343 cases. *Hum Genet* **134**, 439–450 (2015).
25. Batra J, O'Mara T, Patnala R, Lose F, Clements JA. Genetic polymorphisms in the human tissue kallikrein (KLK) locus and their implication in various malignant and non-malignant diseases. *Biol Chem* **393**, 1365–1390 (2012).

26. Amos CI, *et al.* The OncoArray Consortium: A Network for Understanding the Genetic Architecture of Common Cancers. *Cancer Epidemiol Biomarkers Prev* **26**, 126–135 (2017).
27. Lin HY, *et al.* SNP interaction pattern identifier (SIPI): an intensive search for SNP-SNP interaction patterns. *Bioinformatics* **33**, 822–833 (2017).
28. Lin HY, *et al.* Cluster effect for SNP-SNP interaction pairs for predicting complex traits. *Sci Rep* **14**, 18677 (2024).
29. Lin HY, Huang PY. SIPI R Package: <https://github.com/LinHuiyi/SIPI>. (2024).
30. Lambert SA, *et al.* The Polygenic Score Catalog as an open database for reproducibility and systematic evaluation. *Nat Genet* **53**, 420–425 (2021).
31. Schumacher FR, *et al.* Association analyses of more than 140,000 men identify 63 new prostate cancer susceptibility loci. *Nat Genet* **50**, 928–936 (2018).
32. Sutherland GR, *et al.* Human prostate-specific antigen (APS) is a member of the glandular kallikrein gene family at 19q13. *Cytogenet Cell Genet* **48**, 205–207 (1988).
33. Knipe DW, *et al.* Genetic variation in prostate-specific antigen-detected prostate cancer and the effect of control selection on genetic association studies. *Cancer Epidemiol Biomarkers Prev* **23**, 1356–1365 (2014).
34. Li H, Fei X, Shen Y, Wu Z. Association of gene polymorphisms of KLK3 and prostate cancer: A meta-analysis. *Adv Clin Exp Med* **29**, 1001–1009 (2020).
35. Lu S, Lee J, Revelo M, Wang X, Lu S, Dong Z. Smad3 is overexpressed in advanced human prostate cancer and necessary for progressive growth of prostate cancer cells in nude mice. *Clin Cancer Res* **13**, 5692–5702 (2007).
36. Jeon HY, *et al.* SMAD3 promotes expression and activity of the androgen receptor in prostate cancer. *Nucleic Acids Res* **51**, 2655–2670 (2023).
37. Lanktree MB, *et al.* Meta-analysis of Dense Genecentric Association Studies Reveals Common and Uncommon Variants Associated with Height. *Am J Hum Genet* **88**, 6–18 (2011).
38. Lophatananon A, *et al.* Height, selected genetic markers and prostate cancer risk: results from the PRACTICAL consortium. *Br J Cancer* **118**, e16 (2018).

39. Haas NB, *et al.* Blood-based gene expression signature associated with metastatic castrate-resistant prostate cancer patient response to abiraterone plus prednisone or enzalutamide. *Prostate Cancer Prostatic Dis* **24**, 448–456 (2021).
40. Pasquale EB. Eph receptors and ephrins in cancer: bidirectional signalling and beyond. *Nat Rev Cancer* **10**, 165–180 (2010).
41. Phan NN, *et al.* Overexpressed gene signature of EPH receptor A/B family in cancer patients-comprehensive analyses from the public high-throughput database. *Int J Clin Exp Pathol* **13**, 1220–1242 (2020).
42. Chen X, *et al.* DEPTOR is an in vivo tumor suppressor that inhibits prostate tumorigenesis via the inactivation of mTORC1/2 signals. *Oncogene* **39**, 1557–1571 (2020).
43. Peterson TR, *et al.* DEPTOR is an mTOR inhibitor frequently overexpressed in multiple myeloma cells and required for their survival. *Cell* **137**, 873–886 (2009).
44. Cui D, *et al.* DEPTOR is a direct p53 target that suppresses cell growth and chemosensitivity. *Cell Death Dis* **11**, 976 (2020).
45. Rosario SR, Jacobi JJ, Long MD, Affronti HC, Rowsam AM, Smiraglia DJ. JAZF1: A Metabolic Regulator of Sensitivity to a Polyamine-Targeted Therapy. *Mol Cancer Res* **21**, 24–35 (2023).
46. Johansson A, *et al.* Common variants in the JAZF1 gene associated with height identified by linkage and genome-wide association analysis. *Hum Mol Genet* **18**, 373–380 (2009).
47. Hamada S, *et al.* Elevated fatty acid synthase expression in prostate needle biopsy cores predicts upgraded Gleason score in radical prostatectomy specimens. *Prostate* **74**, 90–96 (2014).
48. Johnson IR, *et al.* Endosomal gene expression: a new indicator for prostate cancer patient prognosis? *Oncotarget* **6**, 37919–37929 (2015).
49. Wang R, Xiao Y, Pan M, Chen Z, Yang P. Integrative Analysis of Bulk RNA-Seq and Single-Cell RNA-Seq Unveils the Characteristics of the Immune Microenvironment and Prognosis Signature in Prostate Cancer. *J Oncol* **2022**, 6768139 (2022).
50. Cooperberg M, Meeks W, Fang R, Gaylis F, Catalona W, Makarov D. Mp43-03 Active Surveillance for Low-Risk Prostate Cancer: Time Trends and Variation in the Aua Quality (Aqua) Registry. *Journal of Urology* **207**, (2022).

51. Li X, Zhang Y, Wang Y. A 5-year follow-up assessment of anxiety and depression in postoperative prostate cancer patients: longitudinal progression and prognostic value. *Psychol Health Med* **28**, 529–539 (2023).
52. Hu S, Li L, Wu X, Liu Z, Fu A. Post-surgery anxiety and depression in prostate cancer patients: prevalence, longitudinal progression, and their correlations with survival profiles during a 3-year follow-up. *Ir J Med Sci* **190**, 1363–1372 (2021).
53. Powell IJ, Vigneau FD, Bock CH, Ruterbusch J, Heilbrun LK. Reducing prostate cancer racial disparity: evidence for aggressive early prostate cancer PSA testing of African American men. *Cancer Epidemiol Biomarkers Prev* **23**, 1505–1511 (2014).
54. Fuletra JG, Kamenko A, Ramsey F, Eun DD, Reese AC. African-American men with prostate cancer have larger tumor volume than Caucasian men despite no difference in serum prostate specific antigen. *The Canadian journal of urology* **25**, 9193–9198 (2018).

UKGPCS collaborators

Kenneth R. Muir³, Zsafia Kote-Jarai⁶⁴, Rosalind A. Eeles^{64,66}

APCB BioResource (Australian Prostate Cancer BioResource)

Jyotsna Batra^{8,9,10}

Figure legends

Fig. 1 Process of selecting SNP-SNP interaction pairs based on the UK discovery dataset. SIPI: SNP Interaction Pattern Identifier approach; 3pRule: the 3 p-value rule; RR3x3: Risk Ratio score based on 3×3 genotype pair combinations; stepwise selection is based on logistic regression.

Fig. 2 Prevalence of prostate cancer aggressiveness by 2 polygenic risk scores' percentiles in the 3 study sets. UK: the United Kingdom set; UCA: the USA/Canada/Australia set; and EU: the set of other European countries. The stars (*) are for p-value<0.05 compared with the middle 50% (25-74.9%) risk group based on the two-sided Wald chi-square tests in the logistic model adjusting for the 7 principal components of population stratification. The error bars represent 95% confidence intervals. The data can be found in Supplementary Table 6.

Supplementary Fig. 1 Distributions of four polygenic risk scores for predicting prostate cancer aggressiveness

Table 1. Comparisons of genetic-guided risk groups based on the polygenic risk scores (PRSs) for the 3 study sets

Study set ^a	Top 1% vs. middle 50%		Top 1-10% vs. middle 50%		Bottom 1% vs. middle 50%		Bottom 1-10% vs. middle 50%		Bottom 0-10% vs. middle 50%	
	OR (95% CI) ^b	p-value	OR (95% CI) ^b	p-value	OR (95% CI) ^b	p-value	OR (95% CI) ^b	p-value	OR (95% CI) ^b	p-value
UK										
PRS-m155	1.38 (0.92, 2.08)	0.120	1.04 (0.89, 1.22)	0.595	1 (0.65, 1.54)	0.984	0.81 (0.69, 0.95)	0.012	0.83 (0.71, 0.97)	0.017
PRS-m270	1.40 (0.94, 2.10)	0.101	1.09 (0.94, 1.27)	0.260	0.85 (0.54, 1.34)	0.482	0.86 (0.73, 1.01)	0.070	0.86 (0.74, 1.00)	0.056
PRS-KLK3int	2.38 (1.60, 3.56)	2.2x10⁻⁵	1.40 (1.20, 1.63)	2.2x10⁻⁵	0.83 (0.52, 1.34)	0.448	0.80 (0.68, 0.95)	0.012	0.81 (0.68, 0.95)	0.010
UCA										
PRS-m155	2.06 (1.39, 3.07)	0.0004	1.12 (0.94, 1.33)	0.216	0.77 (0.44, 1.34)	0.352	0.89 (0.74, 1.07)	0.216	0.88 (0.73, 1.05)	0.151
PRS-m270	2.17 (1.46, 3.22)	1.2x10⁻⁴	1.22 (1.03, 1.44)	0.025	0.78 (0.45, 1.36)	0.382	0.83 (0.69, 1.01)	0.057	0.83 (0.69, 0.99)	0.041
PRS-KLK3int	2.56 (1.71, 3.82)	4.3x10⁻⁶	1.45 (1.22, 1.72)	2.5x10⁻⁵	0.65 (0.35, 1.21)	0.175	0.83 (0.68, 1.02)	0.073	0.81 (0.67, 0.99)	0.036
EU										
PRS-m155	1.4 (1, 1.96)	0.052	1.12 (0.99, 1.28)	0.078	0.41 (0.25, 0.67)	0.0003	0.89 (0.78, 1.02)	0.097	0.84 (0.74, 0.96)	0.008
PRS-m270	1.53 (1.09, 2.14)	0.013	1.23 (1.09, 1.40)	0.001	0.61 (0.40, 0.93)	0.022	0.87 (0.76, 1.00)	0.051	0.85 (0.74, 0.96)	0.012
PRS-KLK3int	2.07 (1.48, 2.90)	2.1x10⁻⁵	1.38 (1.21, 1.57)	1.1x10⁻⁶	0.78 (0.52, 1.17)	0.233	0.82 (0.71, 0.95)	0.009	0.82 (0.71, 0.94)	0.005

^a The United Kingdom (UK), USA/Canada/Australia (UCA), and other European countries (EU) sets

^b Adjusted odds ratio (95% confidence interval) with a reference group using the middle 50% group. All models had a PRS and the 7 principal components of population stratification. Significant results with p-value<0.05 based on the two-sided Wald chi-square tests in the logistic model were bold.

ED SUMMARY

Lin et al. developed and validated a polygenic risk score (PRS-KLK3int) that incorporates SNP-SNP interactions involving KLK3 to predict prostate cancer aggressiveness. PRS-KLK3int consistently outperforms existing risk scores and can improve the identification of high-risk groups before the biological onset of aggressive disease.

Peer review information: *Communications Medicine* thanks Anca Gabriela Pavel and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

ARTICLE IN PRESS



