Metabolomic Biomarkers of Prostate Cancer: Prediction, Diagnosis, Progression, Prognosis, and Recurrence

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Abstract

Metabolite profiling is being increasingly employed in the study of prostate cancer as a means of identifying predictive, diagnostic, and prognostic biomarkers. This review provides a summary and critique of the current literature. Thirty-three human case–control studies of prostate cancer exploring disease prediction, diagnosis, progression, or treatment response were identified. All but one demonstrated the ability of metabolite profiling to distinguish cancer from benign, tumor aggressiveness, cases who recurred, and those who responded well to therapy. In the subset of studies where biomarker discriminatory ability was quantified, high AUCs were reported that would potentially outperform the current gold standards in diagnosis, prognosis, and disease recurrence, including PSA testing. There were substantial similarities between the metabolites and the associated pathways reported as significant by independent studies, and important roles for abnormal cell growth, intensive cell proliferation, and dysregulation of lipid metabolism were highlighted. The weight of the evidence therefore suggests metabolic alterations specific to prostate carcinogenesis and progression that may represent potential metabolic biomarkers. However, replication and validation of the most promising biomarkers is currently lacking and a number of outstanding methodologic issues remain to be addressed to maximize the utility of metabolomics in the study of prostate cancer. Cancer Epidemiol Biomarkers Prev; 25(6): 887–906. ©2016 AACR.

Aims and Methods

The aim of this review is to summarize the existing literature where metabolomics has been used to evaluate prostate cancer, to explore potential metabolite biomarkers that could augment current diagnostic, prognostic, or screening strategies. The metabolites and pathways implicated by these studies are also discussed to consider what mechanistic information they may impart about prostate cancer.

PubMed was searched to identify studies of prostate cancer in humans that defined themselves as “metabolomics” studies, or which reported metabolic fingerprints, profiles, or signatures. Studies considering disease prediction, diagnosis, progression or treatment response, and studies using any biologic media were considered. The references of each identified study were screened for further qualifying manuscripts. Studies in animal models and in cell lines were not included. Where the full texts were not available the authors were contacted.

Introduction

Prostate cancer represents the second leading cause of cancer mortality in many western countries and accounted for more than 28,000 deaths in the United States in 2013 (1). However, key questions remain on how best to diagnose and manage this cancer. In particular, the identification of the men at greatest risk from lethal prostate cancer, the prediction of treatment response, and the prediction of recurrence remain challenging.

Most prostate cancers are first found during screening with a prostate-specific antigen (PSA) blood test, alone or in combination with a digital rectal exam, followed by a diagnostic biopsy and potentially imaging if there is a suspicion of cancer spread. After treatment, PSA testing may again be employed to assess disease recurrence. However, there are well documented limitations at each of these stages. Only around 25% of men with an elevated PSA level, defined as > 4.0 ng/mL, are diagnosed with prostate cancer at biopsy, and conversely false-negatives are also common (2). Biopsies frequently miss cancer due to tumor heterogeneity, necessitating the need for multiple repeat biopsies which are potentially hazardous to patients and technically challenging (3). Radical prostatectomies are associated with frequent comorbidities, including erectile dysfunction and incontinence, but are associated with better survival outcomes that radiotherapy (4). Similarly, ADT has a number of adverse side effects and, on average, is only effective for two to three years before the emergence of castration-resistant prostate...
cancer (CRPC), an incurable and often fatal disease. There are currently no known methods to predict duration of treatment response or to identify those men who will respond most effectively (5, 6). Furthermore, due to the aforementioned issues with both screening and biopsy, overtreatment represents a significant problem in the management of prostate cancer; the majority of diagnoses will not prove fatal, but there is a subset of men with aggressive and lethal disease. Identifying these men at the earliest stage possible is of paramount importance to reduce to mortality from prostate cancer.

A number of additional biomarkers are now being explored to try and address these questions and challenges. This has been facilitated, to a large extent, by developments in high-throughput sequencing technologies. Gene expression signatures have been demonstrated to have the ability to group patients with CRPC into high- and low-risk group (7) and the quantification of circulating tumor DNA in the peripheral blood has been shown to determine prognosis and monitor treatment effects (8). However, the development of novel prostate cancer biomarkers is still in its infancy. Increasingly, metabolomics is being explored to address this need. This high-throughput methodology has the dual benefit of identifying biomarkers while also enabling a better understanding of the underlying disease mechanisms.

Metabolomics has been applied as an interdisciplinary “omics” science combining pattern recognition approaches and bioinformatics with epidemiology, analytical biochemistry, and biology in the study of the “metabolome” (9), which has been defined as “the quantitative complement of all of the low molecular weight molecules present in cells in a particular physiologic or developmental state” (10). Metabolomics provides a downstream measure of a whole system’s activity that reflects the genome, epigenome, transcriptome and proteome, and their interactions with the environment (11). The metabolome, as a measure of systemic activity, has also been shown to be indicative of the disease state (12). In particular, neoplastic cells are known to possess unique metabolic signatures (13), including aerobic glycolysis (also known as the Warburg effect characterized by increased glucose uptake and lactate production) and production of choline-containing compounds (9, 14–16). Accordingly, a number of studies have attempted to capture metabolomic biomarkers of prostate cancer.

Prostate cancer represents a particularly attractive model for metabolite profiling. First, there is strong evidence to suggest that dysregulation of metabolism plays an important role in the development and progression of this malignancy. One of the most consistently cited risk factors is metabolic syndrome; a collection of pathophysiologic entities including visceral obesity, insulin resistance, low HDL cholesterol, high triglycerides, elevated C-reactive protein, and low adiponectin levels (17). This syndrome is associated with chronic inflammation and high concentrations of inflammation-related markers, which is unique to prostate cancer cells, are hypothesized to result in a distinctive and specific metabolome that can be captured through metabolomic profiling.

### Selected Studies

A search of the peer-reviewed literature identified a total of 33 qualifying studies (Table 1). The term “metabolomics” was not coined until 2002 by Fiehn and colleagues (21). However, researchers have been exploring the measurements of multiple metabolites as potentially useful biomarkers of prostate cancer. Therefore, three studies pre-dating this specific terminology which attempted to characterize a “metabolomic profile” are also included. Since 2002, there has been a steady increase in the number of metabolomics studies, with more than half of the selected studies published from 2011 onwards.

### Study Designs and Methods

The included studies fell into five broad groups based on their stated aims; studies attempting to identify predictive biomarkers prior to diagnosis (n = 2; refs. 22, 23), studies aiming to distinguish malignant from benign (n = 19; refs. 24–42), studies considering biomarkers of tumor aggressiveness (n = 1; ref. 43), studies investigating the effect of therapy (n = 3; refs. 44–46), and studies considering multiple outcomes (n = 8; refs. 16, 47–53). In common with the majority of the existing metabolomics literature (54), all studies were case–control in design, including two nested within cohorts (22, 23). Twenty-two studies used external controls who were either healthy (n = 13 studies; refs. 22, 23, 34, 37–42, 49–52), suffering from benign prostatic hyperplasia (BPH; n = 3; refs. 26, 29, 53), non-recurrent cases (n = 2; refs. 45, 48), or they included multiple control groups (n = 4; refs. 25, 35, 36, 43). In the remainder, the prostate cancer cases acted as their own controls through the use of matched biologic samples or the measurement of metabolites pre-and post-therapy. The most commonly utilized biologic sample was prostate tissue (n = 14), followed by blood (n = 10), urine (n = 5), and expressed prostatic secretions (n = 1 study). In addition, three studies used a variety of media (Table 1).

The two most commonly used methods for performing metabolomics studies are mass spectrometry (MS) and nuclear magnetic resonance spectroscopy (^1H-NMR). MS involves ionization of chromatographically separated chemical compounds and detection based on their mass-to-charge ratio and retention time during chromatography. Consequently, detection of metabolites by MS is biased towards those that ionize most efficiently. Nevertheless, MS it is the more sensitive of the two techniques and can be performed with smaller amounts of a biologic sample, an important consideration in large-scale human studies. The second method, NMR, subjects a sample to an electromagnetic field and measures the characteristic radio waves displayed by each compound in the sample in response to changes in the magnetic field. For a mixture of metabolites in a biologic sample the different patterns of energy release are represented as peaks in a chromatogram, and the area of the peaks is proportional to the concentration of each metabolite (19). NMR is a more analytically reproducible method, does not require sample separation, and provides

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**Table 1:**

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<tr>
<td>Case–control</td>
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<td>Blood</td>
<td>Osi et al. (2008; ref. 49)</td>
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<td>Miyagi et al. (2011; ref. 50)</td>
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<td>1</td>
<td>Zhou et al. (2012; ref. 40)</td>
<td>Plasma</td>
<td>Blood</td>
<td>ESI-MS/MS</td>
<td>Blood plasma from prostate-cancer-free controls ( n = 56 ) &amp; 74 prostate cancer patients ( n = 18 ) receiving endocrine therapy, 18 healthy men. China</td>
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<td>2</td>
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<td>Serum</td>
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<td>4</td>
<td>Mondul et al. (2015; ref. 23)</td>
<td>Serum</td>
<td>Serum</td>
<td>LC/MS and GC-MS</td>
<td>Blood from age and date of baseline blood sample matched controls</td>
<td>200 prostate cancer cases ( n = 200 ) &amp; 200 controls selected from the Alpha-Tocopherol, Beta-Carotene Cancer Prevention Study cohort of male smokers, Finland</td>
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<td>Zang et al. (2014; ref. 41)</td>
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<td>Serum</td>
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<td>Urine</td>
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<td>7</td>
<td>Wu et al. (2011; ref. 36)</td>
<td>Urine</td>
<td>Urine</td>
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<td>Urine from patients with benign prostatic hyperplasia and healthy controls</td>
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<td>Gamagedara et al. (2012; ref. 37)</td>
<td>Urine</td>
<td>Urine</td>
<td>LC/MS-MS</td>
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<td>9</td>
<td>Zhang et al. (2013; ref. 38)</td>
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<td>Urine</td>
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<td>Prostatic secretions</td>
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<td>Sreekumar et al. (2009; ref. 52)</td>
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<td>Prostate tissue, urine and plasma</td>
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<tr>
<td>13</td>
<td>Thysell et al. (2010; ref. 43)</td>
<td>Prostate tissue, plasma and bone</td>
<td>Prostate tissue, plasma and bone</td>
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<td>Prostate tissue, urine and plasma from patients with benign prostate disease and benign prostatic hyperplasia</td>
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<td>Stabler et al. (2011; ref. 48)</td>
<td>Urine and serum</td>
<td>Urine and serum</td>
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<td>Biomarkers of tumor aggressiveness and biological recurrence</td>
<td>25 recurrent prostate cancer cases ( n = 25 ) &amp; 29 non-recurrent cases, USA</td>
</tr>
</tbody>
</table>

**Table 1:** Metabolomics studies of prostate cancer (Cont'd)

**Abbreviations:** ADT, androgen deprivation therapy; CE-TOF, capillary electrophoresis-time of flight; ESI, electrospray ionization; FIA, flow injection analysis; GC, gas chromatography; HP, high performance; HR, high resolution; LC, liquid chromatography; MAS, magic angle spinning; MS, mass spectrometry; MS/MS, tandem mass spectrometry; NMR, nuclear magnetic resonance; TURP, transurethral resection of the prostate; RP, radical prostatectomy.
both quantitative and structural information (55). However, because sensitivity is limited, it is only able to detect a smaller range of metabolites (2, 19). The majority (n = 21) of the selected studies performed metabolomic profiling using mass spectrometry (MS), with the remainder employing nuclear magnetic resonance (NMR)-based techniques.

Metabolite identification

Metabolomic studies generally fall into two classes; (1) targeted studies which focus on the, often quantitative, measure of specific metabolites, sometimes selected on the basis of biologic rationale, and (2) untargeted studies with no a priori hypothesis which measure a much larger number of metabolites, but the exact identity of many metabolites detected by untargeted MS is not apparent without further study. Seventeen studies took an untargeted approach to the search for discriminatory metabolites, with only 12 employing a targeted search. The targeted approach introduces an inherent bias as it is only able to detect the specific metabolites or metabolite classes, such as methionine metabolites (48), corticoids (35), or lipids (29, 40), which have been previously determined. However, it should be noted that the quantitative nature of the targeted studies offers the distinct advantage of easier translation into a clinical setting. Even with a hypothesis-free approach there is not a single analytical methodology that can, even closely, cover the whole metabolome, which is estimated to lie within the range of 10^3 to 10^5 metabolites (54). Thus, untargeted approaches also carry with them some bias based on their chosen methods such as the chromatography and detection techniques used to measure metabolites.

The number of metabolites identified in the selected studies varied by orders of magnitude and was dependent on the methods and technologies employed. Some studies reported the number of peaks, spectral regions, or metabolite features, which may not necessarily correspond to individual metabolites. Furthermore, while some studies included all metabolites in their analyses, others restricted analysis to those metabolites which could be annotated. This may complicate the interpretation and translation of the findings. In those studies including all metabolites, the unknowns cannot be biologically interpreted and potentially important information linking the metabolites with the disease process may be missed; furthermore, any pathway analysis will be inherently biased towards the known metabolites. Conversely, studies restricting to known metabolites may miss important components in metabolomic signatures reducing their discriminatory ability. When comparing between the two types of study studies, it is difficult to know whether replication was not achieved because it did not exist, or because of differences in the metabolites compared. To date, the definitive annotation of identified metabolites remains a bottleneck in untargeted metabolomics studies; absolute identification and quantification can only be made in the presence of an authentic standard. Only seven of the included studies were quantitative or semiquantitative in nature (16, 32, 35, 39, 47, 48, 50).

Statistical analyses

Regardless of the technologic methods used, complex analytical methods are required to deal with the multivariate, highly collinear noisy datasets produced (56, 57). Metabolomics studies often employ pattern recognition or clustering techniques as a means of reducing dimensionality including unsupervised methods, such as principal components analysis (PCA) which converts a set of observations into a set of linearly uncorrelated variables called principal components, and supervised methodologies, such as orthogonal partial least squares, discriminant analysis (OPLS-DA) a related method that is able to separate the components into predictive and uncorrelated information (9). These were employed by 15 of the selected studies, with the others using more classical statistical methods, including t tests and regression modeling. One study used a novel feature selection algorithm termed associative voting (49), which integrates class association rule data mining and classification, and one utilized an entirely pathway-based approach: subpathway-GM (33) which maps genes and metabolites of interest to metabolic pathways to identify biologically relevant subpathway regions [readers are referred to (49) and (33) for full methodological details]. In fact, the subpathway-GM method revealed novel associations beyond the original analyses of the same dataset using a more classical statistical approach (52). Thus pathway-based methods for analyzing metabolomics data may help to provide an improved mechanistic interpretation, but are limited by the fact that they are entirely reliant on the underlying databases utilized (58), and currently comprise only a small percentage of the metabolomics literature.

Results

The selected studies indicated that distinct clusters based on metabolite profiles could be identified in a variety of biologic media including blood (40, 41, 51), urine (36, 38, 42), tissue (16, 28, 31, 32, 45, 47, 52), and expressed prostatic secretions (39). These clusters were able to distinguish cancer from benign (28, 31, 32, 36, 38–42, 47), tumors by their degree of aggressiveness (16, 32, 47), cases who recurred (45), and those who responded well to therapy (51). The distinction between the groups of interest on the basis of their metabolic profiles suggested that the development of metabolomics-based biomarkers may be possible. Although all included studies were ultimately interested in the identification of discriminatory metabolites or profiles, 17 studies specifically aimed at the development and assessments of biomarkers either for diagnostic or prognostic purposes, and evaluated the utility of these biomarkers using ROC curve analyses and indices of specificity and sensitivity. In the first part of the results section, the findings of these 17 studies (Table 2) will be explored. In the second part, these findings will be placed in a wider biologic context using the results of the remaining 16 papers (Table 3), which did not explicitly search for, or assess biomarkers. The final part will detail the attempts at replicating and validating these findings.

Part 1: Assessing Biomarkers

Biomarkers of prostate cancer

Nine of the studies comparing malignant and nonmalignant prostate cancer samples reported AUCs for diagnostic accuracy ranging from 0.67 for urinary sarcosine levels in a ULS-based case–control study (52) to 0.982 for a biomarker profile including phosphocholine and choline, which was developed by comparing tumor to benign prostate tissue from the same patients (28). The second highest reported AUC was 0.973 from Zhou and colleagues’ case–control study. This blood-based profile included 15 phosphocholine-containing species, and although an AUC
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<tr>
<td>Osl et al. (2008; ref. 49)</td>
<td>112 metabolites</td>
<td>Biomarker profile including lysophosphatidylcholines (LPC) with saturated fatty acid chains, serotonin, a monoamine, aspartic acid (Asp) and ornithine</td>
<td>0.716–0.864</td>
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<td></td>
<td>Cross validation</td>
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<tr>
<td>Serkova et al. (2008; ref. 39)</td>
<td>10 metabolites</td>
<td>Citrate, Myo-inositol, Spermine</td>
<td></td>
<td>0.89</td>
<td>0.87</td>
<td>0.79</td>
<td>Metabolite profiling of blood samples can distinguish healthy cases and controls</td>
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<td>Prospective validation is ongoing</td>
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<tr>
<td>Sreekumar et al. (2009; ref. 52)</td>
<td>Plasma: 478 metabolites, Urine: 583 metabolites, Plasma: 626 metabolites</td>
<td>Sarcosine in urine sediment, Sarcosine in urine supernatant</td>
<td>0.71</td>
<td>0.67</td>
<td></td>
<td></td>
<td>Sarcosine may have potential as a diagnostic biomarker</td>
<td>Sarcosine findings were validated in an independent population, and through cell line studies</td>
</tr>
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<tr>
<td>Lokhov et al. (2010; ref. 34)</td>
<td>25 of the most intense peaks of 1900 detected ions</td>
<td>Aciylcarnitine, arachidonoyl amine</td>
<td>0.97</td>
<td>0.86</td>
<td></td>
<td></td>
<td>Six potential diagnostic markers for prostate cancer, two of which were determined to have higher AUCs than the PSA test in this population</td>
<td>Cross validation and comparison to two other statistical methods</td>
</tr>
<tr>
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</tbody>
</table>

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<table>
<thead>
<tr>
<th>Authors</th>
<th>No. of metabolites</th>
<th>Biomarker</th>
<th>ROC AUC</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Other results</th>
<th>Conclusions</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miyagi et al. (2011; ref. 50)</td>
<td>19 amino acids and related molecules</td>
<td>Ala, Ile, Orn, Lys (downregulated), Gin, Val, Trp and Arg (upregulated)</td>
<td>Linear discrimination analysis model: 0.786</td>
<td>93.60%</td>
<td>90.1%</td>
<td>LPC(22:6) demonstrated the most significant difference in plasma concentrations between cases and control.</td>
<td>Metabolic profiles can be used to distinguish prostate cancer cases from controls</td>
<td>Cross validation</td>
</tr>
<tr>
<td>Wu et al. (2011; ref. 36)</td>
<td>81 (of which 59 could be identified)</td>
<td>First three components of the prostate cancer model based on nine discriminatory metabolites: Pyrimidine, Creatinine, Purine, Glucopyranoside, Xylopyranose and Ribofuranose (downregulated), Propenac acid, Dihyroxybutanonic acid and Xylic acid (upregulated) (discriminatory metabolites</td>
<td>0.943</td>
<td>93.60%</td>
<td>90.1%</td>
<td></td>
<td>Sarcosine levels did not significantly differ between prostate cancer cases and healthy controls</td>
<td>Urinary metabolomic profiles may have potential diagnostic ability</td>
</tr>
<tr>
<td>Zhou et al. (2012; ref. 40)</td>
<td>390 lipid species</td>
<td>Top 15 species, all of which contained phosphocholine</td>
<td>0.973</td>
<td>92.1%</td>
<td>94.4%</td>
<td>Biomarker panel displayed 93% accuracy for discriminating prostate cancer cases from healthy controls</td>
<td>The combined biomarker has diagnostic potential in prostate cancer that is comparable to PSA</td>
<td>Yes-findings were validated in a geographically independent cohort</td>
</tr>
<tr>
<td>Zhang et al. (2013; ref. 38)</td>
<td>5200 features</td>
<td>ureido isobutyric acid, indolylacryloylglycine, acetylvalinalanine and 2-oxoglutarate</td>
<td>0.896</td>
<td>83.3%</td>
<td>83.3%</td>
<td>No significant difference in sarcosine levels between cases and controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Giskeødegaard et al. (2013; ref. 47)</td>
<td>23 metabolites</td>
<td>Levels of citrate, taurine and creatine (downregulated)</td>
<td>86.9%</td>
<td>85.2%</td>
<td>Metabolic profiles were significantly correlated with Gleason score</td>
<td>Metabolic profiles were able to distinguish normal and tumor tissue, and indolent from aggressive prostate cancer</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Zang et al. (2014; ref. 41)</td>
<td>Biomarker panel containing top 40 features</td>
<td>Biomarker panel containing top 40 features</td>
<td>0.93</td>
<td>93%</td>
<td></td>
<td></td>
<td>Interior cross-validation</td>
<td></td>
</tr>
</tbody>
</table>

(Continued on the following page)
Table 2. Assessment of the utility of proposed metabolomics biomarkers (Cont’d)

<table>
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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>A. Aim: malignant vs. benign</td>
<td>1132 features</td>
<td>235 features selected from LC-TOF/MS analyses in positive ionization mode</td>
<td>$R^2 = 0.756$, $Q^2 = 0.579$</td>
<td>Metabolites involved in amino acid, organic acid, sphingolipid, fatty acid, and carbohydrate pathways showed significant differences in the urine of prostate cancer patients compared to healthy controls. Results suggest prostate carcinogenesis is associated with a metabolic phenotype promoting abnormal cell growth and intensive cell proliferation.</td>
<td>0.756, 0.579</td>
<td>28 features selected from GC-MS analyses</td>
<td>$R^2 = 0.763$, $Q^2 = 0.508$</td>
<td>Internal cross-validation</td>
</tr>
<tr>
<td>B. AIM: Normal vs. BHP</td>
<td>450 point spectral region</td>
<td>6 discriminatory spectral regions including those corresponding to citrate, taurine, and glutamate</td>
<td>100.0%</td>
<td>Overall classification accuracy of 96.6% (Training set: 100%, Test set: 92.7%)</td>
<td>100.0%</td>
<td>9 metabolites Acetoacetate, cystine, formate, glutamate, lysine, tyrosine, lipids</td>
<td>0.876</td>
<td>Data was partitioned into a training and test set</td>
</tr>
<tr>
<td>C. Fan et al. (2011; ref. 53)</td>
<td>9 metabolites</td>
<td>Acetoacetate, glutamate, taurine, glutamic acid, taurine, glutamine, lysine, tyrosine, lipids</td>
<td>0.876</td>
<td></td>
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</tr>
<tr>
<td>D. Fan et al. (2011; ref. 53)</td>
<td>9 metabolites</td>
<td>Acetoacetate, glutamate, taurine, glutamic acid, taurine, glutamine, lysine, tyrosine, lipids</td>
<td>0.876</td>
<td></td>
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</tr>
<tr>
<td>E. Osl et al. (2008; ref. 49)</td>
<td>112 metabolites</td>
<td>Prostate included: Phosphatidyl choline, serotonin, aspartate, ornithine, threonine, arachidonic acid, fatty acids, sphingomyelins, tyrosine and leucine</td>
<td>0.522-0.673 (dependent on feature selection method)</td>
<td>Metabolite profiles displayed little ability to discriminate by Gleason grade</td>
<td>0.522-0.673</td>
<td>9 metabolites Acetoacetate, cystine, formate, glutamate, lysine, tyrosine, lipids</td>
<td>0.876</td>
<td>Cross validation</td>
</tr>
<tr>
<td>F. Wu et al. (2011; ref. 36)</td>
<td>81 (of which 59 could be identified)</td>
<td>First three components of a prostate cancer model based on three discriminatory metabolites: dihydroybutanoic acid and xylonic acid (upregulated), pyrimidine, xylopyranose, and ribofuranoside (downregulated)</td>
<td>0.522-0.673</td>
<td>Sarcosine levels did not significantly differ between prostate cancer cases and BPH patients</td>
<td>0.522-0.673</td>
<td></td>
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</tr>
<tr>
<td>G. Kelly et al. (2015; ref. 42)</td>
<td>25 features selected from LC-TOF/MS analyses in negative ionization mode</td>
<td></td>
<td></td>
<td>Metabolomics was outperformed by proteomics at distinguishing BPH from prostate cancer patients</td>
<td>0.522-0.673</td>
<td></td>
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</tr>
<tr>
<td>H. Hahn et al. (1997; ref. 26)</td>
<td>6 discriminatory spectral regions including those corresponding to citrate, taurine, and glutamate</td>
<td>100.0%</td>
<td>Overall classification accuracy of 96.6% (Training set: 100%, Test set: 92.7%)</td>
<td>Urinary metabolic profiles may have potential diagnostic utility in differentiating BPH and prostate cancer patients</td>
<td>0.673, 0.588</td>
<td></td>
<td>0.522-0.673</td>
<td>Cross validation</td>
</tr>
<tr>
<td>I. Osl et al. (2008; ref. 49)</td>
<td>112 metabolites</td>
<td>Phosphatidyl choline, serotonin, aspartate, ornithine, threonine, arachidonic acid, fatty acids, sphingomyelins, tyrosine and leucine</td>
<td>0.522-0.673</td>
<td>Metabolomics does not perform as well as proteomics in classifying tumor types</td>
<td>0.522-0.673</td>
<td>9 metabolites Acetoacetate, glutamate, taurine, glutamic acid, taurine, glutamine, lysine, tyrosine, lipids</td>
<td>0.876</td>
<td>Cross validation</td>
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<tr>
<td>Miyagi et al. (2011; ref. 50)</td>
<td>19 amino acids and related molecules</td>
<td>Alanine, isoleucine, ornithine, lysine (downregulated), glycine, valine, tryptophan, and arginine (upregulated)</td>
<td>Controls vs. Stage II (B) patients: 0.764</td>
<td>Controls vs. Stage III (C) patients: 0.777</td>
<td>Controls vs. Stage IV (D) patients: 0.873</td>
<td>Metabolic profiles can be used to classify prostate cancer stage</td>
<td>Cross validation</td>
<td></td>
</tr>
<tr>
<td>McDunn et al. (2013; ref. 16)</td>
<td>326 compounds identified in both cohorts</td>
<td>5,6-dihydrouracil, choline phosphate, glycerol, and methy/lipidate combined with Gleason score, serum PSA, and clinical stage</td>
<td>0.62</td>
<td>Sarcosine was significantly elevated only in those tissue sections with Gleason pattern 8 or worse prostate cancer</td>
<td>Cross validation</td>
<td></td>
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</tr>
<tr>
<td>Menard et al. (2001; ref. 44)</td>
<td>450 point spectral region</td>
<td>Biomarker profile including choline, creatine, glutamine, and lipids</td>
<td>88.9%</td>
<td>92%</td>
<td>Overall classification accuracy of 91.4%</td>
<td>The inclusion of metabolic markers improved the prediction of tumor aggressiveness compared to clinical indices alone</td>
<td>No, but reanalysis of Sreekumar's data</td>
<td></td>
</tr>
<tr>
<td>Maxien et al. (2010; ref. 45)</td>
<td>27 most common and intense spectral metabolic regions</td>
<td>First nine principal components: major contributors to the profile were glutamine, glutamate, myo-inositol, myo-inositol, scyllo-inositol, phospho/ choline, spermine/ polyamines</td>
<td>0.78</td>
<td>Recurrence was predicted with an accuracy of 78%.</td>
<td>Cross validation</td>
<td>The identified tissue metabolic profiles represent potential biomarkers for the prediction of recurrence</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Stabler et al. (2011; ref. 48)</td>
<td>8 metabolites</td>
<td>Homocysteine</td>
<td>0.74</td>
<td>Addition of serum homocysteine provided the greatest improvement of the logistic regression models compared to the base model with PSA and biopsy Gleason ($P = 0.0007$), followed by cysteine ($P = 0.0017$), and cystathionine ($P = 0.0037$)</td>
<td>No</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>McDunn et al. (2013; ref. 16)</td>
<td>326 compounds identified in both cohorts</td>
<td>7-α-hydroxy-3-oxo-4-cholesten-5-one, pregnenolone disulfate, and mannosyl tryptophan combined with Gleason score, serum PSA, and clinical stage</td>
<td>0.64</td>
<td>Sarcosine was significantly elevated only in those tissue sections with Gleason pattern 8 or worse prostate cancer</td>
<td>Cross validation</td>
<td>The inclusion of metabolic markers improved the prediction of biological recurrence compared to clinical indices alone</td>
<td>No, but reanalysis of Sreekumar's data</td>
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<td>The inclusion of metabolic markers improved the prediction of biological recurrence compared to clinical indices alone</td>
<td>No, but reanalysis of Sreekumar's data</td>
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</tr>
</tbody>
</table>

**Table 2.** Assessment of the utility of proposed metabolomics biomarkers (Cont'd)
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</tr>
</thead>
<tbody>
<tr>
<td>Halliday et al.</td>
<td>49 metabolites</td>
<td>Lactate levels and lipid signals are higher in tumor tissue, citrate levels are decreased.</td>
<td>No</td>
<td>13C NMR spectroscopy can be used to differentiate neoplastic and non-neoplastic prostate tissue.</td>
</tr>
<tr>
<td>Schiebler et al.</td>
<td>13 metabolite peaks</td>
<td>Citrate, acetate, inositol and lactate differed significantly between adenocarcinoma and normal peripheral zone tissue, however there were a number of similarities between the spectra of BPH and adenocarcinoma.</td>
<td>No</td>
<td>The citrate standardized peak area alone cannot be used to diagnose prostate adenocarcinoma.</td>
</tr>
<tr>
<td>Swanson et al.</td>
<td>8 metabolites</td>
<td>Glandular tissue: healthy tissue had significantly higher levels of citrate, Taurine, myo-inositol, and scyllo-inositol and polyamines, and lower levels of choline, phosphocholine (PC), and glycerophosphocholine (GPC) relative to tumor tissue. Stromal tissue: healthy tissue had lower levels of choline compounds and higher levels of Taurine, myo-inositol, and scyllo-inositol.</td>
<td>Cross validation</td>
<td>Distinctive metabolic patterns were identified for tumor and healthy tissues and for cancers of varying grade; however, tissue type may affect the findings.</td>
</tr>
<tr>
<td>Cho et al.</td>
<td>21 corticosteroids</td>
<td>Urinary cortisol levels were significantly higher in prostate cancer patients than in healthy controls and BPH patients.</td>
<td>Currently ongoing in a larger population</td>
<td>The results indicate dysregulated cortisol metabolism in prostate cancer patients and suggest that metabolic profiling may be the optimal way to measure this.</td>
</tr>
<tr>
<td>Thysell et al.</td>
<td>123 metabolites of which 49 could be identified. Tissue: 157 metabolites of which 59 could be identified. Plasma: 179 metabolites of which 50 could be identified</td>
<td>Bone: 58% of metabolites differed between normal and metastatic bone. Amino acid synthesis and metabolism were upregulated in metastatic bone, and high levels of cholesterol, myo-inositol-1-phosphate, citric acid, fumaric acid, glycerol-3-phosphate, and fatty acids detected. Tissue: 8% of metabolites differed between tissue from patients with and without metastases including four of those significantly increased in metastatic bone: asparagine, threonine, fumaric acid, and linoleic acid. Plasma: 15% of metabolites differed in the plasma of patients with and without bone metastases including four identified in metastatic bone: glutamic acid, taurine, and phenylalanine and steanic acid. Sarcosine was found to be increased in the bone of men with metastatic disease but not in their tumor tissue or plasma.</td>
<td>No</td>
<td>Cholesterol is a possible therapeutic target for advanced prostate cancer.</td>
</tr>
<tr>
<td>Komoroski et al.</td>
<td>4 phospholipid metabolites</td>
<td>Phosphoethanolamine and glycerophosphoethanolamine levels differed significantly between the cancer and BPH groups. None of the four metabolites were associated with Gleason score.</td>
<td>No</td>
<td>These metabolites may be useful in the diagnosis of prostate cancer and may help to explain the high choline resonance identified in other studies.</td>
</tr>
</tbody>
</table>

(Continued on the following page)
### Table 3. Results from the metabolomics studies that did not assess biomarker utility (Cont’d)

<table>
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<tr>
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<tbody>
<tr>
<td>Shuster et al. (2011; ref. 30)</td>
<td>260 metabolites</td>
<td>83 (32%) of metabolites were significantly different between cancer and benign tissue. Common amino acids, long chain fatty acids and phospholipids were increased. Higher levels of uracil, kynurenine, glycerol-3-phosphate, leucine and proline were reported in agreement with Sreekumar’s study but sarcosine was below the limit of detection.</td>
<td>No</td>
<td>Molecular biomarkers could augment histology in the characterization of disease.</td>
</tr>
<tr>
<td>Brown et al. (2012; ref. 31)</td>
<td>260 metabolites</td>
<td>Ala, Ile, Orn and Lys were downregulated in prostate cancer patients compared to healthy controls and Gin, Val, Trp and Arg were upregulated.</td>
<td>No</td>
<td>It is possible to determine a metabolomic signature of prostate cancer</td>
</tr>
<tr>
<td>Gamagedara et al. (2012; ref. 37)</td>
<td>4 metabolites</td>
<td>No difference in the mean levels of proline, kynurenine, uracil or Glyceral-3-phosphate between prostate cancer cases and healthy controls</td>
<td>Validating</td>
<td>The explored biomarkers had no diagnostic or prognostic potential in prostate cancer, and could not distinguish prostate cancer from other malignancies</td>
</tr>
<tr>
<td>Saylor et al. (2012)</td>
<td>292 identified metabolites</td>
<td>56 metabolites changed significantly from baseline to three months: Multiple steroids, Markers of lipid beta-oxidation, markers of omega-oxidation and markers of insulin resistance (2-hydroxybutyrate, branch chain keto-acid dehydrogenase complex products) were lower. Most bile acids and their metabolites were higher.</td>
<td>Cross validation</td>
<td>Identified novel and clinically important ADT-induced metabolic changes</td>
</tr>
<tr>
<td>Kami et al. (2013; ref. 32)</td>
<td>86 (of which 39 could be absolutely quantified)</td>
<td>TCA cycle intermediates, Succinate, fumarate, malate, pyruvate and lactate levels were higher, and ADP and phosphoenolpyruvate lower in tumor than in normal tissue.</td>
<td>Cross validation</td>
<td>Tumor metabolic profiles can help to distinguish normal from tumor tissue, and tumor stage</td>
</tr>
<tr>
<td>Li et al. (2013)</td>
<td>626 metabolites</td>
<td>53 metabolites associated with metastatic prostate cancer, 16 significant pathways including amino acid metabolism, tryptophan metabolism, cysteine and methionine metabolism, arachidonic acid metabolism and histidine metabolism</td>
<td>No</td>
<td>Identified novel disease relevant pathways using an alternative statistical method on Sreekumar et al.’s data</td>
</tr>
<tr>
<td>Huang et al. (2014; ref. 51)</td>
<td>8,232 signals</td>
<td>In patients who did not develop castration-resistant prostate cancer (CRPC) for at least 2 years, serum deoxycholic acid (DCA), glycochenodeoxycholate (GCDCA), L-tryptophan, docosapentaenoic acid (DPA), arachidonic acid, deoxyxycycline tri-phosphate, and pyridoxine levels reverted to near healthy control levels during endocrine therapy. In contrast, the metabolite levels remained abnormal in patients who developed CRPC within 1 year.</td>
<td>Validation currently ongoing</td>
<td>DCA, GCDCA, L-tryptophan, DPA, arachidonic acid, deoxyxycycline tri-phosphate, and pyridoxine represent potential biomarkers for evaluating patient response to endocrine therapy. These results suggest a role for cholesterol in prostate cancer progression</td>
</tr>
</tbody>
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(Continued on the following page)
Table 3. Results from the metabolomics studies that did not assess biomarker utility (Cont’d)

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<tr>
<td>Mondul et al. (2014; ref. 22)</td>
<td>420 metabolites</td>
<td>Circulating 1-stearoylglycerol was inversely associated with the risk of developing prostate cancer up to 23 years after blood collection. The magnitude of this association did not differ by disease aggressiveness. There were also suggestive inverse associations for glycerol and alpha-ketoglutarate.</td>
<td>Only the association between alpha-ketoglutarate and aggressive prostate cancer was replicated in a subsequent study including different participants from the same population.</td>
<td>The results support a role for dysregulation of lipid metabolism in the development of prostate cancer</td>
</tr>
<tr>
<td>Mondul et al. (2015; ref. 23)</td>
<td>626 metabolites</td>
<td>Strong inverse associations between energy and lipid metabolites particularly glycerophospholipids and fatty acids and aggressive cancer were observed with aggressive disease risk. Thyroxine and trimethylamine oxide were associated with aggressive disease risk while Alpha-ketoglutarate and citrate were inversely associated. Metabolites associated with nonaggressive cancers included 2-deoxyuridine, adenosine 50-monophosphate (AMP), 11-dehydrocorticosterone, 21-hydroxyprogrenolone monosulfate, cotinine, and hydroxycotinine.</td>
<td>Meta-analyses with the findings of a previous study confirmed a role for glycerophospholipids and long chain fatty acids</td>
<td>Prospective study data indicate that several circulating glycerophospholipid, fatty acid, energy and related metabolites are inversely associated with aggressive prostate cancer up to 20 years prior to diagnosis. Metabolite associations vary by cancer aggressiveness</td>
</tr>
</tbody>
</table>
was not computed, Giskeødegård and colleagues also included phosphocholine in their tissue-based biomarker profile, which had a sensitivity and specificity >85% (47). Three of the articles (34, 39, 52) reported the AUC for individual metabolites, with acylcarnitine ranking the highest (AUC: 0.97 in plasma; ref. 34). Carnitines were also identified in Struck-Lewicka and colleagues’ diagnostic signature in urine. Similarly, another metabolite with a high individual AUC, citrate, which had an AUC of 0.89 in Serekova’s study (39), was a component of Giskeødegård and colleagues’ signature (47). The remaining studies reported on profiles comprising multiple markers. Interestingly, there was some crossover between the profiles developed in the case–control studies of Osl and colleagues (49), Miyagi and colleagues (50), Zang and colleagues (41), and Struck-Lewicka and colleagues (42), with all including multiple amino acids such as lysine, glutamine, and ornithine in their profiles. Osl and colleagues (49) also included arachidonic acid in their signature, a compound related to arachidonoyl amine, which was reported to have an AUC of 0.86 in Lokhov and colleagues’ study (34). Furthermore, Osl and colleagues (49) included a number of phosphorylcholines, in agreement with the findings of Zhou and colleagues’ targeted lipidomics analysis (40), while Zang and colleagues (41) identified multiple lysophospholipids. The sensitivity and specificity of Zang and colleagues’ diagnostic profile, which also contained metabolites of the steroid hormone biosynthesis pathway and bile acids, was 92%, and 94% respectively. Struck-Lewicka and colleagues also did not report AUC’s but rather, the $R^2$ and $Q^2$ values for their partial least squares-discriminant analysis model which were 0.789, 0.711 respectively, under the best performing GC-MS–retained model, indicating a robust signature with good predictive ability (42).

The studies by Osl (49), Miyagi (50), Zhou (40), Zang (41), and Lokhov (34) and colleagues developed their signatures in blood samples, and it is of note that there was little crossover in terms of the specific constituent metabolites with the urine-based diagnostic signatures proposed by Zhang and colleagues (38), Struck-Lewicka and colleagues (42), or Wu and colleagues (36). All but two of the studies (28, 47), compared prostate cancer cases with healthy controls. However, the results of Giskeødegård and colleagues’ and Cheng and colleagues’ interindividual comparisons among prostate cases were markedly concordant with these healthy versus diseased comparisons, both in terms of the constituents of the signatures they developed including phosphocholines, and citrate, and in the predictive ability of these signatures. Similarly, study population size which ranged from 40 (20 prostate cancer cases and 20 healthy controls) in Wu and colleagues’ study (36) to 800 (134 cases and 666 controls) in Miyagi and colleagues’ study (50), did not appear to confer any advantages in terms of the predictive ability of the developed signature.

In summary, the most promising candidate biomarkers for distinguishing prostate cancer cases from healthy controls include sarcosine, choline, phosphocholines, phosphorylcholines, camitines, citrate, amino acids, arachidonoyl amine, and lysophospholipids (Table 2).

Biomarkers of benign prostatic hyperplasia and tumor aggressiveness

Wu and colleagues also reported on a biomarker profile with an AUC of 0.825 to distinguish benign prostatic hyperplasia (BPH) and prostate cancer patients constituting five metabolites (36). All five (dihydroxybutanoic acid, xylonic acid, pyrimidine, xylopyranose, and ribofuranoside) were also constituents of the healthy versus diseased profile. Hahn and colleagues reported that MRS spectra could be used to classify benign and malignant prostate tissue with a sensitivity of 100%, a specificity of 96%, and an overall classification accuracy of 97%, with citrate, glutamate, and taurine playing important discriminatory roles (26). Fan and colleagues’ 9-feature profile had an AUC of 0.876 for distinguishing prostate cancer and BPH patients. Similar to their malignant versus benign analyses, this serum-based signature included glutamate, lysine, and lipid species, suggesting a possible dose-dependent relationship with the progression from normal to BPH to cancer. However Fan and colleagues’ found that the signature did not perform well at distinguishing Gleason 5 from Gleason 7 (AUC, 0.532) or organ-confined from non-organ–confined cancers (AUC, 0.311; ref. 53).

Three other articles also developed biomarker profiles of tumor aggressiveness. Osl and colleagues compared Gleason 6 with Gleason 8–10 cancers, and reported that the discriminatory metabolites, which included a number of sphingomyelin lipids, were distinct from those that differed between normal and tumor tissue (49). However, the AUCs were much lower in the tumor aggressiveness analyses suggesting discriminatory power is poor. Conversely, Miyagi and colleagues reported increasing AUCs when comparing healthy controls to stage II patients (AUC, 0.764), stage III patients (AUC, 0.777), and stage IV patients (AUC, 0.873) using a profile comprising 8 amino acids: alanine, isoleucine, ornithine, lysine, glutamine, valine, tryptophan, and arginine (50). McDunn and colleagues’ study the AUC for a combination of four different biomarkers: 5,6-dihydouracil, glycerol, methylpalmitate, and choline phosphate, was 0.62 for discriminating organ-confined from non-organ–confined prostate cancer (16).

In summary, the most promising candidate biomarkers for identifying BPH and tumor aggressiveness include dihydroxybutanoic acid, xylonic acid, pyrimidine, xylopyranose, ribofuranoside citrate, glutamate, sphingomyelin lipids, amino acids, 5,6-dihydouracil, glycerol, methylpalmitate, and choline phosphate (Table 2). Again, there was little difference in the results between those studies that compared healthy individuals to prostate cancer cases and those investigating intertumor differences within controls, or any differences due to study population size.

Biomarkers of disease recurrence

Interestingly, choline phosphate (phosphorylcholine) was also identified as a major contributor to the metabolic profile predicting recurrence by Maxeiner and colleagues (45), which had an AUC of 0.78. This profile was based on the first nine principal components of all the measured metabolites and the loadings plots determined that myoinositol and spermine, both of which were identified in Serkova and colleagues’ (39) diagnostic signature, and glutamate, which was a component of Fan and colleagues’ (53) aggressiveness signature, were major contributors to the recurrence profile.

Similarly cysteine, a further component of Fan and colleagues’ aggressiveness signature, was investigated as a marker of recurrence by Stabler and colleagues (48). This metabolite was found to have an AUC of 0.82 when combined with PSA, outperforming two other methionine metabolites: homocysteine (AUC, 0.78) and cystathionine (AUC, 0.79). When these three metabolites were combined, the AUC was 0.86, providing
an increased ability to detect recurrence over clinical indices alone.
Although Menard and colleagues (44) did not perform ROC analysis their profile, including choline, creatine, glutamine, and lipids, but they were able to identify a malignant biopsy following radiotherapy with a sensitivity of 89%, a specificity of 92%, and an overall classification accuracy of 91%.

Despite the differences in study designs, Menard and colleagues (44) and McDunn and colleagues (16) considered intertumor differences, while Maxiener and colleagues (45) and Stabler and colleagues (48) compared the recurrent and nonrecurrent cases in tissue and in blood and urine, respectively; the results were largely concordant between the studies. It is also of note that the smallest predictive ability was reported for the largest study (16). In summary, the most promising candidate biomarkers for predicting disease recurrence included phosphorylcholine, myo-inositol, spermine, glutamate, cysteine, choline, creatine, glutamine, and lipids (Table 2).

**PSA testing and current gold standards**
Prostate cancer is a relative rarity among malignancies in that it has been shown to be amenable to population-wide screening programs utilizing prostate-specific antigen (PSA), which is also monitored as a biomarker of biochemical recurrence (6). Therefore, novel biomarkers must perform better than this current gold standard to be useful. Seven of the studies discussed above explicitly compared their biomarkers to the use of PSA (34, 39–41, 48, 52, 53). An often cited study reports an AUC for PSA testing of 0.682 [95% confidence interval (CI) 0.67–0.69] for the diagnosis of prostate cancer, and that a PSA cut-off value of 4.1 ng/mL has a specificity of 93.8% but a sensitivity of only 20.5% (59). Zhou and colleagues’ multi-marker plasma metabolite profiles outperformed these metrics in diagnosis (40), although parsimony must also be taken into account when considering clinical translation. Similarly, Serkova and colleagues reported AUCLs for three metabolites that would outperform PSA, and added that unlike PSA, they are not associated with age, suggesting improved specificity (39). Although it should be noted that Serkova was comparing the discriminatory ability of these metabolites in expressed prostatic secretions to a blood-based PSA test (Lokhov (34), Zang (41), and Stabler and colleagues (48) computed the utility of PSA in their respective study populations for the diagnosis of prostate cancer [Lokhov (34) and Zang and colleagues (41)] and the prediction of recurrence (Stabler and colleagues; ref. 48), and all reported that their blood-based biomarkers outperformed PSA. Although the serum biomarker profile developed by Fan and colleagues outperformed PSA at distinguishing BPH from prostate cancer in their population, it was comparable or inferior to PSA testing in discriminating tumors by their degree of aggressiveness (53). Finally, Sreekumar and colleagues reported that the measurement of sarcosine in urine was superior to PSA at predicting a positive prostate cancer biopsy within the clinical PSA gray zone of 2–10 ng/mL (52).

For the tissue-based diagnostic studies (26, 28, 47), the current gold diagnostic standard is histopathology, but as histopathologic analysis is used to determine the presence of prostate cancer, it cannot be compared with metabolomics profiling. Nevertheless in all the studies, good correlation between the metabolic findings and the histopathologic findings was demonstrated. Furthermore for disease recurrence, McDunn and colleagues reported that the inclusion of a metabolomics profile afforded increased prediction compared with clinical indices alone (16).

**Part 2: Hypothesis-Generating Studies**
Metabolites and pathways implicated in prostate cancer tumorigenesis, progression, and recurrence
In the remaining metabolomics studies, the primary aim was not the identification of biomarkers or indices of biomarker utility were not reported upon. However, among the results, there was substantial crossover with the metabolites and pathways discussed in Part 1, in particular with those thought to be involved in pathogenesis. In studies comparing prostate cancer patients with healthy controls, differences in metabolites and pathways relating to energy metabolism were reported including TCA cycle intermediates (24, 27, 32), lactate (24, 32), citrate (23), phosphoenolpyruvate, and adenosine diphosphate (32). Metabolites vital to cell growth and proliferation were also identified; these included common amino acids (15, 30) bile acids (60), polyamines (27), glycerol-3-phosphate (30), and a number of constituents of cells membranes including long chain fatty acids (22, 23, 51), phospholipids (30), phosphocholines (61), and choline (27, 55). Steroid hormones (23) which help regulate the growth and function of the prostate were also implicated (62), as were inositol and its isomers (27) which are involved in osmoregulation, and have been shown to be dysregulated in several other cancers (55) and cortisol (35) which is thought to be related to cancer development via the mechanism of chronic stress (63). A number of these metabolites, citrate, inositol, lactate (25), and cortisol (35, 63), were additionally observed to differ between BPH and prostate cancer patients, along with phosphoethanolamine, and glycerophosphoethanolamine (29) which are also components of membranes and acetate (25) which is thought to support cell proliferation through de novo lipid biosynthesis (64).

Levels of metabolites including sarcosine, uracil, kynurenine, leucine, and proline (43) were shown to be increased during the progression to metastatic disease (32, 33, 43), as were pathways involved in nitrogen breakdown (43). Nitrogen metabolism is known to be altered in tumors to accommodate their enhanced glucose requirements and the increase in nucleotide and protein synthesis (65). Arachidonic acid metabolism was also altered which is in line with the suspected association between dietary fat and prostate cancer (33, 66). Metabolites from the pathways of energy and lipid metabolism were again demonstrated to be of importance (23, 43) in the degree of disease aggressiveness. Taken together with the results of the biomarkers studies, these findings suggest a particularly important role for pathways involved in abnormal cell growth and intensive cell proliferation in prostate carcinogenesis and progression. Dysregulation of lipid and fatty acid metabolism may be particularly crucial to the disease process.

Multiple steroids, markers of lipid beta-oxidation, markers of omega-oxidation, and markers of insulin resistance (67) were observed to decrease following therapy in the study by Saylor and colleagues (46), while bile acids (60), steroids, and their metabolites increased. This was in line with the findings of Huang and colleagues (51), who reported that the metabolite profiles of patients successfully treated with endocrine therapy closely resembled those of healthy controls. Among all the included studies, one did not report any significant findings (37).
The sarcosine debate

Following the publication of Sreekumar and colleagues’ findings on sarcosine, an intermediate and byproduct in glycine synthesis and degradation, a number of studies attempted to replicate these promising results (52). Li and colleagues’ (33) pathway-based analysis of Sreekumar and colleagues’ dataset reported an association between metastatic prostate cancer and methionine metabolism pathways, which can be involved in the formation of sarcosine. McDunn and colleagues (16) observed significantly elevated sarcosine levels in Gleason grade 8 tumors or higher compared with benign tissue, while Thysell and colleagues (43) found a significant increase in sarcosine in the bone of men with metastatic disease. Although recurrence was not a focus of Sreekumar and colleagues’ original study (52), Stabler and colleagues (48) observed that urinary Sarcosine levels at the time of surgery were significantly higher among those men whose cancer subsequently recurred.

Conversely, Wu (36) and Zhang and colleagues (38), reported no significant differences in urinary sarcosine levels between prostate cancer cases, BPH cases and healthy controls, and sarcosine was not significant in Mondul and colleagues’ (2014) blood-based study (22). Contrary to their findings in bone, Thysell and colleagues found no association between prostate cancer and sarcosine levels in blood or tissue (43). Sarcosine could not be reliably measured in two further studies (30, 37); however, Shuster and colleagues (30) replicated Sreekumar and colleagues’ (52) positive findings for uracil, kynurenine, glycerol-3-phosphate, leucine, and proline levels in tissue (30), while Gamagedara and colleagues (37) observed no diagnostic potential for these metabolites in urine.

It has been suggested that these differences in findings may be the result of technical differences between the studies. It is notable that is it analytically challenging to precisely and accurately measure sarcosine, particularly at low concentrations (68), as is evidenced by the two studies that were unable to do so (30, 37). It has been suggested that liquid chromatography for sample separation prior to MS, may be preferable to gas chromatography for the measurement of sarcosine and that this may explain the conflicting findings (68). However, within the studies reported here, a combination of liquid- and gas-based chromatography was used by both the studies reporting positive findings (16, 43, 48, 52) and those reporting null findings (22, 36, 43, 69). The studies were also coherent with regards to the statistical analyses performed (comparisons of means, OPLS-DA, and ROC curves). With the exception of McDunn and colleagues, all compared to prostate cancer cases to controls and there was no striking differences in population sizes between the positive and null studies (16). It has also been suggested that population differences in sarcosine levels may lead to false-negative or false-positive findings. Among the studies reporting positive findings, three were based in the United States (16, 48, 52) and one in Sweden (43), while among the null studies, two were based in Asia (36, 38) and two in Europe (22, 43). However, the explanation for the differences in findings most likely relates to the multitude of technical challenges and that too, in particular, in the urine-based studies, the difficulty in accurately determining the sarcosine/creatinine ratio is likely to be playing a role (36, 68).

Methodological Considerations

Comparisons with other cancers

One of the most common applications of metabolomics is in the study of cancer (54), and a number of metabolomics biomarkers with discriminatory abilities comparable with or even better than those for prostate cancer have been proposed, particularly in cancers of the gastrointestinal system (70–72) and...
pancreas (73, 74). Malignant cells are known to possess metabolic phenotypes that differ from many normal tissues, characterized by a shift toward aerobic glycolysis and pathway alterations that support biomass accumulation for cell proliferation (14, 15, 75, 76). As such, these reported findings, particularly in the non-tissue-based studies, may identify signatures that reflect malignancy in general and which are not specific to prostate cancer. With this possibility in mind, seven studies investigated additional malignancies (24, 31–33, 37, 43, 50).

Halliday and colleagues (24) compared the metabolic profiles of prostate cancer, lung cancer, and colon adenocarcinoma, and reported tumor-specific differences. Similarly, Kami and colleagues (32) detected a clear distinction between lung and prostate cancer samples based on their metabolic profiles, and reported that lung versus prostate differences were greater than normal versus tumor differences within the same organ. However, they did note that compared with their normal counterparts both tumor types shared a number of features such as higher levels of amino acids, lactate, succinate, fumarate, and malate. Intriguingly, these TCA intermediates have also been shown to be increased in both colon and stomach cancer (77).

Conversely, Gamegedara and colleagues (37), who investigated the biomarkers identified by Sreekumar and colleagues (52) in urine, reported that in their population these biomarkers could not distinguish between prostate cancer cases and controls, nor could they distinguish prostate from breast cancer. While Thysell and colleagues (43), who considered breast, esophageal, lung, and kidney cancer, observed that the significant differences in sarcosine levels between normal bone and the bone metastases of prostate cancer patients were also evident in these other cancers, indicating such differences may not be prostate cancer specific.

Three other studies investigated additional cancers, including kidney (31), colorectal adenoma (33), lung, colorectal, breast, and gastric cancer (50), although they did not specifically compare the metabolome of these malignancies to prostate cancer. A common theme between all cancers was a significant alteration in amino acid levels. A large number of differential metabolites were identified for all the investigated cancers, including prostate, particularly among the amino acids. Nevertheless, Miyagi and colleagues (50) reported that the greatest proportion of differential metabolites were tumor site-specific.

In summary, in these studies, a prostate cancer-specific metabolome was demonstrated both in tissue (24), and in plasma (50), although these metabolomes are characterized more on the basis of the patterns and behaviors of grouped metabolites including lipids and TCA cycle intermediates, rather than on individual metabolites. A prostate cancer-specific metabolome was not demonstrated in urine (37). Within the wider cancer metabolomic literature, a number of the putative “prostate biomarkers” discussed in this review have also been proposed as biomarkers of other malignancies. Aspartic acid, 2-hydroxybutyrate, and kynurenine have been suggested as metabolomics biomarkers of colorectal cancer; the malignancy in which the field of metabolomics is perhaps most advanced (78). Lactate, threonine, acetate, uracil, succinate, lysine and tyrosine, myoinositol, taurine and creatine have been shown to be associated with the presence of rectal cancer, and correlated with its progression (79). Taurine is also increased in squamous cell carcinoma (80), while lactate has additionally been shown to be associated with esophagogastric cancer (81), along with fumarate, valine, glutamine, glutamate (81), xylonic acid (81, 82), tyrosine, phenylalanine, and tryptophan (83). Together, these metabolites indicate a general dysregulation in the metabolism of cellular respiration, energy, amino acids, ketone body, and choline metabolism which, as discussed, could be applicable to all cancers. Similarly, choline, phosphocholine, phosphatidylcholine, lysophosphocholine, and glycerophosphocholine, which are necessary for cell membrane synthesis and intercellular signaling (55), have been identified in metabolomic profiling studies of multiple cancers including brain, breast, lung, and liver (84). One of the prostate diagnostic biomarkers with the highest reported AUCs, acylcarnitine in blood, has also been shown to distinguish kidney cancer patients from controls, and by their degree of severity when measured in urine (85); this is hypothesized to reflect alterations in immune surveillance and again may point to the overall phenotype required to support the growth and proliferation of malignant cells. Even citrate, which could have been hypothesized to be prostate cancer-specific given its importance in the prostate has been shown to be increased in bile samples of patients with biliary tract cancers (86).

In fact, the vast majority of the metabolites reported here have also been identified in other studies supporting the concept of a carcinogenesis metabolome. However, tumors still retain much of their unique organ-specific metabolome (32, 75, and, to date, neither spermine nor sarcosine have been proposed as metabolomic biomarkers of any other malignancies. However whether this denotes these metabolites as prostate specific, or it merely reflects the nature of metabolomics and the possibility these metabolites have not been measured in the profiling of other cancers, remains to be seen.

Technological and analytical issues
In addition to the “epidemiologic validation” of findings through replication, is it also vital to show that a proposed biomarker displays ‘technical validation’ in terms of intrinsic measurement error and analytic sensitivity (87). Much of the between-study heterogeneity and inconsistency can be attributed to the use of differing technological, experimental, and analytical methods, which can affect the measurements of metabolites in an as yet to be determined way (88). Only seven studies reported on their quality control (QC) procedures, to allow the consideration of system stability, with varying degrees of detail (22, 23, 35, 38, 42, 46, 51), while only eight (22, 23, 30, 35, 38, 42, 46, 51) reported on the relative SD (RSD%) threshold for the included features (38).

Bias and confounding
To fully understand the impact of disease, the composition of the “normal” metabolome in healthy individuals must also be established. The metabolome will be dependent on the originating tissue or biologic media, but will additionally vary by age, BMI, diet, and other lifestyle factors (89). This is further complicated by the fact that a genetic component to the metabolome has been demonstrated (90). There is also a wide range of stability among metabolites and those metabolites that are more stable, including amino acids, are more likely to show differences if they exist between cases and controls. The temporal fluctuation of the metabolome also introduces novel challenges particularly in those studies assessing recurrence and treatment response, and it is of note that none of the diagnostic or aggressiveness studies utilized repeat measurements to address this (87). Similarly none
of the studies addressed the temporal fluctuation in the metabolome through the use of repeat samples.

Consequently, as well as technologically induced variation, confounding represents an important issue in any metabolomics study (91). In epidemiologic studies of prostate cancer, a number of potential confounders are commonly included in statistical models including age, race, BMI, and often Gleason grade, due to their reported associations with prostate cancer independence, progression, and lethality (92, 93). Importantly, these variables may also affect the metabolome (94, 95). However they were rarely taken into account in the selected studies.

The impact of interindividual variation represents a strong argument for cases acting as their own controls (96), and in 10 of the studies intratumor differences within the same patients were compared (16, 24, 27, 28, 30–33, 44, 47). Similarly, Saylor and colleagues compared blood samples pre- and post-treatment (46). The remainder utilized external controls. Although the use of external controls ensures that the comparison group is “healthy” and not subject to underlying or latent disease pathology, it also introduces the potential for false positives to arise through batch effects or confounding. Among the studies in this review, the majority of blood- and urine-based studies utilized external controls, so it is difficult to assess whether this resulted in an excess of positive findings. Eight studies matched on age (22, 23, 41, 42, 45, 50, 51, 97), 4 on sampling time (22, 23, 43, 45), one on Gleason grade (45) and one on BMI (42). However, neither age (39, 40), smoking status (22, 50), clinical variables (48), BMI, serum cholesterol, educational level, nor various dietary factors (22, 23) were found to act as confounders in those studies where they were considered. Confounding was not addressed in the remainder of the studies, and none considered other potentially important factors such as subtype heterogeneity (98). Treatment was shown to be a further modifier of the metabolome in the studies investigating its effect (46, 51), and although six studies stated that the biologic samples were collected prior to any radiation or hormonal therapy (32, 36, 47–50), one study included metabolic profiles ascertainment after therapy (43), and the remaining case–control studies did not report on this covariate.

The majority of the studies were conducted in predominantly Caucasian populations with the exception of six Asia-based studies (32, 35, 36, 38, 50, 51), and only two studies (40, 41) reported on the ratio of races within their study. This is of particular importance given the largely unexplained disparities in prostate cancer incidence between ethnicities (99); however, in Zhou and colleagues’ (40) study, race was not found to act as a confounder. Of the remaining studies, 19 were based in North America and eight were based in Europe, therefore given the suspected impact of environmental and dietary factors on the metabolome, the wider generalizability of the reported findings must be considered.

Multiple testing

Despite the high-dimensional nature of metabolomics, only five of the selected studies controlled for multiple testing (16, 22, 23, 47, 52). Although the significant findings reported in these three studies were robust to such correction, many applied a nominal significance level of 0.05 regardless of the number of metabolites under investigation. There was additional possibility of false positives arising in those studies comparing multiple biologic media. Only four studies (16, 40, 50, 53) reported on the statistical power of their approach in the search for discriminatory metabolites.

Biologic samples

The media in which a biomarker can be reliably measured is of importance in the consideration of its forward translation. The tissue-based biomarkers would have no utility in predicting incident disease, and even for diagnostic or prognostic purposes, blood and urine can be obtained in a less invasive and more cost-effective fashion. Furthermore, tissue is a limited resource, and it may be prudent to preserve it for other uses including subsequent histopathologic analysis. Disease-associated metabolites tend to be more concentrated the closer in proximity they are to the organ of interest (30); however, only one study considered prostatic secretions (39), possibly due to challenges related to its collection. Interestingly, the use of tissue did not appear to confer any advantages over the other biologic specimens, with some of the strongest results reported in blood samples.

Discussion

Because widely used PSA testing remains somewhat controversial (36, 100, 101), additional biomarkers that could help refine practices would be a welcome addition to the management of prostate cancer. With the advancement of high-throughput technologies, metabolomics is emerging as a promising tool in biomarker development (9, 12, 69, 91, 102–106). Its downstream nature provides a holistic picture of the malignant state and consequently insight into dysregulated metabolic pathways and inherent disease development. The selected literature provides encouraging results in the field of prostate cancer; however, it also demonstrates the novel challenges faced by metabolomics, which are only just beginning to be addressed.

The metabolomics of prostate cancer remains a small field with the majority of studies focused on the identification of biomarkers to distinguish malignant and benign prostate tissue, with few studies investigating disease progression and treatment response. Only two studies to date have employed a prospective design to look for predictive biomarkers (22, 23). Therefore, important issues of cause and effect must be considered when evaluating the utility of the diagnostic biomarkers and the role of BPH as a disease continuum-intermediate may be particularly important in this respect.

The majority of the included studies reported distinct clustering by metabolome profiles, with differentiation status playing an important role in the determination of the profiles (32). In those studies which developed biomarkers with the potential for clinical translation, the reported AUCs associated with the biomarkers were high. In many cases these AUCs were higher than for PSA, suggesting these new biomarkers would outperform the current gold standard in many cases. This is in line with the generally accepted consensus that the metabolome represents a rich source for biomarker identification. However, replication, particularly between biologic media, and independent validation was lacking. Multiple testing was rarely accounted for, and the extent to which the reported findings may represent false positives is difficult to assess.

This was true even of one of the most commonly cited “metabolomics successes” sarcosine, and the importance of technical issues in metabolomics studies is perhaps best exemplified by the
debate over the potential use of this biomarker. Nevertheless a number of metabolites and pathways were repeatedly implicated by the studies with amino acid and lipid metabolism appearing to play a predominant role in carcinogenesis, progression, and recurrence. Caution must be taken to ensure such findings do not merely reflect the most abundant, easy to measure or stable metabolites, although encouragingly, a number of the studies indicate that the "metabolome" of prostate cancer is distinct from that of other malignancies.

These challenges inherent to metabolomics extend even beyond those facing researchers when they first tried to characterize the human genome, due to the additional temporal component as well as issues regarding the stability, variation, and plasticity of the metabolites (107). Therefore, collaboration between groups conducting metabolomics-based studies is vital, both in terms of standardizing the optimal methods and analytical strategies, to maximize reproducibility, reliability, and sen- sitivity and also for replication or the accrual of sufficient sample sizes for these highly dimensional studies (108).

Clinical translation remains the end goal, but a number of important factors remain to be considered before this is feasible for the current studies, including issues of bias, confounding, and generalizability. Beyond the efficacy of a biomarker, the feasibility of clinical translocation must also be considered. More than two decades since PSA testing was introduced no such biomarkers have been clinically approved (109). In fact it may be that the utility of the metabolites and metabolite profiles identified here lies not in their clinical usage but in the insights they provide into the mechanisms of carcinogenesis. For example McDunn and colleagues (16) postulated that there may be a variety of pathways that lead to the development and progression of prostate cancer, and therefore multiple metabolic models that are able to predict the outcome of interest in a certain subpopulations. The differing results and lack of replication in the included studies may support this theory.

In conclusion, the study of the metabolome of prostate cancer remains in the early phases, but could yet represent an important tool both in the understanding of prostate cancer development and progression, and in the development of biomarkers to aid its management.

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No potential conflicts of interest were disclosed.

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