Seminal plasma enables selection and monitoring of active surveillance candidates using nuclear magnetic resonance-based metabolomics: A preliminary investigation

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1. Introduction

Accurate prostate cancer (CaP) diagnosis to prolong life with minimal morbidity is a daily challenge for urologists. Although early treatment of localized clinically significant CaP (csCaP) with curative intent reduces mortality and metastases, harms associated with overtreatment and treatment of indolent CaP driven by injudicious use of serum prostate specific antigen (PSA) and prostate biopsy have reduced overall CaP detection. Limitations of serum PSA have driven advancements in multiparametric magnetic resonance imaging and biomarkers in serum (e.g., Prostate Health Index) and urine ([prostate cancer antigen 3 (PCA3), TMPRSS2:ERG fusion gene]).3–6 However, due to cost-effectiveness concerns, these are used as adjunctive tests rather than as standalone detection tests despite their improved diagnostic accuracy.5,6

Prostatic fluid, produced as seminal plasma (SP) after physiological prostatic smooth muscle contraction, contains the clinical biomarkers PSA and prostatic acid phosphatase (PAP).5,6 Malignant prostatic cells in ejaculates of men with CaP have been shown to express genes (PCA3, Hepsin) and microRNAs that improve detection compared with serum PSA.8,9–11 Metabolomics is a modern biomarker approach that quantifies small metabolites, most commonly using nuclear magnetic resonance (NMR) spectroscopy
or mass spectrometry. NMR-based metabolomics is highly sensitive and reproducible with affordable sample-to-sample costs. SP metabolite profiles improve PSA-based diagnosis, but require clinical validation.

This study investigates the feasibility of SP analysis using NMR-based metabolomics for the prediction of csCaP in a high-risk clinical cohort and compares metabolite profile CaP diagnosis against prostate biopsy and radical prostatectomy (RP) histology.

2. Materials and methods

Ethical approval was obtained from the University of Queensland Medical Research Ethics Committee (Project no. 2006000262) and the Royal Brisbane and Women’s Hospital Human Research Ethics Committee (HREC/09/QRBW/320, HREC/09/QRBW/305 and 1995/088B).

2.1. Patients and clinical data

Male patients (n = 154) attending either the Royal Brisbane and Women’s Hospital Urology outpatient department or local private consulting rooms for investigation of elevated PSA and/or abnormal digital rectal examination between January 2007 and February 2013 were enrolled in this prospective cohort study. Following informed consent, patients provided ejaculate specimens on site or at home prior to or at least 1 month after prostate biopsy, prior to commencement of any treatment. No specifications to time of day, relation to voiding, urethral meatus sterilization, or other parameters were provided to patients to simplify the sample collection process. Patients denied surgical treatment for benign prostatic hyperplasia and subsequent retrograde ejaculation prohibiting sample collection. Patient data collected included age, serum PSA and detailed cation. Patients were monitored for biopsy progression, such as CaP detection following initial false negative biopsy or upgraded Gleason score with further biopsy or RP (n = 60). Risk stratification (low, intermediate, high risk) was performed according to the D’Amico criteria recommended in the American Urological Association Guidelines and used to determine csCaP presence (intermediate, high risk requiring treatment; Table 1).

Table 1 Demographic information for patients based on biopsy and radical prostatectomy (RP) histology.

| Biopsy                          | n = 151 | Serum PSA (ng/mL) | Pathological stage, n |
|---------------------------------|---------|------------------|-----------------------|
| Overall                         | 61 (55–66) | 6.5 (4.3–9.2)   | pT2                   |
| CaP status                      | 60.5 (55–65) | 6.4 (4.5–11)     | pT3a                  |
| Positive (n = 98)               | 62 (55.75–68.25) | 6.5 (3.6–7.9) | pT3b                  |
| Negative (n = 53)               | 61 (55–66) | 6.75 (4.5–11.9) |                       |
| csCaP status                    | 61 (55–67) | 8.0 (3.6–8.1)   |                       |
| Present (n = 82)                | 3 (1–5) | 10 (6–12)       |                       |
| Absent (n = 69)                 | 19 (1–3) | 23 (7–3)        |                       |
| RP                              | 60 (55–68) | 10 (6–12)       |                       |
| Overall                         | 57 (54–64) | 6.15 (4.1–9.1) |                       |
| ISUP group                      | 56 (54–57) | 6.5 (4–9)       |                       |
| 1 (n = 2)                       | 57.5 (53–64) | 5.5 (4–7) |                       |
| 2 (n = 20)                      | 57 (55–61) | 7.3 (5–12)     |                       |
| 3 (n = 20)                      | 55      | 15              |                       |
| 4 (n = 1)                       | 50 (55–68) | 10 (6–12)      |                       |
| 5 (n = 7)                       | 57 (55–64) | 7.3 (5–12)     |                       |
| Primary/ tertiary pattern       | 57 (51–63) | 5.4 (4–7)       |                       |

Median and interquartile range are shown for age and serum PSA. All comparisons were made using the Mann–Whitney U test (two-tailed).
P < 0.05, **P < 0.01.
CaP, prostate cancer; csCaP, clinically significant prostate cancer; ISUP, International Society of Urological Pathology; NS, not significant; PSA, prostate specific antigen.
suppressed by continuous wave irradiation during the NOESY mixing time of 0.1 seconds and relaxation delay of 3.0 seconds. Tuning/matching, shimming, and data acquisition were performed automatically with the IconNMR interface for high-throughput automation. Samples were measured in one batch per sample collection buffer and ordered randomly within these batches.

2.5. Spectral processing

NMR spectra were processed in TopSpin 3.2 (Bruker Biospin). The free induction decays were baseline corrected by a Gaussian function (0.1 ppm filter width) for postacquisition water deconvolution, followed by multiplication with an exponential window function (0.1 Hz line broadening), and Fourier transformation to 65,536 points. Subsequently, the spectra were manually phased, manually baseline corrected with a cubic spline curve, and referenced to DSS at 0.0 ppm. For all further data manipulation, the spectra were truncated to \( d = 10.0 - 0.25 \) ppm, exported into MATLAB 2015b (The Mathworks Inc., Natick, Massachusetts, USA), and scaled according to the Bruker NC_proc parameter.

2.6. “Add-to-subtract” glucose exclusion

Preliminary analysis revealed glucose at sometimes dominant levels in most samples (Fig. 1). As HBSS contains 1 g/L D-glucose and ejaculate volumes were varied, the exogenous glucose concentration and its influence on subsequent multivariate statistical analysis (MWSA) was unpredictable. Thus, we used the “add-to-subtract” method\(^{20}\) to exclude glucose signals from the NMR spectra: (1) we added 1 \( \mu \)L of 1M D-glucose in PBS to each sample and repeated NMR measurement with identical experimental parameters, leading to a total of 302 spectra for 151 patients (151 original, 151 with additional glucose); (2) using Topspin’s multiple display, we determined the corresponding scaling factor between Spectrum 2 and Spectrum 1 for each sample that ensures elimination of the glucose signal upon subtraction; (3) then the exported Spectra 1 and 2 for each sample were aligned using “icoshift”\(^{21}\) on the glucose peaks at 3.37–3.44 ppm and then along 10 equal segments; and (4) for each sample Spectrum 2 was scaled with the scaling factor recorded in Topspin and subtracted from Spectrum 1. The resulting difference spectra were stored in a separate matrix.

2.7. Spectral alignment and data reduction

The peaks of all difference spectra were aligned at full resolution using “icoshift”, initially on the lactate doublet at 1.32 ppm and subsequently on manually defined segments. No shifting artefacts were identified. Using an in-house MATLAB script, the aligned difference spectra were data reduced to buckets of 0.01 ppm width over the range 10.0–5.08 ppm and 4.52–0.25 ppm, excluding the water signal region.

2.8. Multivariate statistical analysis

Metabolite data (X) matrices containing original and difference (add-to-subtract) data were quantile normalized with the “affy” package\(^{22}\) in R version 3.2.2\(^{22}\) and imported into SIMCA P+ 12.0 (Umetrics, Umeå, Sweden) for MWSA together with clinical data variables (Y-matrix). X-matrices were Pareto-scaled before unsupervised principal components analysis (PCA).\(^{24}\) To determine which metabolite signatures were associated with clinical data (cancer/risk status; Y-
matrix), supervised partial least squares (PLS) was performed. Multivariate model quality was judged by the \( R^2 \) ("goodness of fit") and \( Q^2 \) ("goodness of prediction") figures of merit (Table S1).

PLS models were validated by 200-fold response permutation. Traditional statistical analysis, including the nonparametric Mann–Whitney U test, logistic regression, and receiver operating characteristic analysis were performed in MedCalc 12.7 for Windows (MedCalc Software, Ostend, Belgium).

3. Results

3.1. Clinical cohort demographics

From 151 patients who provided SP samples, 80 were initially diagnosed with CaP and an additional 18 patients diagnosed during the follow-up period. Within these 98 patients, 82 met csCaP criteria. Sixty patients underwent RP for localized CaP in which 59 were determined to be high risk per the D’Amico criteria, with six upgraded from low risk. The Gleason grade subgroups according to International Society of Urological Pathology (ISUP) category with corresponding stage based on RP histology are presented in Table 1. Primary Gleason Pattern 4 or higher or tertiary Pattern 5 was present in 34 patients based on RP histology. The demographic information for each group (Table 1) demonstrated that serum PSA was higher in those with high D’Amico risk or who were ineligible for active surveillance. The remaining 38 patients received radiation based therapy \( (n = 17) \), androgen deprivation therapy for metastatic disease \( (n = 2) \) or embarking on conservative management (active surveillance, watchful waiting; \( n = 12 \)), although seven were lost to follow up.

3.2. Unsupervised multivariate statistical analysis

The SP samples were analyzed with \(^1\)H NMR spectroscopy. One-dimensional NOESY spectra were measured, aligned, and data reduced to 0.01 buckets. For initial PCA, buckets corresponding to ethanol, resulting from sample preparation, were excluded, as were spectra that were outliers due to broad resonances \( (n = 2) \). PCA yielded a model (Table S1 M1) with six principal components (PCs), in which samples clustered per the buffer solution used (PC1/PC2; Figs. 2A–2C), with higher glucose levels in samples prepared in HBSS. In higher PCs, sample variation was observed due to intersample differences of lipids/lipoproteins, phosphocholine, choline, and citrate, as well as spermine (data not shown), which were unrelated to CaP in this analysis.

The "add-to-subtract" method was used to remove glucose signals from NMR spectra. Following measurement of a "baseline spectrum" (Spectrum 1), glucose was added in high concentration to the sample in the same NMR tube and a second spectrum was measured (Spectrum 2). Spectrum 2 was subtracted from Spectrum 1 with an appropriate scaling factor to remove glucose signals but preserve signals of all other compounds in the resulting difference spectrum. The method assumes that introduction of the compound
of interest does not change sample conditions, preserving sample matrix, line shapes, and signal frequencies.

PCA of the difference spectra (Figs. 2D–2F, Table S1 M2) showed no sample grouping due to differences in buffer used (Fig. 2D). The predominant drivers of sample variation were lipids/lipoproteins (PC1), an inverse relationship between choline and phosphocholine as well as citrate. An association with csCaP was suggested by the presence of lipids/lipoproteins, although separation between clinical groups was not observed in any PC.

Given that the inverse relationship observed between phosphocholine and choline is due to PAP-mediated hydrolysis, a reaction which was not inhibited in these samples, choline-based metabolites (choline, phosphocholine, and glycerophosphocholine) were excluded to remove their effect of unbalanced regulation on the MVSA. However, subsequent PCA (Fig. 3, Table S1 M3) showed no obvious clustering, with most variation due to lipids/lipoproteins, citrate, and serine (Figs. 3A, 3B). Fructose and spermine were other significant sources of variation in PC3/PC4 (Figs. 3C, 3D).

3.3. **Supervised multivariate statistical analysis**

In the unsupervised PCAs, which determine sources of variation potentially independent of underlying biology, no sample clustering into clinical groups was seen, prompting the need for supervised MVSA. First, the presence of csCaP according to the D’Amico criteria based on biopsy was used as the predictive variable in PLS analysis (Fig. 4, Table S1 M4) and demonstrated lipids/lipoproteins to be associated with variation for csCaP, which were mostly limited high-risk patients. Furthermore, there was potential subgrouping among the D’Amico risk groups (Fig. 4B).

Based on these results and reports that maximal metabolite disturbances are observed in low- and intermediate-risk tumors, we analyzed with PLS a subgroup of 11 samples correlating to these grades confirmed by RP histology only (Figs. 5A–5C, Table S1 M5). The single low-risk sample was separated from the intermediate-risk samples due to reduced lactate, pyruvate and lipids/lipoproteins and increased citrate, myo-inositol, spermine and fructose (Figs. 5A, 5C). Within these low/intermediate-risk samples, separation was seen in accordance with primary Gleason Pattern 4, associated with higher levels of lipids/lipoproteins, lactate, and pyruvate as well as lower levels of citrate, spermine, and myo-inositol (Figs. 5B, 5C). These relationships were observed when classifiers based on all low/intermediate-risk patients, determined by biopsy or RP, were performed (Figs. 5D, 5E; Table S1 M6). When benign samples were considered with risk group combinations and Primary Gleason Pattern 4 presence, minimal separation was observed and models were weak/nonpredictive (Fig. S1, Table S1 M7–M10).

![Fig. 3. Principal components analysis after exclusion of choline containing metabolites demonstrated that lipids/lipoproteins, citrate, and serine were influential metabolites (A, B) as well as fructose and spermine (C, D). No clustering was present according to CaP status (blue squares – benign; red triangles – CaP). (A, C) Scores plots. (B, D) Loadings plots. CaP, prostate cancer; Cit, citrate; Fru, fructose; Lip, lipids/lipoproteins; PC, principal component; Ser, serine; Spe, spermine.](image-url)
Analysis of only the samples collected in PBS, unaffected by any external glucose (Fig. S2, Table S1 M11–17), showed similar relationships to those seen for the full cohort. Specifically, valid models were obtained for separation between low- and intermediate-risk samples (M12, Figs. S2C, S2D; limited by sample size) and low-risk and benign samples (M13, Figs. S2E, S2F). Findings were confirmed with PCA (M15–17, Fig. S3) and driven by lactate levels (Fig. S4). The presence of the TMPRSS2:ERG fusion gene, detected in the epithelial cell fraction of SP, used as Y variable was weakly but nonpredictively associated with lipid/macromolecule resonances (Fig. S5, Table S1M18).

3.4. Targeted metabolite profiling

SP metabolite quantification with subsequent logistic regression showed that citrate or myo-inositol were not significant predictors...
of CaP status (Table 2). Significant metabolites for CaP status (choline, leucine) and cCaP (leucine, valine) did not significantly improve diagnosis compared with serum PSA metabolite predictability.

4. Discussion

In this paper, we present the largest validation study of SP-based metabolite prediction of CaP using high resolution NMR spectroscopy, having analyzed SP metabolite profiles from 151 men being investigated for CaP. Undue influence of exogenous glucose contained in the HBSS buffer used for RNA analyses was successfully excluded by applying add-to-subtract and revealed inherent variation due to enzyme-dependent changes in choline-based metabolites. SP metabolites best predicted low- and intermediate-risk CaP with differences observed between these groups and benign and high-risk samples. Metabolites previously reported to determine CaP, such as citrate, spermine, and myo-inositol, showed minimal predictive ability in this clinically applicable cohort. These findings were confirmed with targeted metabolite quantification.

Well described prostatic metabolite changes due to CaP, specifically reduced citrate and polyamines (e.g., myo-inositol, spermine) and increased intracellular lactate, choline, and creatine, were not predictive in this study due to the following underlying clinical and biological factors. Clinically, the study population presented here contains patients suspected of harboring CaP, encountered in daily urological practice (Table 1). In earlier reports where SP metabolites significantly improved CaP detection, CaP-positive samples were compared with healthy controls or men unlikely to have CaP, suggested by marked discrepancies in serum PSA between groups. Our population contained heterogeneous disease stages, inclusive of all tumor grades with predominance toward high-risk CaP. Although group separation was observed between CaP risk groups (Fig. 5, Figs. S2, S3), we could not truly exclude CaP in patients with a negative biopsy due to limitations in biopsy-based CaP detection and known metabolic changes in early tumorigenesis, which may lead to confounding overlap between groups and invalid statistical models. To exclude uncertainty among the control group, a subanalysis of the presence or absence of Gleason Pattern 4 on RP histology showed overlap of groups (M10, Figs. S1G, S1H), likely owing to reduced metabolite influence in poorly differentiated tumors. Similarly, limitations of biopsy-based risk stratification given known upstaging at RP in up to 40% of patients may confound the accuracy of risk subgroup analyses.

When analyses based only on RP-based diagnosis were expanded to include biopsy-based diagnosis to increase sample size, sample grouping was less obvious despite similar metabolite patterns being observed in the loadings plot (Fig. 5). Thus, a larger low-intermediate-risk RP cohort would be expected to accurately “upclassify” (upstage) low-risk samples with metabolite patterns similar to intermediate-/high-risk samples, as shown elsewhere.

Biologically, gene expression and metabolite alterations occur early in tumorigenesis and are more pronounced in lower grade (Gleason ≤ 7) compared with higher grade (Gleason > 8) tumors.

Table 2

| Metabolite | Mean (± SE) (mM) | Logistic regression (log base 10) | ROC analysis |
|------------|-----------------|---------------------------------|--------------|
|            | P               | Coefficient | SE   | AUC | Std. Error |
| Prostate cancer status | | | | | |
| Alanine | 0.1734 (0.0208) | 0.7998 | 0.5211 | 2.0552 | 0.555 | 0.0498 |
| Choline | 1.3326 (0.1392) | 0.0291 | 2.0211 | 0.9263 | 0.556 | 0.0495 |
| Citrate | 2.9243 (0.2643) | 0.1490 | −1.2433 | 0.8616 | 0.542 | 0.0490 |
| Creatine | 0.1156 (0.0114) | 0.8786 | -0.1850 | 1.2113 | 0.565 | 0.0492 |
| Fructose | 1.0591 (0.1004) | 0.9631 | -0.0413 | 0.8938 | 0.603 | 0.0510 |
| Glucose | 3.2694 (0.2118) | 0.9144 | -0.0262 | 0.2439 | 0.629 | 0.0487 |
| Glutamine | 0.5802 (0.0604) | 0.8559 | -0.3076 | 1.6943 | 0.541 | 0.0509 |
| Glycerophosphocholine | 0.2259 (0.0236) | 0.9951 | -1.0546 | 0.6318 | 0.603 | 0.0483 |
| Lactate | 0.8520 (0.0645) | 0.5879 | -0.5962 | 1.1003 | 0.579 | 0.0484 |
| Leucine | 0.4067 (0.0416) | 0.5724 | -0.1325 | 0.6774 | 0.572 | 0.0499 |
| Myo-inositol | 0.3251 (0.0238) | 0.9287 | -0.1095 | 1.2238 | 0.592 | 0.0472 |
| Phosphocholine | 0.1810 (0.0459) | 0.1042 | 0.6905 | 0.4250 | 0.543 | 0.0499 |
| Serum PSA | 8.0867 (0.6075)* | 0.0601 | 1.5605 | 0.8299 | 0.593 | 0.0472 |
| Pyruvate | 0.3709 (0.0373) | 0.9736 | -0.0286 | 0.8672 | 0.546 | 0.0493 |
| Uridine | 0.1793 (0.0167) | 0.7146 | 0.1528 | 0.4180 | 0.568 | 0.0495 |
| Valine | 0.3206 (0.0392) | 0.1095 | 1.2238 | 0.6868 | 0.534 | 0.0503 |

| Clinically significant prostate cancer | | | | | |
| Alanine | 0.1734 (0.0208) | 0.1629 | -2.2913 | 1.6421 | 0.592 | 0.0466 |
| Choline | 1.3326 (0.1392) | 0.1595 | 1.1536 | 0.8200 | 0.584 | 0.0467 |
| Citrate | 2.9243 (0.2643) | 0.1147 | -1.4430 | 0.9147 | 0.580 | 0.0466 |
| Creatine | 0.1156 (0.0114) | 0.8808 | -0.1703 | 1.1364 | 0.603 | 0.0465 |
| Fructose | 1.0591 (0.1004) | 0.5227 | -0.5368 | 0.8397 | 0.611 | 0.0470 |
| Glucose | 3.2694 (0.2118) | 0.3728 | 0.1970 | 0.2211 | 0.584 | 0.0475 |
| Glutamine | 0.5802 (0.0604) | 0.4141 | 1.1168 | 1.3674 | 0.572 | 0.0473 |
| Glycerophosphocholine | 0.2259 (0.0236) | 0.4243 | -0.4494 | 0.5624 | 0.599 | 0.0463 |
| Lactate | 0.8520 (0.0645) | 0.8719 | -0.1301 | 0.9313 | 0.582 | 0.0467 |
| Leucine | 0.4067 (0.0416) | 0.0025 | -9.2502 | 3.0562 | 0.597 | 0.0466 |
| Myo-inositol | 0.3251 (0.0238) | 0.4242 | 0.9335 | 1.1681 | 0.609 | 0.0459 |
| Phosphocholine | 0.1810 (0.0459) | 0.2600 | 0.4343 | 0.3856 | 0.506 | 0.0477 |
| Serum PSA | 8.0867 (0.6075)* | 0.0228 | 1.7942 | 0.7880 | 0.617 | 0.0456 |
| Pyruvate | 0.3709 (0.0373) | 0.6820 | -0.3377 | 0.8146 | 0.569 | 0.0472 |
| Uridine | 0.1793 (0.0167) | 0.2795 | 0.4318 | 0.3993 | 0.568 | 0.0473 |
| Valine | 0.3206 (0.0392) | 0.0030 | 9.7952 | 3.2968 | 0.571 | 0.0471 |

Among 151 patients, CaP status (positive 98, negative 53) and D'Amico risk (high = 82, low = 69) were used as dependent variables for logistic regression analysis (P to enter 0.05, P to exclude >0.1). AUC, area under the curve; CaP, prostate cancer; PSA, prostate specific antigen; ROC, receiver operating characteristic; SE, standard error. Bold indicate P < 0.05.

* Serum PSA determined using immunoassay, units ng/mL.
supported by our analysis of low- and intermediate-risk patients (Fig. 5, Figs. S2, S3). In addition to direct metabolic changes, the inverse relationship between lactate and fructose resulting in group separation between low- and intermediate-risk and benign samples may indicate disturbed SP homeostasis of anions (zinc) or enzymes (PSA, PAP) known to improve sperm function, resulting in impaired sperm glycolysis. Indeed, poor discrimination of metabolite profiles from high-risk tumors was demonstrated here and in other studies, likely due to accumulated genetic alterations with disease progression. Thus, patients with lower grade tumors may be amenable to SP-mediated in vitro or magnetic resonance spectroscopic imaging (MRSI)-mediated in vivo assessment or monitoring as a potential substitute for repeat biopsy in active surveillance.

Altered metabolite homeostasis correlates with increased fatty acid synthesis, due to or in association with TMPRSS2:ERG fusion gene translocation associated with aggressive CaP, may account for the overwhelming influence of lipids/lipoproteins in high-risk patients in this study, similar to that reported by others. Higher grade tumors overexpress the oncogene MYC, which is associated with dysregulated lipid metabolism and display altered cholesterol metabolism to increase energy storage. Upregulated lipid substrates have been described between normal, focalized, and metastatic prostatic cells, with choline kinase implicated in de novo lipogenesis in aggressive metastatic cells. Systemically, lipid and energy metabolites in semen have been strongly associated with aggressive CaP and may improve CaP detection.

This study was an opportunistic analysis of SP samples collected initially for cytology and subsequently epithelial cell RNA analyses. The exogenous glucose contained in the HBSS required significant correction using add-to-subtract, which did not introduce further influence into the MVSA. Subsequently, the uninhibited changes in choline-based metabolites showed significant influence in the preliminary MVSA. These metabolite peaks were excluded because PAP-catalyzed hydrolysis of phosphocholine to choline is a rapid, endogenous reaction to enhance spermatozoal function and protection. Variations in time from sample production to processing, despite most being done within 2 hours, are likely to cause significant variation among these metabolites independent of underlying CaP due to the unknown degree of reaction completion. Given the postulated role of choline in tumor progression, as indicated by elevated in vivo levels, reliable quantification of choline-based metabolites in SP is desired. Thus, a sample collection/storage protocol should be implemented that limits the PAP reaction to 2–3% progression, such as our recommendation that ejaculate samples be collected in a sterile urine jar containing 5mM tartrate in 20 mL PBS solution cooled to 4°C. Although malignant prostatic metabolite contribution to SP, considering concurrent contributions from multiple organs and resulting proteolysis, may intuitively be minimal or diluted, our findings are similar to those seen in tissue extracts and in vivo, likely to be enhanced by spectral acquisition at 900 MHz. Although prostateitis is known to reduce prostatic citrate and zinc content and potentially affect MVSA, this influence in the current study would be minimal due to the focus on RP-based and malignant pathology, as well as only being confirmed histologically for two patients.

In conclusion, metabolomics of seminal plasma in vitro may assist diagnosis and monitoring of either low or intermediate grade prostate cancer. Lipids/lipoproteins dominated spectra of high grade samples with fewer contributions from other metabolites. As a validating study, we were unable to replicate previous performance of SP-based metabolic prediction of CaP in 151 men being investigated for CaP. Dedicated metabolomics protocols ideally in serial collections may maximize information recovery. The value of metabolomics analysis of SP for CaP currently appears to be in active surveillance of low- or intermediate-grade tumors suspicious of understaging, in which in vivo correlation with MRSI and monitoring in vitro with SP or in vivo with MRSI may further clinical practice.

Conflicts of interest

All authors have no conflicts of interest to declare.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.prnil.2017.03.005.

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